International Journal of Transportation Science and Technology xxx (xxxx) xxx

Contents lists available at ScienceDirect

International Journal of Transportation Science and Technology

journal homepage: www.elsevier.com/locate/ijtst

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

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A R T I C L E I N F O

Article history:
Received 11 July 2019
Received in revised form 22 January 2020
Accepted 23 January 2020
Available online xxxx

Keywords:
Injury severity
Unobserved heterogeneity
Latent class ordered probit model
Large trucks
Run-off-road

A B S T R A C T

In spite of numerous efforts to quantitatively identify the factors contributing to the injury severity of different crash types in rural and urban settings, the distinction between rural and urban areas regarding the injury severity of run-off-road (ROR) crashes involving large trucks is still not clearly understood. As such, the objective of this study is to investigate the effect of area type (i.e., urban vs. rural) on injury severity outcomes sustained by drivers in ROR crashes involving large trucks while accounting for unobserved heterogeneity. To do this, the latent class ordered probit models with two classes are developed. The crash data pertaining to ROR crashes involving large trucks in Oregon between 2007 and 2014 were utilized. The estimation results reveal that the developed latent class ordered probit models (for urban and rural areas) are substantially distinct in terms of the contributing factors affect urban and rural ROR crash severities. The results indicate that female drivers and speed limit of 55 mph were associated with moderate injuries (non-incapacitating) in rural roadway ROR crashes while no injury outcome is most likely for crashes occurred in urban roadways with raised medians and on areas with a population density between 10,001 and 25,000. Also, the findings show that some factors increase the risk propensity of sustaining higher injury levels regardless of the land use setting such as crashes on horizontal curves, not wearing seatbelt, and driver fatigue. The findings of this study could benefit trucking industry, transportation agencies, and safety practitioners to prevent or alleviate the injury severity of ROR crashes involving large trucks by developing appropriate and cost-effective countermeasures.

1. Introduction

Injury severity analyses have been extensively conducted over the years to better understand the factors that influence injuries sustained by drivers resulting from roadway crashes (Al-Bdairi et al., 2018; Al-Bdairi and Hernandez, 2017; Anarkooli and Hosseinlou, 2016; Anderson and Hernandez, 2017; Behnood and Mannering, 2017; Chang and Chien, 2013; Kim et al., 2013; Lee and Li, 2014; Schneider et al., 2009; Wu et al., 2016, 2014; Xiong and Mannering, 2013; Uddin and

Peer review under responsibility of Tongji University and Tongji University Press.
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https://doi.org/10.1016/j.ijtst.2020.01.004
2046-0430/

Huynh, 2018). Among the many factors that have been found to influence driver injury severity, and of particular interest to this study, is that of land use type (e.g., rural vs. urban) (Al-Bdairi et al., 2018; Islam et al., 2014; Khorashadi et al., 2005; Lee and Mannering, 2002). Recent statistics from the National Highway Traffic Safety Administration (NHTSA) indicate that roadway crashes are disproportionally distributed between urban and rural areas. For instance, in 2015, approximately 35,092 individuals lost their lives due to 32,166 fatal crashes on U.S. roadways. Of these fatal crashes, about 15,293 occurred in rural areas, and roughly 14,414 took place in urban areas (NHTSA, 2017). In the state of Oregon, this distinction between rural and urban crashes and fatalities also holds true. In 2015, Oregon experienced 44,523 total crashes in urban areas, leading to 156 fatalities. In contrast, in the same year, the total crashes in rural areas were roughly one-fourth (10,633) of those reported in urban areas. However, the number of fatalities were about two times (254) more than those experienced on urban roads (Oregon Department of Transportation (ODOT) (2017)). The many reasons underlying this disparity include, but are not limited to: the longer emergency response times for individuals involved in a rural crash (Gonzalez et al., 2007); the higher speed limits and higher travel speeds in rural areas compared to urban areas; the lack of traffic law enforcement in rural areas compared to urban areas; the risky driving behavior in rural areas; the different traffic environments of rural and urban areas, such as traffic volume and roadway conditions (Nordfjærn et al., 2010); the lower use of protective devices, such as seatbelts, in rural areas (Yan et al., 2012); and the differences in individuals' perceiving and estimating the risks of traffic crashes in rural and urban areas.

Run-off-road (ROR) (also known as roadway departure) crashes according to Federal Motor Carrier Safety Administration (FMCSA) are crashes that occur due to a vehicle crossing an edge line or a center line of a roadway or/and leaving the designated lane (FMCSA, 2019). These types of crashes roughly constituted 54% of all traffic fatalities in the U.S. for the period between 2013 and 2015. A similar trend has been observed in the state of Oregon in which nearly 55% of all fatalities between 2009 and 2015 were due to ROR crashes (Federal Highway Administration, 2017). In the present study, ROR crashes involving large trucks are of particular interest for two reasons. First, large trucks play a vital role in the U.S. economy; for example, in 2013, large trucks (i.e., trucks weighing over 10,000 lbs.) moved roughly 55 million tons of freight valued at more than $49.3 billion (U.S. Department of Transportation/Bureau of Transportation Statistics, 2015). Unfortunately, the movement of this much freight does not come without a price in terms of roadway crashes and resulting fatalities (due in part to the operating and vehicle characteristics of large trucks). Second, ROR crashes are a nationwide problem that needs to be thoroughly investigated; in 2010, for instance, they constituted 57% of all fatal crashes and 16% of nonfatal crashes (Blincoe et al., 2015).

Therefore, the objective of this study is to investigate the effect of area type (i.e., urban vs. rural) on injury severity outcomes sustained by drivers in ROR crashes involving large trucks while accounting for unobserved heterogeneity (unobserved factors not present in the data). To achieve this objective, an econometric modeling framework is utilized, specifically, the latent class ordered probit model. The latent class order probit model is developed for both rural and urban contexts using crash data pertaining to ROR crashes involving large trucks in Oregon between 2007 and 2014. This study contributes to the body of knowledge in the context of large truck safety by narrowing the gap in the literature regarding the influence of area type on the injury severity of ROR crashes. A better understanding of these contributing factors in relation to injury severity sustained by large truck drivers (this refers to the size of the vehicle) involved in ROR crashes can provide transportation safety professionals, the trucking industry, and policy makers with valuable insights towards reducing the number of ROR crashes involving large trucks, and their injury severity, through the selection and implementation of appropriate cost-effective countermeasures.

