Contributing Factors to Run-Off-Road Crashes Involving Large Trucks under Lighted and Dark Conditions

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Abstract: Previous studies have examined the relationships between run-off-road (ROR) crashes and the contributing factors; however, the impact of lighting conditions has been insufficiently addressed. As a result, the objective of this study was to research the effect of lighting conditions on the injury severity of ROR crashes that involve large trucks. Based on the crash data pertaining to large trucks in the state of Oregon from 2007 to 2013, two separate mixed logit models were developed to capture the contributing factors that affect injury severity in each lighting condition. The levels of injury severity sustained by truck drivers were categorized into three main categories: severe injury (fatal and incapacitating), minor injury (nonincapacitating and possible injury), and no injury. The mixed logit model was used to account for unobserved factors (i.e., unobserved heterogeneity). Estimation results indicated that there are significant differences between dark and lighted conditions, that the level of injury severity outcomes was highly influenced by several complex interactions between factors, and that the effects of some factors could vary across observations. The contributing factors include driver, traffic flow, roadway geometric features, land use, and time characteristics. **DOI:** 10.1061/JTEPBS.0000104. *© 2017 American Society of Civil Engineers.*

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Introduction

In recent years, critical issues have been addressed through transportation research related to traffic safety, particularly to road users. In general, previous studies have examined risk factors that might be correlated with a particular type of traffic crash under various conditions; still, the effect of roadway lighting on injury severity has been insufficiently addressed. For instance, even though there is less traffic volume during the darkness hours, the injury severity and traffic fatalities at nighttime are higher, particularly when there is no lighting on the roadways. A primary reason for the difference in injury severity outcomes between dark and lighted roadways is due to inadequate visibility. Inadequate visibility jeopardizes driver safety and increases the probability of traffic crashes, as a driver's inability to detect a hazard in dark conditions decreases the driver's likelihood to avoid it. Driving tasks are significantly affected by visibility because most of the signs, guides, and cues that direct drivers must be visually recognized.

In 2014, around 846 of 3,424 (24.7%) fatal crashes that involved large trucks, trucks with a gross vehicle weight rating (GVWR) greater than 10,000 pounds, took place on dark roadways without street lighting in the United States (Federal Motor Carrier Safety Administration 2016). Likewise, Hasson and Lutkevich (2002) and Lutkevich et al. (2012) reported that traffic fatalities at nighttime were three times higher than those that occurred during the day. Moreover, Hasson and Lutkevich (2002) demonstrated that more than 14,000 human lives could be saved if the number of traffic crashes were the same during the day and at night. As a result, assuming \$3.0 million is the value of a human life, up to \$42 billion could be saved annually with a reduction in nighttime crashes.

The statistics provided show a need to better understand the effect of specific factors on crash severity, particularly for run-off-road (ROR) crashes. Moreover, previous studies have focused on the impact of light conditions on crash injury severity as an indicator variable. Further, there is indeed an urgent need to explore the effect of unreported or inaccurate information in crash data to develop a robust statistical inference that supports the study findings. Therefore, to overcome these drawbacks in crash data, the mixed logit model is proposed. By using the mixed logit model, the influence of some attributes that are not captured in crash data (unobserved heterogeneity), including roadway characteristics, vehicle attributes, and driver behaviors, can be accounted for by allowing the estimated parameters to vary across the sample observations.

Lastly, this study can provide state agencies, the trucking industry, and transportation safety researchers with valuable and comprehensive information pertaining to the effect of lighting conditions on the propensity of involvement in ROR crashes that involve large trucks. As a result, the study findings can be useful in proposing countermeasures and policies that might save lives and reduce societal costs. Generally speaking, examining the contributing factors of injury severity for large truck drivers in ROR crashes has been overlooked in previous studies, particularly the impact of roadway lighting conditions. With this in mind, the aim of the current study is to fill the gap in literature regarding the impact of lighting conditions on injury severity of ROR crashes involving large trucks. Moreover, the literature is extended by conducting a model separation test to test if lighting conditions should be analyzed separately.

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Literature Review

Several studies have been conducted over the years to assess the role of roadway lighting. However, analyzing the impact of lighting conditions on injury severity of ROR crashes involving large trucks is less documented. Rodegerdts et al. (2004) stated that nighttime traffic crashes could be decreased by 50% along with approximately a 43% reduction in fatalities if roadway lighting is incorporated. Elvik (1995) conducted a meta-analysis of 37 studies regarding the impact of lights on traffic crashes. Elvik found that providing unlighted roadways with lighting was accompanied by approximately a 65% decline in fatal crashes, whereas the crashes that led to a nonfatal injury were found to be decreased by 32%. Likewise, the no injury outcome was reduced by 15%. Elvik et al. (2009) explained the effect of roadway lighting on traffic crashes based on reviewing previous studies conducted in 13 different countries, including the United States, Great Britain, Switzerland, Sweden, Australia, Denmark, Japan, Finland, Israel, Germany, Norway, Netherlands, and Singapore. They found that providing these roadways with lighting was associated with a 60% decline in fatal and severe crashes, whereas the no injury crashes were decreased by 15%. Kim et al. (2013) used a mixed logit method to analyze injury severity sustained by a driver in single vehicle crashes in California, with a specific focus on age and gender. The results indicated that likelihood of fatal injury crashes increased by 92% without proper lighting.

Wu et al. (2014) found that lighting conditions in New Mexico for single-vehicle and multi-vehicle crashes are highly significant contributing factors in injury severity outcomes. They reported that a higher level of injury severity (severe and fatal) was sustained by drivers because of crashes in dark conditions. They concluded that darkness was associated with roughly a 112.9% increase in driver fatality in multiple-vehicle crashes on rural two-lane highways. Koupaenejad (2010) used multinomial logit and ordered probit models to highlight the contributing factors in a crash that involved passenger cars and large trucks. He concluded that severe injuries were more likely to be sustained by passenger vehicle occupants when crashes occurred on roadways without lighting.

