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Time-of-day variations and the temporal instability of multi-vehicle crash injury severities under the influence of alcohol or drugs after the Great Recession

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ABSTRACT

Using data of multi-vehicle crashes with drivers under the influence of alcohol/drugs in North Carolina from 2008 to 2017, this paper explores time-of-day variations (daytime vs. nighttime) and temporal instabilities of factors affecting alcohol/drug-impaired crash injury severities during three crash cycle phases after the Great Recession. Random parameters logit models with heterogeneity in the means and variances are utilized to identify significant factors, explore unobserved heterogeneity, reveal correlations between factors, and suggest possible impacts of economic conditions on the factors. Different likelihood ratio tests indicate that the effects of factors vary significantly across time-of-day and economic-related cycle periods. Significant time-of-day variations imply more severe injury alcohol/drug involved crashes during the nighttime compared to the daytime. Meanwhile, temporal instabilities are also observed in marginal effects of several factors across three-cycle periods. Proficient and cautious elder drivers were safer than young drivers during the depression period. Also, both depressing and expanding periods could affect the involvement of alcohol/drugs for drivers. Shifts in alcohol/drug use behaviors underscore the importance of accounting time-of-day variations, temporal instabilities, and heterogeneity in the means and variances inherent in alcohol/drug-impaired crash factors after the Great Recession. The insights of this study should be valuable to improve specific enforcements, qualify punishments, organize targeted campaigns, and design other preventive activities for alcohol/drug-impaired crashes.

1. Introduction

Alcohol/drug use can significantly impair the observing, thinking, reacting, and operating abilities of a driver and could result in severe crash-injury outcomes. In the United States, about one-third of all traffic crashes fatalities are related to drunk driving, and the fatalities of alcohol involved crashes at nighttime are 3.4 times higher than those at daytime in 2018 (NHTSA, 2019). Substantial evidence from previous studies shows the adverse effects of driving under the influence (DUI) of alcohol/drugs in increasing crash-injury severities (Lee et al., 2020; Liu et al., 2020).

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A myriad of research has been conducted to understand the frequency of alcohol/drugs impaired crashes (Li et al., 2019; Owen et al., 2019; Ponce et al., 2011). However, the effects of alcohol/drug involvement on crash-injury severities are more complex. Meanwhile, few studies were conducted focusing on the specific topic of DUI crash-injury-severity, and most of them only considered alcohol/drugs involvement as one of the factors in a general model (Song et al., 2020). Identifying specific factors for DUI involved crashes can potentially help to understand the factors of alcohol/drugs involved crash injury-severity and better guide the development of safety countermeasures.

Several studies also pointed out that considerable temporal variabilities exist in the effects of DUI crash-injury severities (Lidbe et al., 2020; Liu et al., 2020; Ponce et al., 2011; Zhang et al., 2014). Most of the research analyzed time-of-day variations of the DUI crashes and indicated that nighttime has potential effects on increasing the DUI crash-injury-severity due to poor visibility (Liu et al., 2020; Ponce et al., 2011; Zhang et al., 2014). Previous research also suggested that the time-of-day variation of the DUI crashes is due to the temporal change of human behaviors and environments. Houwing and Twisk (2015) indicated that young drivers are more often involved in fatigue-related crashes at night and higher alcohol/drug use behaviors at night, and there may be a logical consequence of having dinner, hanging out, and partying. Instead of setting the time-of-day indicator as a factor in a general model, a segmentation of the DUI crashes by time-of-day is needed to further explore the time-of-day variations of the injury-severity determinants.

Except for the time-of-day variations, possible temporal stabilities in DUI crashes (if the estimated parameters vary over years) have not been adequately studied to date. Behnood and Mannering (2015) found that crash-injury-severity models exhibited significant temporal instability over the period of 2004–2012 (which included the periods before and after the Great Recession: December 2007 to June 2009). Maheshri and Winston (2016) indicated that overall U.S. traffic fatality rates declined in the Great Recession as safer drivers drive more frequently during economic downturns. Behnood and Mannering (2016) assessed the effects of economic recession-related periods (pre-recession 2005–2006, recession 2008–2009, and post-recession 2011–2012) on the pedestrian crash-injury and pointed out that global and fundamental shifts in driver/pedestrian behaviors are a compelling reason for the temporal instability of the crash factors. Also, ignorance of the temporal nature of the crash factors would result in inaccurate model estimations and ineffective development of safety countermeasures (Mannering, 2018).

The variations of the economic condition (depression, recovery, and expansion phase) after the Great Recession would significantly affect the income of the residents and employment rate, and therefore may influence alcohol/drug use and DUI behavior consequently. Several studies found that low income and unemployment conditions would increase the potential of DUI behaviors (Li et al., 2019; Lidbe et al., 2020; Owen et al., 2019). However, Ponce et al. (2011) indicated that economically active males (middle-age: 25–54) are more likely to drive under the influence of alcohol. The variations of alcohol consumptions and alcohol/drugs related crashes in North Carolina after the Great Recession suggest the potential temporal instability in the effects of the DUI crash factors. Hence, a thorough study of the temporal instability of the DUI crashes and factors could achieve a better understanding of the variability effects of the factors and help to provide possible insights into inherent reasons for recession-induced shifts in DUI behaviors.

The ongoing methodological frontiers of the crash-injury-severity research are mainly focused on accounting for potential heterogeneity (in the means and variances) and possible temporal instabilities of the factors affecting crash-injury severities (Behnood and Mannering, 2016; Mannering and Bhat, 2014). As mentioned in Mannering et al. (2016), several explanatory variables, such as characteristics of the human, vehicle, location, roadway, traffic, time, and environment, would have potential heterogeneous effects on the likelihood of the crash-injury-severity. Ignoring unobserved heterogeneity and restricting the fixed effects of factors across observations may lead to biased parameter estimation and erroneous inference (Mannering et al., 2016). In this case, there is a strong need for an investigation of DUI crash factors by accounting for possible heterogeneity in the means and variances of the random parameters.

To study the time-of-day variations and temporal stabilities of factors affecting multi-vehicle crashes with drivers under the influence of alcohol/drugs after the Great Recession, police-reported data are collected from North Carolina within three alcohol-related crash cycle phases (depression: 2008–2010; recovery: 2011–2013, and expansion: 2014–2017). A series of random parameters logit (RPL) models with heterogeneity in the means and variances are utilized to identify contributing factors and possible interactions between factors. The rest of the paper is organized as follows: Section 2 summarizes factors affecting DUI crash injury severity and the state-of-art of methodologies for crash-injury severity modeling. Section 3 introduces the random parameters logit model with heterogeneity in the means and variances. Section 4 describes the statistics, temporal features, and empirical classifications of the research data. Section 4 discusses the temporal stability results of the crash data. Section 5 presents and discusses the model results and marginal effects. Finally, all findings and implications are summarized in Section 6.

2. Literature review

2.1. Review of factors affecting alcohol or drugs involved crash injury severities

Table 1 summarizes several factors that have been identified to significantly affect DUI crash-injury severities. These factors mainly include driver characteristics, driver actions, vehicle types, locality characteristics, roadway characteristics, environmental factors, and traffic control factors. Several factors were found to have opposite effects in different research studies,

Table 1
Significant contributing factors to the injury severity of alcohol/drugs involved crashes.

Variables	Findings
Driver Characteristics	
Driver age	***Increase injury-severity:*** Older-age (50–60) (Chen et al., 2016); young-age (<22), older-age (>55) (Behnood and Mannering, 2017b)
Driver gender	***Increase injury-severity:*** male (Zhang et al., 2014)
Belt restraint	***Increase injury-severity:*** without belt (Behnood and Mannering, 2017b); with airbag (Maistros et al., 2014); ***Decrease injury-severity:*** with air bag (Behnood et al., 2014); with-belt (Maistros et al., 2014)
Fail to reduce speed/speeding	***Increase injury-severity:*** Speeding (Behnood and Mannering, 2017b; Maistros et al., 2014); exceeding speed limit (Behnood et al., 2014); failure to reduce speed (Behnood and Mannering, 2017b)
Improper lane use/change and backing/turn	***Decrease injury-severity:*** improper lane usage, improper backing (Behnood and Mannering, 2017b); improper turn, improper lane change (Behnood et al., 2014)
Failed to yield right of way	***Increase injury-severity:*** failed to yield (Behnood et al., 2014);***Decrease injury-severity:*** failed to yield (Behnood and Mannering, 2017b)
Vehicle Types	***Increase injury-severity:*** van/mini-van (Behnood et al., 2014)
Locality Characteristics	
Urban/rural	***Increase injury-severity:*** highway urban (Behnood et al., 2014); rural (Behnood and Mannering, 2017b; Lidbe et al., 2020; Liu and Fan, 2020); rural or small-town (Liu et al., 2020)
Intersection	***Increase injury-severity:*** intersection (Chen et al., 2016);***Decrease injury-severity:*** intersection (Lidbe et al., 2020)
Roadway Characteristics	
Interstate	***Decrease injury-severity:*** interstate (Behnood et al., 2014; Lidbe et al., 2020)
Median divided	***Decrease injury-severity:*** concrete median barrier (Behnood et al., 2014)
Roadway alignment	***Increase injury-severity:*** curve on grade (Behnood et al., 2014; Behnood and Mannering, 2017b; Maistros et al., 2014); downward grade (Lidbe et al., 2020); straight on grade, straight and level, curve and level/hillcrest (Behnood and Mannering, 2017b); level curve (Maistros et al., 2014)**;**straight on hillcrest (Behnood et al., 2014; Behnood and Mannering, 2017b)***Decrease injury-severity:*** curve alignment (Behnood et al., 2014)
Environmental Factors	
Daylight or dark with/without roadway light	***Increase injury-severity:*** night with or without roadway light (Zhang et al., 2014); dark (Lidbe et al., 2020); daylight (Behnood et al., 2014; Maistros et al., 2014)***Decrease injury-severity:*** dark with light road (Behnood and Mannering, 2017b)
Weather	***Decrease injury-severity:*** rain or snow (Behnood et al., 2014); rain/ snow/ice/fog (Behnood and Mannering, 2017b); adverse weather (Liu and Fan, 2020)
Period	***Increase injury-severity:*** off peak periods (Behnood et al., 2014); late nights and early morning, on Friday or Monday, 10 am and 2 pm (Liu et al., 2020); Weekend (Behnood and Mannering, 2017b; Lidbe et al., 2020); ***Decrease injury-severity:*** winter season (Lidbe et al., 2020)
Traffic Control Factors	
Signs or signal control	***Decrease injury-severity:*** stop sign/flasher (Behnood et al., 2014; Behnood and Mannering, 2017b); traffic signal control (Behnood and Mannering, 2017b); with traffic control (Liu and Fan, 2020)
Speed limits	***Increase injury-severity:*** higher speed limit (Liu and Fan, 2020)