2. Literature review

From a methodological perspective, a wide variety of approaches have been applied in the study of injury severity of roadway crashes involving large trucks (Al-Bdairi et al., 2018; Al-Bdairi and Hernandez, 2017; Anderson and Hernandez, 2017; Chen and Chen, 2011; Islam, 2015; Islam and Hernandez, 2013a; Islam et al., 2014; Khorashadi et al., 2005; Lemp et al., 2011; Osman et al., 2016; Pahukula et al., 2015). Most of these studies have investigated the injury severity of truck drivers by utilizing random parameter models, with the exception of Khorashadi et al. (2005) and Lemp et al. (2011), who applied fixed parameter models. To account for unobserved heterogeneity, two main approaches have been widely utilized: random parameter models and latent class models (Mannering et al., 2016; Mannering and Bhat, 2014).

As regard to data disaggregation, several studies have disaggregated data into subpopulations (e.g., by age, gender, time of day, roadway classification, area type, light condition, etc.) to study the effect of those subpopulations on injury severity. For instance, Islam and Mannering (2006) disaggregated crash data into six models for three age groups and for both genders. Morgan and Mannering (2011) followed the same approach by separating driver age into two subpopulations and pavement conditions into three subpopulations (dry, wet, snow/icy). To study the impact of alcohol impairment on large truck crashes, Behnood et al. (2014) investigated the injury severity of alcohol-impaired drivers and those who were sober at the time of the crash by splitting the data according to alcohol-impairment status, driver age, and gender. Pahukula et al. (2015) analyzed the injury severity of heavy vehicle crashes by separating crash data by time of day. Anderson and Hernandez (2017) analyzed the injury severity of heavy vehicle drivers based on roadway classifications. In addition, roadway lighting has been disaggregated to study its effect on the injury severity sustained by large truck drivers (Al-Bdairi et al., 2018; Anarkooli and Hosseinlou, 2016).

Lastly, studies that attempt to quantify the impacts of land use on ROR crashes involving large trucks are sparse. For example, Khorashadi et al. (2005) conducted a study to highlight the differences in driver injury severities between urban and rural settings for crashes involving large trucks by using multinomial logit models. This study, however, ignores the effect of unobserved heterogeneity on injury severities. Moreover, Khorashadi et al. (2005) examined all types of truck-related crashes rather than emphasizing ROR crashes (Khorashadi et al., 2005). In a different vein, Islam et al. (2014) investigated the effects of area type on injury severity, along with the number of vehicles involved in at-fault large truck crashes, by developing a mixed logit model (Islam et al., 2014). Still, the main focus of this study was on at-fault, large truck-related crashes.

In spite of numerous efforts to quantitatively identify the factors contributing to the injury severity of different crash types in rural and urban settings, the distinction between rural and urban areas regarding the injury severity of run-off-road (ROR) crashes involving large trucks is still not clearly understood. Also, past studies have characteristically utilized random parameter modeling frameworks to analyze injury severities. Furthermore, the study of land use type separately (urban vs. rural) as a subpopulation and a contributing factor in a holistic model is sparse, especially from the perspective of ROR crashes involving large trucks. Studying this aspect of ROR injury severities can provide greater insight into the contributing factors of these types of crashes in specific urban and rural area contexts.

3. Data description

The analyses in this study were conducted using eight years of police-reported crash data regarding ROR crashes involving large trucks that occurred in Oregon between 2007 and 2014. The crash data that is maintained by the Oregon Department of Transportation (ODOT) includes detailed information about the characteristics of the crashes, the drivers involved, the environmental conditions, and the roadway inventory. In total, 3054 crashes were included in this study. The crash data was split into two datasets: one for ROR crashes involving large trucks that occurred in rural areas, with 2253 (74% of crashes) observations, and the other one pertaining to crashes that took place in urban areas, with 801 (26% of crashes) observations.

In this study, injury severity is categorized into four main ordered categories: no injury, possible injury, moderate injury (non-incapacitating), and severe injury (incapacitating and fatal). A frequency and percentage distribution of driver injury severity of ROR crashes involving large trucks in urban and rural areas is depicted in Table 1. As this table clearly shows, ROR crashes involving large trucks occurring in urban areas are less severe than those occurring in rural areas. For instance, 84.1% of ROR crashes in urban areas resulted in a no injury outcome, whereas 65.8% of ROR crashes in rural areas resulted in the same outcome. The explanatory variables that were found to be significant at a 95% confidence level are presented in Table 2. The frequency and percentage distribution of explanatory variables for ROR crashes involving large trucks in both urban and rural models are illustrated in Table 3.

4. Methodology

To analyze and determine the potential factors contributing to injury severity of particular crashes, ordered-response discrete choice models such as ordered probit/logit models are commonly utilized (Abdel-Aty, 2003; Al-Bdairi and Hernandez, 2017; Anarkooli and Hosseinlou, 2016; Osman et al., 2016; Zhu and Srinivasan, 2011). Despite the abundance of studies that have examined driver injury severity in the transportation safety context, it is surprising that studies employing latent class ordered probit models are quite scarce. Alternatively, random parameter discrete choice models for ordered-response variables have been extensively used in previous studies (Al-Bdairi and Hernandez, 2017; Islam and Hernandez, 2013a; Naik et al., 2016). The latent class model is an alternative way to address the heterogeneity in injury severity analyses (Mannering et al., 2016). The latent class approach accounts for possible unobserved heterogeneity present the crash data, and it provides a means by which an analyst can bypass the assumptions about the parameter distributions, which may not always be consistent across observations (Mannering et al., 2016). Instead, the latent class modeling framework can account for unobserved heterogeneity through the assumption that observations come from classes that are based on common characteristics and that are distinct in nature (Mannering et al., 2016).