Khorashadi et al. (2005) used a dataset pertaining to crashes that involved large trucks that occurred between 1997 and 2000 to identify the potential risk factors that affect traffic crash severities. This dataset was obtained from the California Department of Transportation (Caltrans). In their study, a multinomial logit model was developed to quantify the impact of specific factors on crash severity outcomes. They found that the probability of involvement in fatal or severe injury crashes was increased under dark conditions.

Overall, the majority of previous works have examined the impact of lighting conditions on crash injury severity using the lighting conditions as an explanatory variable. In other words, even though previous studies have focused on addressing the effect of lighting conditions on crash injury severity, the conclusive findings of these studies cannot be used as guidance for state and trucking agencies because they embodied the impact of lighting by indicator variables (e.g., effect of light conditions on specific injury outcomes). A complex interaction between the risk factors related to light conditions can create a concern regarding the validity of study findings that were obtained by representing the light conditions as indicator variables. For ROR crashes that involve large trucks, there is a need for comprehensive research to reveal the characteristics of ROR crashes under different lighting conditions and the resulting injury outcomes to propose appropriate countermeasures. In the current study, two separate mixed logit models were developed for lighting conditions (dark versus lighted). Lighted conditions include daylight and dark with street lighting, whereas dark conditions include dark with no street lighting. Adopting this approach is particularly useful in capturing the variations in driver behaviors in dark and lighted conditions so that the estimated parameters are statistically accurate and cannot lead to an erroneous inference.

Methodological Approach

Because the crash data used in this study had a discrete unordered nature, the emphasis focused on econometric models that do not consider the ordered data (Savolainen et al. 2011). The models that deal with unordered discrete nature include the multinomial logit model, the nested logit model, and the mixed logit model (Mannering and Bhat 2014). Although the multinomial logit model (MNL) is commonly used, its limitations restrict its suitability in modeling the crash severity. One of the major MNL limitations is the assumption regarding the disturbance terms, which are required to be independently and identically distributed (IID). Therefore, a violation of this assumption can lead to what is referred to as the independence from irrelevant alternatives property (IIA) (Washington et al. 2011). On the other hand, the nested logit model can overcome the IIA property in the MNL by grouping alternatives that are believed to have a correlation within a nest. Thus, the aggregation might lead to uncertainty, which might cause erroneous inferences. Hence, the mixed logit model was used for several reasons. First, it was used to overcome the limitations of the MNL and nested logit models. Second, it accounted for the unobserved heterogeneity by using random parameters that allowed for an explanatory variable to vary across the observations (Behnood et al. 2016). The unobserved heterogeneity stems from different sources, such as variation within variables or crash data that does not provide detailed information. Accordingly, ignoring the unobserved heterogeneity can lead to biased and inefficient estimable parameters (Mannering et al. 2016).

The mixed logit model was also used to examine the effect of potential risk factors in ROR crashes that involve large trucks. Identifying the injury severity outcome formula, which is used to compute the probability of each severity level, can help in developing a formula that pertains to the mixed logit model. Following Washington et al. (2011), the discrete injury severity outcome can be determined by the following function, as shown in Eq. (1):

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

where T_{in} = linear function of injury severity outcome i for an observation n; $\boldsymbol{\beta_i}$ = vector of estimable parameters for injury severity outcome i; $\boldsymbol{X_{in}}$ represents a vector of explanatory variables (e.g., variables related to the driver, vehicle, road, and environmental conditions) for determining the discrete injury severity outcome i (severe, minor, and no injury) for an observation n; and ε_{in} = error or disturbance term. In general, $\boldsymbol{X_{in}}$ differs from other terms in Eq. (1), specifically $\boldsymbol{\beta_i}$ and ε_{in}, because it can be easily observed by the analyst, whereas other terms are not. Moreover, to account for unobserved heterogeneity, the vector of estimable parameters $\boldsymbol{\beta_i}$ in Eq. (1) is given by the following linear formula, as shown in Eq. (2) (Kim et al. 2013):

$$\beta_i = m_i + M s_n + \Gamma_i \eta_{ni} \tag{2}$$

where m_i = fixed parameters, which are constant across all observations; s_n = matrix of factors that might cause an unobserved heterogeneity; whereas M = matrix of the heterogeneous variables. The third term in Eq. (2) represents the randomness in the equation. Γ_i is a triangular matrix, which is used to estimate the correlation of the estimable parameters, whereas η_{ni} is the vector for uncorrelated random variables (Kim et al. 2013). Generally, different distributional assumptions can be considered in the estimation of the random parameters. The common distributions are normal, triangular, uniform, and lognormal. To identify the random parameters in the provided data, all aforementioned distributions should be tested. Kim et al. (2013) and Mannering et al. (2016) demonstrated the criterion that could be followed to discern between fixed-parameters and random-parameters. They asserted that a standard deviation of an explanatory variable is the key to decide whether that explanatory variable is random or fixed across the observations. If the standard deviation corresponding to the explanatory variable is not statistically significant (not different from zero), that variable will be fixed and will not vary across the observations, whereas when the standard deviation is statistically significant (different from zero), the variable is random and varies across the observations.