such as restraint with the belt, equipped with an air bag, failed to yield, intersection, and dark with roadway light. It is also noted that DUI crashes on curved roadways were found to decrease the injury-severity in (Behnood et al., 2014) and increase the injury-severity when combined with grade, level, and hillcrest in (Behnood et al., 2014; Behnood and Mannering, 2017b; Maistros et al., 2014).

2.2. Review of approaches accounting for unobserved heterogeneity

As shown in Table 2, fixed-parameter models, such as multinomial logit (MNL) and ordered logit, have been frequently developed in DUI crash-injury-severity studies because of their excellent performance in model estimations and discrete outcome inferences (Chen et al., 2016; Valen et al., 2019; Zhang et al., 2014). However, the fixed-parameter models (such as MNL) neglect the difference across the crash observations. Also, the simplified assumptions of the fixed-parameter models and the incapacity of accounting unobserved heterogeneity could result in biased estimations and counter-productive countermeasures (Mannering and Bhat, 2014). To account for unobserved heterogeneity, random parameter models (or mixed

Table 2
Summary of methodological approaches used in the study of alcohol/drugs involved crashes injury severities.

Methodological approach	Previous research
Multinominal logit model	(Valen et al., 2019; Zhang et al., 2014)
Ordered logit model	(Chen et al., 2016)
Latent class multinomial logit model	(Behnood et al., 2014; Lidbe et al., 2020)
Mixed logit model	(Behnood and Mannering, 2017b; Liu and Fan, 2020; Maistros et al., 2014)
Geographically and temporally weighted regression	(Liu et al., 2020)

logit models), which allow parameters to vary across observations or groups, have been employed in several DUI studies (Behnood and Mannering, 2017b; Liu and Fan, 2020; Maistros et al., 2014). Moreover, the latent-class approach combined with discrete outcome models was proposed to address unobserved heterogeneity across groups by segmenting the DUI crashes into homogeneous subsets (Behnood et al., 2014; Lidbe et al., 2020).

Recently, the random parameter models were further extended by allowing heterogeneity in the means and variances by assuming that random parameters are specifically distributed across observations (Behnood and Mannering, 2017a). This approach has been proved statistically superior and accurate in several recent studies (Al-Bdairi et al., 2020; Behnood and Mannering, 2019, 2017a; Islam et al., 2020; Islam and Mannering, 2020; Li et al., 2021).

3. Methodology

In this study, the random parameters logit model with heterogeneity in the means and variances is employed to model injury severities in multi-vehicle DUI crashes. A linear injury-severity function for crash observation i at the injury severity level k (k = 1, 2, 3 denotes severe injury, minor injury, and no injury, respectively) is defined as:

$$U_{ki} = \beta_k \mathbf{X}_{ki} + \varepsilon_{ki} \tag{1}$$

where U_{ki} denotes the injury-severity function for crash observation i associated with injury-severity k, $\mathbf{X}_{ki}$ is the vector of explanatory variables for observation i with injury-severity k, β_k indicates the corresponding coefficient vector, and ε_{ki} represents the error term which is independent and identically Gumbel distributed over severity levels. The probability that observation i suffers injury-severity k in the RPL model can be derived as (McFadden and Train, 2000):

$$P_i(k) = \int \frac{\exp(\beta_k \mathbf{X}_{ki})}{\sum \exp(\beta_k \mathbf{X}_{ki})} f(\beta|\varphi) d\beta \tag{2}$$

where $P_i(k)$ is the probability of crash observation i with the injury-severity k, and $f(\beta|\varphi)$ indicates the probability density function of random parameters β with the corresponding distribution parameters φ (mean and variance for the normal distribution). Following the work of (Behnood and Mannering, 2019), the RPL model with heterogeneity in the means and variances can be modeled as:

$$\beta_{ki} = \beta + \delta_{\boldsymbol{ki}} \mathbf{Z}_{\boldsymbol{ki}} + \sigma_{ki} \exp(\omega_{\boldsymbol{ki}} \mathbf{W}_{\boldsymbol{ki}}) v_{ki} \tag{3}$$

where β is the mean parameter and is estimated across all observations. $\mathbf{Z}_{\boldsymbol{ki}}$ represents the vector of explanatory variables that captures heterogeneity in the mean for the injury-severity function under injury severity k, and $\delta_{\boldsymbol{ki}}$ is the corresponding coefficient vector for $\mathbf{Z}_{\boldsymbol{ki}}$. $\mathbf{W}_{\boldsymbol{ki}}$ indicates the vector of explanatory variables that captures heterogeneity in the variance (the standard deviation σ_{ki}), and $\omega_{\boldsymbol{ki}}$ denotes the corresponding coefficient vector associated with $\mathbf{W}_{\boldsymbol{ki}}$. v_{ki} indicates a disturbance term. If the heterogeneity in the means or variances for the explanatory variables $\mathbf{Z}_{\boldsymbol{ki}}$ and $\mathbf{W}_{\boldsymbol{ki}}$ is not statically significant, the RPL with heterogeneity in the means and variances would be collapsed into the RPL with heterogeneity in means only, or RPL with heterogeneity in variances only, or conventional mixed logit model.

In this study, the normal distribution is selected for model estimation since it has been proved to be the most suitable distribution compared to lognormal, triangular, and uniform distributions (Alnawmasi and Mannering, 2019; Behnood and Mannering, 2019). All models are estimated with simulated maximum likelihood by 1,000 Halton draws (Behnood and Mannering, 2019; Song et al., 2021). The Halton sequence is generated as follows:

$$g = \sum_{i=0}^{I} b_i r^i \tag{4}$$

where r is a prime number that is larger than 2. $0 \leqslant b_i \leqslant r-1$ determines the I digit used in term of the base r^i to represent g. The range for I is determined by $r^I \leqslant g < r^{I+1}$. The Halton draws are then obtained as:

$$H(g) = \sum_{i=0}^{I} b_i r^{-i-1} \tag{5}$$

Additionally, to interpret the results of random parameters models with category variables (dummied with 1 to denote the presence of the variable and 0 otherwise), marginal effects are calculated to illustrate the impact of a one-unit change in the explanatory variable on the probability of the crash-injury-severity outcomes.

$$E_{X_{ij}}^{P_i} = \frac{1}{n} \sum_{i=1}^{n} \left[P_i(X_{ij} = 1) - P_i(X_{ij} = 0) \right] \tag{6}$$

where the average difference value of P_i over all observations is calculated when the *j-th* explanatory variable X_{ij} changes from 0 to 1.

4. Empirical settings

This study collects multi-vehicle crashes involving drivers whose physical condition is under the influence of alcohol/-drugs from the Highway Safety Information System (HSIS). 14,926 police-reported observations over ten years (2008 to 2017) in North Carolina are utilized in this study. Also, three injury-severity levels (i.e., severe injury [including fatal/incapacitating injury], minor injury [including non-incapacitating injury], and no injury [including no/possible injury]) are analyzed. The drivers who are impaired due to alcohol/drugs and the most severe crash-injury-severity in the crashes are used and modeled.

Different from the economic cycle classification in Behnood and Mannering (2016), this paper segments the cycle of the DUI crashes mainly based on the temporal features of the alcohol-involved crash rate. Meanwhile, the unemployment rate and alcohol consumption per capita are selected to determine and support the alcohol-involved crash cycle classification since these criteria used can help clearly demonstrate similar fluctuation patterns in the alcohol-involved crashes over time. Previous studies also indicated correlations between economic conditions, alcohol consumption, and alcohol-involved crash frequencies. Čihák (2020) indicated that economic downturns increased alcohol consumption. Several studies also found that low income and unemployment conditions could increase the potential of alcohol-involved behaviors (Li et al., 2019; Lidbe et al., 2020; Owen et al., 2019) while the increase of economic activities would increase the risk of alcohol-involved crashes (Ponce et al., 2011).

