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Original Research Paper

Using random-parameter and fixed-parameter ordered models to explore temporal stability in factors affecting drivers' injury severity in single-vehicle collisions

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HIGHLIGHTS

- An ordinal regression model was developed for each analysis year.
- Temporal stability of the factors affecting drivers' injury severity was evaluated.
- Several factors were found to be temporally unstable.
- Some factors were previously thought to increase injury severity.
- Unstable factors include seatbelt use, driver gender, undivided and rural highways.

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ABSTRACT

Understanding the temporal stability in the factors influencing drivers' injury severity in single-vehicle collisions would help evaluating the effectiveness of implementing different safety treatments so that researchers could understand whether any safety improvements, observed after applying a certain safety treatment, are attributed to the specific treatment or simply attributed to the temporal instability of the factors being addressed. This study investigates the temporal stability of the factors affecting drivers' injury severity in single-vehicle collisions involving light-duty vehicles. The study is based on utilizing ordinal regression modeling to analyze the severity of drivers' injuries in all police-reported light-duty single-vehicle collisions that occurred in North Carolina from January 1, 2007, to December 31, 2013. A separate regression model was estimated for each year so that statistical significance of each risk factor may be compared over the years. The study also estimated random-parameter (mixed) ordered logit models to explore the heterogeneity in data. The most significant factor that was found to increase the severity of drivers' injuries in light-duty single-vehicle collisions is driving under the influence of alcohol or illicit drugs. Other significant factors, in decreasing order in terms of their significance, include driving on a highway curve, exceeding speed limit, lighting conditions, the age of the driver, and the age of the vehicle. In contrast, there were six factors that were found to be significant in only some years and not in all years. These six temporally unstable factors include the use of seatbelt, driver's gender, rural highways, undivided highways, the type of the light-duty vehicle, and weather and road surface conditions. These same factors

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were found by other previous research studies to be significant and stable predictors of drivers' injury severity in single-vehicle collisions.

1. Introduction

Single-vehicle collisions are those involving a single vehicle without involvement of any other vehicles or pedestrians (American Association of State Highway and Transportation Officials, 2010; Council et al., 2006; Huang et al., 2001). Single-vehicle collisions include running off-road, rollover, and colliding with fixed objects (American Association of State Highway and Transportation Officials, 2010). Single-vehicle collisions constitute the largest proportion of fatal collisions in the United States. According to the US National Highway Traffic Safety Administration (NHTSA, 2018a), 59.6% of fatal collisions in 2014 are single-vehicle collisions. Previously, single-vehicle collisions accounted for 60.1%, 60.7%, and 60.5% in years 2013, 2012, and 2011, respectively. The analysis of single-vehicle collisions helps scholars gain valuable insights regarding the behavior of individual drivers involved in those collisions. This contrasts with analyzing a multi-vehicle collision where a collision may result from the interactive actions taken by more than one drivers thus preventing one from determining the degree of culpability for individual drivers.

Numerous studies in the past have attempted to identify the factors that increase injury severity in a single-vehicle collision. For instance, Wu et al. (2016) analyzed the severity of drivers' injuries in single-vehicle collisions on rural and urban roads in New Mexico for years 2010 and 2011. The authors used nested and mixed logit models to analyze crash records and found that injury severity was higher for female drivers and those under the influence of alcohol. They also found that rollover collisions and colliding with fixed objects usually lead to more severe collisions. On the other hand, they found that injury severity was lower for collisions during inclement weather and during peak hours on urban roads. An interesting finding in that study was that injury severity of single-vehicle collisions involving pickup trucks was less than that involving other types of vehicles. The last observation about pickup trucks contradicts the findings in other studies (Dabbour, 2017a, b; Friedman and Grzebieta, 2009; McLean et al., 2005) that found single-vehicle collisions involving pickup trucks to be more severe than those involving passenger cars due to the higher location of the center of gravity as well as the higher height-to-width ratio of pickup trucks.

Russo et al. (2014a) used generalized estimating equation (GEE) with a negative binomial distribution and additional log linkage equation to develop models that estimate the frequency and severity of different types of collisions, including single-vehicle collisions, based on data collected from approximately 600 km of two-lane rural roads in southern Italy. All the roads had low-volume conditions with annual average daily traffic (AADT) volume less than 1000 vehicles per day. The data collected over a period of eight years from 2003 to 2010. An innovative approach in this research is dividing the data into two different subsets where the first subset (data for years 2003–2007) was used to calibrate the models, and the remaining subset (data for years 2008–2010) was used to validate the calibrated models. An injury crash rate prediction model was developed to predict the number of injury crashes per year per kilometer for every 108 vehicles (crash frequency over traffic exposure) that is differentiable for three specific crash types identified on the studied two-lane rural roads (head-on/side collision, rear-end collision, and single-vehicle collision). They found that injury severity typically increases when the road surface is wet, in darkness conditions, and when the roadway segment is curved. They also found that injury severity increases with the increase of the mean speed on the roadway and decreases with the increase of the roadway width.

Lee and Li (2014) used heteroscedastic ordered logit modeling to analyze injury severity for drivers involved in single-vehicle and two-vehicle collisions. They analyzed collisions on provincial highways in Ontario, Canada, for the years from 2004 to 2008. They found that drivers' injury severity in single-vehicle collisions usually increases on curved segments of roads. They also found that injury severity is higher for female drivers and young drivers below the age of 30 years. Besides, they found that injury severity usually decreases on roads with large number of lanes as well as for modern vehicles with advanced safety features. They also found that motorcycle drivers were less likely to be involved in severe single-vehicle collisions. Though the last finding contradicted the results from earlier research (Chang and Yeh, 2006; Savolainen and Mannering, 2007; Yau, 2004).

Using logistic regression, Chang and Yeh (2006) evaluated factors that increased the odds of fatalities in single-vehicle collisions related to motorcycles and other light-duty vehicles by analyzing all fatal collisions that occurred in Taiwan in year 2000. Islam and Mannering (2006) investigated the effect of drivers' age on injury severity in single-vehicle collisions involving passenger cars by analyzing police reports from Indiana in the year 1999. Yau (2004) used logistic regression to identify risk factors that increased injury severity related to single-vehicle traffic collisions using data collected from collisions in Hong Kong during 1999 and 2000. Renski et al. (1999) investigated the effect of speed limit increases on the severity of single-vehicle collisions on North Carolina interstate highways by comparing the severity of collisions one year before the increase in speed limit with the severity of collisions one year after the increase in speed limit. Öström and Eriksson (1993) investigated the effect of alcohol consumption on the severity of single-vehicle collisions in northern Sweden by comparing data related to multi-vehicle collisions with data related to single-vehicle collisions for the years 1980–1989.

Most studies investigating the factors related to drivers' injury severity in single-vehicle collisions were based on pooled data from several years into a single dataset for analysis. Aggregating data from several years into a single file carries the risk of introducing aggregation bias in the analysis. It could be true that a factor might be a significant predictor in the pooled dataset but the same factor may fail to return a statistically significant effect in the year-wise dataset. Thus determining the temporal stability of the factors affecting drivers' injury severity in single-vehicle collisions is critical.

Dabbour (2017b) investigated the temporal stability of the factors affecting the severity of single-vehicle collisions by using logistic regression to analyze all single-vehicle collisions that occurred in North Carolina from 2007 to 2013. It was found that the more severe drivers' injuries were consistently associated with undivided and rural roads, darkness conditions, favorable weather conditions, and male and impaired drivers. Older vehicles and light-duty trucks were also found to be associated with more-severe drivers' injuries. It must be noted that logistic-regression method used in that study allowed for the outcome variable to be binary so that injury severity was coded to be either severe or not severe without investigating more ordinal outcomes.