To determine the probability of injury outcome i for observation n, Eq. (3) is used (Milton et al. 2008)

$$P_{ni} = \int \frac{\mathrm{EXP}[\boldsymbol{\beta}_i \boldsymbol{X}_{in}]}{\sum_I \mathrm{EXP}[\boldsymbol{\beta}_i \boldsymbol{X}_{in}]} f(\boldsymbol{\beta}|\boldsymbol{\varphi}) d\boldsymbol{\beta} \tag{3}$$

where $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$ = density function of $\boldsymbol{\beta}$, whereas all other terms are defined in Eqs. (1) and (2). The maximum simulated likelihood estimation (MSLE) method is typically used to estimate the mixed logit model by using Halton draws.

To identify the effect that a unit change in X_{ijk} has on the probability for crash i to result in outcome j (denoted by P_{ij}), marginal effects were calculated. The marginal effect formula used is described in Eq. (4) (Washington et al. 2011)

$$M_{X_{ijk}}^{P_{ij}} = P_{ij}(\text{given } X_{ijk} = 1) - P_{ij}(\text{given } X_{ijk} = 0) \tag{4}$$

For indicator variables, the marginal effects are computed as the difference in the estimated probabilities when the indicator variables change from zero to one.

In the current study, all distributional forms were examined; however, only the normal distribution was found to be statistically significant. Moreover, 200 Halton draws were used to be consistent with other researchers who demonstrated that this number of draws can provide an accurate estimate regarding random parameters (Anastasopoulos and Mannering 2009; Behnood and Mannering 2015; Bhat 2003).

Empirical Setting

In this study, the dataset pertaining to ROR crashes that involved at least one truck in the state of Oregon was used. The datasets included police reports for the 7-year period of crashes that occurred between 2007 and 2013 and were maintained by the Oregon Department of Transportation (ODOT). Crash data was filtered by vehicle type and type of crash (i.e., ROR) to include only drivers of large trucks involved in ROR crashes. The result was a dataset with 2,486 ROR crashes that involved at least one large truck. Each ROR observation represents the maximum level of injury severity sustained by a driver. The dataset includes a variable for injury severity, which is categorized into five injury levels which are: Fatal injury outcome if an involved individual dies within 30 days because of a crash (K), an incapacitating injury outcome (A), a non-incapacitating injury (B), possible injuries (C), and (O) for noninjury or property-damage only (PDO); also referred to as the KABCO injury severity scale. In the current study, the total observations that corresponded to fatal and incapacitating injuries were low. Accordingly, the injury outcomes were categorized into three main groups: severe injury (KA), minor injury (BC), and no injury (O). Several researchers have used a similar classification for injury outcomes, including Al-Bdairi and Hernandez (2017), Chang and Chien (2013), Eluru et al. (2012), Pahukula et al. (2015), and Wu et al. (2014). After applying the new classification, the dataset included severe injuries with 65 observations (2.6%), minor injuries with 612 observations (24.6%), and no injury with 1,809 observations (72.8%).

The literature regarding roadway infrastructures including roadway lighting is sparse. Previous studies have focused on investigating the impact of various geometric and infrastructural factors such as roadway and shoulders widths, roadway curvatures, and roadway pavement conditions on roadway safety. However, the influence of different lighting conditions is overlooked. Therefore, examining the effect of lighting conditions on the probability of involvement in ROR crashes, particularly for large trucks, and the resulting injury severity was the primary interest of this study. That being said, two different lighting conditions were considered: lighted conditions (daylight and dark with street lighting) and dark conditions (dark with no street lighting). Crashes that occurred in dusk or dawn conditions were excluded. Hence, the dataset that pertained to the ROR crashes was further separated into two datasets based on whether a crash occurred in lighted or dark conditions. The dataset revealed that 634 out of 2,486 crashes occurred in dark conditions, which accounts for approximately 25.5% of the total crashes. In contrast, 1,852 out of 2,486 crashes (74.5%) occurred in lighted conditions. Tables 1 and 2 illustrate the frequency and percentages for the selected factors that were found to be associated with ROR crashes in dark and lighted conditions for each injury level.

Model Separation

To investigate the effect of attributes of ROR crashes that involve large trucks under different lighting conditions, separate mixed logit models were developed to capture the effect of these attributes on each lighting condition. Two tests were performed to test the null hypothesis, which assumed there was no statistical difference between the separate models and a holistic model that combined them using indicator variables for lighted and dark conditions. In other words, the null hypothesis assumed that developing a statistical model for each lighting condition was not a suitable approach as long as the holistic model could accurately estimate the effect of the proposed attributes. The first test performed to determine whether to accept or reject the null hypothesis was a log-likelihood ratio test. The log-likelihood ratio test proposed by Washington et al. (2011) has been used by several researchers (Anarkooli and Hosseinlou 2016; Islam et al. 2014; Pahukula et al. 2015). The log-likelihood ratio test is illustrated in Eq. (5)

$$\chi^2 = -2\left[LL_{Full}(\beta^{Full}) - \sum_{j=1}^{J} LL_j(\beta^j)\right] \tag{5}$$

where $LL_{Full}(\beta^{Full})$ = log-likelihood at convergence for the holistic model, and it is equal to −1,481.10, whereas the $\sum_{j=1}^{J} LL_j(\beta^j)$ represents the log-likelihood for the separate models that were developed. As mentioned, two separate mixed logit models were developed: one for lighted conditions with a log-likelihood at convergence equal to −1,073.05, and the other model was developed for dark conditions with a log-likelihood at convergence equal to −348.28. Applying Eq. (5) for the known log-likelihood values yielded a chi-square (χ^2) statistic of 119.54.