As shown in Fig. 1 and Fig. 2, the variations of the alcohol-involved crash rate, unemployment rate, and alcohol consumption per capita in North Carolina presents three distinct cycles for the alcohol-involved crashes (depression: 2008–2010; recovery: 2011–2013, and expansion: 2014–2017) after the Great Recession in December 2007. It is important to note that this is different from the classification of Behnood and Mannering (2016) in which the year 2010 was treated as a transition year between the recession and post-recession periods and was excluded in the study. In this study, a one-year time-gap is observed between the cycles of the Great Recession and DUI crashes. In 2010, the unemployment rate reaches a peak value (i.e., a change point for different cycle stages). Meanwhile, the alcohol consumption per capita reaches a minimum value (i.e., a trough) in 2010. As the Great Recession ended in 2009, these phenomena indicate the hysteresis (time-lag) of the impacts of the economic conditions on the unemployment rate, alcohol consumption per capita, and the alcohol-involved crash rate. This time-lag is also reasonable as the economic variations have transitional impacts on DUI driving behavior (rather than instant impacts or changes). Hence, the year 2010 is still included in the alcohol-related cycle phases of alcohol-involved crashes.

Also, the decreasing rates of the unemployment rate changed significantly after 2014. In this case, the year 2014 indicates an inflection point based on the elbow method and is therefore classified into the expansion period of the DUI crashes. Moreover, the alcohol consumption per capita in North Carolina shows a decreasing tendency in 2008–2010, and presents two rapidly increasing stages in 2011–2013 and 2014–2017, respectively. It is noted that the frequency of the alcohol/drugs involved crash also indicates similar temporal patterns and time-lags after the Great Recession. Both the crash rate and crash number of DUI crashes show outlier values in 2010 and 2013. Hence, three cycle phases (depression, recovery, and expansion) are classified for DUI crashes after the Great Recession and are investigated to explore the effects of economic conditions on DUI crash-injury severities.

Moreover, Fig. 3 shows significant time-of-day variations in the number of alcohol/drug involved vehicle crashes and total vehicle crashes in North Carolina. The number of total vehicle crashes presents significant fluctuations during the rush hours.

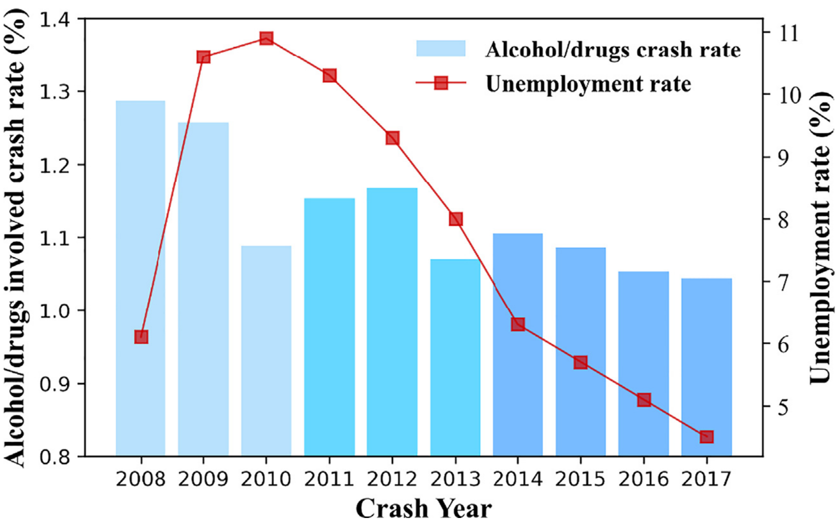

Fig. 1. Alcohol/drug involved vehicle crash rate and unemployment rate in North Carolina.

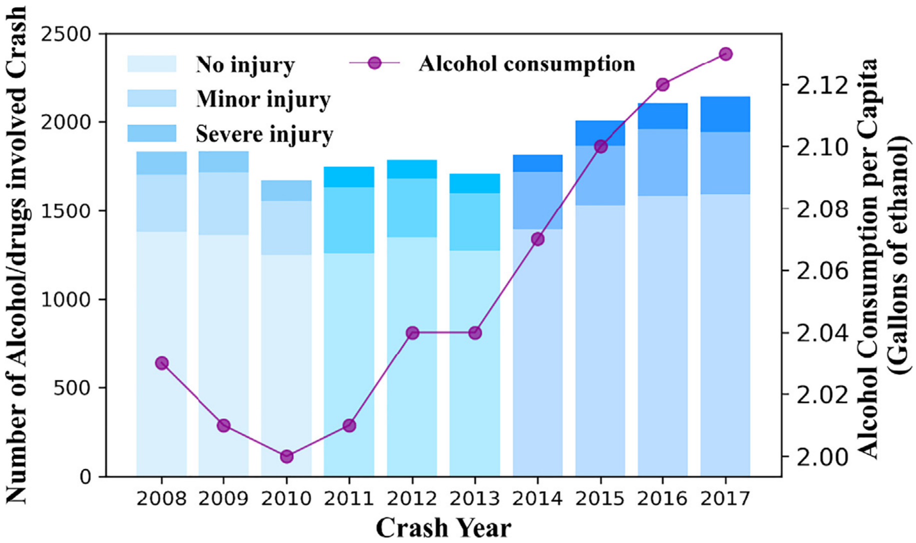

Fig. 2. Number of the alcohol/drug involved vehicle crash and alcohol consumption per capita in North Carolina.

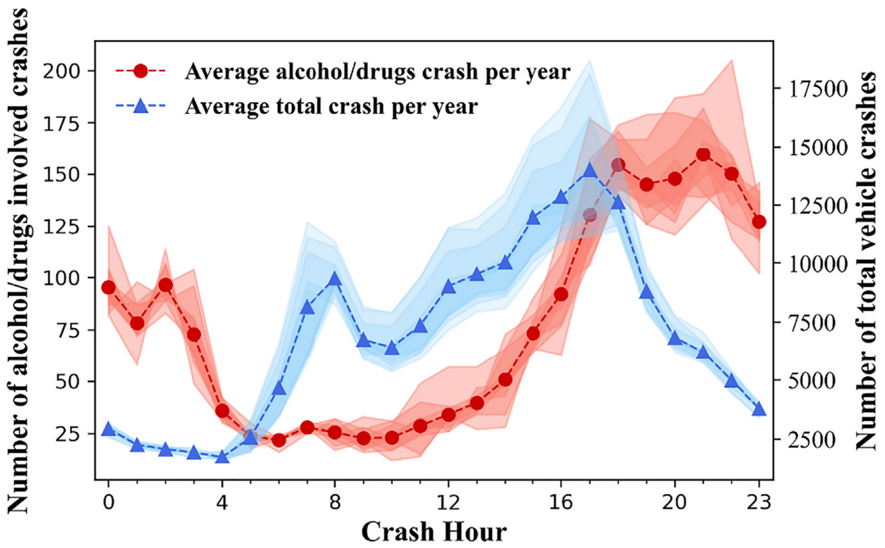

Fig. 3. Time-of-day variations of alcohol/drug involved vehicle crashes and total vehicle crashes in North Carolina (the color boundary indicates the variances within 2008–2017).

However, the DUI crashes have specific time-of-day variation patterns. The number of DUI crashes during the nighttime (4:01 P.M.–4:00 A.M.) is significantly higher than that in the daytime (4:01 A.M.–4:00 P.M.). One possible reason for these differences in the frequency of the crashes might be the difference in travel intentions and driver behaviors. However, it is noted that this classification of daytime and nighttime has about one hour gap between the traditional classification of the daytime and nighttime. As the shifts in driver behaviors are a compelling reason for the temporal instability of the crash factors (Behnood and Mannering, 2016), it is important to study the temporal variations of the alcohol/drugs involved driving behaviors. Thus, in this paper, time-of-day variations of DUI crashes are classified into "daytime" and "nighttime" mainly based on the temporal features of the crash frequency.

Table 3 presents the DUI crash frequency and percentage distribution by injury-severity for each period. Table 4 exhibits the statistics of explanatory variables in the DUI crash by the injury -severity. The explanatory variables are classified into driver, vehicle, location, roadway, environment, and traffic control categories. Also, the first category (shown in bold) of each explanatory variable is set as the base variable in logit models.

Table 3
Alcohol/drugs impaired multi-vehicle crash frequency and percentage distribution by cycle periods (numbers in the parentheses).