Behnood and Mannering (2015) used mixed-logit models to explore the temporal stability of the factors affecting the severity of drivers' injuries in single-vehicle collisions using collision data from Chicago, Illinois, for the years 2004–2012. They found that most factors were temporally unstable, which they attributed to the ongoing improvements in vehicles' safety features and drivers' response to those improved safety features. Because the authors used collisions data from Chicago, their findings might not apply to rural areas where the majority of severe single-vehicle collisions occur (Islam et al., 2014; NHTSA, 2018a; Wu et al., 2016). A similar study by Xiong et al. (2014) also investigated the temporal stability of the factors affecting drivers' injury severity of single-vehicle collisions by using Markov switching random parameters structure to analyze police-reported crash data from Indiana over a five-year period starting in 1995. They also found evidence for temporal instability and attributed temporal instability to the changes in average annual daily traffic, international roughness index, and rut depth.

Table 1 summarizes selected key research studies that are discussed above. The present study contributes to the growing literature investigating the temporal stability of the factors affecting the severity of drivers' injuries in single-vehicle collisions involving light-duty vehicles. This paper applies random-parameter (mixed) and fixed-parameter ordinal models to analyze light-duty single-vehicle collisions that occurred in North Carolina from January 1, 2007 to December 31, 2013. The study used the logit link function in mixed models. For fixed-parameter models, three link functions (probit, logit, and negative log–log) were used (Noruses, 2012). A separate model for each analysis year was estimated in addition to an overall model where the data was pooled from all years into a large dataset.

This paper is organized as follows. The next section describes data and the empirical specifications of the fixed and random parameter ordinal regressions. Afterwards, the paper presents a detailed discussion of the results obtained from fixed and random parameter models. Lastly, the paper offers concluding remarks to highlight the contributions and policy relevance of the findings.

2. Data

Data for all light-duty single-vehicle collisions that occurred in North Carolina from January 1, 2007 to December 31, 2013 were obtained from the Highway Safety Information System, which is managed by the University of North Carolina Highway Safety Research Center under a contract with the Federal Highway Administration (FHWA, 2017). The dataset used for the research is based on collision data collected statewide by all police departments in North Carolina on a standard form as prescribed by state law. The threshold of reporting collisions is personal injury or $1000 property damage. For each analysis year, the following two data files provided the collision details.

(a) The accident file includes information about the collision including, for instance, date, hour, weather conditions, speed limit and roadway characteristics at the collision location, and the number of vehicles involved.
(b) The vehicle file includes information about each vehicle involved in the collision including, for instance, vehicle make and year, number of occupants, estimated travel speed at the time of the collision, driver's age and gender, if the driver was impaired, and whether seatbelts were properly used.

Since the focus of this research is on single-vehicle collisions, every record in the accidents file was associated with only one record in the vehicle file. Records from both files (for each analysis year) were merged into one dataset using the case number to link the records together from both data files. Since substantial characteristic differences exist between light-duty vehicles and others vehicle types (including heavy vehicles and two-wheel vehicles), this research focuses only on single-vehicle collisions involving light-duty vehicles. Light duty vehicles may include passenger cars, pickup trucks, panel trucks, mini-vans, vans, and sports-utility vehicles. Afterwards, each single-vehicle collision was classified into one of the following five severity levels related to driver's injury:

(a) Level 1: no injury (corresponding to level “O” in the Highway Safety Manual).
(b) Level 2: possible injury (corresponding to level “C” in the Highway Safety Manual).
(c) Level 3: evident non-disabling injury (corresponding to level “B” in the Highway Safety Manual).

Table 1 – Selected key research studies related to the severity of drivers' injuries in single-vehicle collisions.

Research study	Data location	Data period	Methodology	Key findings
Wu et al. (2016)	New Mexico (USA)	2010–2011	Nested and mixed logit models	(a) Injury severity was higher for female drivers and those under the influence of alcohol. (b) Rollover collisions and colliding with fixed objects usually lead to more severe collisions. (c) Injury severity was lower for collisions during inclement weather and during peak hours on urban roads. (d) Injury severity of single-vehicle collisions involving pickup trucks was less than that involving other types of vehicles.
Russo et al. (2014a)	Southern Italy	2003–2010	Generalized estimating equation (GEE)	(a) Injury severity typically increases when the road surface is wet, in darkness conditions, and when the roadway segment is curved. (b) Injury severity also increases with the increase of the mean speed on the roadway. (c) Injury severity decreases with the increase of the roadway width.
Lee and Li (2014)	Ontario (Canada)	2004–2008	Heteroscedastic ordered logit modeling	(a) Injury severity increases on curved segments of roads. (b) Injury severity is higher for female drivers and young drivers below the age of 30 years. (c) Injury severity decreases on roads with large number of lanes as well as for modern vehicles with advanced safety features. (d) Motorcycle drivers were less likely to be involved in severe single-vehicle collisions.
Dabbour (2017b)	North Carolina (USA)	2007–2013	Logistic regression	(a) Temporal stability was investigated. (b) More severe drivers' injuries were consistently associated with undivided and rural roads, darkness conditions, favorable weather conditions, and male and impaired drivers. (c) Older vehicles and light-duty trucks were also found to be associated with more-severe drivers' injuries.
Behnood and Mannering (2015)	Chicago, Illinois (USA)	2004–2012	Mixed-logit modeling	(a) Most factors were temporally unstable. (b) The temporal instability was attributed to the ongoing improvements in vehicles' safety features and drivers' response to those improved safety features.
Xiong et al. (2014)	Indiana (USA)	1995–1999	Markov switching random parameters structure	(a) Most factors were temporally unstable. (b) The temporal instability was attributed to the changes in average annual daily traffic, international roughness index, and rut depth.

(d) Level 4: disabling injury (corresponding to level "A" in the Highway Safety Manual).
(e) Level 5: fatal injury resulting in death within 30 days of the collision (corresponding to level "K" in the Highway Safety Manual).

The letters between parenthesis are the corresponding levels of injury severity as defined by the Highway Safety Manual (American Association of State Highway and Transportation Officials, 2010). It must be noted that the severity levels reported in the original dataset were actually in descending order (with level 1 corresponding to fatal injuries and level 5 corresponding to no injury) (Council et al., 2006; Huang et al., 2001). However, for the purpose of this research, the order has been reversed to conform to the requirements for ordered regressions and for the ease of interpreting the estimated coefficients so that a positive coefficient indicates that the risk factor associated with it increase the severity of driver's injury, and vice versa. Incomplete and irrelevant records (accounting for less than 0.68% of records) were excluded. The frequency and percentage of collisions with different injury severity levels for each year are presented in Table 2.

