Journal of Safety Research 56 (2016) 57–65

Contents lists available at ScienceDirect

Journal of Safety Research

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

Analysis of the injury severity of crashes by considering different lighting conditions on two-lane rural roads

A. Jafari Anarkooli, * M. Hadji Hosseinlou [1]

Civil Engineering Department, K.N. Toosi University of Technology, Tehran, Iran

ARTICLE INFO

Article history:
Received 8 June 2015
Received in revised form 23 August 2015
Accepted 8 December 2015
Available online 23 December 2015

Keywords:
Injury severity
Rural roads
Lighting condition
Ordered probit
Fixed effects

ABSTRACT

Introduction: Many studies have examined different factors contributing to the injury severity of crashes; however, relatively few studies have focused on the crashes by considering the specific effects of lighting conditions. This research investigates lighting condition differences in the injury severity of crashes using 3-year (2009–2011) crash data of two-lane rural roads of the state of Washington. *Method:* Separate ordered-probit models were developed to predict the effects of a set of factors expected to influence injury severity in three lighting conditions; daylight, dark, and dark with street lights. A series of likelihood ratio tests were conducted to determine if these lighting condition models were justified. *Results:* The modeling results suggest that injury severity in specific lighting conditions are associated with contributing factors in different ways, and that such differences cannot be uncovered by focusing merely on one aggregate model. Key differences include crash location, speed limit, shoulder width, driver action, and three collision types (head-on, rear-end, and right-side impact collisions). *Practical Applications:* This paper highlights the importance of deploying street lights at and near intersections (or access points) on two-lane rural roads because injury severity highly increases when crashes occur at these points in dark conditions.

1. Introduction

1.1. Background

Road crashes comprise a major public health challenge that requires concentrated efforts for effective and sustainable prevention. Worldwide, 1.2 million people are known to die in road crashes each year and millions of others sustain injuries, with some suffering permanent disabilities (World Health Organization, 2013). In consideration of these issues, injury severity has been a primary interest to researchers in traffic safety, since such research would be aimed not only at prevention of crashes but also at decreasing the severity of them. One way to accomplish injury research is by identifying the significant factors affecting injury severity. These factors include behavioral characteristics of drivers (age, gender, driving under influence of alcohol, etc.), environmental factors and roadway characteristics (weather, surface, lighting conditions, roadway geometry, etc.), traffic conditions, vehicle characteristics (body type and age), and types of collisions (direction of impact or occurrence of a rollover).

Roadway lighting condition has long been considered to be significant parameter to the frequency and severity of traffic crashes. Although many studies have explored the effects of factors influencing injury severity, the relationships between these factors, crash severity and lighting conditions, are still not completely understood. Most of these studies have investigated the effects of lighting conditions by using indicator variables representing different lighting conditions as independent variables in regression models. However, in determining injury severity, the problem is further complicated by the fact that there is a complex interaction between variables that can vary significantly across different lighting conditions. This interaction, especially on two-lane rural roads, depends on many factors; the most significant of them is drivers' visibility to observe roadway components, such as oncoming traffic, roadside objects, and so forth. For example, it is expected that darkness inhibits drivers' visibility, allowing less time for last-minute maneuvering and braking in moments before collision, resulting in more severe crashes.

This paper analyzes lighting condition differences in crash injury severities using the crash data of two-lane rural roads of the state of Washington. The ordered probit model is employed to obtain a better understanding of the complex interactions between lighting conditions and contributing factors found in the dataset. The primary objective of this study is to estimate which of these factors become significant in affecting the probability of injury severity in a crash under three major lighting conditions; daylight, dark, and dark with street lights (dark-lighted).

* Corresponding author. Tel.: +98 911 706 6513.
E-mail addresses: alirezajafari.kntu@gmail.com (A. Jafari Anarkooli), Mansour@Kntu.ac.ir (M. Hadji Hosseinlou).
[1] Tel.: +98 912 337 7434; fax: +9821 8877 9476.

http://dx.doi.org/10.1016/j.jsr.2015.12.003
0022-4375/

Using an unbalanced panel data, this study develops separate models for these lighting conditions. Also, by using the marginal effects of the developed models, it investigates the effects of independent variables on different injury severity levels. Finally, these models are compared to identify the significant differences between the effects of the contributing factors on injury severity in the three lighting conditions.

The remainder of the paper is organized as follows. A review of prior literature is presented followed by the methodology applied to model crash injury severity. The data description is given in the third section. Next, the model specification tests are explained and the results are presented. To identify patterns and differences, a comparison analysis of the models is given and the final section summarizes the findings and presents the conclusions.

1.2. Review of prior studies

Many studies have focused on estimating and modeling traffic crashes and their consequences. A large number of these studies have been conducted to determine significant factors influencing the increased levels of injury severity of crashes. Also, various techniques have been employed in order to explore the effects of these factors on injury severity. These techniques can be classified into four major groups: discrete outcome models, data mining methods, soft computing, and other methods (Mujalli & De Oña, 2013). In addition, we can categorize the contributing factors into five groups: driver conditions, vehicle characteristics, road geometry and traffic conditions, environmental conditions, and types of collisions (Lee & Li, 2014).