Time-of-day	Periods	Severe injury	Minor injury	No injury	Total
Daytime	2008–2010 depression	55 (6%)	407 (48%)	386 (46%)	848
	2011–2013 recovery	50 (5%)	448 (48%)	431 (46%)	929
	2014–2017 expansion	81 (5%)	691 (45%)	773 (50%)	1545
Nighttime	2008–2010 depression	195 (6%)	1519 (49%)	1361 (44%)	3075
	2011–2013 recovery	133 (4%)	1613 (49%)	1551 (47%)	3297
	2014–2017 expansion	286 (5%)	2462 (47%)	2484 (47%)	5232

5. Temporal stability tests

To statistically investigate the temporal stability of the factors contributing to the alcohol/drugs impaired multi-vehicle crash-injury severities under time-of-day and alcohol-related cycle periods, three types of the likelihood ratio tests are employed (Washington et al., 2011). Firstly, this paper investigates the time-of-day variations of alcohol/drugs impaired multi-vehicle crash-injury-severity models between the daytime and nighttime. The following likelihood ratio tests are applied according to (Washington et al., 2011),

$$X^2 = -2\left[LL(\boldsymbol{\beta}_{whole}) - LL(\boldsymbol{\beta}_{daytime}) - LL(\boldsymbol{\beta}_{nighttime})\right] \tag{7}$$

where $LL(\boldsymbol{\beta}_{total})$ is the log-likelihood at the convergence of a model containing the converged parameters based on the whole data. $LL(\boldsymbol{\beta}_{daytime})$ and $LL(\boldsymbol{\beta}_{nighttime})$ denote the log-likelihood at the convergence of a model containing the converged parameters based on the subset of the daytime and nighttime, respectively. The degrees of freedom are calculated by the summation of the number of estimated parameters in two subset models minus the number of estimated parameters in the whole dataset model. The X^2 is χ^2 distributed with the null hypothesis that the parameters in the subset models are equal. The log-likelihood is estimated by basic multinomial logit models, which are usually utilized as the basic models for variable selections (Greene et al., 2005). The value of X^2 is 60.12 which is χ^2 distributed with 42 degrees of freedom. This X^2 value gives a 96.55% confidence level to reject the null hypothesis. This result indicates the significant distinctions between the factors of the alcohol or drugs impaired multi-vehicle crashes during the daytime and nighttime.

Secondly, the whole dataset containing all periods (2008–2017) is segmented by three cycle phases (depression: 2008–2010; recovery: 2011–2013, expansion: 2014–2017). The temporal stability between periods of 2008–2010, 2011–2013, and 2014–2017 is also analyzed.

$$X^2 = -2[LL(\boldsymbol{\beta}_{2008-2017}) - LL(\boldsymbol{\beta}_{2008-2010}) - LL(\boldsymbol{\beta}_{2011-2013}) - LL(\boldsymbol{\beta}_{2014-2017})] \tag{8}$$

where $LL(\boldsymbol{\beta}_{2008-2017})$ is the log-likelihood at the convergence of a model containing the converged parameters based on data from the whole periods (2008–2017). For three cycle segmented periods, $LL(\boldsymbol{\beta}_t)$ denotes the log-likelihood at the convergence of a model containing the converged parameters using the data during segmented period t. The degrees of freedom are calculated by the summation of the number of estimated parameters in three segmented periods models minus the number of estimated parameters in the whole periods model. The value of X^2 is 210.91 which is χ^2 distributed with 84 degrees of freedom. This X^2 value gives a 99.99% confidence level to reject the null hypothesis that the parameters are equal over three segmented periods. This result indicates significant variations between the factors of the alcohol or drugs impaired multi-vehicle crashes across three cycle periods.

Thirdly, to statistically investigate the temporal instability during both time-of-day and cycle segmented periods, a series of likelihood ratio tests are conducted according to (Behnood and Mannering, 2019; Washington et al., 2011),

$$X^2 = -2\left[LL(\boldsymbol{\beta}_{t_2 t_1}) - LL(\boldsymbol{\beta}_{t_1})\right] \tag{9}$$

where $LL(\boldsymbol{\beta}_{t_2 t_1})$ is the log-likelihood at the convergence of a model using the converged parameters from time t_2 (with restricting the parameters to be the estimated parameters of time t_2), while using data in period t_1. $LL(\boldsymbol{\beta}_{t_1})$ is the log-likelihood at the convergence of the model with data in period t_1. This test is also reversed by using $LL(\boldsymbol{\beta}_{t_1 t_2})$ and $LL(\boldsymbol{\beta}_{t_2})$. The resulting value X^2 is χ^2 distributed with degrees of freedom being equal to the number of estimated parameters in $\boldsymbol{\beta}_{t_1 t_2}$. The null hypothesis is that the parameters in periods t_1 and t_2 are equal. The statistical results in Table 5 show the significant existence of the temporal instability of the crash injury severity factors between every two periods since none of the two reversed tests accepts the null hypothesis simultaneously. As mentioned in Behnood and Mannering (2016), variations in human behaviors and changes in economic conditions are all possible reasons for the temporal instability of the factors of crashes. Hence, investigating the factors of the alcohol/drugs impaired multi-vehicle crash-injury severities during the daytime, nighttime, and three cycle phases after the Great Recession might provide insights into inherent reasons for the time-of-day variations and temporal instability of the DUI crashes factors.

Table 4
Statistics of explanatory variables for alcohol/drugs impaired multi-vehicle crash-injury severities.

Variable		Description	Injury Severity %			Total
			Severe injury	Minor injury	No injury	
		Number of observations	800(5.36%)	7140(47.84%)	6986(46.8%)	14,926
Driver Characteristics						
Driver Age	**1**	**Young-age: Age ≤24**	216(6.29%)	1669(48.62%)	1548(45.09%)	3433
	2	Middle-age: 24 < Age ≤ 50	471(5.5%)	4116(48.07%)	3975(46.43%)	8562
	3	Old-age: Age > 50	113(3.86%)	1355(46.23%)	1463(49.91%)	2931
Driver Sex	**1**	**Male**	618(5.54%)	5334(47.83%)	5199(46.62%)	11,151
	2	Female	182(4.82%)	1806(47.84%)	1787(47.34%)	3775
Driver Restraint	**1**	**Without belt**	152(8.71%)	806(46.19%)	787(45.1%)	1745
	2	With belt	648(4.92%)	6334(48.05%)	6199(47.03%)	13,181
Driver Action	**1**	**Impaired by alcohol/drugs only**	393(5.41%)	3483(47.95%)	3388(46.64%)	7264
	2	Disregarded sign or signal	47(6.3%)	446(59.79%)	253(33.91%)	746
	3	Failure to reduce speed	98(3.25%)	1387(45.93%)	1535(50.83%)	3020
	4	Going wrong way/improper lane use	109(12.49%)	447(51.2%)	317(36.31%)	873
	5	Failed to yield right of way	54(5.36%)	544(53.97%)	410(40.67%)	1008
	6	Inattention or aggressive manner	64(4.97%)	594(46.08%)	631(48.95%)	1289
	7	Other improper maneuvers	35(4.82%)	239(32.92%)	452(62.26%)	726
Vehicle Types						
Vehicle Type	**1**	**Small: passenger cars and SUVs**	610(5.38%)	5499(48.48%)	5233(46.14%)	11,342
	2	Middle: Pick-ups and vans	190(5.3%)	1641(45.79%)	1753(48.91%)	3584
Locality Characteristics						
Development	**1**	**Rural**	563(7.08%)	3767(47.35%)	3625(45.57%)	7955
	2	Urban	237(3.4%)	3373(48.39%)	3361(48.21%)	6971
Land use	**1**	**Farms, Woods, Pastures**	401(8.41%)	2317(48.62%)	2048(42.97%)	4766
	2	Residential	175(5.21%)	1600(47.65%)	1583(47.14%)	3358
	3	Commercial	214(3.22%)	3132(47.2%)	3290(49.58%)	6636
	4	Institutional	7(7.29%)	57(59.38%)	32(33.33%)	96
	5	Industrial	3(4.29%)	34(48.57%)	33(47.14%)	70
Terrain	**1**	**Flat**	214(6.46%)	1492(45.06%)	1605(48.47%)	3311
	2	Rolling	532(4.99%)	5245(49.19%)	4886(45.82%)	10,663
	3	Mountainous	54(5.67%)	403(42.33%)	495(52%)	952
Intersection	**1**	**Non-intersection**	593(5.95%)	4653(46.71%)	4715(47.33%)	9961
	2	Intersection	207(4.17%)	2487(50.09%)	2271(45.74%)	4965
Roadway Characteristics						
Road Class	**1**	**Secondary Route**	296(5.12%)	2725(47.15%)	2758(47.72%)	5779
	2	State Route	208(5.95%)	1770(50.64%)	1517(43.4%)	3495
	3	US Route	199(5.1%)	1851(47.47%)	1849(47.42%)	3899
	4	Interstate	97(5.53%)	794(45.29%)	862(49.17%)	1753
Road Configuration	**1**	**One-way, not divided**	9(2.47%)	135(36.99%)	221(60.55%)	365
	2	Two-way, not divided	555(6.12%)	4374(48.21%)	4144(45.67%)	9073
	3	Two-way, divided	236(4.3%)	2631(47.94%)	2621(47.76%)	5488
Road Curve	**1**	**Straight**	602(4.51%)	6350(47.52%)	6410(47.97%)	13,362
	2	Curve	198(12.66%)	790(50.51%)	576(36.83%)	1564
Road Grade	**1**	**Level**	595(4.94%)	5738(47.6%)	5722(47.47%)	12,055
	2	Grade	154(6.65%)	1143(49.33%)	1020(44.02%)	2317
	3	Hillcrest	45(10.32%)	203(46.56%)	188(43.12%)	436
	4	Bottom	6(5.08%)	56(47.46%)	56(47.46%)	118
Environment Characteristics						
Light	**1**	**Dark with roadway light**	420(4.13%)	4781(47.04%)	4962(48.82%)	10,163
	2	Dark without roadway light	380(7.98%)	2359(49.53%)	2024(42.49%)	4763
Weather	**1**	**Clear**	614(5.26%)	5573(47.7%)	5496(47.04%)	11,683
	2	Cloudy	135(6.76%)	953(47.7%)	910(45.55%)	1998
	3	Rain	51(4.1%)	614(49.32%)	580(46.59%)	1245
Traffic control Types						
Traffic Control	**1**	**No control present**	309(5.59%)	2539(45.95%)	2678(48.46%)	5526
	2	Signs	382(7.74%)	2483(50.31%)	2070(41.95%)	4935
	3	Signal	109(2.44%)	2118(47.44%)	2238(50.12%)	4465
Speed Limits	**1**	**Less than 35 mph**	102(2.89%)	1632(46.19%)	1799(50.92%)	3533
	2	36 to 55 mph	607(6.2%)	4778(48.84%)	4398(44.96%)	9783
	3	56 to 70 mph	91(5.65%)	730(45.34%)	789(49.01%)	1610

Note: variables numbered with 1 are set as base variables in logit models.