3. Methodology

Injury severity is an ordinal variable. Traditionally, ordinal regression models are used to account for the ordered structure of such as dependent variable. Ordinal regression models have been frequently used in the past to analyze injury severity in different types of traffic collisions (Hao and Daniel, 2014; Hao et al., 2016; Lee and Li, 2014; McCollister and Pflaum, 2007). An ordinal regression model fits both a coefficient vector and a set of thresholds to a dataset. The dataset analyzed in this research comprise a set of observations with explanatory variable vectors $(X_1, X_2, \cdots, X_i, \cdots, X_n)$ that are associated with outcome response variable $(y_1, y_2, \cdots, y_i, \cdots, y_n)$ where each y_i is an ordinal variable on a scale $(1, 2, \cdots, j, \cdots, K)$. For each observation with explanatory variable vector X_i, ordinal regression may be used to find a set of coefficient vectors, β_i, and a set of thresholds $(k_{1i}, k_{2i}, \cdots, k_{ji}, \cdots, k_{Ki-1})$ with the property that $(k_{1i} < k_{2i} < \cdots < k_{ji} < \cdots < k_{Ki-1})$. This set of thresholds divides the real number line into K disjoint segments, corresponding to the K response levels. Based on that, an ordinal regression model takes the form $[P(y_i \le j|X_i) = \sigma(k_j - \beta_i X_i)]$ (Aitcheson and Silvey, 1957; McElvey and Zavoina, 1975 ; Noruses, 2012). Therefore, the cumulative probability of the outcome variable, y_i, being at most j is given by a function σ (the inverse of the link function) applied to the linear function of X_i. Three different link functions were used in this research, namely probit, logit and negative log–log. Probit link function has been used in numerous studies related to drivers' injury severity (Abdel-Aty, 2003; Gray et al., 2008; Haleem and Abdel-Aty, 2010; Hao and Daniel, 2014; Hao et al., 2016). The probit link function is the quantile function associated with the standard normal distribution, which takes the form $\Phi^{-1}(P)$. Logit link function takes the form $\log(P/(1-P))$. Lastly, the negative log–log link function takes the form $[-\ln(-\ln(P))]$. The latter function has been found to be more suited for the current dataset where lower severity levels are far more frequent than higher ones (Noruses, 2012).

In addition to the fixed-parameter models, this paper also estimates the random-parameter version of the ordinal logit models to account for the heterogeneity in data. A fixed parameter model returns only a mean value of the estimated coefficient. A random parameter model instead reports a mean and a standard deviation of the estimated parameter to account for the individual-level heterogeneity in data. The model assumes the random parameter to follow a statistical distribution. Simulated maximum likelihood techniques are used to estimate the parameters associated with random-parameter models (Train, 2009). A detailed review of simulated maximum likelihood estimation of ordinal regression models may be found in other literature (Sarrias, 2016).

4. Results and discussions

The following risk factors (explanatory variables) were investigated using all the three link functions:

(a) Roadway-related factors: including the presence of a physical median, speed limit on the roadway, whether the collision occurred on a straight or curved segment of the roadway, and whether the roadway is in an urban or a rural area;

Table 2 – Frequency (and percentage) of drivers' injuries resulted from single-vehicle collisions.

Year	Severity Level					Total Collisions
	No Injury (1)	Possible (2)	Evident (3)	Disabling (4)	Fatal (5)	
2007	33,225 (72.5%)	7215 (15.7%)	4458 (9.7%)	573 (1.2%)	379 (0.8%)	45,850 (100%)
2008	35,044 (74.8%)	6759 (14.4%)	4177 (8.9%)	499 (1.1%)	348 (0.7%)	46,827 (100%)
2009	38,942 (76.4%)	7181 (14.1%)	4133 (8.1%)	431 (0.8%)	315 (0.6%)	51,002 (100%)
2010	43,782 (78.3%)	7282 (13.0%)	4134 (7.4%)	417 (0.7%)	281 (0.5%)	55,896 (100%)
2011	40,121 (78.0%)	6673 (13.0%)	3917 (7.6%)	432 (0.8%)	284 (0.6%)	51,427 (100%)
2012	39,693 (77.7%)	6776 (13.3%)	3889 (7.6%)	415 (0.8%)	298 (0.6%)	51,071 (100%)
2013	41,683 (78.6%)	6801 (12.8%)	3852 (7.3%)	375 (0.7%)	298 (0.6%)	53,009 (100%)
Overall	272,490 (76.7%)	48,687 (13.7%)	28,560 (8.0%)	3142 (0.9%)	2203 (0.6%)	355,082 (100%)

(b) Vehicle-related factors: including vehicle age, travel speed, and the type of the light-duty vehicle;
(c) Driver-related factors: including age, gender, being impaired, and the use of seatbelt;
(d) Lighting condition factors: whether the collision occurred during day time or night time, and whether the roadway was illuminated during night time.
(e) Environmental-related factors: including the season of the year, the weather, and the road surface conditions.

From the above factors, only the ones that exhibited a statistically significant correlation with drivers' injury severity are reported in the final ordinal regression models. Table 3 shows the model fitting statistics including the pseudo R-square variates as were specified by Cox and Snell (1989), Nagelkerke (1991), and McFadden (1974). The reported models returned significant Chi-square statistics indicating that the final models provide significant statistical improvement when compared to their respective intercept-only models.

The final models using the three link functions are shown in Tables 4–6 for the probit, logit, and negative log–log link functions respectively. The results shown in Tables 4 and 5 for the probit and logit link functions yielded similar significant factors, for respective years albeit with differences in significance levels. This trend was previously observed by other researchers (Abdel-Aty, 2003; Haleem and Abdel-Aty, 2010). However, the significant factors identified using the negative log–log link function, as shown in Table 6, are different from those identified using the probit and logit link functions shown in Tables 4 and 5, respectively. Tables 4–6 also show the estimated threshold values where k_1 is the threshold between injury severity levels 1 and 2; k_2 is the threshold between injury severity levels 2 and 3; k_3 is the threshold between injury severity levels 3 and 4; and k_4 is the threshold between injury severity levels 4 and 5. All the factors shown in Tables 4–6 are significant at 0.05 significance level. A missing value from the tables, denoted with a dash "–" indicates that the corresponding factor was not found to be significant at 0.05 significance level.

Several prior research studies (Biancardo et al., 2017) provided validation procedures for the developed models by conducting residual analysis to identify any jumps in the differences between estimated and observed values. Those jumps may indicate lack of flexibility in the models. However, the models developed in this research are ordinal discrete models that predict the level of injury severity with five discrete values that are either "no injury", "possible injury", "evident non-disabling injury", "disabling injury", or "fatal injury". Therefore, it is not possible to perform residual analysis for the developed ordinal models due to their discrete nature. However, after removing the continuous explanatory variable (vehicle age) from the developed models, it was possible to compare observed and expected counts and calculate Pearson's Chi-square test

Table 3 – Model fitting, goodness-of-fit and Pseudo R-square information of the final models.

Link function	Year	Chi-square	Degree of freedom	Pseudo R-square			Pearson's goodness-of-fit	
				Cox & Snell[a]	Nagelkerke[b]	McFadden[c]	Chi-square	Significance
Probit	2007	8525.768	13	0.170	0.208	0.110	23.561	0.023
	2008	7697.042	14	0.152	0.190	0.103	25.542	0.020
	2009	7143.594	11	0.131	0.168	0.092	27.625	0.003
	2010	7839.686	10	0.131	0.172	0.098	25.328	0.003
	2011	6679.511	11	0.122	0.159	0.090	31.638	0.000
	2012	6300.039	11	0.116	0.151	0.085	34.781	0.000
	2013	5926.293	10	0.106	0.140	0.079	37.328	0.000
	Overall	45,013.271	14	0.119	0.153	0.084	28.364	0.008
Logit	2007	8369.121	13	0.167	0.205	0.108	24.632	0.017
	2008	7521.108	14	0.148	0.185	0.101	28.287	0.008
	2009	6872.877	11	0.126	0.162	0.089	34.227	0.000
	2010	7584.970	10	0.127	0.167	0.095	31.231	0.000
	2011	6592.708	11	0.120	0.157	0.089	33.327	0.000
	2012	6168.438	11	0.114	0.148	0.083	38.639	0.000
	2013	5797.061	10	0.104	0.137	0.077	41.293	0.000
	Overall	44,251.286	14	0.117	0.151	0.083	32.328	0.002
Negative log–log	2007	7690.104	13	0.254	0.289	0.219	16.615	0.165
	2008	6905.162	14	0.237	0.272	0.193	17.928	0.160
	2009	6317.187	12	0.217	0.249	0.182	18.122	0.079
	2010	7043.236	11	0.218	0.256	0.188	18.029	0.054
	2011	6209.948	11	0.214	0.249	0.183	18.236	0.051
	2012	5749.375	12	0.206	0.239	0.177	18.412	0.073
	2013	5430.943	11	0.297	0.229	0.172	18.511	0.051
	Overall	41,447.039	13	0.263	0.242	0.198	17.818	0.121

Note:
[a] As estimated by Cox and Snell (1989).
[b] As estimated by Nagelkerke (1991).
[c] As estimated by McFadden (1974).

