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An analysis of single-vehicle truck crashes on rural curved segments accounting for unobserved heterogeneity

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ABSTRACT

Introduction:: Medium to large truck crashes, particularly on rural curved roadways, lead to a disproportionately higher number of fatalities and serious injuries relative to other passenger vehicles over time. The intent of this study is to identify and quantify the factors affecting injury severity outcomes for single-vehicle truck crashes on rural curved segments in North Carolina. The crash data were extracted from the Highway Safety Information System (HSIS) from 2010 to 2017. *Method:* This study applied a mixed logit with heterogeneity in means and variances approach to model driver injury severity. The approach accounts for possible unobserved heterogeneity in the data resulting from driver, roadway, vehicle, traffic characteristics and/or environmental conditions. *Results' Conclusion:* The model results indicate that there is a complex interaction of driver characteristics such as demographics (male and female drivers, age below 30 years, and age between 50 to 65 years), driver physical condition (normal driving condition and sleepy while driving), driver actions (unsafe speed, overcorrection, and careless driving), restraint usage (lap-shoulder belt usage and unbelted), roadway and traffic characteristics (undivided road, medium right shoulder width, graded surface, low and medium speed limit, low traffic volume), environmental conditions (rainy condition), vehicle characteristics (tractor-trailer and semi-trailer), and crashes characteristics (fixed object crashes and rollover crashes). In addition, this study compared the contributing factor leading to driver injury severity for curved and straight rural segments. *Practical Applications:* The results clearly indicate the importance of driving behavior, such as, exceeding the speed limit and careless driving along the high-speed curved segments, need to be prioritized for the trucking agency. Similarly, the suggested countermeasures for roadway design and maintenance agency encompass warning signs and advisory speed limit, roadside barrier with chevrons, and edge line rumble strips are important concerning curved segments in rural highways.

1. Introduction

Single-vehicle crashes on curved roadway segments primarily result in fatalities and serious injuries due to the consequence of run-off-road, rollover, and fixed object crashes. Relative to straight segments, curved segments are riskier for any drivers of all vehicle types and experience about 30% more fatal crashes involving a single-vehicle (Liu & Subramanian, 2009). This is particularly important for medium to heavy trucks (Gross Vehicle Weight Rating (GVWR) more than 10,000 lbs). Due to operational and physical characteristics (i.e., the center of gravity, loading condition, weight-height ratio, and sight distance), the risk associated with medium and large trucks for rollover is significantly higher and different from those of passenger vehicles on curved roadway segments. The increased risk of rollover due to higher center of gravity for large trucks on curved roadway segments could lead to 45% of the deaths among occupants of large trucks involved in rollover crashes in 2018 (Insurance Institute for Highway Safety, 2021; Azimi et al., 2020; Teoh et al., 2017). Khattak et al. (2002) investigated whether large truck crashes in North Carolina were overrepresented considering relatively difficult maneuverability of large truck, rollover propensity, and more frequent injury crashes on curved segments relative to straight segments. Another study by Huang et al. (2001) researched the risks associated with

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curved segments in North Carolina since curved roads were especially dangerous for single-vehicle crashes, a larger proportion of North Carolina's roads have curves, a larger proportion of North Carolina's traffic occur on curved roads, and North Carolina's curved roads are more dangerous. The HSIS analysis showed that crashes on curves were more likely to be severe than other crashes. Run-off-road and head-on crashes were more likely to take place on curved roads than other crash types (Hung et al., 2001). Another study by Li et al. (2020) found that curved road, grade road, and curved with grade road are more likely to result in severe large truck crashes compared to a straight level road segment. This is because large truck drivers have limited sight distance when approaching the road segments with curves, slopes, or curved slopes. In addition, it is difficult for a large truck driver to apply brakes sufficiently on a curved grade road. Moreover, the HSIS crash data (2010–17) for North Carolina shows that these single-truck crashes on curved segments are over-represented in rural areas (85–90%) compared to urban settings (10–15%). Relative to other neighboring states (e.g., South Carolina, Tennessee, and Virginia)[1] due to geographic characteristics (e.g., roadway alignment), Federal Motor Carrier Safety Administration's (FMCSA) large truck-involved crash data (2010–17) clearly suggests the fatal crashes involving single-vehicle large trucks in North Carolina is overrepresented. This highly signifies the driver demographics, behaviors, and overall risk perception at different ambient conditions with roadway characteristics in rural areas. As such, it is essential to understand the factors associated with single-vehicle truck crashes on curved roadway segments relative to straight segments, particularly those resulting in fatalities and severe injuries in rural areas.

From conventional safety programming, the frequency-based approach could potentially lead to the safety funding allocated to urban areas. A severity-based approach uncovers a promising frontier for safety improvements in rural areas. A study by Islam and Pande (2020) clearly indicates the importance of severity-based safety analysis on rural curved segments following the argument established by Milton et al. (2008). Moreover, separate severity-frequency models result in erroneous estimation as it is assumed that the factors responsible for the occurrence of a crash are independent across severity outcomes. Considering Milton's (2008) argument on underutilized performance measures in safety programming from the severity distribution on crashes, 'Vision Zero' philosophy (FHWA, 2018) needs to reemphasize the importance of the severity-based approach in overall safety programming (Islam & Pande, 2020). It becomes critically important for medium to large truck safety in rural areas since an estimated 19% of the U.S. population lives in rural areas (per the 2018 America Community Survey from Census Bureau) with 57% fatal crashes involving large truck on rural highways (NHTSA, 2020). We note that only 30% of the total vehicle miles traveled in 2018 were in rural areas (per FHWA study), while rural areas accounted for 45% of all traffic fatalities (NHTSA, 2020).

There are several modeling approaches available to analyze the injury severity of drivers involved in crashes. The application of random parameter logit models, also known as the mixed logit model, has gained a great deal of attention recently. This model is being considered as a promising alternative approach in injury-severity analysis. One of the advantages of this approach is to consider the unobserved heterogeneity by allowing variation of some variables across the population. This advantage makes this approach superior to the fixed-parameter model (Hensher & Greene, 2003). Many previous research studies have proven this capability of the mixed logit model in considering unobserved effects such as driver behavior, roadway, and environmental characteristics (Milton et al., 2008; Kim et al., 2013).

In this study, we focused on driver injury severity models accounting for unobserved factors related to independent variables in the police-report crash database. These factors include the roadway-related factors and crash specific factors that are readily available (i.e., weather, lighting, surface type, roadway classes, roadway character, speed limit, traffic volume, left and right shoulder width, median types and width, roadside information, and driver age and gender, physical condition, maneuvers). State of North Carolina crash data from the Highway Safety Information System (HSIS) database (HSIS, 2014) was used to establish the crash injury-severity potential for rural roadway segments with horizontal curves in a multivariate severity modeling framework. With this advanced statistical technique, we considered the means and variances of the random parameters to vary across the observations in the dataset to better account for unobserved heterogeneity in this dataset extracted from the HSIS database system.

The paper is organized as follows: a review of the literature works on driver injury severity for truck-involved crashes, methodological literature for injury severity modeling, and a description of mixed logit with heterogeneity in means and variances approach, which is provided in the next section. It is followed by details of the HSIS data and the empirical setting. Finally, modeling results and marginal effects of the variables are explained and followed by conclusions at the end.

2. Literature review

During the past few decades, truck-related crashes have drawn a great deal of research interest. Many studies have been dedicated to identifying and investigating the risk factors influencing the severity and frequency of crashes involving large and medium trucks. One of the initial studies in this field was conducted in 1987 when Golob et al. (1987) investigated contributing factors and severity of large truck-related crashes as well as the crash duration and lane closure by employing log-linear models. They used two years of crash data that occurred on freeways located in Los Angeles. They showed that hit-object and single-vehicle crashes are the most severe crashes involving large trucks. They also indicated that crash duration follows a log-normal distribution, and overturns have the longest durations. In 2003, Charbotel et al. (2003) analyzed five years of trauma registry data to investigate contributing factors affecting truck drivers' crashes compared to car drivers' crashes by developing Chi-square tests. They showed that truck-related crashes are more severe, with an odds ratio of 1.87. They also indicated that not wearing a seatbelt is one of the leading factors for truck drivers' crashes.

Koupaenejad (2010) assessed significant factors that contributed to large truck-related crashes by developing multinomial logit ordered probit models on one-year North California crash data. Wang et al. (2011) studied large truck-related crashes at freeway diverge-sections using negative binomial (NB) models. They found various geometric elements related to deceleration areas, median/shoulder width, number of lanes, grade, curvature, speed limit, AADT, and truck percentage to be key factors in large truck-related crashes at those sections of freeway. Qin et al. (2013) investigated the factors contributing to the frequency and severity of truck-related crashes on arterial streets using NB and multinomial logit (MNL) models. Contrarily, in a similar study using the NB and multinomial logit (MNL) models, Taylor et al. (2018) showed that geometric characteristics of roadway (e.g., median and shoulder widths, number of lanes) and specific crash types are not significant factors in affecting frequency and severity

[1] FMCSA large-truck involved crash data (2010–17) clearly suggests that North Carolina experienced the highest (about 30%) fatal crashes involving single-vehicle large trucks among the neighboring states, such as, South Carolina, Tennessee, and Virginia.

of freight truck-related crashes. Fitzsimmons et al. (2013) focused on the associations between environmental and roadway characteristics and injury severity of large truck-related crashes that occurred at horizontal curves of two-lane highways in rural areas of Kansas. They concluded that single-vehicle crashes are more severe in comparison with multi-vehicle crashes. In 2013, Islam and Hernandez (2013a) developed a study to investigate the contributing factors affecting the injury severity of truck-related crashes that occurred in Texas by employing a mixed logit model. They showed factors such as lighting conditions, traffic flow, time characteristics, land use, weather, and driver demographics are among the leading factors. In the same year, they also conducted another similar study to explore contributing factors using large truck-related crash data occurring on U.S. interstates (Islam & Hernandez, 2013b).