Table 5
Likelihood ratio test results between different period pairs ($\chi2$ values with the degrees of freedom in parenthesis and the confidence level in brackets).

t1	t2					
	2008–2010 daytime	2008–2010 nighttime	2011–2013 daytime	2011–2013 nighttime	2014–2017 daytime	2014–2017 nighttime
2008–2010 daytime	–	41.10 (22) [99.20%]	9.08 (13) [23.32%]	38.79 (25) [96.13%]	22.60 (20) [69.11%]	41.98 (25) [98.20%]
2008–2010 nighttime	150.18 (20) [99.99%]	–	86.86 (13) [99.99%]	38.42 (25) [95.79%]	35.86 (20) [98.40%]	48.67 (25) [99.79%]
2011–2013 daytime	95.57 (20) [99.99%]	90.89 (22) [99.99%]	–	32.35 (25) [85.19%]	23.25 (20) [72.33%]	29.34 (25) [74.99%]
2011–2013 nighttime	251.27 (20) [99.99%]	133.86 (22) [99.99%]	67.82 (13) [99.99%]	–	50.43 (20) [99.98%]	48.78 (25) [99.70%]
2014–2017 daytime	144.14 (20) [99.99%]	96.21 (22) [99.99%]	24.63 (13) [97.42%]	41.96 (25) [98.18%]	–	29.54 (25) [75.81%]
2014–2017 nighttime	441.74 (20) [99.99%]	256.48 (22) [99.99%]	120.32 (13) [99.99%]	89.73 (25) [99.99%]	98.35 (20) [99.99%]	–

6. Model results and discussion

6.1. Parameter estimation results

The estimation results for six period combinations are presented in Tables 6–11. The multinominal logit model is utilized as the basic model for the variable selection. Then, RPL model and possible heterogeneity in the means and variances are further explored. It is noted that PRL models with heterogeneity in the means are obtained in models of the 2008–2010 daytime, 2014–2017 daytime, and 2014–2017 nighttime. Also, random parameters with heterogeneity in the means and variances are estimated in the 2008–2010 nighttime model. Meanwhile, Table 12 presents the comparison of marginal effects of the significant variables to investigate the impact of such explanatory variables on the probability of alcohol/drugs impaired crash-injury outcomes. Considerable variations in the estimated parameters and corresponding marginal effects are found during six period combinations. Specific discussions of the estimation results by variable categories are presented as follows.

6.2. Discussions of the significant factors

6.2.1. Driver characteristics

The age of the driver is divided into three categories considering different physical conditions and the proportion of injury-severity (Song and Fan, 2020). In comparison with young drivers (age less than 25), middle-aged drivers (age between 25 and 50) decrease the probability of severe injury (SI) by 0.037 during the daytime of 2011–2013. Older-age drivers (age over 50) decrease the probability of the severe injury in the daytime and nighttime of the depression (2008–2010) and recovery periods (2011–2013). One possible reason for the decrease during the depression period might be that elder drivers are more cautious and proficient in driving compared to young drivers (Lee et al., 2020). This is in accord with Maheshri and Winston (2016) who indicated that safer drivers drive more frequently during economic downturns. Also, during the recovery period (2011–2013), older-age drivers reduce the probability of the severe injury in the daytime and nighttime by 0.041 and 0.0028, respectively. This indicates that nighttime environments could result in more severe injuries compared to the daytime. Compared to male drivers, female drivers increase the probability of the minor injury and slightly decrease the probability of the severe injury in the daytime of 2011–2013. One possible reason for this is that male drivers are more aggressive, more likely to overuse alcohol or drugs, and more likely to take risky behaviors (Lee et al., 2020).

In comparison with drivers not restrained with a belt, drivers with a belt significantly decrease the probability of both the severe injury and minor injury in the daytime and nighttime of 2008–2010. Driving without a belt is found to associate with alcohol/drugs use and is the main reason for fatal outcomes (Bogstrand et al., 2015). Meanwhile, driver actions that mainly contribute to crashes are taken into consideration. In comparison with crashes when drivers were only under the influence of alcohol/drug, drivers who also disregarded traffic signs or signals slightly increase the probability of both the severe injury and minor injury in the nighttime of all three cycle phases and the daytime of the expansion phase (2014–2017). A possible reason for this is drivers are more likely to disregard the sign or signal during the nighttime. For drivers who also failed to reduce the speed, a slight decrease in the probability of the severe injury and minor injury is shown in the 2011–2013 daytime and 2014–2017 nighttime. For drivers who also go the wrong way or use an improper lane, a slight increase in the probability of the severe injury is observed in the nighttime of all periods and the daytime of 2008–2010. One possible reason for this is that drivers are more likely to go into the wrong way or use an improper lane during the nighttime, and similar results are shown in Behnood et al. (2014) and Behnood and Mannering (2017b). Moreover, for drivers who also failed to yield to the right of way, a slight increase in the probability of both the severe injury and minor injury is shown in the nighttime of 2014–2017. This is also supported by Behnood et al. (2014).

6.2.2. Vehicle types

The vehicles that are controlled by DUI drivers are classified into small-size (passenger cars and sport utility vehicles [SUVs]) and middle-size vehicles (pick-ups and vans). It is noted that large-size vehicles such as buses and trucks are excluded because of the limited number of large-size vehicles that are involved with DUI crashes. Compared to crashes with small-size vehicles, alcohol/drugs impaired drivers with middle-size vehicles decrease the probability of the minor injury by

Table 6
Significant variable coefficients of alcohol/drugs impaired crashes during the daytime, 2008–2010 (depression period).

Variable	Description	Coefficient	z-value
Defined for no injury (NI)			
Intercept	Constant	−1.200	−1.87
Driver Restraint 2	With belt (Base: Without belt)	3.433	4.99
Driver Action 4	Going wrong way/improper lane use (Base: Impaired by alcohol/drug)	−2.267	−3.49
Land Use 3	Commercial (Base: Farms, Woods, Pastures)	0.986	2.22
Road Curve 2	Curve (Base: Straight)	−1.464	−3.14
Road Grade 3	Hillcrest (Base: Level)	2.394	2.38
Traffic Control 3	Signal (Base: No Control Present)	2.237	2.60
Vehicle Type 2	Middle: Pick-ups and vans (Base: Small: passenger cars and SUVs)	1.029	2.04
Random Parameter	*Standard deviation of Vehicle Type 2*	2.266	2.43
Land Use 2	Residential (Base: Farms, Woods, Pastures)	1.574	2.55
Random Parameter	*Standard deviation of Land Use 2*	1.912	1.90
Defined for minor injury (MI)			
Intercept	Constant	0.930	2.51
Road Curve 2	Curve (Base: Straight)	−1.109	−1.90
Traffic Control 3	Signal (Base: No Control Present)	2.244	2.60
Driver Restraint 2	With belt (Base: Without belt)	1.353	2.49
Random Parameter	*Standard deviation of Driver Restraint 2*	5.248	2.36
Defined for severe injury (SI)			
Driver Age 3	Old-age: Age >50 (Base: Young-age: Age ≤24)	−1.366	−1.93
Road Class 3	US Route (Base: Secondary Route)	0.949	2.27
Heterogeneity in the means of the random parameters			
Land Use 2 (Commercial) [NI]: Road Class 2 (State Route)		−2.291	−2.29
Driver Restraint 2 (With belt) [MI]: Intersection 2 (Intersection)		1.397	1.93
Model statistics			
N	Number of observations	848	
K	Degree of freedom	20	
$LL(0)$	Log-likelihood at zero	−931.62	
$LL(\beta)$	Log-likelihood at convergence	−688.27	
$1 - LL(\beta)/LL(0)$	McFadden Pseudo R-squared	0.261	

0.018 and 0.07 in the daytime of 2008–2010 and 2011–2013 periods, respectively. This is different from previous findings as van/mini-van would increase the DUI crash-injury-severity (Behnood et al., 2014). One possible reason for this is that middle-size vehicles could provide more protection in DUI crashes compared to small-size vehicles.