From the methodological standpoint, the discrete outcome models are of the most practical techniques employed to analyze crash injury severity (Bedard, Guyatt, Stones, & Hirdes, 2002; Wood & Simms, 2002; Pai & Saleh, 2008; Xie, Zhao, & Huynh, 2012, Washington, Karlaftis, & Mannering, 2012; Dong, Richards, Huang, & Jiang, 2013; Obeng, 2011; Pahukula, Hernandez, & Unnikrishnan, 2015). Multinomial logit and ordered logit/probit models have been found to be the most prominent types of discrete outcome models used for traffic crash severity analysis (Savolainen, Mannering, Lord, & Quddus, 2011). For instance, Dong et al. (2013) have estimated the effects of the characteristics of traffic, driver, geometry, and environment on injury severity of truck-involved crashes with a multinomial logit model. Their results indicated that lower traffic volume with higher truck percentage was associated with fatal/incapacitating injury, while a non-standard geometric design was the main cause of non-incapacitating crashes. Also, they concluded that the effects of weather are significant for the possible injury category, while driver condition is the principal cause of property damage-only crashes. Also, Obeng (2011) developed separate fixed-effects ordered probit models by gender differences to explore factors affecting injury severity at signalized intersections. The explanatory variables included the characteristics of the crash, vehicle, and driver. He found major gender differences on the impacts of driver condition, seatbelt use, and airbag deployment on injury severity risks. In addition, he pointed out that better and more in-depth information about gender differences in injury severity risks were gained by estimating separate models for females and males.

Some of past crash severity-related studies have suggested that environmental factors such as lighting conditions are closely related to the increased levels of injury severity (Duncan, Khattak, & Council, 1998; Khorashadi, Niemeier, Shankar, & Mannering, 2005; Rana, Sikder, & Pinjari, 2010; Zhu & Srinivasan, 2011; Obeng, 2011; Pahukula et al., 2015). For example Duncan et al. (1998), using ordered probit models, examined the injury sustained by passenger-car occupants in the case of rear-end collisions between heavy trucks and passenger cars. They indicated that darkness increases the severity of rear-end crashes. Khorashadi et al. (2005) analyzed the differences between rural and urban injury severities of crashes involving large trucks. They captured the effects of lighting conditions by using indicator variables representing different times of day as independent variables in a multinomial logit model. Their study, for instance, suggested that crashes in the morning (5:31–8:00) are less likely to result in evident or fatal injury category in both urban and rural areas. Another study with 10-year crash data for the state of Illinois was carried out with a mixed logit method and found that non-bright conditions significantly increases the probability of severe injuries or fatality in multivehicle crashes (Chen & Chen, 2011). Using the ordered probit models, Zhu and Srinivasan (2011) analyzed 4 years of data from the Large Truck Crash Causation Study (LTCCS). They found that crashes happening during "dark but lighted" conditions (7:30 p.m. to 5:30 a.m.) lead to most severe crashes relative to dark and daylight lighting conditions. In addition, Xie et al. (2012) utilizing a latent class logit model, studied the injury severity of single-vehicle crashes on rural roads. Quite surprisingly, their results indicated that darkness can increase drivers' probabilities of being involved in no-injury crashes. They claimed that drivers tend to be more cautious when it is dark without street lights.

In contrast to the other literature, in which they captured the effects of lighting conditions by using independent variables, Pahukula et al. (2015) focused on the effects of time of day on injury severity. They developed mixed logit models by using the Crash Records Information System (CRIS) database in Texas including large truck-involved crashes occurring on urban freeways between 2006 and 2010. Crashes were separated into five time periods including early morning, morning, mid-day, afternoon, and evening. The results of the individual time of day models demonstrated noticeable differences among the outcome of these models. These differences suggested that different time periods have different significant factors to each injury severity level. The main differences comprised the traffic volume, lighting condition, roadway surface condition, time of year, and percentage of trucks on the road. The authors also highlighted the significance of analysis of injury severity on the basis of individual time of day models.

Overall, almost all of the current literature captured the effects of lighting conditions on crash severity by using an independent variable approach representing association of darkness with the variation of injury severity levels. However, such an approach appears to be limited because different factors under different lighting conditions interact with each other and influence injury severity in complex ways. With this in mind, the intent of the present study is to capture the effects of different factors on injury severity levels under different lighting conditions by using completely separate models. The model estimation results indicate that modeling injury severity in specific lighting conditions is associated with the contributing factors in different ways.