Regarding the latent class ordered probit model, it is assumed that large truck drivers are distributed into C homogenous classes based on the characteristics of ROR crashes. It should be noted that an analyst does not know from which class an observation is drawn. Moreover, each class has its own explanatory factors (Greene and Hensher, 2010). Within each class, the contributing factors that affect driver injury severity involving ROR crashes are assumed to be fixed.

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Table 1
Frequency and percentage distribution of driver injury in urban and rural models.

Injury severity	Urban		Rural	
	Observations	Percent	Observations	Percent
Severe injury (fatal & incapacitating)	15	1.9%	76	3.4%
Moderate (non-incapacitating)	45	5.6%	370	16.4%
Possible injury	67	8.4%	325	14.4%
No injury	674	84.1%	1482	65.8%
Total observations	801	–	2253	–

Table 2
Description of selected explanatory variables used in the analyses of urban and rural models.

Variable	Description of variables	Effect of variable	
		On urban	On rural
DITCH	Harmful event (1 for colliding with ditch, 0 otherwise)	✓	✓
GRADE	Roadway characteristics (1 for vertical curve, 0 otherwise)	✓	
POP25K	Population density (1 if between 10,001 and 25,000, 0 otherwise)	✓	
DRY	Roadway surface condition (1 for dry, 0 otherwise)	✓	✓
LOSTCTRL	Losing control of vehicle (1 for yes, 0 otherwise)	✓	
DLIT	Lighting condition (1 if darkness with street lights, 0 otherwise)	✓	✓
NOSPED	Exceeding the posted speed or driving too fast for conditions (1 for no, 0 otherwise)	✓	✓
NOBELT	Driver safety seatbelt (1 if not used, 0 otherwise)	✓	✓
FALL	Month of the year (1 if between September and December, 0 otherwise)	✓	
FATIGUE	Driver was fatigued (1 for yes, 0 otherwise)	✓	✓
CURVE	Roadway characteristics (1 for horizontal curve, 0 otherwise)	✓	✓
RSDMEDN	Median type (1 for raised median, 0 otherwise)	✓	
MPH55	Speed limit (1 if 55 mph, 0 otherwise)		✓
OVRTURN	Harmful event (1 for overturn, 0 otherwise)		✓
NODEPLOY	Airbag deployment (1 if did not deploy, 0 otherwise)		✓
YOUNG	Driver age (1 if between 20 and 45 years, 0 otherwise)		✓
FEMALE	Driver gender (1 if female, 0 otherwise)		✓

defined. This function can be used to determine the discrete injury severity outcomes of truck drivers involved in ROR crashes conditional on driver i belonging to class c, as written in Eq. (1) (Washington et al., 2011).

$$y_i^*|(i\epsilon c) = X_i\beta_c + \varepsilon_{ic}, y_{ic} = j, \text{if } \mu_{i,j-1,c} < y_i^* < \mu_{i,j,c} \quad (1)$$

where X_i is a vector of explanatory variables that contribute to driver injury severity; β_c is the associated vector of estimable parameters that belong to class c; ε_{ic} is an error term or a disturbance term, which is assumed to be independently randomly distributed; and $\mu_{i,j,c}$ denotes the upper threshold associated with a particular class c that defines the injury severity outcome j for a driver i (Yasmin et al., 2014). Now, to determine the probability that large truck driver i sustains injury severity outcome j when involved in ROR crashes conditional on driver i belonging to class c, Greene and Hensher (2010) and Yasmin et al. (2014) illustrate Eq. (2) as follows:

$$P_i(j)|c = \Phi\left(\mu_{i,j,c} - X_i\beta_c\right) - \Phi\left(\mu_{i,j-1,c} - X_i\beta_c\right) \quad (2)$$

where $\Phi(.)$ denotes the standard normal cumulative distribution function for the error term. Since the analyst is unable to know which class a driver i belongs to, a vector representing observed crash factors η_i is utilized to identify that class. Greene and Hensher (2010) proposed using a multinomial logit structure to determine the probability of assigning a driver i to class c while forcing the class probabilities to be between zero and one and to sum to one, as shown in Eq. (3).

$$P_{ic} = \frac{\exp(\alpha_c\eta_i)}{\sum_c \exp(\alpha_c\eta_i)} \quad (3)$$

where α_c is a vector of estimated parameters. Next, to determine the unconditional probability of driver i sustaining injury severity j, Yasmin et al. (2014) used the formula illustrated in Eq. (4). Finally, Eq. (5) represents the log-likelihood function for the entire dataset (Yasmin et al., 2014).

$$P_i(j) = \sum_{c=1}^{C} (P_i(j)|c) \times (P_{ic}) \quad (4)$$

Table 3
Frequency and percentage distribution of explanatory variables in urban and rural models.

Variable	Urban area					Rural area				
	Severe injury	Moderate injury	Possible injury	No injury	Total	Severe injury	Moderate injury	Possible injury	No injury	Total
MPH55	–	–	–	–	–	44 (3.2%)	252 (18.2%)	221 (16.0%)	867 (62.6%)	1384
NODEPLOY	–	–	–	–	–	11 (2.2%)	71 (14.3%)	71 (14.3%)	342 (69.1%)	495
OVRTURN	–	–	–	–	–	10 (2.4%)	108 (26.1%)	85 (20.5%)	211 (51.0%)	414
FEMALE	–	–	–	–	–	5 (5.2%)	22 (22.7%)	19 (19.6%)	51 (52.6%)	97
YOUNG	–	–	–	–	–	25 (2.3%)	140 (13.0%)	174 (16.2%)	738 (68.5%)	1077
DRY	13 (2.4%)	35 (6.6%)	43 (8.1%)	440 (82.9%)	531	54 (4.6%)	259 (21.9%)	165 (14.0%)	702 (59.5%)	1180
DLIT	3 (3.2%)	4 (4.3%)	12 (12.9%)	74 (79.6%)	93	1 (1.8%)	4 (7.0%)	10 (17.5%)	42 (73.7%)	57
DITCH	2 (3.3%)	8 (13.3%)	9 (15.0%)	41 (68.3%)	60	36 (7.0%)	113 (22.1%)	88 (17.2%)	274 (53.6%)	511
FATIGUE	0 (0.0%)	4 (20.0%)	5 (25.0%)	11 (55.0%)	20	3 (2.5%)	41 (34.5%)	21 (17.6%)	54 (45.4%)	119
NOSPED	8 (1.3%)	24 (4.0%)	38 (6.4%)	524 (88.2%)	594	41 (3.7%)	192 (17.3%)	145 (13.1%)	733 (66.0%)	1111
CURVE	2 (1.8%)	10 (9.2%)	17 (15.6%)	80 (73.4%)	109	34 (4.4%)	170 (22.1%)	123 (16.0%)	442 (57.5%)	769
NOBELT	4 (12.9%)	7 (22.6%)	5 (16.1%)	15 (48.4%)	31	24 (17.5%)	52 (38.0%)	28 (20.4%)	33 (24.1%)	137
FALL	5 (2.3%)	13 (5.9%)	21 (9.5%)	183 (82.4%)	222	–	–	–	–	–
GRADE	2 (3.8%)	8 (15.4%)	10 (19.2%)	32 (61.5%)	52	–	–	–	–	–
RSDMEDN	5 (3.6%)	5 (3.6%)	14 (10.1%)	114 (82.6%)	138	–	–	–	–	–
POP25K	1 (0.7%)	4 (2.9%)	8 (5.8%)	124 (90.5%)	137	–	–	–	–	–
LOSTCTRL	5 (3.4%)	16 (11.0%)	24 (16.6%)	100 (69.0%)	145	–	–	–	–	–