Table 4 – Parameter coefficients (with standard errors) associated with final models – probit link function.

Parameter	2007	2008	2009	2010	2011	2012	2013	Overall
Threshold k_1	1.101 (0.019)	1.078 (0.021)	1.156 (0.016)	1.220 (0.015)	1.187 (0.018)	1.215 (0.018)	1.144 (0.015)	1.126 (0.008)
Threshold k_2	1.792 (0.020)	1.741 (0.022)	1.829 (0.017)	1.888 (0.016)	1.833 (0.019)	1.866 (0.019)	1.788 (0.016)	1.777 (0.009)
Threshold k_3	2.829 (0.025)	2.772 (0.026)	2.860 (0.023)	2.943 (0.023)	2.816 (0.024)	2.843 (0.024)	2.759 (0.022)	2.756 (0.010)
Threshold k_4	3.271 (0.030)	3.190 (0.031)	3.247 (0.028)	3.348 (0.029)	3.201 (0.029)	3.207 (0.029)	3.090 (0.027)	3.128 (0.012)
Darkness	−0.232 (0.013)	−0.240 (0.013)	−0.264 (0.013)	−0.276 (0.012)	−0.294 (0.013)	−0.254 (0.013)	−0.244 (0.012)	−0.255 (0.005)
Over speed limit	0.518 (0.015)	0.486 (0.015)	0.477 (0.015)	0.447 (0.014)	0.529 (0.015)	0.453 (0.015)	0.545 (0.015)	0.523 (0.006)
Favor. env. cond.[a]	–	−0.039 (0.014)	–	–	–	–	–	−0.013 (0.005)
Spring season	0.089 (0.015)	0.094 (0.015)	0.107 (0.015)	0.132 (0.015)	0.097 (0.015)	0.117 (0.015)	0.057 (0.014)	0.102 (0.006)
Rural highway	0.056 (0.013)	0.041 (0.014)	0.052 (0.013)	0.075 (0.013)	–	–	–	0.028 (0.005)
Undivided highway	0.055 (0.015)	0.085 (0.016)	–	–	0.087 (0.015)	0.097 (0.015)	–	0.065 (0.006)
Highway curve	0.502 (0.014)	0.464 (0.014)	0.444 (0.013)	0.447 (0.013)	0.468 (0.014)	0.489 (0.014)	0.427 (0.013)	0.465 (0.005)
Vehicle age	0.021 (0.001)	0.011 (0.001)	0.011 (0.001)	0.013 (0.001)	0.013 (0.001)	0.014 (0.001)	0.016 (0.001)	0.014 (0.000)
Vehicle type[b]	0.067 (0.013)	0.041 (0.013)	0.058 (0.012)	–	0.087 (0.013)	0.080 (0.013)	0.066 (0.013)	0.068 (0.005)
Young driver[c]	0.104 (0.015)	0.154 (0.016)	0.164 (0.015)	0.160 (0.016)	0.168 (0.016)	0.152 (0.016)	0.099 (0.017)	0.146 (0.006)
Senior driver[d]	0.193 (0.031)	0.277 (0.029)	0.157 (0.028)	0.120 (0.026)	0.166 (0.028)	0.180 (0.027)	0.203 (0.026)	0.185 (0.010)
Male driver	−0.171 (0.013)	−0.140 (0.013)	–	–	−0.098 (0.013)	−0.094 (0.013)	−0.115 (0.013)	−0.130 (0.009)
Influenced driver	0.485 (0.021)	0.553 (0.021)	0.539 (0.020)	0.603 (0.020)	0.756 (0.020)	0.743 (0.019)	0.668 (0.020)	0.703 (0.008)
Seatbelt not properly used	0.821 (0.021)	0.826 (0.021)	0.682 (0.021)	0.735 (0.021)	–	–	–	0.037 (0.005)

Note:
[a] Favorable environmental conditions exist when the road surface is dry and the weather is either clear or cloudy.
[b] Light-duty vehicle type [0 for a passenger car; and 1 for other vehicle types (e.g., a van, a light truck, or a sports-utility vehicle)].
[c] Age is less than 21 years.
[d] Age is more than 65 years.

Table 5 – Parameter coefficients (with standard errors) associated with final models – logit link function.

Parameter	2007	2008	2009	2010	2011	2012	2013	Overall
Threshold k_1	1.858 (0.034)	1.815 (0.038)	1.942 (0.029)	2.069 (0.027)	1.987 (0.033)	2.034 (0.033)	1.902 (0.027)	1.870 (0.015)
Threshold k_2	3.088 (0.037)	3.005 (0.040)	3.153 (0.032)	3.288 (0.031)	3.163 (0.035)	3.217 (0.035)	3.079 (0.030)	3.048 (0.016)
Threshold k_3	5.140 (0.049)	5.071 (0.052)	5.263 (0.047)	5.466 (0.048)	5.227 (0.050)	5.270 (0.050)	5.150 (0.047)	5.090 (0.021)
Threshold k_4	6.124 (0.063)	6.016 (0.066)	6.164 (0.064)	6.416 (0.066)	6.179 (0.068)	6.167 (0.067)	5.984 (0.064)	6.003 (0.026)
Darkness	−0.405 (0.023)	−0.420 (0.023)	−0.468 (0.023)	−0.494 (0.022)	−0.524 (0.023)	−0.451 (0.023)	−0.432 (0.023)	−0.454 (0.009)
Over speed limit	0.892 (0.025)	0.847 (0.026)	0.821 (0.025)	0.783 (0.025)	0.920 (0.026)	0.787 (0.026)	0.935 (0.026)	0.897 (0.010)
Favor. env. cond.[a]	–	−0.063 (0.025)	–	–	–	–	–	−0.021 (0.010)
Spring season	0.160 (0.026)	0.165 (0.027)	0.189 (0.026)	0.236 (0.026)	0.180 (0.026)	0.211 (0.026)	0.101 (0.026)	0.182 (0.010)
Rural highway	0.101 (0.024)	0.079 (0.024)	0.099 (0.024)	0.146 (0.023)	–	–	–	0.054 (0.009)
Undivided highway	0.118 (0.028)	0.167 (0.029)	–	–	0.160 (0.027)	0.183 (0.028)	–	0.126 (0.011)
Highway curve	0.887 (0.024)	0.826 (0.025)	0.794 (0.023)	0.808 (0.023)	0.835 (0.024)	0.859 (0.024)	0.763 (0.024)	0.824 (0.009)
Vehicle age	0.038 (0.002)	0.018 (0.001)	0.018 (0.001)	0.022 (0.001)	0.022 (0.001)	0.024 (0.001)	0.027 (0.001)	0.023 (0.001)
Vehicle type[b]	0.116 (0.023)	0.069 (0.023)	0.097 (0.022)	–	0.153 (0.023)	0.145 (0.023)	0.113 (0.023)	0.114 (0.009)
Young driver[c]	0.180 (0.027)	0.282 (0.028)	0.291 (0.027)	0.287 (0.028)	0.310 (0.029)	0.280 (0.029)	0.188 (0.029)	0.265 (0.011)
Senior driver[d]	0.305 (0.055)	0.452 (0.051)	0.221 (0.051)	0.169 (0.048)	0.263 (0.050)	0.311 (0.048)	0.334 (0.046)	0.297 (0.019)
Male driver	−0.334 (0.023)	−0.278 (0.023)	–	–	−0.209 (0.023)	−0.206 (0.023)	−0.238 (0.023)	−0.223 (0.009)
Influenced driver	0.876 (0.036)	1.004 (0.036)	0.964 (0.035)	1.076 (0.034)	1.339 (0.034)	1.316 (0.033)	1.179 (0.034)	1.243 (0.013)
Seatbelt not properly used	1.396 (0.035)	1.411 (0.036)	1.146 (0.035)	1.247 (0.035)	–	–	–	0.039 (0.009)