6.2.3. Locality characteristics

In comparison with rural areas, crashes that occurred in urban areas result in lower probabilities of both the severe injury and no injury and higher probabilities of the minor injury in the daytime and nighttime of 2014–2017. The possible reason for this is that urban areas have lower speed limits but more complicated traffic flow compared to rural areas (Behnood and Mannering, 2017b; Lidbe et al., 2020; Liu and Fan, 2020).

Compared to the areas with farms, woods, and pastures, DUI crashes that occurred in institutional areas indicate a slight increase of the severe injury in the daytime of 2014–2017 (expansion period). Moreover, residential areas decrease the minor injury in 2008–2010 daytime and 2014–2017 nighttime. Also, crashes that occurred in commercial areas can slightly decrease the probabilities of the minor injury and severe injury during the daytime of 2008–2010 and the daytime and nighttime of 2014–2017. Possible reasons for this include: residential and commercial areas have lower speed limits and more traffic signs to alert drivers (Song and Fan, 2020), and alcohol/drugs might take a while to be effective for drivers when they are away from these starting areas. The significant effects of residential and commercial areas during the daytime of depression and expansion periods indicate that alcohol/drug use behaviors are potentially affected by economic conditions. Also, both depressing and expanding economic conditions might increase the behavior of driving under the influence of the alcohol/drug. Previous studies also found that low income and unemployment status could increase the potential of DUI behaviors (Li et al., 2019; Lidbe et al., 2020; Owen et al., 2019). Meanwhile, economically active males were found to increase the risk of DUI crashes (Ponce et al., 2011).

Compared with flat terrains, crashes that occurred in rolling areas increase the probability of the minor injury and decrease the probability of the no injury in the nighttime of the recovery period (2011–2013) and expansion period (2014–2017). A possible reason for this is that drivers would decrease the speed in rolling areas. For crashes that occurred in mountainous areas during the daytime of 2011–2013, the probability of the severe injury and minor injury can be decreased by 0.013 and 0.125, respectively. Previous studies also showed mountainous areas could decrease the crash-injury-severity due to the lower speed limits (Song and Fan, 2020). Compared to non-intersection areas, crashes at the intersection can result in an increase in the minor injury and a slight decrease in severe injury during the nighttime of 2014–2017. This result is also found in Chen et al. (2016).

Table 7
Significant variable coefficients of alcohol/drugs impaired crashes during the nighttime, 2008–2010 (depression period).

Variable	Description	Coefficient	z-value
Defined for no injury (NI)			
Intercept	Constant	2.024	4.36
Driver Age 3	Old-age: Age >50 (Base: Young-age: Age ≤24)	0.932	2.16
Driver Action 2	Disregarded sign or signal (Base: Impaired by alcohol/drug)	−2.745	−3.10
Road Class 2	State Route (Base: Secondary route)	−1.004	−3.37
Road Class 3	US route (Base: Secondary route)	−0.909	−3.03
Road Curve 2	Curve (Base: Straight)	−2.352	−5.32
Speed Limits 2	36–55 mph (Base: ≤35 mph)	−1.178	−2.80
Speed Limits 3	56–70 mph (Base: ≤35 mph)	−1.769	−2.81
Driver Restraint 2	With belt (Base: Without belt)	5.302	4.37
Random Parameter	*Standard deviation of Driver Restraint 2*	3.796	3.33
Defined for minor injury (MI)			
Intercept	Constant	2.102	4.90
Driver Age 3	Old-age: Age >50 (Base: Young-age: Age ≤24)	1.089	2.65
Driver Action 7	Other improper maneuvers (Base: Impaired by alcohol/drug)	−3.398	−2.06
Road Curve 2	Curve (Base: Straight)	−0.986	−3.16
Speed Limits 2	36–55 mph (Base: ≤35 mph)	−1.222	−2.93
Speed Limits 3	56–70 mph (Base: ≤35 mph)	−1.480	−2.35
Driver Restraint 2	With belt (Base: Without belt)	3.994	3.74
Random Parameter	*Standard deviation of Driver Restraint 2*	9.672	2.71
Defined for severe injury (SI)			
Driver Action 4	Going wrong way/improper lane use (Base: Impaired by alcohol/drug)	1.481	3.86
Heterogeneity in the means of the random parameter			
Driver Restraint 2 (With belt) [NI]: Light 2 (Dark without roadway light)	−1.346	−2.81	
Driver Restraint 2 (With belt) [NI]: Driver Action 5 (Failed to yield right of way)	−2.186	−3.02	
Heterogeneity in the variances of random parameter			
Driver Restraint 2 (With belt) [NI]: Traffic Control 3 (Signal)	−0.332	−1.93	
Model statistics			
N	Number of observations	3075	
K	Degree of freedom	22	
LL(0)	Log-likelihood at zero	−3378.23	
LL(β)	Log-likelihood at convergence	−2545.49	
1-*LL*(β)/*LL*(0)	McFadden Pseudo R-squared	0.247	

6.2.4. Roadway characteristics

Compared to secondary routes, state routes increase the probability of the severe injury and minor injury in the nighttime of 2008–2010 (depression) and 2011–2013 (recovery). Meanwhile, US routes increase the probability of the severe injury while slightly decrease the probability of the minor injury during 2008–2010 daytime and 2011–2013 nighttime. For the interstate routes, a 0.008 increase in the probability of the severe injury is observed in the daytime of 2014–2017 (expansion). In comparison with one-way undivided roadways, two-way undivided roadways increase the probability of the minor injury and severe injury by 0.073 and 0.016 in the nighttime of 2014–2017. Also, for two-way roadways with divided mediums, the probability of the minor injury is increased by about 0.05 during the daytime and nighttime of 2014–2017. Meanwhile, a slight decrease of the severe injury is observed in the daytime of 2014–2017. This indicates the preventive effect of the divided roadway in DUI crashes (Behnood et al., 2014). However, the preventive effect of the median barrier seems to be less effective in the nighttime as a slight increase in the probability of the severe injury is observed during the nighttime of 2014–2017.

Compared to straight roadways, curve roadways increase the probability of the severe injury and decrease the no injury in all periods. Compared with level roadways, grade roadways increase the probability of the severe injury in the daytime of 2014–2017. It is hard for DUI drivers to maneuver vehicles in curve and grade roadways compared to straight and level roadways (Behnood et al., 2014; Behnood and Mannering, 2017b; Maistros et al., 2014). For vehicles in the hillcrest, a slight decrease is observed in the severe injury during the daytime of 2008–2010 and an increase in the severe injury during the nighttime of 2011–2013 and 2014–2017. One possible reason for the heterogeneous result is that driving in the hillcrest has a shorter vision range and could increase the injury-severity during the nighttime; while in the daytime, drivers would decrease the speed timely before approaching the hillcrest and thus reduce the crash-injury-severity.

Table 8
Significant variable coefficients of alcohol/drugs impaired crashes during the daytime, 2011–2013 (recovery period).

Variable	Description	Coefficient	*z*-value
Defined for no injury (NI)			
Intercept	Constant	2.029	6.60
Driver Action 3	Failure to reduce speed (Base: Impaired by alcohol/drug)	0.354	2.08
Driver Action 7	Other improper maneuvers (Base: Impaired by alcohol/drug)	0.816	2.80
Vehicle Type 2	Middle: Pick-ups and vans (Base: Small: passenger cars and SUVs)	0.337	2.17
Terrain 3	Mountainous (Base: Flat)	0.583	2.14
Road Curve 2	Curve (Base: Straight)	−0.472	−2.22
Speed Limits 2	36–55 mph (Base: ≤35 mph)	−0.291	−2.01
Traffic Control 2	Signs (Base: No control present)	−0.930	−2.96
Defined for minor injury (MI)			
Intercept	Constant	1.970	6.79
Driver Sex 2	Female (Base: Male)	0.354	2.25
Traffic Control 2	Signs (Base: No control present)	−0.903	−2.96
Defined for severe injury (SI)			
Driver Age 2	Middle-age: 24 < Age ≤ 50 (Base: Young-age: Age ≤24)	−0.741	−2.23
Driver Age 3	Old-age: Age >50 (Base: Young-age: Age ≤24)	−0.826	−1.94
Model statistics			
N	Number of observations	929	
K	Degree of freedom	13	
LL(c)	Log-likelihood with Constants only	−803.85	
LL(β)	Log-likelihood at convergence	−776.47	
1-*LL*(β)/*LL*(c)	R-squared	0.034	

Table 9
Significant variable coefficients of alcohol/drugs impaired crashes during the nighttime, 2011–2013 (recovery period).