$$L = \sum_{i=1}^{N} log\left[\sum_{c=1}^{C} (P_i(j)|c) \times (P_{ic})\right] \tag{5}$$

Together, these equations provide a flexible methodology by which injury severity of ROR crashes involving large trucks on urban and rural roadways can be studied. Lastly, marginal effects are computed for a better interpretation of the results and to determine the effect of each explanatory parameter on the injury severity outcome probabilities. Since indicator variables are created in this study, the marginal effects represent the numerical difference of the injury severity outcome probabilities, while the indicator variables change from zero to one (Washington et al., 2011).

$$M_{X_{ij}}^{P_i(j)} = P_i(j)(\text{given}X_{ij} = 1) - P_i(j)(\text{given}X_{ij} = 0) \tag{6}$$

5. Model separation tests

Despite the substantial differences between injury severities sustained by large truck drivers involved in ROR crashes in rural and urban areas, robust statistical methods need to be used to highlight those differences, as well as the commonalities between the two models. Such methods can be used to validate developing separate models for rural and urban ROR crashes over one aggregated model. To achieve this, two series of likelihood ratio tests are commonly used. The first log-likelihood ratio test can be conducted to examine whether the contributing factors to injury severities in two separated models (rural and urban) are similar to those in a holistic model that combines rural and urban crashes as a whole (Washington et al., 2011). In this test, it is hypothesized that the holistic model and the separate models are the same from the perspective of the contributing factors in the sense that the difference is not statistically significant as illustrated in Eq. (7) (Washington et al., 2011).

$$\chi^2 = -2[LL(\beta_H) - LL(\beta_U) - LL(\beta_R)] \tag{7}$$

where $LL(\beta_H)$ is the log-likelihood at convergence for the holistic model that combines ROR crashes occurring in both rural and urban areas; $LL(\beta_U)$ is the log-likelihood at convergence for the urban model; and $LL(\beta_R)$ represents the log-likelihood at convergence for the rural model. In this study, the obtained value of log-likelihood at convergence for the holistic model is -2479.445, with 17 estimated parameters (degrees of freedom). The chi-square statistic obtained after applying Eq. (7) is distributed with seven degrees of freedom (the total number of estimated parameters in both the rural and urban model minus those in the holistic model). From the separated models, the values of log-likelihood at convergence for rural and urban models are −1989.500 and −391.102, respectively. That is, the chi-square statistic χ^2 determined by Eq. (7) is equal to 197.686 with seven corresponding degrees of freedom. Accordingly, the null hypothesis that there is an insignificant statistical difference between the holistic model and the separate models as regards to the contribution factors must be rejected with well over 99% confidence, meaning that the models for ROR crashes involving large trucks in rural and urban areas must be developed and estimated separately.

The second log-likelihood ratio test is the parameter transferability test by which the stability of parameter estimates can be tested. This test is another approach that justifies using separate models in terms of ROR crashes in rural and urban areas in lieu of a holistic one that combines crashes in both areas. Washington et al. (2011) formulated the parameter transferability test as shown in Eq. (8).

$$\chi^2 = -2[LL(\beta_{ba}) - LL(\beta_a)] \tag{8}$$

where $LL(\beta_a)$ is the log-likelihood at convergence for model a (i.e., rural model) that is estimated based on a's data (rural data) without any restriction, and $LL(\beta_{ba})$ is the log-likelihood at convergence for model a (rural model), using the converged parameters from model b (urban model). This test was also reversed in this study. Applying Eq. (8) can yield a chi-square statistic χ^2 that follows a chi-square distribution with degrees of freedom equal to the number of estimated parameters in $LL(\beta_{ba})$. Table 4 shows the values of the chi-square statistics and the corresponding degrees of freedom determined by Eq. (8). Once again, with over 99% confidence, the developed separate models representing ROR crashes involving large trucks in rural and urban areas have different estimated parameters.

6. Estimation results

In this study, two[1] classes were used in the analyses for latent class ordered probit models that were developed by using NLOGIT 6.0 to estimate the impacts of contributing factors on injury severity of ROR crashes involving large trucks in urban and rural areas. Table 5 shows the estimated probabilities and shares of severity outcomes of each class for both models. Table 5 demonstrates that the probability of large truck drivers involved in ROR crashes on urban roadways being assigned to class 1 is higher (58.0%) than the probability of being assigned to class 2. However, this distribution regarding the probability of assigning drivers to classes is completely reversed for ROR crashes occurring on rural roadways in the sense that the likelihood of drivers being assigned to class 2 is higher (51.0%) than being assigned to class 1.