By utilizing the Crash Records Information System (CRIS) database, Islam and Hernandez (2014) examined the impact of time of the day on leading factors associated with large truck crashes in Texas. They used random parameter logit models verified by log-likelihood ratio tests in this study. Naik et al. (2016) focused on the weather effect on the injury severity of single-vehicle truck crashes by incorporating weather data as well as roadway and crash data. In this study, they developed multinomial regression and random parameters ordinal models. They found that warmer air temperature, rain, and greater wind speed result in severe single-vehicle truck crashes. By developing random parameter order probit models, Zou et al. (2017) examined contributing factors affecting injury severity of single- and multi-vehicle truck crashes that occurred in New York city separately. The study showed some differences between the leading factors associated with injury severity of both types of crashes. The study also indicated the significant heterogeneous impacts of truck weight on the injury severity of both crashes.

By incorporating five years of Ohio HSIS crash data, Uddin and Huynh (2017) developed six mixed logit models to explore the contributing factors related to truck-involved crashes occurred in both urban and rural roadways under three lighting conditions. They concluded that different area type and lighting conditions affect differently on injury severity of crashes involving trucks. Balakrishnan et al. (2017) focused on the risk factors impacting injury severity of angle crashes involving heavy vehicles by utilizing the skewed logistic (Scobit) model. They revealed that vehicles' age, type, fire status, movement, point-of-impact and damage, occupants' age, gender, and restraint use, intersection type, road classification, time of day, and the number of occupants are the risk factors associated with heavy vehicle angle crashes. In 2017, Al-Bdairi and Hernandez (2017) explored the influence of leading factors on injury severity of run-off-road crashes related to large trucks using the ordered random parameter probit model. Afterward, they made it more specific and attempted to conduct similar studies to investigate the importance of area type, including urban and rural, and lighting conditions on the injury severity of run-off-road crashes (Al-Bdairi et al., 2018; Al-Bdairi & Hernandez, 2020). In these studies, they incorporated mixed logit models to analyze seven years of Oregon crash data. In 2018, Mashhadi et al. (2018) proposed a study investigating the contributing factors associated with the single-vehicle truck and multiple vehicle-related crashes in which at least one truck is involved. Moreover, they employed truck-related violations of driver actions to estimate future violations and crashes. They showed that higher posted speed limits, rollover or jackknife crashes, roadways with dry surfaces, driver distraction, and speed compliance failure are the leading factors impacting injury and fatality of the single-vehicle truck and multiple truck crashes. Uddin and Huynh (2018) implemented fixed and random parameters ordered probit models for examining the significant factors impacting the severity of HAZMAT crashes involving large trucks. They found that truck driver, male occupants, rural road classification, dark lighted and unlighted conditions, and weekdays are leading factors causing severe injuries. Eustace et al. (2018) developed a classification tree model for identifying contributing factors impacting injury severity of large truck-related crashes. They analyzed three years of crash data in Ohio and found that contributing factors include speed-related, intersection-related, collision event, posted speed limit, and collision type. By employing the gradient boosting method, Zheng et al. (2018) determined risk factors influencing injury severity of commercial truck-related crashes. The results indicated that trucking company attributes and commerce status, registration condition, driver's age, time of day, first harmful events, and safety inspection values are the most significant factors affecting injury severity. In 2019, determining the contributing factors related to large truck fatal crashes by considering four categories of driver's age was the primary goal of a study conducted by Islam and Ozkul (2019). By employing four logit models, the authors found 30 variables significantly associated with crashes involving commercial/large trucks.

In 2020, Das et al. (2020) incorporated taxicab correspondence analysis (TCA) for extracting the interaction between factors associated with large truck-related crashes. As a result of this study, they proposed five clouds of clusters representing the association between attributes such as driver impairment, posted speed limit, weather, intersection type, and the number of vehicles. Azimi et al. (2020) determined the contributing factors related to injury severity of large truck rollover crashes in Florida. To this end, they analyzed 10 years of crash data by developing random parameter ordered logit models. They found that sandy roadway surface, speed of 50 to 75 mph, ill or fatigued driver, downhill grade, airbag deployment, no seatbelt use, curvature alignment, aggressive driving behavior, unpaved shoulders, hazardous materials, tire defects, and person control device presence are factors leading to more severe large truck rollover crashes. Haq et al. (2020a) developed occupant injury severity models for truck occupants, car passengers, and car drivers using the Bayesian inference approach. They applied the Hamiltonian Monte Carlo sampling method for sampling the model's parameter estimates. They concluded that occupant characteristics (e.g., dangerous driving, fatigue, and impaired driving), inclement weather conditions, presence of junctions, downgrades, and curves, unlit conditions, and challenging roadway geometry are the leading factors significantly impact the occupant injury severity. Along the same line, Haq et al. (2020b) focused on the contributing factors associated with injury severity of occupants involved in truck-related crashes according to the vehicle type. They utilized 10-year-crash data that occurred in Wyoming for proposing binary logistic models of occupant injury severity. They presented that factors such as truck driver occupation, age and gender of occupants, weather, and downgrades are among the leading factors. Uncovering contributing factors affecting injury severity of truck-involved crashes for different weather conditions by developing three mixed logit models was the main objective of a study conducted by Uddin and Huynh (2020). The study indicated that different weather conditions associated with different contributing factors.

A summary of the key variables used by previous studies is provided in Table 1. As reviewed in the literature, a majority of the previous studies in general explored contributing factors associated with truck crashes, and few of them particularly investigated particularly on the curved segments of the roadway. Moreover, it is noteworthy that all these studies introduced presence of curve as an indicator variable in the models and did not investigate the contributing factors in detail focusing on curved segments. Hence, to fill this gap in the existing literature, this research study aims at identifying the significant factors affecting injury severity of dri-

Table 1
Summary of variables considered in medium and large truck-related studies.

Variable name	Variable description	Studies
Driver/Occupant characteristics	Action or inaction by drivers (maneuver, braking, acceleration, deceleration, running red lights)	Islam and Hernandez (2013a), Balakrishnan et al. (2017), Al-Bdairi and Hernandez (2017), Haq et al. (2020a), Haq et al. (2020b), Azimi et al. (2020)
	Fatigue	Al-Bdairi and Hernandez (2017), Haq et al. (2020a), Haq et al. (2020b), Azimi et al. (2020)
	Speeding	Qin et al. (2013), Islam and Hernandez (2013b), Eustace et al. (2018), Azimi et al. (2020)
	Age	Charbotel et al. (2003), Koupaenejad (2010), Taylor et al. (2018), Islam and Hernandez (2013a), Islam and Hernandez (2013b), Uddin and Huynh (2018), Islam and Ozkul (2019), Balakrishnan et al. (2017), Zheng et al. (2018), Eustace et al. (2018), Naik et al. (2016), Haq et al. (2020a), Haq et al. (2020b)
	Gender	Charbotel et al. (2003), Koupaenejad (2010), Taylor et al. (2018), Islam and Hernandez (2013a), Uddin and Huynh (2018), Balakrishnan et al. (2017), Eustace et al. (2018), Mashhadi et al. (2018), Haq et al. (2020a), Haq et al. (2020b)
	Driver licensing	Islam and Hernandez (2013b), Al-Bdairi and Hernandez (2017), Zheng et al. (2018)
	Number of occupants	Islam and Hernandez (2013b)
	Laws and features(seat belt law, driving under the influence [DUI] law, distracted driving, airbags)	Charbotel et al. (2003), Taylor et al. (2018), Islam and Hernandez (2013a), Balakrishnan et al. (2017), Eustace et al. (2018), Naik et al. (2016), Mashhadi et al. (2018), Haq et al. (2020a), Haq et al. (2020b), Azimi et al. (2020)
Roadway, crash, and environmental characteristics	Roadway condition (classification, terrain, visibility of markings, surface condition)	Charbotel et al. (2003), Qin et al. (2013), Taylor et al. (2018), Fitzsimmons et al. (2013), Uddin and Huynh (2018), Balakrishnan et al. (2017), Al-Bdairi and Hernandez (2017), Al-Bdairi and Hernandez (2020), Eustace et al. (2018), Naik et al. (2016), Zou et al. (2017), Mashhadi et al. (2018), Azimi et al. (2020)
	Adverse weather effect	Taylor et al. (2018), Fitzsimmons et al. (2013), Islam and Hernandez (2013b), Eustace et al. (2018), Naik et al. (2016), Zou et al. (2017), Haq et al. (2020a), Haq et al. (2020b), Haq et al. (2020b)
	Interruptions in traffic flow (intersection, previous crash, work zone, peak hour congestion)	Eustace et al. (2018)
	Roadway design elements (curvature, grade, width, median)	Wang et al. (2011), Qin et al. (2013), Taylor et al. (2018), Fitzsimmons et al. (2013), Islam and Hernandez (2013a), Islam and Hernandez (2013b), Al-Bdairi and Hernandez (2017), Eustace et al. (2018), Naik et al. (2016), Haq et al. (2020a), Haq et al. (2020b), Azimi et al. (2020)
	Traffic control condition (presence of traffic signal/ sign, presence of police officer)	Zou et al. (2017), Azimi et al. (2020)
	Lighting condition	Koupaenejad (2010), Taylor et al. (2018), Fitzsimmons et al. (2013), Islam and Hernandez (2013a), Pahukula et al. (2015), Uddin and Huynh (2018), Al-Bdairi and Hernandez (2018), Eustace et al. (2018), Naik et al. (2016), Zou et al. (2017), Haq et al. (2020a), Haq et al. (2020b)
	Divided/undivided	Koupaenejad (2010), Qin et al. (2013), Taylor et al. (2018), Al-Bdairi and Hernandez (2017)
	Posted speed limit	Qin et al. (2013), Taylor et al. (2018), Fitzsimmons et al. (2013), Balakrishnan et al. (2017), Eustace et al. (2018), Mashhadi et al. (2018)
	Temporal attributes (time of year, time of day, or day of the week)	Charbotel et al. (2003), Fitzsimmons et al. (2013), Islam and Hernandez (2013a), Islam and Hernandez (2013b), Islam and Hernandez (2014), Uddin and Huynh (2018), Balakrishnan et al. (2017), Zheng et al. (2018), Eustace et al. (2018), Naik et al. (2016), Mashhadi et al. (2018), Azimi et al. (2020)
	Crash type (fixed object, head on, t-collision, angle and rear-end crashes, roll over, jackknife)	Golob et al. (1987), Charbotel et al. (2003), Koupaenejad (2010), Taylor et al. (2018), Fitzsimmons et al. (2013), Islam and Hernandez (2013a), Islam and Hernandez (2013b), Uddin and Huynh (2018), Balakrishnan et al. (2017), Al-Bdairi and Hernandez (2017), Zheng et al. (2018), Eustace et al. (2018), Zou et al. (2017), Mashhadi et al. (2018)
	Miscellaneous (Truck company attributes)	Zheng et al. (2018)
	Built environment (job density)	Zou et al. (2017)
Vehicle characteristics	Vehicle types	Charbotel et al. (2003), Qin et al. (2013), Taylor et al. (2018), Uddin and Huynh (2018), Balakrishnan et al. (2017)
	Vehicle defects (brake failure, loss of control, tire)	Al-Bdairi and Hernandez (2017)
	Vehicle design elements (front and rear overhang, width, weight, length, trailing unit)	Koupaenejad (2010), Islam and Hernandez (2013b), Zheng et al. (2018), Zou et al. (2017)
	Number of trucks or other vehicles (truck percentages, traffic volume, vehicles involved in the crash)	Golob et al. (1987), Wang et al. (2011), Qin et al. (2013), Taylor et al. (2018), Islam and Hernandez (2013a), Al-Bdairi and Hernandez (2017), Zou et al. (2017)
	Hazardous material	Azimi et al. (2020), Uddin and Huynh (2018)