Table 1. Frequency Distribution of the Selected Variables under Dark Conditions

Variable	Severe injury	Minor injury	No injury	Total
Injury severity	12 (1.9%)	157 (24.8%)	465 (73.3%)	634
Driver safety seatbelt (1 for not used, 0 otherwise)	2 (10.5%)	12 (63.2%)	5 (26.3%)	19
Driver was fatigued (1 for yes, 0 otherwise)	0 (0.0%)	30 (53.6%)	26 (46.4%)	56
Crash type (1 for overturn, 0 otherwise)	1 (0.9%)	44 (39.6%)	66 (59.5%)	111
Roadway characteristics (1 for horizontal curve, 0 otherwise)	6 (3.0%)	75 (37.5%)	119 (59.5%)	200
Crash hour (1 if the crash occurred between 4:00 a.m. and 6:00 a.m., 0 otherwise)	2 (1.1%)	55 (30.4%)	124 (68.5%)	181
Roadway characteristics (1 for vertical curve, 0 otherwise)	1 (0.8%)	29 (24.4%)	89 (74.8%)	119
Months (1 if crash occurred between September and December, 0 otherwise)	5 (1.9%)	75 (28.0%)	188 (70.1%)	268
Sobriety indicator (1 for sober at time of collision, 0 otherwise)	10 (1.6%)	153 (24.6%)	459 (73.8%)	622
Exceeding speed limit (1 for no, 0 otherwise)	11 (1.8%)	146 (23.8%)	457 (74.4%)	614
Median type (1 for raised median, 0 otherwise)	1 (0.7%)	23 (15.4%)	125 (83.9%)	149
Roadway surface condition (1 for dry, 0 otherwise)	10 (3.9%)	84 (32.4%)	165 (63.7%)	259
Losing control of vehicle (1 for yes, 0 otherwise)	5 (1.8%)	72 (26.1%)	199 (72.1%)	276
Crash type (1 for colliding with a fix object, 0 otherwise)	11 (2.5%)	104 (23.7%)	324 (73.8%)	439

Table 2. Frequency Distribution of the Selected Variables under Lighted Conditions

Variable	Severe injury	Minor injury	No injury	Total
Injury severity	53 (2.9%)	455 (24.5%)	1344 (72.6%)	1,852
Driver safety seatbelt (1 if not used, 0 otherwise)	15 (15.6%)	44 (45.8%)	37 (38.6%)	96
Age (1 if more than 65 years, 0 otherwise)	7 (7.0%)	16 (16.0%)	77 (77.0%)	100
Driver was fatigued (1 for yes, 0 otherwise)	0 (0.0%)	18 (33.3%)	36 (66.7%)	54
Crash type (1 for overturn, 0 otherwise)	7 (2.4%)	138 (47.8%)	144 (49.8%)	289
Driver sobriety (1 if sober, 0 otherwise)	49 (2.7%)	452 (24.7%)	1330 (72.6%)	1,831
Roadway characteristics (1 for horizontal curve, 0 otherwise)	19 (3.7%)	176 (34.7%)	312 (61.6%)	507
Number of vehicles involved in the crash (1 if two cars, 0 otherwise)	3 (0.8%)	40 (10.4%)	342 (88.8%)	385
Driver residency (1 if non-Oregon resident, 0 otherwise)	17 (2.2%)	174 (22.7%)	576 (75.1%)	767
Vehicle maneuver before the crash (1 if going straight, 0 otherwise)	51 (3.5%)	422 (28.9%)	986 (67.6%)	1,459
Vehicle maneuver before the crash (1 if turning right, 0 otherwise)	1 (0.5%)	10 (4.8%)	198 (94.7%)	209
Driver was ill (1 if yes, 0 otherwise)	6 (12.8%)	27 (57.4%)	14 (29.8%)	47
Area type (1 for rural, 0 otherwise)	44 (3.5%)	376 (29.7%)	846 (66.8%)	1,266
Losing control of vehicle (1 for yes, 0 otherwise)	27 (4.3%)	219 (34.8%)	383 (60.9%)	629

Then, to determine the confidence level of the null hypothesis, the degrees of freedom that correspond to the chi-square statistic were determined. The degree of freedom was 13 (the summation of estimated parameters in both dark and lighted conditions models minus the number of estimated parameters in the full model or aggregate model). A chi-square statistic of 119.54 with 13 degrees of freedom resulted in a 99.99% confidence level. Accordingly, the null hypothesis was rejected, and the parameters of the separate models were statistically different.

The second log-likelihood test was conducted to justify using two separate mixed logit models to examine the effect of lighting conditions on ROR crashes that involved large trucks rather than a holistic model that captures the effect of lighting conditions using indicator variables. This test is referred to as a parameter transferability test. According to Washington et al. (2011), the parameter transferability test is presented in Eq. (6)

$$\chi^2 = -2[LL(\beta_{ba}) - LL(\beta_a)] \tag{6}$$

where $LL(\beta_{ba})$ = log-likelihood at convergence for Model a using the converged parameters from Model b (using b's data) on lighting condition a's data (constraining the parameters to be estimated b's parameters), whereas $LL(\beta_a)$ is the log-likelihood at the convergence of the model using a's data (without constraining the parameters). The degrees of freedom corresponding to chi-square statistic χ^2 is the number of estimated parameters in (β_{ba}). Therefore, the estimated parameters in the lighted condition model were restricted to be the dark condition estimated parameters, and vice versa, then Eq. (6) was applied. This yielded values of the chi-square statistics for both cases of 1,036 and 590, respectively. These values, with corresponding degrees of freedom (herein, 6 for both cases), indicate with over 99.99% confidence that the lighting conditions need to be modeled separately. Hence, developing two separate models for lighting conditions is justified, as the estimated parameters are statistically different by lighting condition.

Estimation Results

Several distributions regarding the estimation of the random parameters were considered, including normal, lognormal, triangular, and uniform; however, only the normal distribution was found to yield statistically significant results. If the standard deviation of an estimated parameter is statistically significant for the proposed distribution, the parameter is considered random and varies across observations. In contrast, statistically insignificant standard deviations (not different from 0) for a particular parameter indicates the parameter is homogenous across observations. Tables 3 and 4 show that the values of log-likelihood at convergence for both lighting conditions are statistically superior to the log-likelihood at zero, therefore indicating a better fit model.