Note:
[a] Favorable environmental conditions exist when the road surface is dry and the weather is either clear or cloudy.
[b] Light-duty vehicle type [0 for a passenger car; and 1 for other vehicle types (e.g., a van, a light truck, or a sports-utility vehicle)].
[c] Age is less than 21 years.
[d] Age is more than 65 years.

results and the associated significance levels. These statistics are shown in the last two columns of Table 3 for the three link functions. For the probit and logit link functions, the Pearson's significance levels were not significant for most of the years, indicating that the predicted and estimated counts significantly differ from each other. However, for the negative log–log function, the Pearson's significance levels were found to be insignificant for all years, indicating that the predicted and estimated counts are close to each other. Therefore, it could be concluded that the negative-log-log models are capable of estimating the ordinal dependent variable (the level of severity of drivers' injuries) with an acceptable level of precision based on the predictors used in the models.

Table 6 – Parameter coefficients (with standard errors) associated with final models – negative log–log link function.

Parameter	2007	2008	2009	2010	2011	2012	2013	Overall
Threshold k_1	1.838 (0.029)	1.830 (0.032)	1.961 (0.027)	2.078 (0.026)	1.975 (0.028)	1.951 (0.032)	1.904 (0.026)	1.874 (0.012)
Threshold k_2	2.860 (0.031)	2.835 (0.034)	3.005 (0.030)	3.136 (0.029)	2.998 (0.031)	2.983 (0.034)	2.941 (0.029)	2.896 (0.013)
Threshold k_3	4.717 (0.043)	4.723 (0.046)	4.973 (0.045)	5.165 (0.046)	4.946 (0.046)	4.925 (0.049)	4.917 (0.046)	4.825 (0.018)
Threshold k_4	5.658 (0.059)	5.631 (0.062)	5.849 (0.062)	6.088 (0.065)	5.881 (0.065)	5.807 (0.066)	5.739 (0.063)	5.722 (0.024)
Darkness	−0.313 (0.019)	−0.334 (0.019)	−0.384 (0.019)	−0.410 (0.019)	−0.427 (0.020)	−0.368 (0.020)	−0.374 (0.020)	−0.374 (0.007)
Over speed limit	0.684 (0.020)	0.656 (0.021)	0.645 (0.020)	0.631 (0.021)	0.736 (0.021)	0.630 (0.021)	0.756 (0.022)	0.709 (0.008)
Favor. env. cond.[a]	–	−0.046 (0.021)	–	–	–	−0.051 (0.022)	–	–
Spring season	0.122 (0.021)	0.135 (0.022)	0.144 (0.022)	0.192 (0.022)	0.148 (0.022)	0.174 (0.022)	0.082 (0.022)	0.144 (0.008)
Rural highway	0.097 (0.019)	0.074 (0.020)	0.073 (0.021)	0.120 (0.021)	–	–	0.062 (0.020)	0.049 (0.008)
Undivided highway	0.119 (0.023)	0.143 (0.025)	0.060 (0.024)	0.057 (0.024)	0.131 (0.024)	0.162 (0.024)	–	0.108 (0.009)
Highway curve	0.708 (0.019)	0.662 (0.020)	0.643 (0.020)	0.664 (0.019)	0.687 (0.020)	0.694 (0.020)	0.627 (0.020)	0.674 (0.007)
Vehicle age	0.024 (0.001)	0.013 (0.001)	0.012 (0.001)	0.015 (0.001)	0.015 (0.001)	0.015 (0.001)	0.017 (0.001)	0.015 (0.000)
Vehicle type[b]	0.093 (0.019)	0.068 (0.019)	0.080 (0.019)	–	0.137 (0.019)	0.128 (0.019)	0.089 (0.020)	0.096 (0.007)
Young driver[c]	0.142 (0.022)	0.238 (0.023)	0.232 (0.022)	0.240 (0.023)	0.267 (0.024)	0.239 (0.024)	0.168 (0.025)	0.223 (0.009)
Senior driver[d]	0.245 (0.046)	0.354 (0.043)	0.128 (0.044)	0.097 (0.042)	0.224 (0.043)	0.273 (0.041)	0.267 (0.040)	0.238 (0.016)
Male driver	−0.285 (0.019)	−0.253 (0.020)	–	–	−0.192 (0.020)	−0.193 (0.020)	−0.209 (0.022)	−0.224 (0.007)
Influenced driver	0.617 (0.027)	0.719 (0.027)	0.705 (0.027)	0.801 (0.026)	1.007 (0.026)	0.992 (0.026)	0.902 (0.027)	0.923 (0.010)
Seatbelt not properly used	0.953 (0.025)	0.977 (0.026)	0.795 (0.027)	0.890 (0.027)	–	–	–	0.055 (0.006)

Note:
[a] Favorable environmental conditions exist when the road surface is dry and the weather is either clear or cloudy.
[b] Light-duty vehicle type [0 for a passenger car; and 1 for other vehicle types (e.g., a van, a light truck, or a sports-utility vehicle)].
[c] Age is less than 21 years.
[d] Age is more than 65 years.

4.1. *Temporally-stable factors*

As shown in Tables 4–6, the following factors are found to consistently increase the severity of drivers' injuries involving single-vehicle collisions.

(a) Driving under the influence of alcohol or illicit drugs.
(b) Driving on a highway curve.
(c) Exceeding the speed limit.
(d) When the road is illuminated by either daylight or road lighting.
(e) When the driver is senior (i.e. above the age of 65 years).
(f) When the driver is young (i.e. below the age of 21 years).
(g) Spring season.
(h) The age of the vehicle.

The above factors are listed in decreasing order in terms of their significance on increasing the severity of drivers' injuries involving single-vehicle collisions. Conversely, the remaining factors shown in Tables 4–6 returned statistically significant coefficients for some years but not for others suggesting a statistically significant correlation with drivers' injury severity in some years and having no influence in other years. Those insignificant factors will be later discussed in a separate section.

Driving under the influence of alcohol or illicit drugs was found to be the most significant risk factor that increases the severity of drivers' injuries related to single-vehicle collisions. This factor exhibited high level of significance throughout the entire analysis period. 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, influenced by 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, given that it is inevitable.

Driving on a curved segment of a highway was also found to be a highly-significant factor that consistently increased the severity of drivers' injuries in single-vehicle collisions. This finding is consistent with the findings of other previous research studies (Chen et al., 2016a; Lee and Li, 2014; Wu et al., 2016). The finding may be explained by the limited sight distance on highway curves so that drivers would have less time to react to emergency situations and make any corrective actions needed to reduce the severity of a collisions, should it be inevitable. Furthermore, the highway curvature reduces cornering stability of vehicles so that drivers would lose control over their vehicles and either rollover or collide with a fixed roadside object resulting in increased injury severity (Dabbour, 2017a; Friedman and Grzebieta, 2009; Lee and Li, 2014; McLean et al., 2005).