vers involved in truck-related crashes occurring on roadway segments with horizontal curves and comparing that of driver injury severities with roadway segments without horizontal curves (i.e., straight segments).

3. Data description

Single-vehicle truck (medium to large trucks) crashes on rural curved, and straight segments were obtained from the Highway Safety Information System (HSIS) database for the state of North Carolina. These crashes occurred between January 1, 2010, and December 31, 2017. A single-year crash data might not be enough for a reasonable sample for such a modeling framework due to the smaller sample size for each severity level, particularly for the severe injury category.[2]

Records from the crash, roadway, and vehicle dataset were aggregated and filtered. Crash and roadway databases were linked

[2] This limited sample size restricted on exploring the temporal instability for single-vehicle truck crashes on rural curved segments.

based on milepost locations within the same roadway system. The vehicle information dataset was then linked using the unique identifier (i.e., case number) for each crash observation in the crash dataset. The filtering process for the number of involved vehicles (i.e., single-vehicle), roadway characteristics (i.e., curve - level, curve - grade, the curve - hillcrest, and curve - bottom), the rural designated area resulted in a dataset of 3,199 crashes. Injury severity is defined as the injury level of the most severely injured person in the observed crash. The five driver injury severity levels (K – fatal, A – Incapacitating injury, B – Non-incapacitating injury, C – Possible injury, and O – Property-Damage-Only) were aggregated into three levels; severe injury crashes (K and A; 90 or 3% of total crashes), minor injury crashes (B and C; 1,074 or 34% of total crashes), and no injury crashes (PDO crashes; 2,035 or 64% of total crashes). Fig. 1 shows the relative frequency distribution of the driver injury severity on straight and curved rural roadways resulting from crashes involving a single-vehicle truck in North Carolina (2010–17). It illustrates the importance of estimating the factors associated with the severity levels of such crashes on rural curved roadways where injury severities on curved roadways are higher relative to those on straight segments (Fig. 2) also presents the proportion of crash involvement of single-vehicle trucks by vehicle types on curved and straight segments on rural roadways in North Carolina (2010-17).It is important to note that single-unit truck (3+ axle; 2 axle, 6 tires), tractor/semi-trailer experienced relatively higher involvement in crashes on curved segment than straight segments. However, that crash involvement for truck/trailer and light trucks are different – higher proportion on straight segments than curved segments.

Table 2 presents the descriptive statistics for the variables found statistically significant in the models. These variables are categorized into speed, environmental, traffic, roadway, crash, and driver characteristics with detailed explanations in Section 5 (see the details in subsection 5.2.1 to 5.2.7).

4. Methodology

Over the years, a wealth of research studies on crash-related injury severities have been conducted with a variety of ordered and unordered discrete outcome approaches, including ordered logit/probit models, multinomial logit models, dual-state multinomial logit models, nested logit models, latent-class logit models, mixed (random parameters) logit models, Markov-switching models, and others (Islam & Hernandez, 2013a; Savolainen et al., 2011; Mannering & Bhat, 2014; Fountas & Rye, 2019). Ye and Lord (2014) noted that mixed logit models generally require a larger sample size. To account for possible unobserved heterogeneity in the data, more recent research has focused on random parameter approaches (Anastasopoulos & Mannering, 2011; Eluru et al., 2008; Kim et al., 2013; Morgan & Mannering, 2011; Behnood & Mannering, 2015; Venkataraman et al., 2013), latent class models (Behnood et al., 2014; Cerwick et al., 2014; Shaheed & Gkritza, 2014; Yasmin et al., 2014; Fountas et al., 2018) or combination of both (Xiong & Mannering, 2015) and heterogeneity in means and variances (Venkataraman et al., 2014; Behnood & Mannering, 2017a; Behnood & Mannering 2017b; Seraneeprakarn et al., 2017; Islam & Mannering, 2020; Islam et al., 2020, Islam & Mannering, 2021; Islam, 2021) to model the injury severities. In this study, a random parameter logit model with heterogeneity in means and variances was estimated to account for any possible heterogeneity in the dataset focusing on single-vehicle truck crashes on rural segments in North Carolina. Restricting the variable effect to be the same across observations (i.e., the standard mixed logit formulation) may cause biased estimates and erroneous inferences.

The conventional crash databases extracted from the police reports covers part of a wealth of information apparently originating from the crash scene. Considering the given limitations in the police-reported crash database, the intent of these "heterogeneity" models were to provide accurate inferences by explicitly accounting for observation-specific variations in the effects of influential factors (as unobserved heterogeneity).[3]

In this study, a random parameter multinomial logit model that accounts for possible heterogeneity in the means and variances of the random parameters has been utilized to address the possible unobserved heterogeneity in the single-vehicle truck-involved crash data. The injury severity of drivers in single-vehicle truck crashes on rural curved segments is considered with possible injury outcomes of no injury, minor injury (possible injury and non-incapacitating injury), and severe injury (incapacitating injury and fatality). Following the recent work, the modeling approach starts by defining a function that determines injury-severity,

$$S_{in} = \beta_i X_{in} + \varepsilon_{in} \tag{1}$$

where, S_{in} is an injury-severity function determining the probability of injury-severity outcome i in single-vehicle truck crash n, $\boldsymbol{X}_{in}$ is a vector of explanatory variables that affect single-vehicle truck crash injury-severity level i, $\boldsymbol{\beta}_i$ is a vector of estimable parameters, and ε_{in} is the error term. If this error term is assumed to be generalized extreme value distributed, a standard multinomial logit model results as McFadden (1981)

$$\mathrm{P_n}(i) = \frac{\mathrm{EXP}[\boldsymbol{\beta}_\mathrm{i}\boldsymbol{X}_\mathrm{in}]}{\sum_{\forall \mathrm{I}}\mathrm{EXP}[\boldsymbol{\beta}_\mathrm{i}\boldsymbol{X}_\mathrm{in}]} \tag{2}$$

where, $P_n(i)$ is the probability that a single-vehicle truck crash n will result in driver-injury severity outcome i and I is the set of the three injury-severity outcomes. The following form of Equation (2) allows for the possibility of one or more parameter estimates in the vector $\boldsymbol{\beta}_i$ to vary across each crash (i.e., each observation; Washington et al., 2020):

$$\mathrm{P}_n(i) = \int \frac{EXP(\boldsymbol{\beta}_i\boldsymbol{X}_{in})}{\sum_{\forall I}EXP(\boldsymbol{\beta}_i\boldsymbol{X}_{in})} f(\boldsymbol{\beta}_i|\boldsymbol{\varphi}_i)\,d\boldsymbol{\beta}_i \tag{3}$$

where, $f(\boldsymbol{\beta}_i|\boldsymbol{\varphi}_i)$ is the density function of $\boldsymbol{\beta}_i$ and $\boldsymbol{\varphi}_i$ is a vector of parameters describing the density function (mean and variance), and all other terms are as previously defined.

To account for the possibility of unobserved heterogeneity in the means and variances of parameters, let $\boldsymbol{\beta}_{in}$ be a vector of estimable parameters that varies across single-vehicle truck crashes defined as (a similar formulation used by Behnood & Mannering, 2017b; Seraneeprakarn et al., 2017; Alnawmasi and Mannering, 2019; Behnood & Mannering, 2019; Waseem et al., 2019; Islam & Mannering, 2020; Islam & Mannering, 2021; Islam 2021) in other injury severity contexts.

$$\boldsymbol{\beta}_{in} = \beta_i + \Theta_{in}\boldsymbol{Z}_{in} + \sigma_{in}EXP(\psi_{in}\boldsymbol{W}_{in})v_{in} \tag{4}$$

where, β_i is the mean parameter estimate across all single-vehicle truck crashes, $\boldsymbol{Z}_{in}$ is a vector of crash-specific explanatory variables that captures heterogeneity in the mean that affects injury-severity level i, $\boldsymbol{\Theta}_{in}$ is a corresponding vector of estimable parameters, $\boldsymbol{W}_{in}$ is a vector of crash-specific explanatory variables that captures heterogeneity in the standard deviation σ_{in} with corresponding parameter vector $\boldsymbol{\Psi}_{in}$, and v_{in} is a disturbance term.

[3] The extensive discussions and justifications for accounting for unobserved heterogeneity in the crash data modeling are highlighted in a study by Mannering et al. (2016). Considering the paradigm shift from the other traditional models, if unobserved heterogeneity is ignored, and the effects of observable variables is restricted to be the same across all observations, the model will be mis-specified and the estimated parameters will, in general, be biased and inefficient, which could in turn lead to erroneous inferences and predictions.