Since the latent class ordered probit models with two distinct classes were developed in this study, each variable in the analyses has two estimated parameters, as clearly shown in Table 6. Further, Table 6 reveals that some parameters have different signs across the two classes (i.e., fatigued drivers in both models), others have similar signs across classes (i.e., dry surface in both models), and other parameters are significant only in a specific class. Such variation in the effects of the parameters on injury severity incurred by large truck drivers involved in ROR crashes across classes indicates that there is a significant heterogeneity between the two classes. The marginal effects will be used in the interpretation of the findings because the latent class ordered probit model is an extension of the traditional ordered probit model, in which the impact of an estimated parameter on increasing or decreasing the probability of extreme ordered discrete injury severity levels (in this study, severe injury and no injury) is clear while the effect of that parameter on the probability of intermediate injury levels (moderate and possible injuries) is ambiguous (Washington et al., 2011).

Table 6 presents the estimation results for both models. The marginal effects that were used to assess the effect of the estimated parameters in the urban and rural models are shown in Tables 7 and 8, respectively. Clearly, Table 6 shows that in each model, 12 factors were found to be statistically significant in impacting the injury severity incurred by drivers. Also, seven factors were found to be significant in both models. To ease the interpretations of the study findings, the discussion of results will be presented in three subsequent sections. The first section will discuss the mutual factors in both models, while the second and third sections will highlight the exclusive factors that were found to affect injury severity in the urban and rural models, respectively.

6.1. Factors contributing to ROR crashes in both models

As mentioned previously, seven variables were found to be statistically significant in both models, meaning that these variables have a substantial impact on injury severity sustained by truck drivers involved in ROR crashes, regardless of the area type. These variables are driver fatigue, dry roadway surface condition, dark with street lights, colliding with a ditch, seatbelt not used, the presence of horizontal curves, and neither exceeding the posted speed nor driving too fast for the conditions.

With regard to the influence of fatigue on injury severity sustained by large truck drivers, this variable was found to be statistically significant in both models. Further, this variable has different signs across the two classes in the sense it is neg-

[1] Different number of classes have been examined, however, only two classes turned out to be statistically significant in terms of estimated parameters and an overall statistical fit. This finding is in line with past research (Behnood et al., 2014; Behnood and Mannering, 2016; Fountas et al., 2018; Shaheed and Gkritza, 2014).

Please cite this article as: N. S. S. Al-Bdairi and S. Hernandez, 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, https://doi.org/10.1016/j.ijtst.2020.01.004

Table 4
Chi-square statistics for parameters separation test (degrees of freedom in parentheses).

a	*b*	
	Urban	Rural
Urban	0.0	181 (7)
Rural	695 (7)	0.0

Table 5
Estimated probabilities for each latent class in urban and rural models.

Components	Urban		Rural	
	Latent Class 1	Latent Class 2	Latent Class 1	Latent Class 2
Class characteristics				
Crash population share	0.580	0.420	0.490	0.510
Injury severity outcomes				
Severe injury	0.003	0.108	0.003	0.091
Moderate	0.026	0.225	0.087	0.310
Possible injury	0.048	0.283	0.079	0.268
No injury	0.922	0.383	0.830	0.331

Table 6
Estimation results of latent class ordered probit for urban and rural models.

Variable	Urban				Rural			
	Latent Class 1		Latent Class 2		Latent Class 1		Latent Class 2	
	Parameter estimate	t-stat	Parameter estimate	t-stat	Parameter estimate	t-stat	Parameter estimate	t-stat
Constant	5.347	5.61[a]	3.112	6.51[a]	5.515	6.29[a]	2.050	15.19[a]
DITCH	0.355	0.57	−0.947	−1.94[c]	−0.381	−1.67[c]	−0.571	−4.82[a]
GRADE	−1.597	−3.49[a]	−0.222	−0.51	–	–	–	–
POP25K	−1.282	−2.38[b]	8.564	0.00	–	–	–	–
DRY	−1.270	−2.54[b]	−0.738	−2.67[a]	−0.275	−1.36	−0.488	−4.41[a]
LOSTCTRL	−1.413	−2.87[a]	−0.361	−1.15	–	–	–	–
DLIT	−1.546	−2.93[a]	−0.087	−0.21	−1.124	−2.31[b]	1.362	1.31
NOSPED	2.417	3.76[a]	−0.133	−0.33	0.344	1.73[c]	0.065	0.65
NOBELT	−1.785	−2.33[b]	−2.015	−2.93[a]	−1.555	−4.92[a]	−1.157	−6.24[a]
FALL	−0.870	−2.35[b]	0.266	0.93	–	–	–	–
FATIGUE	−4.069	−4.13[a]	1.802	0.44	−1.420	−3.37[a]	0.054	0.20
CURVE	1.125	1.70[c]	−1.165	−2.57[b]	−0.206	−1.08	−0.336	−3.37[a]
RSDMEDN	1.250	2.07[b]	−0.586	−1.89[c]	–	–	–	–
MPH55	–	–	–	–	−0.799	−3.12[a]	0.025	0.24
OVRTURN	–	–	–	–	−2.049	−4.51[a]	0.697	2.74[a]
NODEPLOY	–	–	–	–	0.535	1.97[b]	−0.066	−0.58
YOUNG	–	–	–	–	0.292	1.61	0.349	3.52[a]
FEMALE	–	–	–	–	−0.585	−1.48	−0.462	−1.99[b]
Threshold 1	1.709	3.24[a]	0.821	4.98[a]	2.551	4.91[a]	1.151	14.14[a]
Threshold 2	2.986	4.31[a]	1.431	6.72[a]	3.390	5.71[a]	1.712	14.90[a]
Class Probability (t-stat)		0.58 (6.73[a])	0.42 (4.96[a])		0.49 (6.28[a])		0.51 (6.59[a])	
Number of Observations		801			2253			
Log likelihood at convergence		−391.102			−1989.500			
Log likelihood at zero		−471.823			−2176.024			
McFadden Rho-squared		0.171			0.086			

Note a, b, and c are significance level at 99%, 95%, and 90%, respectively.

ative and significant in class 1, but positive and insignificant in class 2 for both models, meaning that this variable has a heterogeneous impact on injury severity. Tables 7 and 8 illustrate that ROR crashes involving fatigued drivers are less likely to cause no injuries, with −0.2232 and −0.1298 for urban and rural models, respectively. This finding underscores the impact of fatigue of large truck drivers regardless of the area type because, in both models, the moderate injury severity will increase by slightly the same probability. In general, large truck drivers are characterized by some unique factors compared to passenger vehicle drivers, such as irregular schedules, long working hours, night driving, and economic pressures. All these factors could increase the possibility of truck driver being fatigued. Previous studies also found that crashes involving fatigued drivers were associated with a higher level of severity. For example, Chen and Chen (2011) found that fatigue was associated

Table 7
Estimated marginal effects for latent class ordered probit of urban model.