Exceeding the speed limit increases the crash impact and therefore increases injury severity. Exceeding the speed limit also reduces the perception-reaction time available for the driver given that the given highway is designed according to a design speed close to the speed limit. Reducing the perception-reaction time allows less time for the driver to take any actions necessary to reduce the severity of a collision (such as steering, accelerating, or braking) given that a collision is inevitable.

The severity of drivers' injuries involving single-vehicle collisions were found to decrease in collisions taking place in poor light. Drivers are usually more vigilant in poor lighting conditions and therefore are likely to execute necessary measures to reduce the severity of a single-vehicle collisions, should it be inevitable. This finding contradicts findings of some previous research (Abdel-Aty, 2003; Kim et al., 2013). However, other researchers found that darkness conditions may reduce the probability of more severe single-vehicle collisions, such as rollovers because of the increased attention and cautious driving exercised by drivers in darkness conditions (Dabbour, 2017a; McLean et al., 2005; Xie et al., 2012). It must be noted that the National Motor Vehicle Crash Causation Survey (NMVCCS) created by the National Highway Traffic Safety Administration (NHTSA, 2018b) shows that more severe collisions occur during darkness conditions. However, the sample included in NMVCCS covers only crashes that occur between 6 A.M. and midnight (NHTSA, 2008) and therefore the sample is not representative of all crashes that occurred in dark conditions. More research may be needed to investigate if the findings of this research study, in terms of decreased injury severity in poor lighting, are applicable outside of the geographical area, North Carolina, from which this research data were collected.

Driver's age was found to be another significant factor that influences the severity of drivers' injuries in single-vehicle collisions. As shown in Tables 4–6, the severity increases when a driver is young (i.e., below the age of 21 years) or a senior (i.e., above the age of 65 years). For young drivers, this finding may be explained by their lack of experience in taking the appropriate evasive measures (in terms of proper steering and/or braking or accelerating) that could have reduced the severity of a single-vehicle collision, given that such a collision was inevitable. As for senior drivers, the finding may be explained by their prolonged perception-reaction time as well as by their deteriorating health conditions that make them more susceptible to injuries in case of a collision.

Single-vehicle collisions that occurred in spring seasons were found to be more severe than those that occurred in other seasons of the year. This finding is consistent with the findings of earlier studies (Jung et al., 2010; Savolainen and Ghosh, 2008). This finding may be explained by the poor pavement conditions during spring season when the ice contained in the subgrade soil thaws and significantly decreases the bearing capacity of the subgrade soil (Huang, 2003).

Modern vehicles are designed with improved passive safety features and driver assistance systems that protect drivers, and other occupants, in case of a collision. Therefore, older vehicles, with the absence of those advanced safety features, are likely to be associated with more severe injuries to drivers than newer vehicles in case of a collision. This finding is consistent with the findings of several prior research studies (Behnood and Mannering, 2015; Behnood et al., 2014; Kim et al., 2013; Yau, 2004).

4.2. Temporally-unstable factors

As shown in Tables 4–6, the following factors were found to be temporally unstable.

(a) The use of seatbelt.
(b) Driver's gender.
(c) Environmental conditions.
(d) Rural highways.
(e) Undivided highways.
(f) The type of the light-duty vehicle.

It is important to note that prior research studies have identified several of the aforementioned temporally-unstable factors as significant factors that increased driver's injury severity in single-vehicle collisions. The most surprising finding is the temporal instability related to the use of seatbelts. Numerous studies in the past have concluded that an inappropriate use of the seatbelt was a significant factor that increased drivers' injuries in single-vehicle collisions (Abdel-Aty, 2003; Chen and Chen, 2011; Kim et al., 2013; Yau, 2004).

The temporal instability of the effect of driver's gender on the severity of drivers' injuries in a single-vehicle collision, observed in the models reported in this paper, is in line with the lack of consensus observed in previous studies. Several studies found that male drivers are more likely to be involved in severe single-vehicle collisions (Chang and Yeh, 2006; Kim et al., 2013; Morgan and Mannering, 2011; Ulfarsson and Mannering, 2004; Yau, 2004). However, other studies found that injury severity is worse for female drivers than male drivers in single-vehicle rollover collisions (Wu et al., 2016) as well as in other types of vehicular collisions (Abdel-Aty, 2003; Xiong et al., 2014), and collisions between vehicles and trains (Dabbour et al., 2017; Eluru et al., 2012; Haleem and Gan, 2015; Hao and Daniel, 2014; Zhao and Khattak, 2015). In another in-depth study by Russo et al. (2014b), safety performance functions were developed to predict the number of injury collisions for two-lane rural roads in Italy based on driver's gender, driver's age, roadway width, mean speed, road surface condition, lighting condition, and the existence of roadway curvature. It was found that male drivers are more involved in injury single-vehicle collisions during daylight on roadway curved segment while the roadway surface is wet. Other scenarios where male drivers were also involved in more injury single-vehicle collisions include driving on dry roadway surface on a curved segment of the roadway during daylight, driving on dry roadway surface on a curved segment of the roadway during nighttime, driving on wet roadway surface on a curved segment of the roadway during daytime, and driving on wet roadway surface on a curved segment of the roadway during nighttime.

To address the correlation between road surface conditions (e.g., whether the road surface is dry or wet) and weather conditions, the two variables were merged into a dichotomous variable that represents the existence of favorable environmental conditions. That variable takes the value of “1” when the road surface is dry and the weather is either clear or cloudy, and the value of “0” otherwise. Favorable road and weather conditions were found to have a temporally-unstable effect on the severity of drivers' injuries in single-vehicle collisions. Prior studies, though, have observed that environmental conditions have a significant effect on driver's injury severity in single-vehicle conditions (Adams, 1985; Behnood et al., 2014; Behnood and Mannering, 2015; Jung et al., 2010; Krull et al., 2000).

Driving on a rural highway was found to be another significant factor that has temporally-unstable effect on the severity of drivers' injuries in single-vehicle collisions. This is despite prior studies that found that rural highways have significant effects on the severity of drivers' injuries in single-vehicle collisions (Chen et al., 2016b; Islam et al., 2014; Wu et al., 2016). Similarly, other studies found that undivided roads have a significant effect on the severity of drivers' injuries in single-vehicle collisions (Gattis et al., 2005; Xie et al., 2012). However, this research found these factors to be temporally unstable.

Earlier studies observed that light-duty vehicles that are not passenger cars usually have a higher location of center-of-gravity and a higher height-to-width ratio than those of a passenger car (Dabbour, 2017a; Friedman and Grzebieta, 2009; McLean et al., 2005). Therefore, such vehicles are more susceptible to severe single-vehicle collisions such as rollovers, which may increase the severity of their drivers' injuries. The light-duty vehicles identified in earlier research to increase the severity of drivers' injuries in single-vehicle collisions include pickup trucks, panel trucks, mini-vans, vans, and sports-utility vehicles. However, models estimated here found that the type of light duty vehicle has a temporally unstable effect on drivers' injury severity as shown in Tables 3–5.

5. Aggregate models

Tables 4–6 present results from models estimated individually for each year in the study period. Another alternative to study driver injury severity is to pool data from all years (from January 1, 2007 to December 31, 2013) into one dataset and re-estimate ordinal regression models using probit, logit, and negative log–log links on that combined dataset. This exercise will reveal any changes in statistical significance of the estimated parameters resulting from possible aggregation bias.