2. Methodology

As discussed in the literature, many studies have used discrete outcome models including ordered probit/logit models, nested logit models, and multinomial logit models (see Savolainen et al., 2011). However, since injury severity levels are commonly recorded in the ordinal scale, some studies suggested unordered discrete choice models such as multinomial or nested logit models, while accounting for the categorical nature of dependent variables, are at the expense of neglecting ordered nature of the injury levels (Greene & Hensher, 2010; Borooah, 2002; Pai & Saleh, 2008; Wang & Abdel-Aty, 2008; Obeng, 2011; Zhu & Srinivasan, 2011). In consideration of this issue, the ordered probit model was used to achieve the purpose of this study.

This research uses an unbalanced panel data for crashes on two-lane rural roads and estimates separate fixed-effects[2] ordered probit models for the three lighting conditions: daylight, dark, and dark-lighted. The effects of the explanatory variables on the injury levels are explored

[2] To account for the possibility of unobserved heterogeneity due to the unbalanced panel data three possible approaches can be used. They are to estimate a latent class, fixed-effects or random-effects model (Obeng, 2011). In this study, we estimate fixed-effects models using STATA13 software.

by using the marginal effects, so that the conditions causing a crash to be in a specific severity level are determined depending on its related independent variables. Evidence of employing the fixed-effects ordered probit models for estimating injury severity can also be found in the studies of Abdel-Aty and Keller (2005) and Obeng (2011).

To study injury severity, the present methodology follows Washington et al. (2012). Following the usual ordered response models, unobserved continuous injury propensity is:

$$U_{in} = \beta_i' x_{in} + \epsilon_{in} \tag{1}$$

where U_{in} is a severity function determining injury severity level i in crash n, β_i' is a set of coefficients for injury severity level i, x_{in} is a subset of explanatory variables affecting injury severity level i in crash n; and ϵ_{in} is a random error capturing the effect of unobserved factors (factors other than those included in the vector x), which is assumed to be normally distributed. We can also calculate the conditional probability that a crash is in the specific severity level, in the following way:

$$\begin{aligned} &P(I=0) = \varphi(-\beta' x) \\ &P(I=1) = \varphi(\mu_1 - \beta' x) - \varphi(-\beta' x) \\ &P(I=2) = \varphi(\mu_2 - \beta' x) - \varphi(\mu_1 - \beta' x) \\ &\ldots \\ &P(I=j) = 1 - \varphi\left(\mu_{j-1} - \beta' x\right) \end{aligned} \tag{2}$$

where $\mu_1 < \mu_2$ are two thresholds by which categorical responses are estimated and j is the highest injury level (for the fatal/disabling level, $j = 3$). The predicted probability is calculated for each crash and it is limited between 0 and 1.

When estimating ordered probit models, it is common and informative to report marginal effects after reporting the coefficients. The marginal effects show, holding all other variables constant, the changes in the probabilities of the injury categories when an explanatory variable increases by one unit. For continuous variables, this represents the instantaneous change given that the unit may be very small. Also, for binary variables, the change is from 0 to 1 (Gelman & Hill, 2006). The marginal effects of each explanatory variable on the specific level of injury severity is calculated as

$$\frac{\partial P(I=j)}{\partial x} = \left[\varphi\left(\mu_{j-1} - \beta' x\right) - \varphi\left(\mu_j - \beta' x\right)\right]\beta \tag{3}$$

In the present study, the marginal effects are used to determine the significant factors contributing to the injury severity levels in each lighting condition.

3. Dataset for analysis

The data used in this study are from 3-year (2009–2011) crash records for two-lane rural roads in the state of Washington provided by the Highway Safety Information System (HSIS). The HSIS dataset consists of some separate files including crashes, drivers, and roadway inventory (about specific attributes of the roadway environment). These were merged on the basis of crash number to obtain records of 17,937 crashes.

In the HSIS dataset, the severity of crashes is recorded with five injury levels that are commonly defined with KABCO injury scale; fatality (K), disabling injury (A), evident injury (B), possible injury (C), and no-injury (O). The fatal injury category includes crashes resulting in death within 30 days of occurrence. The disabling injury is one which prevents the injured person from walking or continuing the activities the person was capable of doing before being injured. The evident injury category is classified as any injury, other than a fatal injury or a disabling injury, which is evident to the observer at the scene of the crash. The possible category is that if the victim complains of pain which improved rapidly in the interval between evaluation at the crash scene and examination at the hospital. Lastly, if the reported crash does not result in any injury, it is defined as the no-injury category. In this study, due to the limited number of crashes that resulted in fatality and disabling, the KABCO injury scale was collapsed into four categories: fatal/disabling, evident injury, possible injury, and no-injury. Also, many studies in the past have used four or three categories to overcome this limitation in the dataset (Obeng, 2011; Islam, Jones, & Dye, 2014; Pahukula et al., 2015). In the case of multiple-injury crashes, each record represents the maximum level of injury sustained by occupants (driver and passengers).

The HSIS dataset contains over 50 variables; however, most of these variables are only related to very few specific cases. Therefore, 23 factors expected to affect crash severity on two-lane rural roads were selected as explanatory variables. These variables include road condition (geometric design variables, environmental factors, traffic conditions, and crash location), driver condition (using alcohol, inattention, falling asleep, and driver action), and collision type (type of collision and its related information).