Variable	Marginal effects			
	Severe injury	Moderate injury	Possible injury	No injury
DITCH	0.0116	0.0351	0.0427	−0.0894
GRADE	0.0308	0.0769	0.0810	−0.1887
POP25K	−0.0055	−0.0212	−0.0319	0.0586
DRY	0.0107	0.0395	0.0578	−0.1080
LOSTCTR	0.0111	0.0347	0.0435	−0.0893
DLIT	0.0117	0.0355	0.0436	−0.0908
NOSPED	−0.0165	−0.0500	−0.0615	0.1280
NOBELT	0.0894	0.1560	0.1244	−0.3698
FALL	0.0021	0.0074	0.0101	−0.0196
FATIGUE	0.0402	0.0923	0.0907	−0.2232
CURVE	0.0079	0.0254	0.0324	−0.0657
RSDMEDN	−0.0008	−0.0028	−0.0039	0.0074

Table 8
Estimated marginal effects for latent class ordered probit of rural model.

Variable	Marginal effects			
	Severe injury	Moderate injury	Possible injury	No injury
DITCH	0.0271	0.0924	0.0383	−0.1578
DRY	0.0166	0.0677	0.0341	−0.1184
DLIT	−0.0082	−0.0380	−0.0216	0.0679
NOSPED	−0.0058	−0.0236	−0.0118	0.0412
NOBELT	0.1129	0.2181	0.0414	−0.3724
CURVE	0.0133	0.0513	0.0242	−0.0888
YOUNG	−0.0104	−0.0429	−0.0216	0.0749
FEMALE	0.0253	0.0811	0.0309	−0.1374
FATIGUE	0.0235	0.0765	0.0298	−0.1298
MPH55	0.0063	0.0261	0.0134	−0.0457
OVRTURN	0.0219	0.0759	0.0319	−0.1296
NODEPLOY	−0.0013	−0.0054	−0.0027	0.0094

with increase in the probability of injury in multiple truck crashes compared to single truck crashes. Islam et al. (2014) came up with the same conclusion in their study, in which they found that the impact of driver fatigue on injury severity resulting from crashes occurring in rural areas was higher, while this impact was insignificant for crashes occurring in the counterpart urban areas. In relation to past studies that emphasized on ROR crashes involving large trucks, the findings of this study support the findings of Al-Bdairi et al. (2018) and Al-Bdairi and Hernandez (2017), which indicate that non-incapacitating and possible injuries were more likely to be sustained in ROR crashes involving fatigued drivers. However, the findings of this study contradict the findings of Peng and Boyle (2012), which found that fatigue leads to fatal ROR crashes.

Roadway surface conditions, specifically the variable representing dry surfaces, was found to affect injury severity in both models, with negative signs in both classes, as shown in Table 6. This finding suggests that this variable has homogeneous effects across classes. Tables 7 and 8 demonstrate that ROR crashes involving large trucks occurring on dry roadway surfaces, whether in rural or urban areas, are less likely to result in no injuries with probabilities of 0.1080 and 0.1184 for urban and rural areas, respectively. A possible explanation could be attributed to driver behavior in the sense that drivers may underestimate the risk of injury severity resulting from ROR crashes on dry roadway surfaces. As such, drivers tend to increase their driving speed on dry roadway surfaces. A similar finding was reported in previous studies (Al-Bdairi et al., 2018; Al-Bdairi and Hernandez, 2017; Anderson and Hernandez, 2017; Islam and Hernandez, 2013b; Peng and Boyle, 2012).

In terms of the lighting conditions, the variable of dark with lighted streets was found to have different effects on injury severity based on the area type. Table 7 confirms that ROR crashes involving large trucks occurring on urban roadways in the dark but with street light, would decrease the probability of no injuries by 0.0908. Conversely, ROR crashes occurring in the dark but with street light, on the rural roadways would have a 0.0679 higher probability of resulting in no injuries, as shown in Table 8. This finding could be used to prompt transportation agencies to deploy street lighting along hotspot locations on rural roadways such as horizontal curves.

Not surprisingly, not using seatbelts can dramatically increase the odds of large truck drivers being involved in fatal crashes. Therefore, transportation agencies should stringently enforce existing seatbelt laws and conduct public education campaigns to save drivers' and other road users' lives. In the current study, the variable of not using seatbelts was found to have negative signs and was statistically significant in the two classes for both models. Intuitively, this means that this variable has homogeneous influences on the injury severity of ROR crashes occurring in urban and rural areas in the sense that drivers who do not wear seatbelts would be at a high risk of sustaining severe injuries. In the urban model, not wearing seatbelts decreased the probability of no injuries for large truck drivers involved in ROR crashes by 0.3698, while increasing the likelihood of moderate injuries by 0.1560, as shown in Table 7. Table 8 reveals that large truck drivers who did not use seatbelts had a 0.3724 lower probability of incurring no injuries when they were involved in ROR crashes in rural areas, whereas the moderate injury outcome would increase by 0.2181. Obviously, a careful examination of the impacts of not wearing seatbelts on the safety of large truck drivers in urban and rural areas implies that the influence of this variable on ROR crashes involving large trucks in rural areas is higher than in urban areas. This variation could be attributed to the high speed that characterizes rural roadways. This finding agrees with previous studies that found unbelted drivers are at a high risk of incurring severe and fatal injuries (Chen and Chen, 2011; Russo et al., 2014; Schneider et al., 2009). Specifically, Chen and Chen (2011) concluded that unbelted large truck drivers had a 47.1% and 37.1% higher probability of being in fatal crashes involving single and multiple trucks, respectively. Hence, the trucking industry could benefit from this finding by imposing strict enforcement of safety seatbelt usage on their drivers.