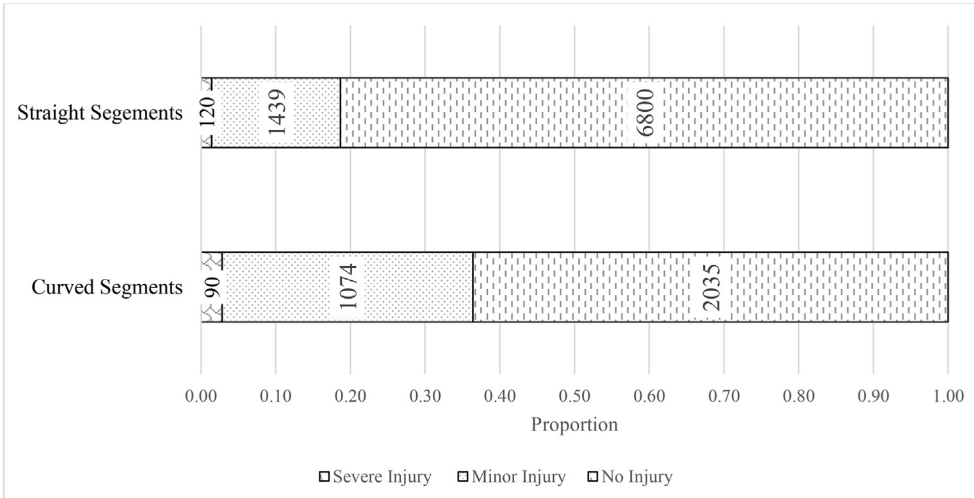

Fig. 1. Proportion of Driver Injury Severity involving a Large Truck on Curved and Straight Segments on Rural Roadways in North Carolina (2010–17).

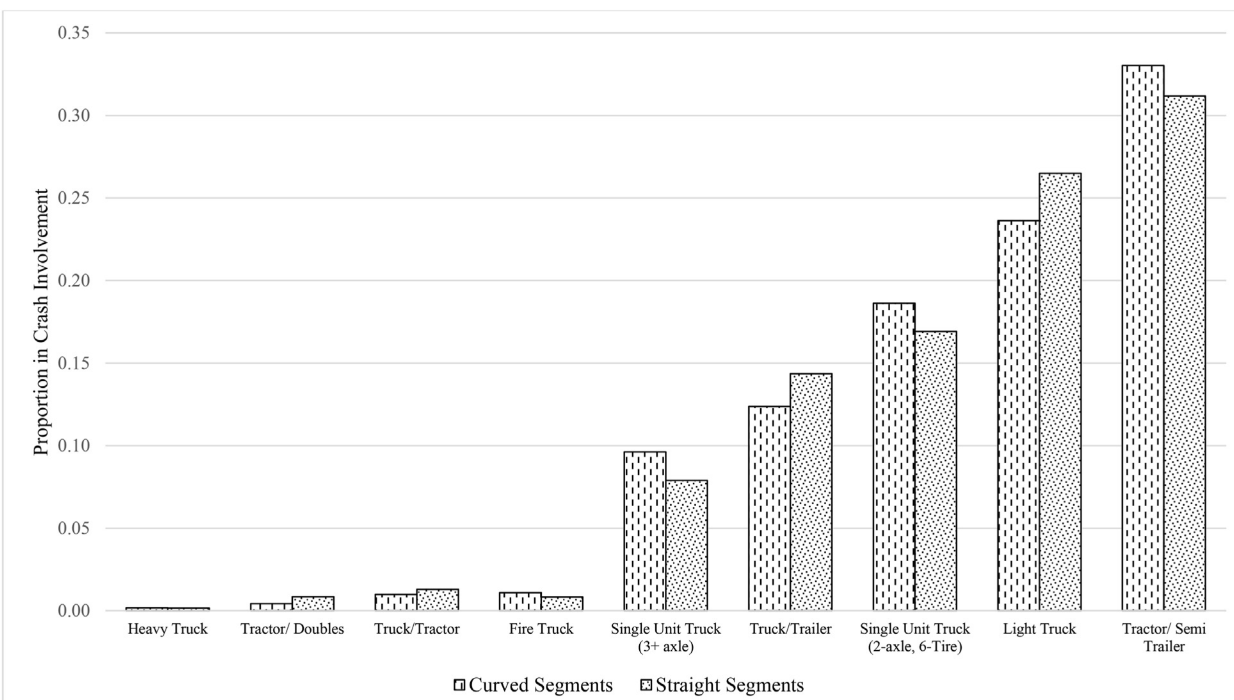

Fig. 2. Proportion of Involvement in Single-vehicle Truck Crashes by Vehicle Types on Curved and Straight Segments on Rural Roadways in North Carolina (2010–17).

During model estimation, several density functions (e.g., uniform, triangular, log normal, Weibull) were empirically evaluated for the term $f(\boldsymbol{\beta}_i|\boldsymbol{\varphi}_i)$. However, normal distribution was found to be statistically superior to all and was used in model estimation (this finding is consistent with past work including (Islam & Mannering, 2020; Islam et al., 2020; Islam & Mannering, 2021; Islam 2021; Behnood & Mannering, 2017a; Alnawmasi and Mannering, 2019). The model estimations used simulated maximum likelihood with 1,000 Halton draws (Train, 2009; McFadden & Train, 2000; Bhat 2001). Marginal effects are estimated to determine the effect of explanatory variables on injury-severity probabilities. The marginal effect provides the effect that a one-unit increase (or presence of indicator variable from '0' to '1') in an explanatory variable has on the injury-outcome probabilities. The average marginal effects over the whole set of observations are provided with the model results.

$$P_{in}{}^{\wedge} = \frac{1}{R}\sum_{r=1}^{R} P_{in} = \frac{1}{R}\sum_{r=1}^{R} \int \frac{EXP(\boldsymbol{\beta}_i \boldsymbol{X}_{in})}{\sum_{\forall I} EXP(\boldsymbol{\beta}_i \boldsymbol{X}_{in})} f(\boldsymbol{\beta}_i|\boldsymbol{\varphi}_i)\, d\boldsymbol{\beta}_i \quad (5)$$

where R is the total number of draws.

5. Results and discussions

This section is explained with likelihood ratio tests on injury severity (subsection 5.1) and estimated model parameters for curved and straight segments (subsection 5.2) in rural roadways in North Carolina.

Table 2
Descriptive statistics of key variables in the models.

Variables	Straight Segment		Curved Segment	
	Mean	SStd. Dev.	Mean	Std. Dev.
Speed characteristics				
Low speed limit indicator (1 if speed limit below 40 mph, 0 otherwise)	0.078	0.268	0.079	0.270
Medium speed limit indicator (1 if speed limit between 55 and 65 mph, 0 otherwise)	0.707	0.455	0.756	0.429
Environmental characteristics				
Rainy weather indicator (1 if rainy weather, 0 otherwise)	0.090	0.287	0.109	0.312
Traffic characteristics				
Low traffic volume indicator (1 if AADT below 5,000 vehicles/day, 0 otherwise)	0.366	0.481	0.535	0.498
Vehicle characteristics				
Truck-trailer indicator (1 if truck-trailer involved, 0 otherwise)	0.143	0.350	0.123	0.329
Semi-trailer indicator (1 if semi-trailer is involved, 0 otherwise)	0.311	0.463	0.330	0.470
Roadway characteristics				
Undivided roadway indicator (1 if roadway facilities are undivided, 0 otherwise)	0.398	0.489	0.492	0.499
Medium right shoulder indicator (1 if right shoulder with between 4 to 8 feet, 0 otherwise)	0.366	0.481	0.400	0.489
Graded surface indicator (1 if road surface is graded/drained, 0 otherwise)	0.317	0.465	0.324	0.468
Bituminous surface indicator (1 if road surface is bituminous, 0 otherwise)	0.184	0.387	0.188	0.391
Short, curved segment indicator (1 if curved segment is less than 0.25 mile, 0 otherwise)	0.347	0.476	0.264	0.441
Crash characteristics				
Rollover indicator (1 if rollover crash, 0 otherwise)	0.096	0.294	0.248	0.432
Fixed object crash indicator (1 if fixed object crash, 0 otherwise)	0.460	0.498	0.537	0.498
Driver characteristics				
Age below 30 years indicator (1 if drivers age below 30 years, 0 otherwise)	0.159	0.365	0.196	0.397
Age between 50 to 65 years indicator (1 if drivers age between 50 to 65 years, 0 otherwise)	0.315	0.464	0.262	0.440
Male driver indicator (1 if driver is male, 0 otherwise)	0.859	0.347	0.877	0.327
Female driver indicator (1 if driver is female, 0 otherwise)	0.140	0.347	0.122	0.327
Normal driving indicator (1 if driver was physically in normal condition, 0 otherwise)	0.912	0.282	0.905	0.291
Falling asleep while driving indicator (1 if driver fell asleep while driving, 0 otherwise)	0.030	0.171	0.025	0.158
Exceeded safe speed indicator (1 if driver exceeded safe speed for conditions, 0 otherwise)	0.077	0.267	0.277	0.447
Overcorrected indicator (1 if driver overcorrected in the maneuver, 0 otherwise)	0.071	0.257	0.096	0.294
Careless driving indicator (1 if driver operated in careless or reckless manner, 0 otherwise)	0.045	0.209	0.055	0.229
Inattention indicator (1 if driver was inattentive, 0 otherwise)	0.106	0.307	0.124	0.330
Non-restraint usage indicator (1 if shoulder and lap belt not used, 0 otherwise)	0.029	0.170	0.049	0.217
Restraint usage indicator (1 if shoulder and lap belt used, 0 otherwise)	0.825	0.379	0.799	0.400
Other characteristics				
No contributing factor indicator (1 if no contributing factor identified, 0 otherwise)	0.396	0.489	0.139	0.346

Std. Dev. = Standard Deviation.