The effect of lighting condition on injury severity is the focus of this study. Therefore, the analysis examined three different lighting conditions: daylight, dark, and dark-lighted. In this research, the daylight condition dataset includes all of the crashes that occurred in the daytime period except the crashes at dawn and dusk conditions. The dataset of dark condition comprises the crashes in darkness, without street lights, and those with street lights but they were off. Also, the dark-lighted condition dataset includes the crashes which occurred in dark conditions with street lights that were on. It is noted that, based on the objective of this study, crashes that occurred at dusk or dawn were excluded from the dataset. Moreover, observations with missing values were omitted from the original dataset before performing the models.

Finally, a new dataset was formed including 16,932 crashes resulting in 10,104 (59.7%) no-injury, 3527 (20.8%) possible injury, 2558 (15.1%) non-disabling injury, and 789 (4.6%) fatality or disabling injury. In addition, of these crashes, 11,783 (69.6%), 3906 (23.1%), and 1154 (6.8%) occurred in daylight, dark, and dark-lighted conditions, respectively. The individual datasets separated by these three lighting conditions are presented in Table 1.

Using information from Table 1, there are several differences worth mentioning. For instance, most of the crashes in the dark-lighted condition dataset (65.2%) occurred at intersections (or access points), whereas only 15.4% of the crashes in the dark condition were related to the intersections. Also, collision type distribution is remarkably different between the lighting condition datasets. For example, rear-end is the most prevalent collision type in the daylight condition dataset including 36% of crashes, while they comprise only 10% of crashes in the dark condition dataset.

4. Model specification tests

In the prior studies, researchers used likelihood-ratio tests to check the suitability of separate models over one aggregate model (Pahukula et al., 2015; Washington et al., 2012; Islam et al., 2014). Similarly in this study, once the models were developed, log likelihood ratio tests were conducted to determine if separate models based on lighting condition were justified following the procedures found in (Washington et al., 2012).

The models were compared with two methods. The first test compared the full model against all of the lighting condition models while the second test compared the models individually with each other. The first log likelihood ratio test for transferability is as follows:

$$X^2 = -2\left[LL(\beta_T) - \sum_{k}^{k=j} LL(\beta_k)\right] \tag{4}$$

Table 1
Descriptive statistics of variables.

Variables and description	Daylight		Dark		Dark-lighted	
	Mean	Std.dev	Mean	Std.dev	Mean	Std.dev
Injury severity						
Fatality and disabling (1 if true; otherwise 0)	0.0461		0.0488		0.0418	
Evident injury (1 if true; otherwise 0)	0.1525		0.1549		0.1175	
Possible injury (1 if true; otherwise 0)	0.2296		0.1459		0.2447	
No-injury (1 if true; otherwise 0)	0.5719		0.6604		0.5960	
Road condition						
Crash location (1 if at intersection; otherwise 0)	0.4926	0.2588	0.1544	0.3652	0.6521	0.4722
LogAADT (AADT varied between 140 and 25,000 veh/day)	7.0693	5.6181	5.2149	4.6121	8.6212	5.9645
Speed limit/10 (speed limit varied between of 20 and 65 mph)	4.8445	1.0856	5.2235	0.9853	4.4562	1.4242
Segment length (segment length varied between 0.01 and 4.82 miles)	0.1534	0.2482	0.2231	0.2945	0.1042	0.1612
Curve (1 if in curve; otherwise 0)	0.2458	0.4305	0.2778	0.4479	0.2656	0.4785
Curve direction (1 if right; left 0)	0.5139	0.4998	0.5062	0.5112	0.5012	0.4825
Steep grade (1 if grade more than 5% [1]; otherwise 0)	0.1585	0.3652	0.1245	0.3856	0.1021	0.4213
Grade direction (1 if uphill; downhill 0)	0.6010	0.4897	0.5882	0.4985	0.6342	0.4852
Curve-grade (1 if curved section with a grade more than 5%; otherwise 0)	0.1423	0.3826	0.1462	0.3532	0.1222	0.3422
Shoulder width (shoulder width varied between 0 and 24 ft)	3.3920	2.4317	3.4451	2.5623	3.6244	2.5642
Road surface (1 if wet, icy, and snowy; otherwise 0)	0.2893	0.4534	0.4321	0.4956	0.4527	0.4832
Wet-grade (1 if wet with a grade more than 5%; otherwise 0)	0.0525	0.2231	0.0623	0.2372	0.4536	0.2456
Driver info						
Alcohol (1 if driving under influence of alcohol or drug; otherwise 0)	0.0556	0.2292	0.1285	0.3356	0.1253	0.3312
Asleep (1 if apparently asleep; otherwise 0)	0.0491	0.2162	0.0334	0.1785	0.0211	0.1442
Inattention (1 if reported inattention, otherwise 0)	0.0653	0.2471	0.0234	0.3954	0.0203	0.1412
Driver action (vehicle maneuver just before impending crash, 1 if going straight; otherwise 0)	0.6128	0.4871	0.8625	0.3342	0.5928	0.4862
Collision info						
Head-on (front side) (1 if head-on collision; otherwise 0)	0.0526	0.2423	0.0348	0.1823	0.0662	0.2424
Rear-end (back side) (1 if rear-end collision; otherwise 0)	0.3609	0.4802	0.0994	0.2952	0.2549	0.4362
Left-side (1 if left-side impact; otherwise 0)	0.1627	0.3691	0.0842	0.2725	0.2125	0.4581
Right-side (1 if right-side impact; otherwise 0)	0.1086	0.3112	0.0409	0.1985	0.1379	0.3441
Rollover (1 if rollover; otherwise 0)	0.0485	0.2148	0.0683	0.2532	0.0242	0.1532
Object (1 if collision with roadside objects; otherwise 0)	0.1308	0.3372	0.2623	0.435	0.1769	0.3812
Animal (1 if collision with an animal; otherwise 0)	0.0367	0.1885	0.2224	0.8462	0.0555	0.229