Variable	Description	Coefficient	*z*-value
Defined for no injury (NI)			
Intercept	Constant	3.249	12.83
Driver Age 3	Old-age: Age >50 (Base: Young-age: Age ≤24)	0.674	2.29
Driver Action 2	Disregarded sign or signal (Base: Impaired by alcohol/drug)	−0.782	−2.96
Driver Action 4	Going wrong way/improper lane use (Base: Impaired by alcohol/drug)	−0.538	−2.70
Driver Action 7	Other improper maneuvers (Base: Impaired by alcohol/drug)	0.801	2.98
Road Class 2	State Route (Base: Secondary route)	−0.432	−3.27
Road Class 3	US route (Base: Secondary route)	−0.329	−2.41
Road Curve 2	Curve (Base: Straight)	−1.316	−5.95
Road Grade 3	Hillcrest (Base: Level)	−1.513	−3.74
Weather 3	Rain (Base: Clear)	1.404	2.31
Speed Limits 2	36–55 mph (Base: ≤35 mph)	−0.477	−2.00
Light 2	Dark without roadway light (Base: Dark with roadway light)	−0.588	−2.95
Traffic Control 3	Signal (Base: No control present)	1.503	2.68
Random Parameter	*Standard deviation of Traffic Control 3*	3.205	2.02
Defined for minor injury (MI)			
Intercept	Constant	2.777	10.37
Driver Age 3	Old-age: Age > 50 (Base: Young-age: Age ≤24)	0.651	2.16
Intersection 2	Intersection (Base: Non-intersection)	0.313	2.43
Road Curve 2	Curve (Base: Straight)	−1.038	−4.48
Road Grade 3	Hillcrest (Base: Level)	−0.966	−2.34
Weather 3	Rain (Base: Clear)	1.534	2.49
Speed Limits 2	36–55 mph (Base: ≤35 mph)	−0.441	−1.81
Traffic Control 3	Signal (Base: No control present)	1.048	2.10
Light 2	Dark without roadway light (Base: Dark with roadway light)	−0.470	−2.29
Terrain 2	Rolling (Base: Flat)	0.275	2.43
Random Parameter	*Standard deviation of Terrain 2*	1.743	2.15
Model statistics			
N	Number of observations	3297	
K	Degree of freedom	25	
LL(0)	Log-likelihood at zero	−3622.12	
LL(β)	Log-likelihood at convergence	−2660.22	
1-*LL*(β)/*LL*(0)	McFadden Pseudo R-squared	0.266	

6.2.5. Environment characteristics

It is noted that only nighttime models consider the factor of dark without roadway light. Compared to the dark with roadway light conditions, the dark without roadway light increases the probability of the severe injury and minor injury in the

Table 10
Significant variable coefficients of alcohol/drugs impaired crashes during the daytime, 2014–2017 (expansion period).

Variable	Description	Coefficient	z-value
Defined for no injury (NI)			
Intercept	Constant	2.923	11.85
Driver Action 2	Disregarded sign or signal (Base: Impaired by alcohol/drug)	−1.116	−2.97
Land Use 3	Commercial (Base: Farms, Woods, Pastures)	0.341	1.99
Land Use 4	Institutional (Base: Farms, Woods, Pastures)	−3.236	−2.30
Road Class 4	Interstate (Base: Secondary route)	−0.678	−1.98
Road Curve 2	Curve (Base: Straight)	−0.691	−2.68
Traffic Control 2	Signs (Base: No control present)	−0.479	−2.36
Speed Limits 2	36–55 mph (Base: $\leq$35 mph)	−0.328	−1.72
Random Parameter	*Standard deviation of Speed Limits 2*	1.961	2.43
Defined for minor injury (MI)			
Intercept	Constant	2.162	12.68
Driver Action 7	Other improper maneuvers (Base: Impaired by alcohol/drug)	−1.303	−3.17
Development 2	Urban (Base: Rural)	0.500	2.65
Road Class 4	Interstate (Base: Secondary route)	−1.305	−3.09
Road Configuration 3	Two-way, divided (Base: One-way, not divided)	0.932	3.49
Random Parameter	*Standard deviation of Road Configuration 3*	1.663	2.00
Defined for severe injury (SI)			
Road Grade 2	Grade (Base: Level)	0.557	2.07
Heterogeneity in the means of the random parameters			
Speed Limits 2 (36–55 mph) [NI]: Driver Action 3 (Unsafe speed)		0.621	1.88
Speed Limits 2 (36–55 mph) [NI]: Road Class 2 (State Route)		−0.478	−1.78
Road Configuration 3 (Two-way, divided) [MI]: Traffic Control 3 (Signal)		−0.795	−2.22
Road Configuration 3 (Two-way, divided) [MI]: Road Grade 3 (Hillcrest)		−4.422	−2.60
Model statistics			
N	Number of observations	1545	
K	Degree of freedom	20	
$LL(0)$	Log-likelihood at zero	−1697.36	
$LL(\beta)$	Log-likelihood at convergence	−1277.82	
$1-LL(\beta)/LL(0)$	McFadden Pseudo R-squared	0.247	

nighttime of 2011–2013 and 2014–2017. As people are more likely to drink alcohol or use drugs during the nighttime, the results indicate that roadway lights are needed, especially in the surrounding residential or commercial areas. Compared to clear weather conditions, driving in the rain decreases the probability of the severe injury and increases the probability of the minor injury during the nighttime of 2011–2013. One possible reason is drivers would slow their speed and be more cautious when driving in the rain. Similar results were mentioned in Behnood et al. (2014) and Behnood and Mannering (2017b).

6.2.6. Traffic Control types

Compared with no traffic control conditions, traffic sign controls present an increase in the probability of the severe injury and a decrease in the probability of the no injury during the daytime of 2011–2013 (recovery) and 2014–2017 (expansion). However, traffic signal controls indicate a decrease in the severe injury during the daytime of 2008–2010 and the nighttime of 2011–2013 and 2014–2017. Possible reasons for the opposite results of traffic signs and signals during the daytime and nighttime of recovery and expansion periods are: 1) traffic signals work better during the nighttime compared to traffic signs; 2) both traffic signs and signals could alert the drivers and could mitigate crash injury severities (Behnood and Mannering, 2017b); 3) traffic signs are usually set at crash-prone areas with severe crash-injury, hence, crashes at locations with traffic signs also suffer more severe crash-injury. Considering all of these, setting more electronic traffic signs to alert drivers at night might be a good solution to mitigate alcohol/drugs impaired crash-injury-severity.

Compared with speed limits less than 35 mph, speed limits between 36 and 55 mph all present an increase in the probability of the severe injury in the daytime and nighttime of the recovery (2011–2013) and expansion periods (2014–2017). Also, both speed limits between 36 and 55 and 56–70 increase the probability of the severe injury in the nighttime of the depression period (2008–2010). This indicates that speed limits are less effective in the nighttime of recent recovery and expansion periods. Liu and Fan (2020) also found that higher speed limits could increase the DUI-related crash-injury-severity.

6.2.7. Heterogeneity in the means of random parameters

As indicated in Table 7, two random variables show heterogeneity in the means during the daytime of the depression period (2008–2010). State route decreases the means of the commercial area indicator (making no injury less likely and, in turn, making the crash injury more severe). Also, the intersection increases the mean of the with-belt indicator, and this increases the probability of the minor injury.

Table 11
Significant variable coefficients of alcohol/drugs impaired crashes during the nighttime, 2014–2017 (expansion period).

Variable	Description	Coefficient	*z*-value
Defined for no injury (NI)			
Intercept	Constant	3.040	8.63
Driver Action 2	Disregarded sign or signal (Base: Impaired by alcohol/drug)	−0.975	−4.05
Driver Action 3	Failure to reduce speed (Base: Impaired by alcohol/drug)	0.266	2.26
Driver Action 4	Going wrong way/improper lane use (Base: Impaired by alcohol/drug)	−0.517	−2.51
Driver Action 5	Failed to yield right of way (Base: Impaired by alcohol/drug)	−0.742	−3.96
Driver Action 7	Other improper maneuvers (Base: Impaired by alcohol/drug)	0.903	4.12
Land Use 2	Residential (Base: Farms, Woods, Pastures)	0.723	3.79
Land Use 3	Commercial (Base: Farms, Woods, Pastures)	0.535	3.13
Road Curve 2	Curve (Base: Straight)	−0.414	−2.62
Road Grade 3	Hillcrest (Base: Level)	−1.156	−3.41
Road Configuration 2	Two-way, not divided (Base: One-way, not divided)	−0.967	−3.30
Road Configuration 3	Two-way, divided (Base: One-way, not divided)	−0.909	−3.08
Traffic Control 3	Signal (Base: No control present)	0.755	3.77
Light 2	Dark without roadway light (Base: Dark with roadway light)	−0.370	−3.50
Speed Limits 2	36–55 mph (Base: $\leq$35 mph)	−0.182	−2.04
Random Parameter	*Standard deviation of Speed Limits 2*	1.233	1.96
Defined for minor injury (MI)			
Intercept	Constant	1.270	8.29
Random Parameter	*Standard deviation of Intercept*	1.624	2.85
Development 2	Urban (Base: Rural)	0.424	3.39
Land Use 2	Residential (Base: Farms, Woods, Pastures)	0.568	2.86
Terrain 2	Rolling (Base: Flat)	0.530	3.96
Road Grade 3	Hillcrest (Base: Level)	−1.022	−2.88
Traffic Control 3	Signal (Base: No control present)	0.689	3.33
Land Use 3	Commercial (Base: Farms, Woods, Pastures)	0.384	2.03
Heterogeneity in the means of the random parameters			
Speed Limits 2 (36–55 mph) [NI]: Road Grade 2 (Grade)		−0.342	−1.96
Model statistics			
N	Number of observations	5232	
K	Degree of freedom	25	
$LL(0)$	Log-likelihood at zero	−5747.94	
$LL(\beta)$	Log-likelihood at convergence	−4406.09	
$1\text{-}LL(\beta)/LL(0)$	McFadden Pseudo R-squared	0.233	

Table 11 shows two random variables with heterogeneity in the means during the daytime of the expansion period (2014–2017). For the crash with speed limits of 36–55 mph, failure to reduce the speed increases its mean (resulting in more no injury crashes), while state route decreases its mean (making the crash injury more severe). For random parameter of two-way with-divided roadways, both with traffic signals and at the hillcrest can decrease its mean (making minor injury less likely).