5.1. Test for differences in severity on straight and curved segments

After extensively testing for differences between injury severity on straight and curved segments, it was determined that statistically significant differences existed in the injury-severity data for straight and curved segments. This was confirmed by a series of likelihood-ratio tests. The first test was based on a model estimated for straight and curved segments with available data (2010–17) and each converged model representing straight segments and curved segments. Using the converged models, the likelihood ratio test for this case is

$$X^2 = -2\left[LL(\boldsymbol{\beta}_{Straight-Curve}) - LL(\boldsymbol{\beta}_{Straight}) - LL(\boldsymbol{\beta}_{Curve})\right] \tag{6}$$

where, $LL(\boldsymbol{\beta}_{\text{Straight-Curve}})$ is the log-likelihood at the convergence of the model that used all the available data for all segments, $LL(\boldsymbol{\beta}_{\text{Straight}})$ and $LL(\boldsymbol{\beta}_{\text{Curve}})$ is the log-likelihood at the convergence of a model based on straight and curved-data, respectively. Model estimates gave an X^2 of 824.748, which is χ^2 distributed with 23 degrees of freedom (the number of parameters found to be statistically significant in the model using all the segments [straight and curved] data, 2010–2017 excluding the numbers of parameters found statistically significant in segment type). This χ^2 value gives 99.9% confidence that the null hypothesis that the parameters are equal in all the years can be rejected. To test for differences in injury severity for straight and curved segments further, additional likelihood ratio tests were run as (Washington et al., 2020),

$$X^2 = -2\left[LL(\boldsymbol{\beta}_{Straight,Curve}) - LL(\boldsymbol{\beta}_{Curve})\right] \tag{7}$$

$$X^2 = -2\left[LL(\boldsymbol{\beta}_{Curve,Straight}) - LL(\boldsymbol{\beta}_{Straight})\right] \tag{8}$$

where, $LL(\boldsymbol{\beta}_{\text{Straight, Curve}})$ is the log-likelihood at the convergence of a model containing converged parameters based on using curved-data while using data from straight-data, and $LL(\boldsymbol{\beta}_{\text{Curve}})$ is the log-likelihood at the convergence of the model using curve-data, with parameters no longer restricted to using curved converged parameters as is the case for $LL(\boldsymbol{\beta}_{\text{Straight, Curve}})$. Using the converged parameters of the straight segment model as starting values and applying them to the curved segment data gave X^2 = 49.720 and, with 23 degrees of freedom, this also gave a χ^2 confidence level of more than 99.9% that the null hypothesis that the injury severity on both segments is the same can be rejected. Similarly, using the converged parameters of the curved segment model as starting values and applying them to the straight segment data gave X^2 = 283.096. With 23 degrees of freedom, this gave a χ^2 confidence level of more than 99.9% that the null hypothesis that the injury severity on two segments is the same can be rejected.

5.2. Model estimation results

Mixed logit with heterogeneity in means and variances for single-vehicle truck crashes on rural curved segments, and straight segments are presented in Table 3 and Table 4, respectively. The comparison of the marginal effects of these two models is presented in Table 5. The model has an overall statistical fit with McFadden pseudo-R-squared value of 0.371 in rural curved segments and 0.578 in rural, straight segments. We note that the constant term specific to minor injury was found to be the only statistically significant random parameter that is normally distributed in both models. Considering the mean (−4.878) and standard deviation (7.241) of the random parameter (i.e., the constant

Table 3
Model results of mixed logit with heterogeneity in means and variance in single-vehicle truck crashes on curved segments in North Carolina, 2010–17.

Variable*	Parameter Estimates	t-stat.	Marginal Effects		
			No Injury	Minor Injury	Severe Injury
Constant [SI]	−2.764	−5.70			
Random parameter (normally distributed)					
Constant [MI] (*Standard deviation of parameter distribution*)	−*4.878* (*7.241*)	−*4.42* (*3.42*)			
Heterogeneity in the mean of random parameter					
Constant [MI]: fixed object (1 if first harmful event was hitting the fixed objects, 0 otherwise)	1.938	3.45			
Heterogeneity in the variance of random parameter					
Constant [MI]: male driver indicator (1 if driver was male, 0 otherwise)	−0.458	−2.66			
Speed characteristics					
Low speed limit indicator (1 if speed limit below 40 mph, 0 otherwise) [MI]	−1.764	−2.75	0.0072	−0.0074	0.0002
Medium speed limit indicator (1 if speed limit between 55 to 65 mph, 0 otherwise) [SI]	0.518	1.64	−0.0097	−0.0016	0.0113
Environmental characteristics					
Rainy weather indicator (1 if rainy weather, 0 otherwise) [MI]	−0.795	−1.82	0.0050	−0.0053	0.0003
Traffic characteristics	−0.625	−3.11	−0.0302	0.0213	0.0089
Low traffic volume indicator (1 if AADT below 5,000 vehicles/day, 0 otherwise) [NI]					
Vehicle characteristics					
Truck-trailer indicator (1 if truck-trailer involved, 0 otherwise) [MI]	−1.082	−2.38	0.0081	−0.0085	0.0004
Roadway characteristics					
Undivided roadway indicator (1 if roadway facilities are undivided by trafficdirection, 0 otherwise) [SI]	−0.822	−2.75	0.0080	0.0013	−0.0093
Medium right shoulder indicator (1 if right shoulder with between 4 to 8 feet, 0 otherwise) [NI]	−0.349	−1.79	−0.0128	0.0089	0.0039
Graded surface indicator (1 if road surface is graded/drained, 0 otherwise) [NI]	−0.412	−1.82	−0.0113	0.0085	0.0028
Short segment indicator (1 if segment length is less than 0.25 mile, 0 otherwise) [NI]	0.651	2.69	0.0127	−0.0102	−0.0025
Crash characteristics					
Rollover indicator (1 if rollover, 0 otherwise) [MI]	4.325	4.04	−0.0794	0.0841	−0.0047
Driver characteristics					
Age below 30 years indicator (1 if drivers age below 30 years, 0 otherwise) [MI]	−0.646	−1.88	0.0076	−0.0081	0.0005
Normal driving indicator (1 if driver was physically in normal condition, 0 otherwise) [SI]	−1.334	−4.09	0.0229	0.0034	−0.0264
Falling asleep while driving indicator (1 if driver fell asleep while driving, 0 otherwise) [MI]	2.797	3.08	−0.0046	0.0053	−0.0007
Exceeded safe speed indicator (1 if driver exceeded safe speed for conditions, 0 otherwise) [NI]	−1.140	−4.38	−0.0295	0.0207	0.0088
Overcorrection indicator (1 if driver overcorrected in the maneuver, 0 otherwise) [NI]	−1.189	−3.75	−0.0112	0.0076	0.0036
Careless driving indicator (1 if driver operated in careless or reckless manner, 0 otherwise) [SI]	1.314	3.57	−0.0040	−0.0007	0.0047
Non-restraint usage indicator (1 if shoulder and lap belt not used, 0 otherwise) [SI]	1.902	4.72	−0.0110	−0.0024	0.0134
Restraint usage indicator (1 if shoulder and lap belt used, 0 otherwise) [SI]	−0.790	−2.41	0.0101	0.0014	−0.0115
Number of observations	3,199				
Number of estimated parameters	23				
Log-likelihood at zero	−3514.461				
Log-likelihood at convergence	−2209.259				
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.371				

*SI = Severe Injury; MI = Minor Injury; NI = No Injury.

specific to minor injury) in the model, it implies that the intercept for minor injury is more than zero for 25.03% of the target crashes (i.e., single-vehicle truck crashes on rural curved segments) and tend to increase the likelihood of minor injury. It was found that the mean of the random parameter varied by whether the single-vehicle truck crashes were fixed objects. In this model, the fixed object crashes increased the mean of the random parameter making minor injury more likely. The variance of the constant for minor injury was a function of the male drivers. Male drivers were likely to be involved in minor injury and making the variance of constant specific to minor injury smaller.

In addition to parameter estimates for the mixed logit with heterogeneity in means and variances, estimated marginal effects are also included in Table 3. Marginal effects indicate the effect of a one-unit increase in an explanatory variable on the injury-outcome probabilities. The likelihood ratio or McFadden pseudo-R-squared, ρ^2 is 0.371 for the estimated model (reported in Table 3). Domencich and McFadden (1975) noted that the likelihood ratio or McFadden pseudo-R-squared values between 0.2 and 0.4 corresponds to R^2 values of 0.7 through 0.9 for a linear function. Hence, the ρ^2 value of 0.371 indicates a reasonable goodness-of-fit for the estimated model.

5.2.1. Speed characteristics

Relative to other speed limits, a speed limit below 40 was less likely to result in minor injury crashes (with an average marginal effect of −0.0074) but more likely to result in no injury crashes. Relative to other speed limits, a speed limit between 55 and 65 mph was more likely to result in severe injury on the curved segment but less likely on straight segments (marginal effect of 0.0113 on curved vs. −0.0006 on straight segments). The opposite effect is true for minor injury crashes (marginal effect of −0.0016 on curved vs. 0.0224 on the straight segment). Previous studied also showed that high speed could result in more sever crashes (Taylor et al., 2016; Mashhadi et al., 2018; Rahimi et al., 2020; Islam & Hernandez, 2013b).

5.2.2. Environmental characteristics

Relative to other weather conditions, the rainy condition was less likely to result in minor injury crashes (with an average marginal effect of −0.0053) but more likely to result in severe, and no injury crashes on curved segments. A study conducted by Naik et al. (2016) and Uddin and Huynh (2017) also suggested that rainy weather condition increases the likelihood of severe truck crashes.

5.2.3. Traffic characteristics

Relative to other traffic volumes, traffic volume less than 5,000 vehicles per day was more likely to result in severe injury crashes on curved and straight segments (marginal effect of 0.0089 on curved vs. 0.0014 on straight segments) and minor injury crashes (marginal effect of 0.0213 on curved vs. 0.0083 on straight

Table 4
Model results of mixed logit with heterogeneity in means and variance in single-vehicle truck crashes on rural straight segments in North Carolina, 2010–17.