where $LL(\beta_T)$ is the log-likelihood at convergence for the total model (-3053.45); $LL(\beta_k)$ is the log-likelihood at convergence for the lighting condition models (daylight, dark, and dark-lighted) using the same variables of the total model, and K is the total number of data subsets ($\sum_k^{k=j} LL(\beta_k) = -2995.76$). The chi-square statistic for the likelihood ratio test with 42 degrees of freedom gave a value greater than the 99.99% (X^2=-115.4) confidence limit that means the null hypothesis, that the parameters of total and separate lighting condition models are the same, is rejected. Therefore, we can conclude that the models have statistically significantly different model parameters.

For further justification of employing the three separate models, the second log likelihood test was conducted to test the transferability of regression coefficients from the total model to each lighting condition models:

$$X^2 = -2\left[LL(\beta_{k_1k_2}) - LL(\beta_{k_1})\right] \tag{5}$$

where $LL(\beta_{k_1k_2})$ is the log likelihood at convergence of a model using the parameters from model k_2 for lighting condition k_1's data and $LL(\beta_{k_1})$ is the log likelihood at convergence of the model using lighting condition k_1's data(without constraining the parameters). The X^2 statistic with degrees of freedom equal to the number of estimated parameters in $\beta_{k_1k_2}$ provides the probability that the models have different parameters. Each test statistic is higher than the corresponding X^2 value with specific degrees of freedom at 99.99% confidence level ($p = 0.0001$). Therefore, it is further validating that separate models by lighting condition is justified. Table 2 shows the results of the second transferability test (Eq.(5)).

The combination of these two likelihood ratio tests yields a good assessment of the statistical differences among the three lighting conditions (Morgan & Mannering, 2011). Therefore, it was determined that the three separate severity models were statistically justified (with confidence levels exceeding 99.99%).

5. Estimation results

Variables with a p-value less than of 0.05 (commonly accepted level) are statistically significant and they will affect injury severity at the 95% confidence level. A positive coefficient value for an explanatory variable means it is positively associated with the increased levels of injury severity and increases the propensity of injury severity with an increase in its magnitude.

The marginal effects are computed for each of the variables that are statistically significant in each model. The marginal effects show the effect of one unit change of the variable on each injury severity level, separately.

5.1. Daylight condition model

Table 3 shows the estimation results of injury severity for the daylight condition model. As regards road condition variables effects on injury severity in daylight conditions, the indicator variable representing speed limit is positively associated with severe crashes. This is likely

Table 2
Transferability test comparing the three models.

	k_2		
k_1	Daylight	Dark	Dark-lighted
Daylight	0.00	6622.24 ($df = 14$)	1932.42 ($df = 9$)
Dark	3416.12 ($df = 16$)	0.00	168.66 ($df = 9$)
Dark-lighted	1058.62 ($df = 16$)	1138.40 ($df = 14$)	0.00

Table 3
Injury severity model for the daylight condition.