As presented in Table 12, the speed limit within 36–55 mph shows heterogeneity in the mean during the nighttime of the expansion period (2014–2017). The grade roadways decrease its mean (decreasing the likelihood of no injury, which in turn increasing the crash-injury-severity).

6.2.8. Heterogeneity in the means and variances of random parameters

As shown in Table 8, in the nighttime of the depression period (2008–2010), the indicator of with-belt is found to produce random parameters with heterogeneity in the means and variances. Driving in the dark without roadway light and drivers failing to yield to the right-of-way both indicate a decrease in its mean. Also, traffic controlled with signals could decrease its variances. All these variables make no injury crashes less likely, and in turn, result in more severe injuries.

7. Conclusions

Using data of multi-vehicle crashes with drivers under the influence of alcohol/drugs in North Carolina from 2008 to 2017, this paper explores the time-of-day variations (daytime vs. nighttime) and temporal instabilities of factors affecting alcohol/drugs impaired crash-injury severities during three cycle phases (depression: 2008–2010; recovery: 2011–2013; and expansion: 2014–2017) after the Great Recession. Random parameters logit models with heterogeneity in the means and variances are utilized to model three possible injury severities (severe injury, minor injury, and no injury) and identify significant factors, such as characteristics of the driver, vehicle, locality, roadway, environment, and traffic control.

Results of different likelihood ratio tests indicate that the effects of factors vary significantly across two time-of-day periods, three cycle periods, and six combined periods of time-of-day and alcohol-related cycles. Also, the results of RPL with heterogeneity in the means and variances during the depression and expansion periods reveal correlations between factors

Table 12
Comparison of marginal effects between daytime and nighttime alcohol/drugs impaired multi-vehicle crashes over three cycle periods.

Periods	2008–2010 Daytime			2008–2010 Nighttime			2011–2013 Daytime			2011–2013 Nighttime			2014–2017 Daytime			2014–2017 Nighttime		
Variables	SI	MI	NI	SI	MI	NI	SI	MI	NI	SI	MI	NI	SI	MI	NI	SI	MI	NI
Driver Characteristics																		
Middle-age: 24 < Age ≤ 50 (Young-age: Age ≤24)							−0.0369	0.0197	0.0172									
Old-age: Age > 50	−0.0040	0.0015	0.0025	−0.0035	0.0027	0.0008	−0.0411	0.0220	0.0191	−0.0028	0.0006	0.0022						
Female (Male)							−0.0094	0.0854	−0.0760									
With belt (Without belt)	−0.0858	−0.0703	0.1561	−0.0186	−0.0171	0.0357												
Disregarded sign or signal (Impaired by alcohol/drug)				0.0030	0.0041	−0.0071				0.0006	0.0053	−0.0059	0.0009	0.0066	−0.0075	0.0011	0.0054	−0.0065
Failure to reduce speed							−0.0082	−0.0760	0.0842							−0.001	−0.0071	0.0081
Going wrong way/improper lane use	0.0071	0.0067	−0.0138	0.0058	−0.0028	−0.0030				0.0011	0.0048	−0.0060				0.0009	0.0033	−0.0041
Failed to yield right of way																0.0014	0.0064	−0.0078
Other improper maneuvers				0.0007	−0.0056	0.0049	−0.0189	−0.1752	0.1941	−0.0005	−0.0056	0.0061	0.0018	−0.0083	0.0066	−0.0008	−0.0061	0.0068
Vehicle Types																		
Middle: Pick-ups and vans (Small: passenger cars and SUVs)	−0.0001	−0.0182	0.0183				−0.0078	−0.0724	0.0802									
Locality Characteristics																		
Urban (Rural)													−0.0038	0.0368	−0.0330	−0.0029	0.0341	−0.0312
Residential (Farms, Woods, Pastures)	−0.0006	−0.0182	0.0189													−0.0059	−0.0028	0.0085
Commercial	−0.0052	−0.0303	0.0355										−0.0028	−0.0219	0.0246	−0.0074	−0.0076	0.0150
Institutional													0.0002	0.0012	−0.0014			
Rolling (Flat)										0.0008	0.0248	−0.0257				−0.0074	0.0613	−0.0540
Mountainous							−0.0135	−0.1254	0.1389									
Intersection (Non-intersection)										−0.0014	0.0149	−0.0134						
Roadway Characteristics																		
State Route (Secondary Route)				0.0039	0.0090	−0.0128				0.0019	0.0139	−0.0159						
US Route	0.0135	−0.0050	−0.0085							0.0012	0.0117	−0.0129						
Interstate													0.0076	−0.0168	0.0092			
Two-way, not divided (One-way, not divided)																0.0162	0.0733	−0.0894
Two-way, divided													−0.0017	0.0417	−0.0400	0.0089	0.0519	−0.0608
Curve (Straight)	0.0165	−0.0057	−0.0108	0.0114	0.0001	−0.0115	0.0109	0.1015	−0.1124	0.0124	−0.0013	−0.0111	0.0019	0.0104	−0.0123	0.0014	0.0049	−0.0063
Grade (Level)													0.0073	−0.0042	−0.0031			
Hillcrest	−0.0012	−0.0066	0.0079							0.0029	0.0006	−0.0035				0.0026	−0.0006	−0.0020
Environment Factors																		
Dark without roadway light (Dark with roadway light)										0.0110	0.0025	−0.0135				0.0046	0.0169	−0.0215
Rain (Clear)										−0.0012	0.0024	−0.0011						
Traffic Control Factors																		
Signs (No Control Present)							0.0456	−0.0180	−0.0276				0.0031	0.0217	−0.0248			
Signal	−0.0047	0.0075	−0.0028							−0.0031	−0.0094	0.0125				−0.0055	−0.0007	0.0061
36–55 mph (≤35 mph)				0.0328	−0.0169	−0.0160	0.0067	0.0624	−0.0692	0.0131	−0.0024	−0.0107	0.0059	0.0183	−0.0242	0.0085	0.0088	−0.0173
56–70 mph				0.0045	−0.0009	−0.0036												

Note: Variable in the parentheses is the base category variable. Severe injury (SI), minor injury (MI), and no injury (NI).

and suggest possible impacts of economic conditions on the factors. For example, in the nighttime of the depression period (2008–2010), without roadway light, failing to yield, and traffic controlled with signals could increase the injury-severity when drivers were equipped with a belt.

Significant time-of-day variations are presented in effects of several factors, and all of them indicate more severe outcomes during the nighttime compared to the daytime. These factors mainly include older-age drivers, going the wrong way or using an improper lane, disregarding the sign or signal, two-way roadways with divided medium, hillcrest, and locations with traffic signs. Considering that traffic signals could decrease the probability of the severe injury during the nighttime, setting or changing conventional traffic signs into electronic traffic signs might be a good solution to mitigate DUI-related crash injury severity in the nighttime. Moreover, the decrease in the preventive effect of the divided roadway in the nighttime requires painting median barriers with reflecting materials or install flashlights to alert DUI drivers.

Meanwhile, temporal instabilities are also observed in marginal effects of several factors during specific alcohol-related cycle periods. It is noted that elder drivers (who are more proficient and cautious in driving compared to young drivers) are less likely to get involved in severe injury during the depression period. This is in accord with Maheshri and Winston (2016) who suggested that safer drivers drive more frequently during economic downturns. Moreover, the significant effects of residential and commercial areas during the daytime of depression and expansion periods indicate that alcohol/drug use behaviors are potentially affected by economic conditions. Both depressing and expanding economic conditions might increase the use of alcohol/drugs for drivers in residential or commercial areas. For the depression period after the Great Recession, unemployment rates in North Carolina increased to a peak-value. Hence, people are more likely to drink alcohol or use drugs to mitigate the pressure under bad economic conditions. Previous studies also found that low income and unemployment conditions could increase the potential of DUI behaviors (Li et al., 2019; Lidbe et al., 2020; Owen et al., 2019). Additionally, during the expansion period, the commercial area indicator is significant in both the daytime and nighttime. One possible reason for this is that people are more likely to drink alcohol during the daytime for commercial activities or entertainment with the boosting of the economy. Previous research also found that economically active males could increase the risk of DUI crashes (Ponce et al., 2011).

The insights of this paper underscore the importance of accounting for time-of-day variations, temporal instabilities, and heterogeneity in the means and variances inherent in alcohol/drugs impaired crash factors after the Great Recession. The results indicate shifts in alcohol/drug use behaviors of the drivers are highly related to economic conditions after the Great Recession. The findings of this study should be valuable to researchers, decision-makers, and engineers to improve prevention of alcohol/drugs impaired multi-vehicle crashes. Future works could improve specific enforcements, qualify punishments, and organize targeted campaigns based on the findings of this research. Also, the effect of using different criteria to classify DUI crashes into different cycles also needs further investigation. Moreover, future research could model the injury-severity/frequency of the DUI crashes considering spatiotemporal features and patterns.

Declaration of Competing Interest

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

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