Variable*	Parameter Estimates	t-stat.	Marginal Effects No Injury	Marginal Effects Minor Injury	Marginal Effects Severe Injury
Constant [SI]	−0.811	−3.56			
Random parameter (normally distributed)					
Constant [MI] (*Standard deviation of parameter distribution*)	−5.555 (*2.253*)	−5.54 (*3.31*)			
Heterogeneity in the mean of random parameter					
Constant [MI]: fixed object (1 if first harmful event was hitting the fixed objects, 0 otherwise)	2.084	5.37			
Heterogeneity in the variance of random parameter					
Constant [MI]: male driver indicator (1 if driver was male, 0 otherwise)	0.327	2.18			
Speed characteristics					
Medium speed limit indicator (1 if speed limit between 55 to 65 mph, 0 otherwise) [SI]	0.468	2.85	−0.0218	0.0224	−0.0006
Traffic characteristics					
Low traffic volume indicator (1 if AADT below 5,000 vehicles/day, 0 otherwise) [NI]	−0.326	−2.70	−0.0097	0.0083	0.0014
Vehicle characteristics					
Truck-trailer indicator (1 if truck-trailer is involved, 0 otherwise) [MI]	−0.868	−3.63	0.0064	−0.0066	0.0002
Semi-trailer indicator (1 if semi-trailer is involved, 0 otherwise) [NI]	0.518	3.72	0.0107	−0.0093	−0.0014
Roadway characteristics					
Undivided roadway indicator (1 if roadway facilities are undivided by trafficdirection, 0 otherwise) [SI]	−0.858	−3.52	0.0026	0.0004	−0.0030
Bituminous surface indicator (1 if road surface is bituminous, 0 otherwise) [SI]	−0.675	−2.14	0.0011	0.0002	−0.0013
Short segment indicator (1 if segment length is less than 0.25 mile, 0 otherwise) [NI]	0.434	3.38	0.0100	−0.0086	−0.0014
Crash characteristics					
Rollover indicator (1 if rollover, 0 otherwise) [MI]	4.005	5.43	−0.0393	0.0405	−0.0012
Driver characteristics					
Age between 50 to 65 years indicator (1 if drivers age between 50 to 65 years, 0 otherwise) [MI]	−0.252	−1.98	−0.0053	0.0043	0.0010
Female driver indicator (1 if driver was female, 0 otherwise) [MI]	1.313	3.57	−0.0142	0.0146	−0.0004
Normal driving indicator (1 if driver was physically in normal condition, 0 otherwise) [SI]	−2.085	−9.59	0.0143	0.0018	−0.0161
Falling asleep while driving indicator (1 if driver fell asleep while driving, 0 otherwise) [MI]	2.275	4.66	−0.0065	0.0073	−0.0008
Exceeded safe speed indicator (1 if driver exceeded safe speed for conditions, 0 otherwise) [NI]	−0.487	−2.59	−0.0036	0.0031	0.0006
Overcorrection indicator (1 if driver overcorrected in the maneuver, 0 otherwise) [NI]	−1.452	−6.17	−0.0129	0.0095	0.0034
Careless driving indicator (1 if driver operated in careless or reckless manner, 0 otherwise) [SI]	1.544	4.31	−0.0066	0.0071	−0.0005
Inattention indicator (1 if driver was inattentive, 0 otherwise) [MI]	−0.502	−1.60	0.0004	0.0001	−0.0005
Restraint usage indicator (1 if shoulder and lap belt used, 0 otherwise) [SI]	−1.333	−6.25	0.0096	0.0014	−0.0109
Other characteristics					
No contributing factor indicator (1 if no contributing factor identified, 0 otherwise) [SI]	−1.483	−3.84	0.0015	0.0001	−0.0016
Number of observations	8,359				
Number of estimated parameters	23				
Log-likelihood at zero	−9183.300				
Log-likelihood at convergence	−3873.411				
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$	0.578				

*SI = Severe Injury; MI = Minor Injury; NI = No Injury.

segments). This result is consistent with studies developed by Islam and Hernandez (2013a) and Uddin and Huynh (2017).

5.2.4. Vehicle characteristics

Relative to other truck types, the truck-trailer involved in the crash was more likely to result in severe injury crashes (marginal effect of 0.0004 on curved vs. 0.0002 on straight segments), but less likely to result in minor injury crashes on curved and straight segments. A different result was found in a study by Islam and Hernandez (2013b) and Uddin and Huynh (2017) considering truck-trailer involved in crashes or crashes in dark condition on rural roadways.

5.2.5. Roadway characteristics

Relative to other median types, single-vehicle trucks were less likely to result in severe injury crashes (marginal effect of −0.0093 on curved vs. −0.0030 on the straight segment) on undivided roadways but more likely to increase in minor injury crashes (marginal effect of 0.0013 on curved vs. 0.0004 on straight segments). Relative to other right shoulder widths, width between 4 to 8 feet was more likely to result in minor and severe injury crashes (with an average marginal effect of 0.0089 and 0.0039, respectively), but less likely to result in no injury crashes on curved segments. A similar result was found in study by Islam and Hernandez (2013a) where increase in right shoulder width increased the likelihood of incapacitating injury cashes. Relative to other road surface types, graded or drained surface was more likely to result in minor and severe injury crashes (with an average marginal effect of 0.0085 and 0.0028, respectively) but less likely to result in no injury crashes on curved segments. Relative to other segment lengths, length below 0.25 mile was less likely to result in minor and severe injury crashes (marginal effect of −0.0102 and −0.0025, respectively on curved segment vs. −0.0086 and −0.1020, respectively on straight segments) but more likely to result in no injury crashes.

5.2.6. Crash characteristics

Relative to other crash mechanisms, drivers involved in a rollover were more likely to be involved in minor injury crashes (with an average marginal effect of 0.0841 on curved vs. 0.0405 on straight segments) but less likely to be involved in severe and no injury crashes on curved and straight segments. Islam and Hernandez (2013b) also concluded that truck rollovers could lead to less severe crashes.

5.2.7. Driver characteristics

Relative to other age groups, drivers below 30 years were found less likely to be involved in minor injury crashes (with an average marginal effect of −0.0081) but more likely to be involved in no injury crashes on curved segments. On the other hands, relative

Table 5
Comparison of marginal effects of driver injuries on rural straight and curved segments.

	No Injury		Minor Injury		Severe Injury	
	Straight	Curved	Straight	Curved	Straight	Curved
Speed characteristics						
Low speed limit indicator (1 if speed limit below 40 mph, 0 otherwise)	–	0.0072	–	−0.0074	–	0.0002
Medium speed limit indicator (1 if speed limit between 55 and 65 mph, 0 otherwise)	−0.0218	−0.0097	0.0224	−0.0016	−0.0006	0.0113
Environmental characteristics						
Rainy weather indicator (1 if rainy weather, 0 otherwise)	–	0.0050	–	−0.0053	–	0.0003
Traffic characteristics						
Low traffic volume indicator (1 if AADT below 5,000 vehicles/day, 0 otherwise)	−0.0097	−0.0302	0.0083	0.0213	0.0014	0.0089
Vehicle characteristics						
Truck-trailer indicator (1 if truck-trailer is involved, 0 otherwise)	0.0064	0.0081	−0.0066	−0.0085	0.0002	0.0004
Semi-trailer indicator (1 if semi-trailer is involved, 0 otherwise)	0.0107	–	−0.0093	–	−0.0014	–
Roadway characteristics						
Undivided roadway indicator (1 if roadway facilities are undivided, 0 otherwise)	0.0026	0.0080	0.0004	0.0013	−0.0030	−0.0093
Medium right shoulder indicator (1 if right shoulder with between 4 to 8 feet, 0 otherwise)	–	−0.0128	–	0.0089	–	0.0039
Graded surface indicator (1 if road surface is graded/drained, 0 otherwise)	–	−0.0113	–	0.0085	–	0.0028
Bituminous surface indicator (1 if road surface is bituminous, 0 otherwise)	0.0011	–	0.0002	–	−0.0013	–
Short segment indicator (1 if segment length is less than 0.25 mile, 0 otherwise)	0.0100	0.0127	−0.0086	−0.0102	−0.0014	−0.0025
Crash characteristics						
Rollover indicator (1 if rollover crash, 0 otherwise)	−0.0393	−0.0794	0.0405	0.0841	−0.0012	−0.0047
Driver characteristics						
Age below 30 years indicator (1 if drivers age below 30 years, 0 otherwise)	–	0.0076	–	−0.0081	–	0.0005
Age between 50 to 65 years indicator (1 if drivers age between 50 to 65 years, 0 otherwise)	−0.0053	–	0.0043	–	0.0010	–
Female driver indicator (1 if driver is female, 0 otherwise)	−0.0142	–	0.0146	–	−0.0004	–
Normal driving indicator (1 if driver was physically in normal condition, 0 otherwise)	0.0143	0.0229	0.0018	0.0034	−0.0161	−0.0264
Falling asleep while driving indicator (1 if driver fell asleep while driving, 0 otherwise)	−0.0065	−0.0046	0.0073	0.0053	−0.0008	−0.0007
Exceeded safe speed indicator (1 if driver exceeded safe speed for conditions, 0 otherwise)	−0.0036	−0.0295	0.0031	0.0207	0.0006	0.0088
Overcorrected indicator (1 if driver overcorrected in the maneuver, 0 otherwise)	−0.0129	−0.0112	0.0095	0.0076	0.0034	0.0036
Careless driving indicator (1 if driver operated in careless or reckless manner, 0 otherwise)	−0.0066	−0.0040	0.0071	−0.0007	−0.0005	0.0047
Inattention indicator (1 if driver was inattentive, 0 otherwise)	0.0004	–	0.0001	–	−0.0005	–
Non-restraint usage indicator (1 if shoulder and lap belt not used, 0 otherwise)	–	−0.0110	–	−0.0024	–	0.0134
Restraint usage indicator (1 if shoulder and lap belt used, 0 otherwise)	0.0096	0.0101	0.0014	0.0014	−0.0109	−0.0115
Other characteristics						
No contributing factor indicator (1 if no contributing factor identified, 0 otherwise)	0.0015	–	0.0001	–	−0.0016	–