Six parameters were found to affect injury severity of large truck drivers involved in ROR crashes in both models. The indicator variable of not wearing a seatbelt was found to be associated with

Table 3. Mixed Logit Estimation Results for Dark Conditions

Variable	Parameter estimate	t-Statistics	Marginal effects: Severe injury	Marginal effects: Minor injury	Marginal effects: No injury
Severe injury					
Constant	−1.090	−2.53	—	—	—
Driver safety seatbelt (1 for not used, 0 otherwise)	2.371	2.75	0.0078	−0.0022	−0.0056
Minor injury					
Driver was fatigued (1 for yes, 0 otherwise)	2.085	4.44	−0.0009	0.0284	−0.0275
Crash type (1 for overturn, 0 otherwise)	1.242 (3.638)	1.57 (1.87)	−0.0005	0.0301	−0.0296
Roadway characteristics (1 for horizontal curve, 0 otherwise)	1.408	4.26	−0.0032	0.0628	−0.0596
Crash hour (1 if the crash occurred between 4:00 a.m. and 6:00 a.m., 0 otherwise)	0.719	2.25	−0.0010	0.0240	−0.0230
Roadway characteristics (1 for vertical curve, 0 otherwise)	−0.737 (3.791)	−0.57 (1.97)	0.0004	−0.0185	0.0181
Months (1 if crash occurred between September and December, 0 otherwise)	0.255 (1.690)	0.62 (2.25)	−0.0007	0.0359	−0.0352
No injury					
Sobriety indicator (1 for sober at time of collision, 0 otherwise)	2.099	3.69	−0.0282	−0.1977	0.2258
Exceeding speed limit (1 for no, 0 otherwise)	1.958	3.64	−0.0261	−0.1826	0.2087
Median type (1 for raised median, 0 otherwise)	1.040	2.91	−0.0018	−0.0197	0.0215
Roadway surface condition (1 for dry, 0 otherwise)	−0.844	−2.81	0.0069	0.0400	−0.0469
Losing control of vehicle (1 for yes, 0 otherwise)	−0.662	−2.12	0.0043	0.0284	−0.0327
Crash type (1 for colliding with a fix object, 0 otherwise)	−0.832	−1.91	0.0096	0.0616	−0.0712
Model statistics					
Number of observations	634				
Log-likelihood at zero	−696.52				
Log-likelihood at convergence	−348.28				
Adjusted ρ^2	0.50				

Note: Values in parentheses indicate the standard deviation of the random parameters distribution.

Table 4. Mixed Logit Estimation Results for Lighted Conditions

Variable	Parameter estimate	t-Statistics	Marginal effects: Severe injury	Marginal effects: Minor injury	Marginal effects: No injury
Severe injury					
Constant	−4.705	−3.06	—	—	—
Driver safety seatbelt (1 for not used, 0 otherwise)	2.425	4.50	0.0057	−0.0027	−0.0030
Sobriety indicator (1 for sober at time of collision, 0 otherwise)	−3.565	−3.17	−0.0533	0.0300	0.0233
Age (1 if more than 65 years, 0 otherwise)	1.830	2.53	0.0034	−0.0019	−0.0016
Vehicle maneuver before the crash (1 if going straight, 0 otherwise)	2.892	2.51	0.0436	−0.0241	−0.0195
Minor injury					
Constant	−3.110	−6.60	—	—	—
Driver was fatigued (1 for yes, 0 otherwise)	1.625	2.29	−0.0003	0.0038	−0.0035
Crash type (1 for overturn, 0 otherwise)	3.188	5.17	−0.0023	0.0341	−0.0318
Vehicle maneuver before the crash (1 if turning right, 0 otherwise)	−3.346	−3.28	0.0009	−0.0060	0.0051
Roadway characteristics (1 for horizontal curve, 0 otherwise)	0.677 (3.347)	1.42 (3.22)	0.0018	0.0176	−0.0194
Losing control of vehicle (1 for yes, 0 otherwise)	0.541 (4.877)	0.93 (3.31)	0.0032	0.0302	−0.0335
No injury					
Driver was ill (1 yes, 0 otherwise)	−6.714	−3.97	0.0020	0.0084	−0.0104
Area type (1 for rural, 0 otherwise)	0.196 (4.682)	0.33 (3.36)	0.0180	0.0297	−0.0477
Number of vehicles involved in the crash (1 if two vehicles, 0 otherwise)	3.979 (4.501)	2.10 (2.45)	0.0001	−0.0009	0.0008
Driver residency (1 if non-Oregon resident, 0 otherwise)	1.667 (3.586)	2.57 (3.74)	0.0017	−0.0074	0.0057
Model statistic					
Number of observations	1,852				
Log-likelihood at zero	−2,034.63				
Log-likelihood at convergence	−1,073.05				
Adjusted ρ^2	0.47				

Note: Values in parentheses indicate the standard deviation of the random parameters distribution.

severe injury in both light condition models. As shown in Table 3, not wearing a seatbelt increases the probability of being involved in a severe injury by 0.0078 when the crash occurred in a dark condition, whereas the same variable leads to an increase in the probability of a severe injury by 0.0057 when the crash occurred in lighted conditions (Table 4). This finding illustrates the role of seatbelts in saving drivers' lives and mitigating severe injuries, therefore showing a need for efforts that encourage large truck drivers to wear seatbelts. Such efforts can be undertaken by state Departments of Transportation (e.g., larger penalties for unbelted drivers), driver training programs, and the trucking industry as a whole.