The model fit for the aggregate (overall) models is reported in Table 3 and the estimated coefficients (with their respective standard errors) are reported in the last columns of Tables 4–6. The overall models found four factors namely environmental conditions, rural highway, undivided highway, and the use of seatbelt to be statistically significant even when the same factors were found to be temporally unstable in the disaggregate yearly models.

The above disparity between the results obtained from the model estimated for aggregate data and the ones obtained from disaggregate yearly models presents a policy challenge. Basing policy recommendations on aggregate data without realizing the temporal instability of results found in the yearly data might be misleading. For instance, if investments were allocated to install highway barriers to address the factor of undivided highway, it would be difficult to determine whether any potential safety improvements (in terms of reduced severity of drivers' injuries) are attributed to the applied safety treatments or to the temporal instability of the identified factors being addressed.

6. Random-parameter mixed ordinal models

To account for individual-level heterogeneity in the data, mixed (random-parameter) ordinal regression models were also developed for this research. Whereas the fixed parameter models return just the coefficient, the mixed models return the mean value and the standard deviation for each coefficient. The results for the random coefficient models estimated individually for each year are reported in Table 7.

Given the computationally intensive nature of simulated maximum likelihood estimation, it was not possible to estimate models by declaring all coefficients being random. Instead, a series of random parameter models were estimated such that in each estimation only one of the variables was estimated as a random parameter. This process was iterated until all factors were introduced independently as random variables in models estimated separately for each year in the dataset. Therefore, the mean and standard deviation of individual parameters listed in Table 7 are obtained from separate models such that the fixed parameters from the respective models are not reported to conserve space. Furthermore, random parameters were assumed to be normally distributed.

The first random parameter reported in Table 7 is darkness. The coefficient associated with the parameter was found to be negative for all years with statistically insignificant standard deviation for all analysis years. Therefore, it could be concluded that darkness conditions are associated with less severe drivers' injuries related to single-vehicle collisions. Because the standard deviation for the darkness variable is statistically insignificant in all analysis years, it is considered stable over time.

The main coefficient for speeding is statistically significant and positive for all years. Furthermore, the standard deviation of the estimated coefficient is statistically insignificant for most recent analysis years. Therefore, it could be concluded that speeding is another temporally-stable factor that affects driver injury severity in single-vehicle collisions involving light-duty vehicles. Similarly, it could also be concluded that drivers' injury severity related to single-vehicle collisions consistently increase with both young and senior drivers. As shown in Table 7, the aforementioned factors have statistically significant coefficients with insignificant standard deviation for all analysis years. Rural highways were found to be another factor that increased drivers' injury severity in most of the early years, but not in the most recent analysis years of 2012 and 2013; and therefore, it should not be considered as a temporally-stable factor. Similar conclusion may also be drawn regarding the effect of spring season, where it was found to be significant in only the first four analysis years but not significant in the most-recent three analysis years. Based on the mean and standard deviation values associated with the coefficient, and based on the assumption that the coefficient is normally distributed, the probability of a positive correlation between spring season and increased severity of drivers' injury is only 56%, 57%, and 49% for the years 2011, 2012, and 2013, respectively.

Similarly, the mean coefficient associated with the improper use of seat belts is statistically significant and positively correlated with drivers' injury severity for the analysis years 2007–2010. However, the mean of the coefficient reverses the sign such that the improper use of seatbelts is negatively correlated with driver's injury severity for the years 2011, 2012, and 2013. At the same time, the standard deviation for the use of seat belts for all years is statistically significant suggesting of the presence of strong heterogeneity

Table 7 – Parameter coefficients (with standard errors) associated with final mixed logit models.

Parameter	2007	2008	2009	2010	2011	2012	2013
Darkness (mean)	−0.406 (0.023)	−0.421 (0.025)	−0.047 (0.023)	−0.498 (0.022)	−0.529 (0.023)	−0.454 (0.028)	−0.446 (0.027)
Darkness (std. dev.)	–	–	–	–	–	–	–
Over speed limit (mean)	0.776 (0.031)	0.713 (0.033)	0.775 (0.025)	0.737 (0.026)	0.925 (0.026)	0.790 (0.026)	0.944 (0.026)
Over speed limit (std. dev.)	1.121 (0.060)	1.099 (0.063)	–	–	–	–	–
Favor. env. cond.[a] (mean)	–	0.139 (0.034)	–	−0.059 (0.024)	−0.095 (0.037)	−0.156 (0.037)	−0.139 (0.037)
Favor. env. cond.[a] (std. dev.)	0.600 (0.083)	0.564 (0.085)	–	–	0.453 (0.112)	0.622 (0.086)	0.589 (0.091)
Spring season (mean)	0.159 (0.026)	0.165 (0.026)	0.187 (0.025)	0.239 (0.025)	0.089 (0.039)	0.114 (0.039)	–
Spring season (std. dev.)	–	–	–	–	0.640 (0.097)	0.671 (0.094)	0.705 (0.094)
Rural highway (mean)	0.101 (0.024)	0.070 (0.030)	0.058 (0.025)	0.119 (0.024)	0.042 (0.017)	–	–
Rural highway (std. dev.)	–	–	–	–	–	0.528 (0.094)	–
Undivided highway (mean)	0.088 (0.034)	0.068 (0.037)	–	0.054 (0.030)	–	–	−0.112 (0.043)
Undivided highway (std. dev.)	0.341 (0.122)	0.658 (0.079)	0.329 (0.141)	–	0.610 (0.091)	0.760 (0.078)	0.790 (0.080)
Highway curve (mean)	0.889 (0.024)	0.738 (0.030)	0.673 (0.030)	0.709 (0.030)	0.791 (0.032)	0.691 (0.033)	0.587 (0.033)
Highway curve (std. dev.)	–	0.789 (0.068)	0.760 (0.077)	0.540 (0.097)	0.835 (0.072)	1.057 (0.066)	0.971 (0.067)
Vehicle age (mean)	0.031 (0.003)	0.022 (0.002)	0.020 (0.002)	0.024 (0.002)	0.028 (0.003)	0.027 (0.003)	0.026 (0.003)
Vehicle age (std. dev.)	0.068 (0.004)	0.067 (0.004)	0.062 (0.005)	0.059 (0.004)	0.071 (0.004)	0.079 (0.004)	0.072 (0.004)
Vehicle type[b] (mean)	0.055 (0.031)	–	0.061 (0.032)	–	0.085 (0.036)	0.075 (0.036)	–
Vehicle type[b] (std. dev.)	0.530 (0.093)	0.573 (0.092)	0.364 (0.134)	0.565 (0.101)	0.518 (0.107)	0.529 (0.104)	0.810 (0.078)
Young driver[c] (mean)	0.180 (0.026)	0.282 (0.027)	0.289 (0.026)	0.287 (0.025)	0.309 (0.027)	0.277 (0.028)	0.182 (0.028)
Young driver[c] (std. dev.)	–	–	–	–	–	–	–
Senior driver[d] (mean)	0.302 (0.054)	0.422 (0.052)	0.220 (0.051)	0.180 (0.048)	0.265 (0.047)	0.315 (0.059)	0.333 (0.045)
Senior driver[d] (std. dev.)	–	–	–	–	–	–	–
Male driver (mean)	−0.689 (0.037)	−0.666 (0.039)	−5.897 (0.198)	−5.692 (0.170)	−0.577 (0.041)	−0.644 (0.042)	0.643 (0.043)
Male driver (std. dev.)	1.268 (0.055)	1.299 (0.056)	1.545 (0.133)	1.278 (0.123)	1.237 (0.062)	1.367 (0.060)	1.277 (0.061)
Influenced driver (mean)	0.795 (0.043)	0.899 (0.044)	0.790 (0.046)	0.910 (0.045)	1.245 (0.044)	1.202 (0.044)	1.045 (0.045)
Influenced driver (std. dev.)	1.078 (0.073)	1.181 (0.072)	1.301 (0.085)	1.325 (0.085)	1.264 (0.077)	1.336 (0.075)	1.287 (0.078)
Seatbelt not properly used (mean)	1.353 (0.051)	1.324 (0.055)	0.700 (0.062)	0.829 (0.063)	−0.384 (0.203)	−0.996 (0.211)	−0.417 (0.225)
Seatbelt not properly used (std. dev.)	1.860 (0.078)	1.955 (0.082)	2.269 (0.101)	2.373 (0.106)	1.388 (0.130)	1.671 (0.144)	1.581 (0.133)

Note:

[a] Favorable environmental conditions exist when the road surface is dry and the weather is either clear or cloudy.