to other age groups, drivers between 50 and 65 years were found more likely to be involved in severe and minor injury crashes (with an average marginal effect of 0.0010 and 0.0043, respectively) but less likely to be involved in no injury crashes on straight segments. Relative to other physical conditions, drivers with normal driving conditions (i.e., without any physical/emotional impairment) were less likely to be involved in severe injury crashes (with an average marginal effect of −0.0264 on curved vs. −0.0161 on straight segments) but more likely to be involved in minor injury crashes (marginal effects of 0.0034 on curved vs. 0.0018 on straight segments, respectively) on curved and straight segments. A study conducted by Rahimi et al. (2020) and Islam and Ozkul (2019) also reported that older drivers experienced more severe crashes compared to other groups. Relative to other physical conditions, drivers falling asleep while driving were more likely to be involved in minor injury crashes (marginal effect of 0.0053 on curved vs. 0.0073 on straight segments) but less likely to be involved in no injury crashes (marginal effect of −0.0046 on curved vs. −0.0065 on straight segments) on curved and straight segments. Relative to other driving actions at the crash, drivers exceeded the safe speed for the conditions were more likely to be involved in severe injury crashes (marginal effect of 0.0088 on curved vs. 0.0006 on straight segments) but less likely to be involved in no injury crashes on the curved and straight segment. Islam and Hernandez (2013b) and Azimi et al. (2020) also reported that speeding can lead to more severe crashes. Relative to other driving actions at the crash, drivers overcorrected/oversteered were more likely to be involved in severe and minor injury crashes (marginal effect of 0.0036 and 0.0076, respectively on curved vs. 0.0034 and 0.0095, respectively on straight segments) but less likely to be involved in no injury crashes on curved and straight segments. Relative to other driving actions at the crash, careless or reckless drivers were more likely to be involved in severe injury crashes on curved (marginal effect of 0.0047) but less likely in severe injury crashes on the straight segment (marginal effect of −0.0005). However, that is not the case for minor injury crashes in which minor injury is likely to occur on the straight segment (marginal effect of −0.0071) compared to curved segments (marginal effect of −0.0007). Relative to other restraint usages at the crash, drivers not wearing lap and shoulder belts were more likely to be involved in severe (with an average marginal effect of 0.0134) but less likely to be involved in minor and no injury crashes on curved segments. This result is in consistent with a study by Chen et al. (2020). It is noteworthy that the restraint usage resulted in a very similar effect (by magnitude) on injury severity on both curved and straight segments.

6. Conclusions

In this study, we analyzed the factors leading to single-vehicle truck crashes on curved and straight segments in rural roadways in North Carolina by applying a random parameters logit model (with heterogeneity in mean and variance). The crash data were extracted from the HSIS crash database system over a period from 2010 to 2017. Three crash injury severities were considered in the models: no injury, minor injury (combining possible and non-incapacitating injury), and severe injury (combining incapacitating and fatal injury). The estimated model results include a wide variety of factors, such as speed, environmental, vehicular, traffic, crash, and driver characteristics.

The estimated models captured a total of 24 variables that significantly influence driver injury severity in single-vehicle truck crashes on the rural curved and straight segments. Of these variables, 12 variables showed shared effects on both curved and straight segments. Some of the variables in the curved segments model were not found statistically significant in the straight segments model. These variables include roadway segment with low-speed limit (below 40 mph), rainy weather, medium right shoulder width (4 to 8 ft), graded surface, young drivers (below 30 years), and not using restraint system influence the injury severity on curved segments. The effect of the statistically significant variables indicates the severity of curved segments is higher than that on straight segments. More interestingly, the driver characteristics, such as exceeding the speed for the conditions, careless driving behavior, and roadway segment with speed limit (55 mph to 65 mph) on horizontal curves, increased the likelihood of severe injury of the driver in single-vehicle truck crashes relative to straight segments. The countermeasures from the roadway design, particularly the warning signs along with the risky curved segments, flashing advisory speed limit, and chevron with guard rails at appropriate slope and edge line rumble strips are potentially important. Moreover, the drivers of truck-trailers need to be more professionally trained to avoid the risk of rollover while driving along with the curved segments. The findings of this research based on the data-driven approach contribute to the growing body of truck safety research focusing on roadway geometry focusing on the horizontal curves.

Conflict of interest

There is no conflict of interest with any entities involved with this study. This study is primarily focused to improve our understanding in the field of truck safety.

8. Disclaimer

This study was conducted when the first author was working at the University of South Florida.

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References

Al-Bdairi, N. S., Hernandez, S., & Anderson, J. (2018). Contributing factors to run-off-road crashes involving large trucks under lighted and dark conditions. *Journal of Transportation Engineering, Part A: Systems, 144*(1), 04017066.

Al-Bdairi, N. S., & Hernandez, S. (2017). An empirical analysis of run-off-road injury severity crashes involving large trucks. *Accident Analysis & Prevention, 102*, 93–100.

Al-Bdairi, N. S., & Hernandez, S. (2020). Comparison of contributing factors for injury severity of large truck drivers in run-off-road crashes on rural and urban roadways: Accounting for unobserved heterogeneity. *International Journal of Transportation Science and Technology, 9*(2), 116–127.

Alnawmasi, N., & Mannering, F. (2019). A statistical assessment of temporal instability in the factors determining motorcyclist injury severities. *Analytic Methods in Accident Research, 22*, 100090.

Anastasopoulos, P. C., & Mannering, F. L. (2011). An empirical assessment of fixed and random parameter logit models using crash-and non-crash-specific injury data. *Accident Analysis & Prevention, 43*(3), 1140–1147.

Azimi, G., Rahimi, A., Asgari, H., & Jin, X. (2020). Severity analysis for large truck rollover crashes using a random parameter ordered logit model. *Accident Analysis & Prevention, 135*, 105355.

Balakrishnan, S., Moridpour, S., & Tay, R. (2017). Analysis of injury severity in heavy vehicles angle crashes. *Accident Analysis & Prevention, 71*, 286–295.

Behnood, A., & Mannering, F. (2017a). Determinants of bicyclist injury severities in bicycle-vehicle crashes: a random parameters approach with heterogeneity in means and variances. *Analytic Methods in Accident Research, 16*, 35–47.

Behnood, A., & Mannering, F. (2017b). The effect of passengers on driver-injury severities in single-vehicle crashes: a random parameters heterogeneity-in-means approach. *Analytic Methods in Accident Research, 14*, 41–53.

Behnood, A., & Mannering, F. L. (2015). The temporal stability of factors affecting driver-injury severities in single-vehicle crashes: Some empirical evidence. *Analytic Methods in Accident Research, 8*, 7–32.

Behnood, A., & Mannering, F. (2019). Time-of-day variations and temporal instability of factors affecting injury severities in large-truck crashes. *Analytic Methods in Accident Research, 23*, 100102.

Behnood, A., Roshandeh, A. M., & Mannering, F. L. (2014). Latent class analysis of the effects of age, gender, and alcohol consumption on driver-injury severities. *Analytic Methods in Accident Research, 3-4*, 56–91.

Bhat, C. R. (2001). Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. *Transportation Research Part B: Methodological, 35*(7), 677–693.

Cerwick, D. M., Gkritza, K., Shaheed, M. S., & Hans, Z. (2014). A comparison of the mixed logit and latent class methods for crash severity analysis. *Analytic Methods in Accident Research, 3-4*, 11–27.

Chen, S., Zhang, S., Xing, Y., & Lu, J. (2020). Identifying the factors contributing to the severity of truck-involved crashes in Shanghai River-Crossing Tunnel. *International journal of environmental research and public health, 17(9)*, 3155

Charbotel, B., Martin, J. L., Gadegbeku, B., & Chiron, M. (2003). Severity factors for truck drivers' injuries. *American Journal of Epidemiology, 158*(8), 753–759.

Das, S., Islam, M., Dutta, A., & Shimu, T. (2020). Uncovering deep structure of determinants in large truck fatal crashes. *Transportation Research Record, 2674*(9), 742–754.

Domencich, T. A., & McFadden, D. (1975). *Urban travel demand: A behavioral analysis*. American Elseviewer: North-Holland.

Eluru, N., Bhat, C. R., & Hensher, D. A. (2008). A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. *Accident Analysis & Prevention, 40*(3), 1033–1054.

Eustace, D., Alqahtani, T., & Hovey, P. W. (2018). Classification tree modelling of factors impacting severity of truck-related crashes in Ohio. Presentation at the 97th Annual Meeting of the Transportation Research Board, Washington DC.

Federal Highway Administration. Safety Culture and the Zero Deaths Vision - Safety | [Internet]. [cited 2020 Jul 29]. Available from: https://safety.fhwa.dot.gov/zerodeaths/.

Federal Motor Carrier Safety Administration, Large Truck and Bus Crash Facts 2017. https://www.fmcsa.dot.gov/safety/data-and-statistics/large-truck-and-bus-crash-facts-2017.

Fitzsimmons, E. J., Lindheimer, T. E., Schrock, S. D., & Gonterwitz, K. (2013). Evaluation of large truck crashes at horizontal curves on two-lane rural highways in Kansas. Presentation at the 92nd Annual Meeting of the Transportation Research Board, Washington DC.

Fountas, G., Anastasopoulos, P. C., & Mannering, F. L. (2018). Analysis of vehicle accident-injury severities: A comparison of segment-versus accident-based latent class ordered probit models with class-probability functions. *Analytic Methods in Accident Research, 18*, 15–32.

Fountas, G., & Rye, T. (2019). A note on accounting for underlying injury-severity states in statistical modeling of injury accident data. *Procedia Computer Science, 151*, 202–209.

Golob, T. F., Recker, W. W., & Leonard, J. D. (1987). An analysis of the severity and incident duration of truck-involved freeway accidents. *Accident Analysis & Prevention., 19*(5), 375–395.