The next parameter that significantly affects injury severity of large truck drivers in both models is the indicator variable for a horizontal curve. The indicator variable for horizontal curve was associated with minor injury. In dark conditions, the indicator variable for a horizontal curve was homogeneous across observations, whereas in the lighted condition, the estimated parameter was found to be random and normally distributed with a mean of 0.677 and a standard deviation of 3.347. Based on the mean and standard deviation values, the normal distribution curve implies that 42% of the distribution is less than 0 and 58% of the distribution is greater than 0. In other words, approximately 42% of ROR crashes that occurred on horizontal curves were less likely to result in a minor injury, whereas 58% of these crashes had an increase in the likelihood of a minor injury. This variation in the effect of lighting conditions on injury severity of large truck crashes that occurred on horizontal curves may be attributed to the risk-taking behaviors of drivers when they negotiate horizontal curves. In particular, drivers tend to drive slowly and cautiously when negotiating horizontal curves; but, on the other hand, it is difficult to control large trucks on horizontal curves despite the cautious driving. Moreover, visibility is highly reduced during dark conditions and drivers may not be able to see an upcoming curve. Therefore, drivers may fail to reduce their speed to safely negotiate curves, which may not be the case in lighted conditions.

Dark Conditions

Mixed logit estimation results for the dark condition model are shown in Table 3. Marginal effects were calculated to examine the impact of contributing factors on injury severity, where marginal effects refer to a one-unit change in a particular variable while holding all others constant. Overall, 13 parameters were found to affect injury severity of ROR crashes in dark conditions. Among these, three parameters were random parameters, including overturning crash type, the presence of a vertical curve on the roadway, and crashes that occurred between September and December.

Regarding driver-related factors, five factors were found to significantly affect injury severity in dark conditions, all of which were homogenous across observations. These factors are the indicator variable for driver sobriety at the time of the crash, the indicator variable for not exceeding the speed limit, the indicator variable for not wearing a seatbelt at the time of a crash, fatigued drivers, and losing control of a vehicle. The first two driver-related factors that were found to lead to no injury are the indicator variable for driver sobriety at the time of the crash and indicator variable for not exceeding the speed limit. The marginal effects in terms of no injury for the two variables were 0.2258 and 0.2087, respectively. This finding implies that there is a 0.2258 and 0.2087 increase in the probability of no injury when drivers are sober and when drivers do not exceed the speed limit, respectively. These findings are intuitive, as sober drivers can react to unexpected hazards more quickly than intoxicated drivers. This finding is in agreement with Khattak et al. (2012), which concluded that truck drivers who were intoxicated at the time of the crash were more likely to be involved in severe crashes compared to sober drivers, and this emphasizes the need for more efforts devoted to reducing impaired driving. Similarly, abiding by the speed limit can protect drivers from involvement in fatal crashes because crash severity and speed are inextricably linked.

In addition, the indicator variable for not wearing a seatbelt at the time of a crash was found to significantly affect the injury severity. Marginal effects show that the probability of sustaining a severe injury increases by 0.0078 if a seatbelt is not used. This finding reveals the importance of seatbelt enforcement, particularly among truck drivers, to reduce the loss of lives and mitigate more severe injuries. This finding is consistent with Dissanayake and Kotikalapudi (2012), which found truck drivers were less likely to be involved in severe crashes when they wore a seatbelt at the time of the crash.

The seasonal effect, which is represented by the month of the year, was also found to affect the injury outcomes of ROR crashes involving large trucks. Crashes that occurred between September and December were found to be associated with minor injuries, and marginal effects indicate there is 0.0359 increase in the probability of sustaining a minor injury. A possible explanation might be linked to weather conditions between September and December in Oregon, when rainy weather is predominant. Therefore, Oregonian drivers are accustomed to these circumstances and are less likely to be involved in fatal or serious injury crashes. In addition, the estimated parameter was also found to be random with a mean of 0.255 and a standard deviation of 1.690. Based on values of the mean and standard deviation, the normal distribution curve indicates that 44% of the ROR crashes that occurred between September and December were less than 0. In other words, 44% of crashes that took place in the aforementioned period were less likely to result in minor injury outcomes, whereas 56% of these crashes were more likely to lead to minor injury outcomes. This finding varies from that found by Islam and Hernandez (2013b) in the context of heterogeneity; specifically, Islam and Hernandez (2013b) found the parameter to be homogenous for large truck crashes that occurred between September and December and less likely to lead to a nonincapacitating injury. The heterogeneous effects of this estimated parameter (between Oregon and Texas) may be related to the geographical differences between these two states and shows the importance of accounting for heterogeneity during data analysis techniques—model estimates and inferences would have been inaccurate had a nonheterogeneity method not been applied.

In term of crash-related factors, two variables were found to statistically affect injury severity—namely, overturning crashes and colliding with fixed objects. The estimated parameter for the indicator variable for an overturning crash was found to be random with a mean of 1.242 and a standard deviation of 3.638. Given these estimates, the normal distribution curve indicates that 36.6% of crashes with overturning trucks were less than 0. In other words, approximately 36.6% of crashes with overturning trucks were less likely to result in minor injury outcomes, whereas 63.4% of these crashes increased the likelihood of a minor injury. The randomness in this parameter may attempt to capture the variation in driver's experience that may help in avoiding serious crashes and also quality of a truck compartment that protects drivers from serious crashes. Next, colliding with a fixed object was found to decrease the likelihood of no injury, and according to marginal effects, results in a 0.0712 lower probability of no injury. The impact of darkness could increase the injury severity level of crashes that occurred because of colliding with a fixed object. The possible cause of sustaining a higher level of injury rather than no injury in fixed object crashes that occurred under dark lighting conditions is the degradation in visibility that may affect injury severity of collision with fixed objects as opposed to lighted conditions.