Variable	Coefficient	Std. Error	*t*-statistics	Marginal effects			
				No injury	Possible injury	Evident injury	Fatal or disabling
Speed limit/10	0.2037	0.0160	12.73	−0.0401	0.1212	0.0257	0.0123
Road surface	−0.1628	0.0238	−6.82	0.0641	−0.0176	−0.0285	−0.0181
Wet-grade	−0.1755	0.0492	−3.57	0.0691	−0.0182	−0.0322	−0.0188
Curve	0.1354	0.0245	5.52	−0.0532	0.0145	0.0236	0.0151
Curve-grade	0.1566	0.0365	4.26	−0.0432	0.0141	0.0167	0.0121
Segment length	0.1085	0.0423	2.56	−0.0428	0.0126	0.0189	0.0122
Log AADT	−0.0161	0.0019	−8.47	0.0063	−0.0017	−0.0028	−0.0017
Grade direction	−0.0632	0.0222	−2.84	0.0241	−0.0067	−0.0109	−0.0072
Alcohol	0.3995	0.0615	6.49	−0.1577	0.0377	0.0735	0.0464
Asleep	0.2544	0.0656	3.87	−0.1004	0.0239	0.0467	0.0298
Driver action	0.1335	0.0218	6.10	−0.0526	0.0143	0.0236	0.0146
Head-on	0.3834	0.0425	9.02	−0.1514	0.0412	0.0672	0.0426
Rollover	0.4541	0.0472	9.60	−0.179	0.0496	0.079	0.0504
Right side	−0.1046	0.0347	−3.01	0.0412	−0.0112	−0.0182	−0.118
Rear-end	−.0506	0.0222	−2.30	0.0119	−0.0054	−0.0088	0.056
Animal	−0.888	0.0729	−12.18	0.3498	−0.0972	−0.1547	−0.0979
Model statistics							
μ_1	1.7234	0.0364	26.38				
μ_2	2.6236	0.0642	22.44				
Log likelihood at convergence	−1808.6						
Log likelihood ratio index (ρ^2)	0.0706						
Number of observations	11,783						

because a higher speed limit leads to the higher impact speed in a collision, resulting in increasing the likelihood of severe crashes.

Table 3 also indicates, in daylight conditions, the probability of severe crashes decreases on wet or snow/icy surfaces relative to dry surfaces. A possible explanation for this finding is that drivers are usually more cautious on wet or snow/icy surfaces, resulting in decreasing the probability of severe crashes. Furthermore, the combined variable of wet-grade, representing the combination of wet or snowy/icy surfaces and steep grades, has a roughly same effect on the increased levels of injury severity on two-lane rural roads.

Using Table 3, when a crash occurs in a curved road section, the likelihood of occupants (drivers and passengers) sustaining severe injuries increases. One possible explanation for this finding may be that drivers are more likely to experience severe collision types, such as impacts of fixed roadside objects and rollover, in curved road sections relative to the straight ones. Moreover, on two-lane rural roads, because of limited sight distance in the curves, drivers are not able to react promptly for collisions related to oncoming vehicles, resulting in increasing the likelihood of severe crashes. Similarly, the indicator variable representing the combined effect of curved sections with steep grades is positively associated with the increased injury severity levels.

The indicator variable of segment length, representing the length that all geometric characteristics are the same, is the next statistically significant variable in the daylight condition model. This continuous variable is positively associated with the increased levels of injury severity. This is likely because the variable of segment length may be capturing the effects of driving speed in daylight conditions, since drivers tend to drive at higher speeds when the length of a segment increases, resulting in increasing the likelihood of more severe injuries.

Table 3 also shows the variables of LogAADT and grade direction are statistically significant in the model. These variables are negatively associated with the increased levels of injury severity. However, their marginal effects indicate that they are not associated with a very large shift in the injury severity levels.

As regards condition of driver and its effects on injury severity, when the primary cause of a crash is driving under influence of alcohol or drugs injury severity noticeably increases. Also, as one might guess, the severe injury levels increase when the primary cause of a crash is falling asleep.

The indicator variable of driver action representing going straight (compared to making right/left turn, slowing or stopping in a traffic lane, etc.) is positively associated with the increased levels of injury severity. A possible explanation for this positive association may be that increased sight distance, as a result of going straight in daylight conditions, provides additional confidence for the driver and promotes higher speeds leading to more severe injury crashes.

Regarding the effects of collision types in daylight conditions, most of the collision types are statistically significant in the model. Table 3 shows rollover and head-on collisions highly increase the probabilities of severe crashes. In contrast, under daylight conditions, when rear-end, right-side impact, and animal involved crashes occur a lower level of injury severity is a possible outcome.

5.2. Dark condition model

Estimation results for injury severity in dark lighting conditions (without street lights) are presented in Table 4. Examining the effects of the statistically significant variables in the dark and daylight condition models shows there are several striking differences in the two models.

Regarding the effects of road/environment condition variables, only four variables are statistically significant in the dark condition model; crash location, LogAADT, curve, and roadway surface. The indicator variable of crash location, representing intersection related crashes, is highly associated with the increased injury severity levels in the dark lighting condition model. To be more precise, by examining the dark condition crash dataset, 8.5% of the intersection related crashes have a fatal/disabling level that is 1.55 times more than non-intersection-related crashes. This result is generally expected because drivers may have less reaction time and perception ability on crash risk at intersections under dark conditions.

Turning to the assessment of driver condition variables, Table 4 indicates that there are three statistically significant variables; using alcohol or drugs, falling asleep, and driver action. The indicator variable representing driving under influence of alcohol or drugs strongly influences on the increased levels of injury severity. Similarly, when falling asleep is the primary cause of a crash the probability of severe crashes increases. In contrast, the indicator variable of driver action is negatively associated with severe crashes. Decreasing the probability of severe crashes by this variable could be due to the limitation of driver's sight distance under dark conditions. In such situations, drivers are more likely to be faced with unexpected events, such as sudden turning to

Table 4
Injury severity model for the dark lighting condition.