Haq, M. T., Zlatkovic, M., & Ksaibati, K. (2020). Occupant injury severity in passenger car-truck collisions on interstate 80 in Wyoming: A Hamiltonian Monte Carlo Markov Chain Bayesian inference approach. *Journal of Transportation Safety & Security*, 1–25.

Haq, M. T., Zlatkovic, M., & Ksaibati, K. (2020). Investigating occupant injury severity of truck-involved crashes based on vehicle types on a mountainous freeway: A hierarchical Bayesian random intercept approach. *Accident Analysis & Prevention, 144*, 105654.

Hensher, D., & Greene, W. (2003). The mixed logit model: The state of practice. *Transportation, 30*(2), 133–176.

Highway Safety Information System (HSIS). Guidebook for Data Files North Carolina. Washington, D.C., 2014. [cited 2020 Jul 29]. [cited 2020 Jul 29]. Available from: https://www.hsisinfo.org/pdf/guidebook_NC.pdf.

Huang, H.F., Schneider, R.J., Zegeer, C.V., Khattak, A.J., Amerlynck, V.J., & Lacy, J.K. (2001). Identification of severe crash factors and countermeasures in North Carolina (No. FHWA/NC/2001-003).

Islam, M. B., & Hernandez, S. (2013). Modeling injury outcomes of crashes involving heavy vehicles on Texas highways. *Transportation Research Record, 2388*(1), 28–36.

Islam, M., & Hernandez, S. (2013). Large truck-involved crashes: Exploratory injury severity analysis. *Journal of Transportation Engineering, 139*(6), 596–604.

Islam, M., & Hernandez, S. (2014). An analysis of injury outcomes of crashes involving large trucks by time of day in urban areas in Texas. 2014. 94th TRB Annual Meeting, Washington DC.

Islam, M., & Ozkul, S. (2019). Identifying fatality risk factors for the commercial vehicle driver population. *Transportation Research Record, 2673*(9), 297–310.

Islam, M., & Pande, A. (2020). Analysis of single-vehicle roadway departure crashes on rural curved segments accounting for unobserved heterogeneity. *Transportation Research Record., 2674*(10), 146–157.

Islam, M., Alnawmasi, N., & Mannering, F. (2020). Unobserved heterogeneity and temporal instability in the analysis of work-zone crash-injury severities. *Analytic Methods in Accident Research, 28*, 100130.

Islam, M., & Mannering, F. (2020). (2020) A temporal analysis of driver-injury severities in crashes involving aggressive and non-aggressive driving. *Analytic Methods in Accident Research, 27*, 100128.

Islam, M. (2021). The effect of motorcyclists' age on injury severities in single-motorcycle crashes with unobserved heterogeneity. *Journal of Safety Research, 77*, 125–138.

Islam, M., & Mannering, F. (2021). The role of gender and temporal instability in driver-injury severities in crashes caused by speeds too fast for conditions. *Accident Analysis & Prevention, 153*, 106039.

Insurance Institute for Highway Safety, 2021. Large Trucks. Available from: https://www.iihs.org/topics/large-trucks.

Khattak, A.J., Schneider, R.J., & Targa, F. (2002). A Comparison of Rollovers with Non-rollovers and Analysis of Injury Severity in Large Truck Crashes. Southeastern Transportation Center University of Tennessee, Knoxville.

Kim, J.-K., Ulfarsson, G. F., Kim, S., & Shankar, V. N. (2013). Driver-injury severity in single-vehicle crashes in California: A mixed logit analysis of heterogeneity due to age and gender. *Accident Analysis & Prevention, 50*, 1073–1081.

Koupaenejad, A. 2010. Statistical modeling and analysis of injury severity sustained by occupants of passenger vehicles involved in crashes with large trucks. UNLV Theses, Dissertations, Professional Papers, and Capstones; 2010.

Li, J., Liu, J., Liu, P., & Qi, Y. (2020). Analysis of factors contributing to the severity of large truck crashes. *Entropy*, *22*(11), 1191.

Liu, C., & Subramanian, R. (2009). Factors related to fatal single-vehicle run-off-road crashes. NHTSA Technical Report, Report No. DOT HS 811 232.

Mannering, F. L., & Bhat, C. R. (2014). Analytic methods in accident research: Methodological frontier and future directions. *Analytic Methods in Accident Research, 1*, 1–22.

Mannering, F., Shankar, V., & Bhat, C. (2016). Unobserved heterogeneity and the statistical analysis of highway accident data. *Analytic Methods in Accident Research, 11*, 1–16.

Mashhadi, M. M. R., Wulff, S. S., & Ksaibati, K. (2018). A comprehensive study of single and multiple truck crashes using violation and crash data. *The Open Transportation Journal, 12*(1), 43–56.

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics, 15*(5), 447–470.

McFadden, D. (1981). Econometric models of probabilistic choice. *Structural Analysis of Discrete Data with Econometric Applications*, 198–272.

Milton, J. C., Shankar, V. N., & Mannering, F. L. (2008). Highway accident severities and the mixed logit model: An exploratory empirical analysis. *Accident Analysis & Prevention, 40*(1), 260–266.

Morgan, A., & Mannering, F. L. (2011). The effects of road-surface conditions, age, and gender on driver-injury severities. *Accident Analysis & Prevention, 43*(5), 1852–1863.

Naik, B., Tung, L., Zhao, S., & Khattak, A. J. (2016). Weather impacts on single-vehicle truck crash injury severity. *Journal of Safety Research, 58*, 57–65.

National Highway Traffic Safety Administration, Rural/Urban Comparison of Traffic Fatalities, DOT HS 812 957, 2020. Available from: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812957.

National Highway Traffic Safety Administration, Large Truck, DOT HS 812 891, 2020. Available from: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812891.

Qin, X., Sultana, M. A., Chitturi, M. V., & Noyce, D. A. (2013). Developing truck corridor crash severity index. *Transportation Research Record, 2386*(1), 103–111.

Rahimi, E., Shamshiripour, A., Samimi, A., & Mohammadian, A. K. (2020). Investigating the injury severity of single-vehicle truck crashes in a developing country. *Accident Analysis & Prevention*, *137*, 105444.

Savolainen, P. T., Mannering, F. L., Lord, D., & Quddus, M. A. (2011). The statistical analysis of highway crash-injury severities: A review and assessment of methodological alternatives. *Accident Analysis & Prevention, 43*(5), 1666–1676.

Seraneeprakarn, P., Huang, S., Shankar, V., Mannering, F., Venkataraman, N., & Milton, J. Occupant injury severities in hybrid-vehicle involved crashes: a random parameters approach with heterogeneity in means and variances. *Analytic Methods in Accident Research, 15,* 41-55.

Shaheed, M. S., & Gkritza, K. (2014). A latent class analysis of single-vehicle motorcycle crash severity outcomes. *Analytic Methods in Accident Research, 2*, 30–38.

Taylor, S. G., Russo, B. J., & James, E. (2018). A comparative analysis of factors affecting the frequency and severity of freight-involved and non-freight crashes on a major freight corridor freeway. *Transportation Research Record., 2672*(34), 49–62.

Teoh, E. R., Carter, D. L., Smith, S., & McCartt, A. T. (2017). Crash risk factors for interstate large trucks in North Carolina. *Journal of Safety Research, 62*, 13–21.

Train, K. (2009). *Discrete choice methods with simulation*. Cambridge University Press.

Uddin, M., & Huynh, N. (2018). Factors influencing injury severity of crashes involving HAZMAT trucks. *International Journal of Transportation Science and Technology, 7*(1), 1–9.

Uddin, M., & Huynh, N. (2017). Truck-involved crashes injury severity analysis for different lighting conditions on rural and urban roadways. *Accident Analysis & Prevention, 108*, 44–55.

Uddin, M., & Huynh, N. (2020). Injury severity analysis of truck-involved crashes under different weather conditions. *Accident Analysis & Prevention, 141*, 105529. https://doi.org/10.1016/j.aap.2020.105529.

Venkataraman, N., Shankar, V., Ulfarsson, G. F., & Deptuch, D. (2014). A heterogeneity-in-means count model for evaluating the effects of interchange type on heterogeneous influences of interstate geometrics on crash frequencies. *Analytic Methods in Accident Research, 2*, 12–20.

Venkataraman, N., Ulfarsson, G. F., & Shankar, V. N. (2013). Random parameter models of interstate crash frequencies by severity, number of vehicles involved, collision and location type. *Accident Analysis & Prevention, 59*, 309–318.

Wang, Z., Cao, B., Deng, W., Zhang, Z., Lu, J., & Chen, H. (2011). Safety evaluation of truck-related crashes at freeway diverge areas. *Proc. 90th TRB Annu. Meeting Compendium Papers*.

Waseem, M., Ahmed, A., & Saeed, T. U. (2019). Factors affecting motorcyclists' injury severities: An empirical assessment using random parameters logit model with heterogeneity in means and variances. *Accident Analysis & Prevention, 123*, 12–19.

Washington, S., Karlaftis, M., Mannering, F., & Anastasopoulos, P. (2020). *Statistical and econometric methods for transportation data analysis* (Third Edition). Taylor and Francis Group, New York, NY: CRC Press.

Xiong, Y., & Mannering, F. L. (2013). The heterogeneous effects of guardian supervision on adolescent driver-injury severities: A finite-mixture random-parameters approach. *Transportation Research Part B: Methodological, 49*, 39–54.

Yasmin, S., Eluru, N., Bhat, C. R., & Tay, R. (2014). A latent segmentation based generalized ordered logit model to examine factors influencing driver injury severity. *Analytic Methods in Accident Research, 1*, 23–38.

Ye, F., & Lord, D. (2014). Comparing three commonly used crash severity models on sample size requirements: Multinomial logit, ordered probit and mixed logit models. *Analytic Methods in Accident Research, 1*, 72–85.

Zheng, Z., Lu, P., & Lantz, B. (2018). Commercial truck crash injury severity analysis using gradient boosting data mining model. *Journal of Safety Research, 65*, 115–124.

Zou, W., Wang, X., & Zhang, D. (2017). Truck crash severity in New York city: An investigation of the spatial and the time of day effects. *Accident Analysis & Prevention, 99*, 249–261.

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