Roadway alignment and horizontal curves play a vital role in the occurrence of ROR crashes involving large trucks because the operational characteristics of trucks, such as weight and length, can create centrifugal forces that push trucks away from the curve, which in turn increases the odds of trucks being overturned. In this study, it was observed that the variable of the horizontal curve was statistically significant in both models. Moreover, it was found that ROR crashes involving large trucks occurring on horizontal curves in urban areas have heterogeneous impacts on injury severity because this variable has a positive sign in class 1 and a negative sign in class 2. Further explanation regarding the effect of this variable in the urban model could be achieved through the marginal effects shown in Table 7. Marginal effects disclose that large truck drivers involved in ROR crashes on horizontal curves in urban areas have a 0.0657 lower probability of being injured, while the likelihood of sustaining possible injuries increases by 0.0324. The variable of ROR crashes occurring on horizontal curves in rural areas has homogeneous effects across the two classes because it has a negative sign in both classes. Table 8 reveals that large truck drivers involved in ROR crashes on horizontal curves in rural areas are 0.0888 less likely to incur no injuries, while increasing their odds by 0.0513 of sustaining moderate injuries. Evidently, ROR crashes involving large trucks on horizontal curves in rural areas tend to be more severe than those taking place in the counterpart areas. A possible explanation could be attributed to the higher posted speed on rural roadways as opposed to urban roadways. Moreover, other behavioral factors could aggravate ROR crashes in rural areas such as unbelted drivers and fatigue. This finding can help guide safety practitioners to identify the hotspot locations, particularly on rural roadways, that experience a high number of ROR crashes related to horizontal curves. Accordingly, appropriate safety countermeasures could be taken, such as better curve delineation and installing curve warning signs to alert drivers to upcoming curves. This finding is consistent with previous studies that found that large truck crashes occurring on horizontal curves were associated with non-incapacitating injuries (Al-Bdairi et al., 2018; Al-Bdairi and Hernandez, 2017; Lemp et al., 2011). However, other studies concluded that such crashes increased the probability of incapacitating and fatal injuries (Islam and Hernandez, 2013a; Naik et al., 2016).

Lastly, the factor of large truck drivers who abide by the speed limit was found to drastically increase the probability of sustaining no injuries when they are involved in ROR crashes in both urban and rural areas. The effect of this variable is more pronounced in the urban model, in which drivers abiding by the speed limit would be 0.1280 more likely to incur no injuries (see Table 7). In the rural model, this variable has a similar effect but to a lesser extent since a no injury outcome would be increased by 0.0412. Al-Bdairi and Hernandez (2017) have reported a similar finding.

6.2. Factors contributing to ROR crashes on urban roadways

Five estimated parameters were found to be statistically significant in affecting the injury severity of ROR crashes involving large trucks in the urban model. However, only three of these parameters will be discussed due to their higher marginal effects, namely, crashes occurring on vertical curves, urban areas with a population density of between 10,001 and 25,000 and losing control of a vehicle. Regarding ROR crashes on vertical curves, this variable was found to be significant in class 1 and insignificant in class 2, with a negative sign in the two classes, meaning that this variable has a heterogeneous influence. This variable has also been found to be heterogeneous in a study conducted by Al-Bdairi et al. (2018), in which ROR crashes involving large trucks occurring in dark conditions on vertical curves were found to be random in their injury outcomes. In this sense, the minor injury severity sustained by large truck drivers involved in such crashes would increase by approximately 42.3%, while being involved in crashes resulting in minor injuries would be 57.7% less likely. Also, in this study, the variable of ROR crashes occurring on vertical curves has a 0.1887 lower likelihood of resulting in no injuries, while increasing the probability of possible injuries by 0.0810. A possible explanation could be the limited visibility and sight distance on vertical curves compared to straight roadways, which in turn increase the odds of ROR crashes involving large trucks of being less likely to result in no injuries. This finding is consistent with previous studies that found that large truck crashes on vertical curves would increase the likelihood of minor injuries (Al-Bdairi et al., 2018; Anderson and Hernandez, 2017).

Regarding the effect of population density on ROR crashes involving large trucks, the variable of urban areas with a population density of between 10,001 and 25,000 was found to be significant, with a negative sign in class 1, but it is insignificant with a positive sign in class 2, indicating that this variable has heterogeneous impacts. Table 7 shows that no injury outcomes would have a 0.0586 higher probability of being sustained by large truck drivers involved in ROR crashes occurring in urban areas with a population density of between 10,001 and 25,000. This finding indicates that large truck drivers tend to drive cautiously in urban areas with such a population density to avoid being involved in a crash. Next, the variable of losing control of a vehicle was found to be significant and has negative signs in both classes, meaning that this variable has fixed effects. Further, ROR crashes occurring due to losing control of vehicles were 0.0893 less likely to result in no injuries, and, in fact, this variable would increase the probability of possible injuries by 0.0435, as shown in Table 7. Al-Bdairi and Hernandez (2017) also found that ROR crashes involving large trucks that occur due to losing control of vehicles would be 95.5% less likely to cause no injuries. However, Al-Bdairi and Hernandez (2017) found that the variable of losing control of a vehicle was random, whereas this is not the case in this study.

6.3. Factors contributing to ROR crashes on rural roadways

In the rural model, the estimation results shown in Table 6 illustrate that five estimated parameters were exclusively significant in the rural model. However, only the parameters with higher impacts (higher marginal effects) will be presented here. Those parameters are young drivers between 20 and 45 years, female drivers, and overturning crashes. In terms of driver characteristics, two factors play a key role in ROR crashes involving large trucks in rural areas: driver age and female drivers. The indicator of young drivers has positive signs in the two classes and significantly impacts injury severity. Table 8 demonstrates that young drivers have a 0.0749 higher probability of sustaining no injuries when they are involved in ROR crashes in rural areas. This finding could be attributed to the physiological capabilities that characterize this age group, which make them more resilient in ROR crashes involving large trucks so that they are less likely to sustain severe injuries. Similarly, Anderson and Hernandez (2017) and Pahukula et al. (2015) found that large truck drivers between 35 and 45 years were more likely to sustain no injuries.