Variable	Coefficient	Std. Error	*t*-statistics	Marginal effects			
				No injury	Possible injury	Evident injury	Fatal or disabling
Location type	0.3631	0.0515	7.05	−0.1326	0.0304	0.0606	0.0418
Curve	0.0908	0.0434	2.09	−0.0332	0.0075	0.0151	0.0106
Road surface	−0.0784	0.0396	−1.98	0.0287	−0.0064	0.0131	0.0092
LogAADT	0.0095	0.0041	2.29	−0.0034	0.0008	0.0015	0.0011
Alcohol	0.6553	0.5472	10.66	−0.2395	0.0563	0.1122	0.0711
Asleep	0.5624	0.4825	2.00	−0.1290	0.0284	0.0644	0.0362
Driver action	0.1598	0.0552	−2.8	0.0584	−0.0131	−0.0265	−0.0186
Head-on	1.1372	0.0962	11.81	−0.4172	0.0965	0.1947	0.1249
Roll	0.4508	0.073	6.17	−0.1649	0.0374	0.0752	0.0521
Right side	0.4037	0.0916	4.41	−0.1478	0.0334	0.0674	0.0469
Left-side	0.1235	0.0682	1.81	−0.0452	0.0101	0.0205	0.0144
Rear-end	0.2515	0.0609	4.12	−0.0919	0.0208	0.0417	0.0294
Fixed object	0.123	0.0445	2.77	−0.0451	0.0102	0.0205	0.0144
Animal	−1.1512	0.0601	−19.12	0.4085	−0.1104	−0.1925	−0.1055
Model statistics							
μ_1	1.7483	0.0442	24.6				
μ_2	2.6342	0.0624	22.4				
Log likelihood at convergence	−974.92						
Log likelihood ratio index (ρ^2)	0.1124						
Number of observations	3906						

left or right, so that they may not have sufficient time to avoid severe crashes. Therefore, when vehicles maneuver just before impending crash is going straight the probability of occupants being involved in severe crashes decreases.

With regard to the collision types in dark lighting conditions, all of the collisions were found statistically significant in the model. Quite interestingly, almost all of them (except animal involved crashes) are positively associated with the increased levels of injury severity. According to Table 4, head-on collision was found as the most significant collision type increasing the probability of severe crashes on two-lane rural roads. Also, rollover crashes are more likely to have a higher injury severity level in dark conditions.

Unlike the daylight condition model, rear-end, right-side impact, left-side impact, and fixed object-related crashes lead to increased probability of severe injuries in the dark condition model. The possible explanation for the rear-end crashes may be that darkness reduces the available reaction distance, thus increases the closing speed, resulting in increasing the likelihood of severe crashes.

Using Table 4, right-side and left-side impact-related collisions are positively associated with the increased levels of injury severity under dark lighting conditions. To be more precise, 11.2% of right-side impact and 6.4% of left-side impact crashes that occurred in darkness have a fatal/disabling injury level. The fact that right-side impact collisions increase the probability of severe injuries may seem somewhat counterintuitive. Nevertheless, on two-lane, two-way rural roads, increased impact speed under insufficient lighting conditions may increase injury severity of the right-side impact crashes related to the vehicles coming from the opposite direction. Table 4 also shows fixed object-related crashes are more likely to be severe. Finally, as expected, animal-involved crashes are negatively associated with increased injury severity levels.

5.3. Dark-lighted condition model

The variables that are statistically significant in the dark-lighted condition model are shown in Table 5. Regarding road condition variables and their effects on injury severity in dark-lighted conditions, the indicator variable of segment length is statistically significant in the model. Also, the variable of grade direction is statistically significant in the dark lighting condition model and the sign of its coefficient indicates a relative decrease in injury severity levels for uphill grades compared to downhill grades.

Curve direction is another statistically significant road condition variable in the dark-lighted condition model, which its negative coefficient sign indicates that left curves are more likely to have severe crashes compared to right curves. It should be noted that, the relatively small number of crashes which occurred in curves under dark-lighted conditions (248 observations) may lead to a biased estimation. Therefore, the combined effect of curve direction and dark-lighted conditions on crash severity requires further research.

Using Table 5, shoulder width is positively associated with increased injury severity levels. This is somewhat counterintuitive; however, this is likely because wider shoulders encourage drivers for merging and lane-changing maneuvers, so that vehicles traveling in the traffic lane are forced to cross the centerline to avoid a sideswipe collision with such vehicles, leading to more severe crashes such as head-on collision.