Regarding roadway-related variables, four variables were statistically significant and affected the injury severity level of drivers involved in ROR crashes in dark conditions. These variables included dry surface conditions, raised median type, the presence of horizontal curves, and the presence of vertical curves. With the exception of the indicator variable of vertical curves, the other variables were found to have no variation across observations.

Table 3 illustrates the probability of minor injury is lower by 0.0185 on vertical curves compared to flat roadways. A possible explanation is that drivers tend to reduce their driving speed when they negotiate a vertical curve, particularly under dark conditions, to react faster to unexpected hazards that are not as easily identified under dark conditions (e.g., animal crossing the roadway, an oncoming vehicle that is crossing the centerline, vehicles parking on the shoulder, etc.). This estimated parameter was also found to be random with a mean of −0.737 and a standard deviation of 3.791. By using mean and standard deviation values, the normal distribution curve shows that 42.3% of ROR crashes that occurred on a vertical curve under dark conditions were greater than 0. This finding means approximately 42.3% of crashes that occurred on vertical curves were more likely to result in a minor injury, whereas 57.7% of these crashes were less likely to cause a minor injury. The randomness in this parameter may be capturing the variation in driver behaviors related to negotiating vertical curves and the geometry of those curves. For instance, the percent grade is not provided in the data and is likely to impact severity outcomes (i.e., avoiding a crash or attempting to stop on a steep grade is more difficult than on a minor grade). In addition, the direction of travel in relation to the vertical curve or if the crash occurred at the pinnacle of the curve is not provided; therefore, these results may be attempting to capture the effects of these characteristics as well.

The indicator variable for horizontal curves was found to increase the probability of minor injuries by 0.0628. This finding agrees with Islam (2015) that found the parameter representing curved section highways was fixed and less likely to cause no injury. Regarding the impact of dry surface conditions, it was found that crashes on dry surface conditions decrease the possibility of no injury by 0.0469. Increased driving speed might be a potential factor in reducing the likelihood of no injury on dry surfaces. On dry surfaces, drivers may assume such surfaces are safe because the skid resistance is higher; therefore, they may increase their speed and the resulting crash is less likely to result in no injury (i.e., driver loses control while driving too fast and swerves into oncoming traffic or hits a fixed object, such as a concrete barrier or tree). Lastly, the presence of a raised median was associated with no injury crashes and marginal effects show that there is a 0.0215 higher probability of no injury for ROR crashes that occurred on a roadway in which a raised median was present.

Lighted Conditions

The estimation results of the mixed logit model for lighted conditions are presented in Table 4. In this model, five variables were found to have random and normally distributed estimated parameters. These parameters correspond to the indicator variables for a rural area, non-Oregonian drivers, the indicator variable of two vehicles involved in a crash, horizontal curve, and losing control of a vehicle.

The effect of losing control of a vehicle on the injury level sustained by drivers of large trucks in lighted conditions was found to be statistically significant and random. The mean of the estimated parameter for losing control of a vehicle is 0.541 and the standard deviation is 4.877. Given these estimates, the normal distribution curve implies that 45.6% of ROR crashes that occurred in lighted conditions due to losing control of a vehicle were less than 0. To illustrate, approximately 45.6% of ROR crashes that occurred because of losing control of a vehicle had a decrease in the likelihood of a minor injury. In contrast, 54.4% of these crashes were more likely to cause a minor injury. A possible explanation for the heterogeneous effects of this variable could be related to driver behavior, such as the ability to regain control to avoid a more serious crash. On the other hand, a proportion of drivers may be less experienced in driving a large truck and are unable to regain control, therefore increasing the chance of sustaining severe injury.

As shown in Table 4, some driver-related factors were found to be statistically significant and drastically affect the injury severity of truck drivers in lighted conditions. These variables include the indicator variables of an older driver (more than 65 years), driver illness, and non-Oregonian drivers. The probability of large truck drivers older than 65 years to sustain a severe injury increased by 0.0034. One potential reason is that older drivers are characterized by particular health problems, such as vision problems, changes to cognitive functioning, and physical changes that compromise their driving abilities. This finding could motivate state agencies to develop campaigns to suggest that older drivers drive only under good weather conditions. Also, restrictions regarding renewals of driver licenses for older drivers should be implemented to protect them and other road users from being involving in a crash.

Regarding the residency of drivers, it was found that non-Oregonian drivers are more likely to be involved in no injury crashes. This parameter was also found to be random with a mean of 1.667 and the standard deviation of 3.586. Given these estimates, the normal distribution curve indicates that 32.1% of the ROR crashes that involved non-Oregonian drivers were less than 0. This finding means that 32.1% of non-Oregonian drivers were less likely to be involved in no injury crashes, whereas 67.9% of those drivers were more likely to be involved in no injury outcomes. Unfamiliarity with Oregon roadways and traffic laws might encourage non-Oregonian drivers to be cautious and drive slowly. As a result, severity of a crash injury is lower for this group. Further, the variation in this parameter estimate may be attempting to capture the diverse geographical nature of Oregon compared to other states. In addition, this result further illustrates the importance of applying a method that can capture the heterogeneous effects within specific variables. As such, state agencies can better devote efforts to mitigate crashes for all drivers and not just a percentage of them.