In addition to driver age, driver gender (female) was also found to be more vulnerable to severe injuries. Table 8 shows that female drivers had a 0.1374 lower probability of sustaining no injuries, while their likelihood of sustaining moderate injuries increased by 0.0811. The difference between males and females in incurring injuries may explain why female drivers are at a high risk of being involved in severe crashes as opposed to male drivers. This finding has been confirmed by (Chen and Chen, 2011; Islam et al., 2014). With respect to overturning crashes, this event in rural areas is 0.1296 less likely to result in injuries, while it has a 0.0759 higher likelihood of causing moderate injuries, as shown in Table 8. This variable was found to be statistically significant in the two classes, with a negative sign in class 1 and a positive one in class 2, indicating heterogeneous influences. This finding is consistent with Al-Bdairi et al. (2018) and Chen and Chen (2011) that found homogeneously that overturning crashes were associated with possible and non-incapacitating injuries in large truck drivers.

A posted speed limit is widely documented as a risk factor associated with ROR crashes involving large trucks. In the current study, the speed limit of 55 mph on rural roadways was found to affect injury severity of ROR crashes involving large trucks and associated with 0.0457 decrease in the probability of sustaining no injury. This is attributable to the difficulty of controlling the vehicle at higher speeds. Despite the finding of this study, in 2017, ODOT recommends raising truck speed from 55 mph to 60 mph in the interstate highway system. This policy has been recommended to enhance safety because raising posted speeds can substantially reduce differential speed limits between passenger vehicles and trucks on rural freeways, which in turn may minimize the risk of traffic crashes and resultant injuries/fatalities. This might be related to behavior of large truck drivers in the sense that they tend to be more cautious while driving to avoid being cited, which may jeopardize their driving privileges.

7. Summary and conclusions

The present study analyzes the injury severity sustained by large truck drivers involved in ROR crashes at a disaggregate level for crashes occurring in urban and rural areas in the state of Oregon. Eight years of crash data pertaining to ROR crashes involving large trucks between 2007 and 2014 were used. In this study, injury severity was grouped into four main categories: no injury, possible injury, moderate injury (non-incapacitating), and severe injury (incapacitating and fatal). Recognizing the ordinal nature of injury severity and the heterogeneity in crash data, latent class ordered probit models were developed to investigate the impact of area type on the injury severity of large truck drivers, while accounting for unobserved heterogeneity in crash data. Log-likelihood ratio tests were conducted to validate using separate models for urban and rural areas rather than a holistic model that combines them. The results of these tests indicate that the injury severity of ROR crashes occurring in urban and rural areas is quite different and therefore needs to be modeled separately.

The estimation results reveal that the developed latent class ordered probit models (for urban and rural areas) are substantially distinct in terms of the contributing factors. However, seven parameters were found to be significant in both the urban and rural models, but with remarkable differences in terms of their impacts on the injury severity incurred by large truck drivers involved in ROR crashes. For example, ROR crashes involving large trucks occurring on urban roadways at dark, but with street light, would decrease the probability of no injuries by 0.0908, whereas such crashes in the counterpart area would have a 0.0679 higher probability of resulting in no injuries. This variation underscores the substantial role of street lighting on rural roadways. As such, a safety countermeasure that could be recommended is the deployment of street lights along rural roadways in an attempt to reduce or avoid severe injuries resulting from ROR crashes involving large trucks. Further, some variables were found to be exclusively significant in one model (urban or rural), but not both.

In each model, five estimated parameters were found to be uniquely significant. In the urban model, for example, ROR crashes occurring on vertical curves were found to decrease the no injury outcome by 0.1887 while increasing the probability of possible injuries by 0.0810. The limited visibility and sight distance on vertical curves could be underlying factors in this finding. Such a finding can motivate transportation agencies in Oregon to make further efforts to improve the vertical curves in urban areas in terms of visibility, sight distance, traffic control management, and posted speed limits. In the rural model, driver gender was found to play a vital role in injury severity outcomes. For instance, female drivers have a 0.1374 lower probability of sustaining no injuries, while their likelihood of sustaining moderate injuries increases by 0.0811. This could be related to the behavioral and physiological differences between male and female drivers such as driving experience, driving characteristics (i.e., aggression and risk perception), and the ability of the body to withstand impact. These differences between males and females in incurring injuries may explain why female drivers are at a high risk of being involved in severe crashes as opposed to male drivers.

To the best of the authors' knowledge, utilizing separate latent class ordered probit models to analyze the injury severity of large truck drivers involved in ROR crashes in urban and rural areas is the first attempt to extend the literature of analyzing the injury severity of large truck crashes. It also fills the gap in the literature in terms of examining the injury severity of ROR crashes involving large trucks by area type (urban and rural). The trucking industry, transportation agencies, and safety practitioners could benefit from the findings of the current study to prevent or alleviate the injury severity of ROR crashes involving large trucks by developing appropriate and cost-effective countermeasures. To this end, some countermeasures could be suggested including, but are not limited to: removing or relocating roadside objects, flattening slopes, flattening curves, improving ditch design, and installing edge line rumble strips.

Despite the fact that the findings of this study can provide better understanding in terms of the factors contributing to the injury severity of large truck drivers involved in ROR crashes in each area type, some limitations should be pointed out. Some important factors that may contribute to ROR crashes are missing in the Oregon crash data, such as pavement conditions, shoulder type, shoulder width, and roadside characteristics. Therefore, future studies should consider these limitations and aim to collect even more comprehensive crash data. Further, alternative advanced methods that address heterogeneity in the crash data, such as latent class models with random parameters within classes, could be used in future research. Also, a temporal stability of the estimated parameters could be investigated in the future research.

Conflict of interest

The author does not have any conflict of interest with other entities or researchers.

Acknowledgement

We would like to acknowledge the Oregon Department of Transportation, specifically, the Transportation Data Department, for providing the crash dataset and for helping in our understanding of the data.

Funding sources

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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