[b] Light-duty vehicle type [0 for a passenger car; and 1 for other vehicle types (e.g. a van, a light truck, or a sports-utility vehicle)].

[c] Age is less than 21 years.

[d] Age is more than 65 years.

in the data set. Whereas the mean for improper seatbelt use returned a negative coefficient of −0.417, a standard deviation of 1.581 for the random coefficient suggests that 40% collisions would have had a positive correlation between improper use of seatbelts and injury severity. This finding is similar to the findings of the fixed-parameter models developed in this research. The proper use of seat belts has been the cornerstone of prudent traffic safety policy for years. Numerous studies in the past have repeatedly shown that the improper use of seatbelts is associated with a greater injury severity in case of vehicular collisions. However, the results of both fixed-parameter and random-parameter models presented in this paper indicate the presence of strong variance between the proper use of seat belts and drivers' injury severity in single vehicle collisions involving light duty vehicles.

Driver's impairment was another factor that was found by the mixed models to be insignificant in all analysis years with the probability of a positive correlation between this factor and the increased severity of drivers' injuries ranging between 73% (in 2009) to 84% (in 2011). If a confidence level of 95% is used, then those probabilities may be considered insignificant. Other factors found by the mixed models to be temporally-unstable, at 95% confidence level, include favorable environmental conditions, undivided highways, highway curves, vehicle age, vehicle type, and driver's gender.

The key findings of this research, in terms of both temporally-stable and temporally-unstable factors, are summarized in Table 8 along with a comparison with the findings of previous research studies in respect to the factors being addressed. As shown in Table 8, most temporally-unstable

Table 8 – Comparing temporally-stable and temporally-unstable factors with the findings of previous research studies.

Factor	Fixed-parameter	Random-parameter	Research studies found the factor significantly positive[c]	Research studies found the factor significantly negative[d]
Darkness	Stable (negative)[d]	Stable (negative)[d]	(a) Kim et al. (2013) (b) Abdel-Aty (2003)	(a) Dabbour (2017a) (b) Xie et al. (2012) (c) McLean et al. (2005)
Favor. env. cond.[a]	Unstable	Unstable	(a) Behnood and Mannering (2015) (b) Behnood et al. (2014) (c) Jung et al. (2010) (d) Krull et al. (2000) (e) Adams (1985)	
Spring season	Stable (positive)[c]	Unstable	(a) Jung et al. (2010) (b) Savolainen and Ghosh (2008)	
Rural highway	Unstable	Unstable	(a) Wu et al. (2016) (b) Chen et al. (2016b) (c) Islam et al. (2014).	
Undivided highway	Unstable	Unstable	(a) Xie et al. (2012) (b) Gattis et al. (2005)	
Highway curve	Stable (positive)[c]	Unstable	(a) Chen et al. (2016a) (b) Wu et al. (2016) (c) Lee and Li (2014)	
Vehicle age	Stable (positive)[c]	Unstable	(a) Behnood and Mannering (2015) (b) Behnood et al. (2014) (c) Kim et al. (2013) (d) Yau (2004)	
Vehicle type[b]	Unstable	Unstable	(a) Dabbour (2017a) (b) Friedman and Grzebieta (2009) (c) McLean et al. (2005)	
Male driver	Unstable	Unstable	(a) Kim et al. (2013) (b) Morgan and Mannering (2011) (c) Chang and Yeh (2006) (d) Ulfarsson and Mannering (2004) (e) Yau (2004) (f) Russo et al. (2014b)	(a) Wu et al. (2016) (b) Abdel-Aty (2003) (c) Xiong et al. (2014) (d) Haleem and Gan (2015) (e) Zhao and Khattak (2015) (f) Hao and Daniel (2014) (g) Eluru et al. (2012)
Influenced driver	Stable (positive)[c]	Unstable	(a) Behnood and Mannering (2015) (b) Behnood et al. (2014) (c) Kim et al. (2013) (d) Suriyawongpaisal et al. (2002)	
Seatbelt not properly used	Unstable	Unstable	(a) Kim et al. (2013) (b) Chen and Chen (2011) (c) Yau (2004) (d) Abdel-Aty (2003)	

Note:
[a] Road surface is dry, and the weather is either clear or cloudy.
[b] Light-duty vehicle other than passenger cars (e.g., a van, a light truck, or a sports-utility vehicle).
[c] The factor increases the severity of drivers' injuries.
[d] The factor decreases the severity of drivers' injuries.

factors, as identified in this research, were found to be significant by prior research studies that did not investigate the temporal stability of those factors.

7. Conclusions

In this study, both fixed-parameter and random-parameter ordinal regression models were used to identify significant factors that may increase the severity of drivers' injuries in single-vehicle collisions involving light-duty vehicles. The study is based on analyzing annual records of all single-vehicle collisions that occurred in North Carolina from January 1, 2007 to December 31, 2013. The seven-year analysis period allowed for testing the temporal stability of the identified factors. The fixed-parameter ordinal regression models were estimated using three link functions, namely probit, logit, and negative log–log link. A model was estimated for each analysis year using each of the three link functions. From among the three link functions, the negative log–log function was found to be capable of estimating the ordinal dependent variable (the level of severity of drivers' injuries) with an acceptable level of precision based on the predictors used in the models. The study compared the output from individual yearly-based models to determine the temporal stability of the identified factors. Both fixed-parameter and random-parameter models identified several factors to be temporally-unstable in explaining the severity of drivers' injuries in single-vehicle collisions. Those temporally-unstable factors include the use of seatbelt, driver's gender, environmental conditions, rural highways, undivided highways, and the type of the light-duty vehicle.

Furthermore, random-parameter models identified four more factors to be temporally-unstable, including vehicle age, season of the year, highway curve, and driver's impairment. Those four factors were actually identified by the fixed-parameter models to be temporally stable. Most of the temporally-unstable factors identified in this research were found by previous research studies to have a statistically significant impact on the severity of drivers' injuries in single-vehicle collisions. To further illustrate the contribution of this study, observations from all years were also aggregated into a single dataset to estimate overall models. Interestingly, the overall models identified four statistically significant factors (environmental conditions, rural highway, undivided highway, and the use of seatbelt) that individual year models considered temporally unstable. If safety treatments were to be applied by considering only the overall models without investigating the temporal stability of the identified factors (e.g., by providing highway barriers to address the factor of undivided highway that was identified as a significant factor by other previous research studies), it would be difficult to determine whether any potential safety improvement (in terms of reduced severity of drivers' injuries) is attributed to the applied safety treatments or to the temporal instability of the identified factors. This study recommends that measures to improve traffic safety should be based on analysis that accounts for the temporal instability and heterogeneity in data so that measures that are stable and depict the least heterogeneity are given preference for implementation.

Conflicts of interest

The authors do not have any conflict of interest with other entities or researchers.

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