The area type also impacts injury severity. Table 4 shows that the indicator variable of a rural area decreases the likelihood of no injury crashes. Furthermore, this estimated parameter was random with a mean of 0.196 and a standard deviation of 4.682. Based on the mean and standard deviation values, the normal distribution curve shows that 48.3% of crashes that occurred in a rural area were less than 0. Specifically, 48.3% of ROR crashes that took place in a lighted rural area were less likely to cause no injury, whereas 51.7% of these crashes were more likely to cause no injury. One possible reason that substantiates the heterogeneous effect of this estimated parameter could be related to rural areas being characterized by a relatively higher speed compared to urban areas. Accordingly, ROR crashes in a lighted rural area would result in a higher level of injury severity. Moreover, drivers may be inclined to drive without safety equipment (i.e., seatbelt) in rural areas, as opposed to urban areas, because of lower law enforcement presence in rural areas. On the other hand, some drivers tend to drive cautiously and carefully in rural areas, particularly in Oregon, to avoid colliding with crossing animals that are predominant in such locations.

Lastly, the estimated parameter for the indicator variable of two vehicles involved in ROR crashes was found to be random with a mean of 3.979 and a standard deviation of 4.501. Given these estimates, the normal distribution curve implies that 18.8% of ROR crashes involving multiple vehicles in lighted conditions were less than 0. That is to say, 18.8% of ROR crashes involving multiple vehicles in lighted conditions decrease the likelihood of no injury crashes, whereas 81.2% of these crashes are more likely to cause no injury. The randomness in this estimated parameter may be capturing the effect of vehicle body type in reducing the impact of injuries sustained by drivers of large trucks (e.g., a 2-axle truck compared to a tractor trailer). This finding is in line with Islam and Hernandez (2013a), which found the parameter representing the number of vehicles involved in a crash was random and more likely to lead to no injury severity. These findings suggest that regardless of geographic region (e.g., Oregon, Texas, etc.), multivehicle crashes involving large trucks have heterogeneous effects on injury severity. That is, there are several characteristics that come into the fold when multiple vehicles are involved in a crash (i.e., crash locations, lighting conditions, and vehicle preventing technology) and injury severity can be strongly influenced by these crash-specific characteristics.

Summary and Conclusions

Despite the large number of studies that have been conducted to address the relationships between ROR crashes and the contributing factors, the impact of lighting conditions has been insufficiently addressed. Thus, the objective of this study was to research the effect of lighting conditions on the injury severity of ROR crashes that involve large trucks. Based on the crash data pertaining to large trucks in the state of Oregon from 2007 to 2013, two separate mixed logit models were developed to capture the contributing factors that affect injury severity in each lighting condition. The mixed logit model was used to account for unobserved heterogeneity. Log-likelihood ratio tests were performed to verify the validity of using separate mixed logit models rather than one holistic model that represents both lighting conditions (i.e., lighted and dark conditions) by indicator variables. The results of the log-likelihood ratio tests revealed that using separate mixed logit models was justified. Two different lighting conditions were considered: lighted conditions (daylight and dark with street lighting) and dark conditions (dark with no street lighting).

Regarding the contributing factors that affect the injury severity of drivers of large trucks involved in ROR crashes, the estimation results revealed that there are significant differences between dark and lighted conditions. Moreover, some variables were found to affect the injury severity regardless of the lighting conditions. These variables are the indicator variable of not wearing a seatbelt, the indicator variable of a horizontal curve, the indicator variable of fatigued drivers, the indicator variable of overturning crashes, the indicator variable of losing control of a vehicle, and the indicator variable of driver sobriety; however, their impacts on injury severity were varied.

For the dark condition model, crashes that occurred in the early morning (between 4:00 a.m. and 6:00 a.m.) are more likely to lead to minor injury crashes. The estimation results also showed that not drinking alcohol and not speeding were associated with no injury crashes. These findings reveal the importance of abiding by traffic laws regarding alcohol consumption and speed limits. Among the interesting findings in the lighted condition model, older drivers (more than 65 years) were more likely to sustain severe injuries when involved in ROR crashes. This finding is plausible because older drivers are more vulnerable to sustaining fatal or severe injuries due to health problems associated with age. Regarding lighted conditions, if large trucks are involved in ROR crashes in rural areas, the drivers are less likely to sustain no injury because these areas are usually characterized by higher speeds.

The study findings can provide insight for safety researchers and traffic agencies to identify the contributing factors and the possible causes of ROR crashes that involve large trucks as well as how these factors differ based on lighting conditions. By addressing these factors, potential countermeasures could be proposed to potentially mitigate the number and the severity of ROR crashes. In particular, because the primary interest of the current paper was to study the effect of lighting conditions on the injury severity of ROR crashes involving large trucks, it was found that the installation of roadside lights could significantly alleviate the injury severity that results from ROR crashes.

In future work, the authors will explore the effects of disaggregating the model by setting (urban or rural) and by time of day. Moreover, to obtain more in-depth results regarding the effect of lighting conditions, the data will be divided by area type and the spatial transferability of the models to other state specific datasets will be examined.

Although this research applies a formal modeling framework (i.e., mixed logit), a nonparametric analysis can be considered. Whereas nonparametric analyses have shown good model fit, it has been shown to be the least precise because of its robustness (Greene 2016). With such an analysis, inferences regarding the association between a discrete outcome and the covariates are broad and results in no more than a rough representation of that association (Greene 2016). Being that nonparametric analyses do not rely on statistical distributions, these methods are often best used for ordinal type variables, when dealing with smaller sample sizes, or when the assumptions used for parametric methods are in question (Washington et al. 2011). In addition, in some cases (e.g., crash data) data are collected at many locations throughout a region. For such data, characteristics of different crashes may be similar if crashes are geospatially close to one another (Ott and Longnecker 2010; Washington et al. 2011). As such, statistical methods based on the t-distribution result in probabilities that are different from the intended values, both in terms of confidence intervals and p-values (Ott and Longnecker 2010). If this dependency exists, a more advanced analysis is required (Anselin 1988; Greene 2012). If the data being analyzed meets these requirements, an alternate model estimation approach may need to be explored.

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