As expected, the indicator variable representing speed limit increases the possibility of more severe crashes. However, based on the marginal effects, speed limit is not associated with a large shift in injury severity outcomes in the dark-lighted condition model (less than 1% in each category). One possible explanation for this finding is that the variable of speed limit may be capturing the influence of locational factors. To be more precise, using Table 1, 65.2% of crashes related to dark-lighted conditions have occurred at intersections (or access points) which they have lower speed limits, resulting in this variable has less influence on the increased levels of injury severity compared to the daylight condition model.

As regards driver condition variables and their effects on injury severity, using alcohol or drugs and driver action are statistically significant in the dark-lighted condition model. As expected, when driving under influence of alcohol is the primary causation of a crash (it is in the case of 12.5% of all crashes which occurred in dark-lighted conditions) its influence on severe crashes is strongly significant. In addition, like the daylight condition model, going straight increases the probability of occupants being involved in severe crashes in dark-lighted conditions.

Finally, the variables related to collision types are presented next. As illustrated in Table 5, three types of collisions were found to be statistically significant in dark-lighted conditions: head-on, rear-end, and animal-involved crashes. The indicator variable representing head-on collision is significant and more likely to lead to crashes that are more severe. In contrast, rear-end and animal-involved crashes are negatively associated with increased levels of injury severity in dark-lighted conditions. Lastly, like the other lighting condition models, animal-involved

Table 5
Injury severity model for the dark-lighted condition.

Variable	Coefficient	Std. Error	t-statistics	Marginal effects			
				No injury	Possible injury	Evident injury	Fatal or disabling
Segment length	0.6764	0.2109	3.21	−0.2634	0.0936	0.0994	0.0704
Curve direction	0.3478	0.1524	−2.29	0.1314	−0.0397	−0.0625	−0.0292
Grade direction	−0.0147	0.0742	−2.00	0.0582	−0.0201	−0.0219	0.0163
Shoulder width	0.0566	0.0134	4.21	−0.0224	0.0078	0.0083	0.0058
Speed limit	0.0454	0.0232	1.96	−0.0171	0.0062	0.0066	0.0047
Alcohol	0.4601	0.1012	4.55	−0.1795	0.0649	0.0682	0.0462
Driver action	0.1542	0.0771	2.18	−0.0602	0.0212	0.0226	0.0162
Head-on	0.6672	0.1284	5.21	0.2601	0.0941	0.0982	0.0678
Rear-end	0.1542	0.0794	−1.96	0.0602	−0.0214	−0.0227	−0.0161
Animal	−0.9817	0.2010	−4.93	0.3814	−0.1392	−0.1433	−0.0991
Model statistics							
μ_1	1.7183	0.0642	24.26				
μ_2	2.6042	0.0824	20.71				
Log likelihood at convergence	−212.27						
Log likelihood ratio index (ρ^2)	0.1323						
Number of observations	1154						

crashes result in less severe crashes relative to the other collision types in dark-lighted conditions.

6. Discussion

Separate models of injury severity by lighting conditions provide valuable insights into contributing factors affecting the injury severity levels of crashes. To identify patterns and differences, Table 6 summarizes the effects of the variables on injury severity by the three lighting conditions.

As regards road condition variables, segment length is positively associated with the increased levels of injury severity in daylight and dark-lighted conditions. As mentioned, this variable may be capturing the varying speed in a roadway. Since drivers are usually less cautious in daylight and dark-lighted conditions compared to the limited lighting conditions (darkness), by increasing a segment length they are encouraged to travel at higher speeds which results in increasing the probability of severe crashes. Moreover, based on the marginal effects, the increased values of injury severity in dark-lighted conditions are more noticeable relative to the daylight conditions. The combination of increased travel speeds and sight distance could explain this finding. Since there are lower traffic volumes during nighttime periods and relatively sufficient sight distance in dark-lighted conditions, by increasing a segment length drivers are more likely to travel at higher speeds, which result in increasing the likelihood of more severe crashes.

The difference in the significance of crash location effects on injury severity is worth noting. Based on the estimation results, the indicator variable representing crash locations provides a high statistically significant coefficient only in the dark condition model. The marginal effects of the crash location variable for the dark condition model indicate intersection crashes are more likely to be severe than those on the

Table 6
A summary of the variables affecting injury severity among the three lighting conditions.

Variables and description	Daylight	Dark	Dark-lighted
Road condition			
Segment length (segment length varied between 0.01 and 4.82 miles)	Positive		Positive
Crash location (1 if at intersection; otherwise 0)		Positive	
LogAADT (AADT varied between 140 and 25,000 veh/day)	Negative	Positive	
Curve (1 if in curve; otherwise 0)	Positive	Positive	
Curve direction (1 if right; left 0)			Negative
Steep grade (1 if grade more than 5%; otherwise 0)			
Grade direction (1 if uphill; downhill 0)	Negative		Positive
Curve grade (1 if curved section with a grade more than 5%; otherwise 0)	Positive	Positive	
Shoulder width (shoulder width varied between 0 and 24 ft)			Positive
Road surface (1 if wet, icy, and snowy; otherwise 0)	Negative	Positive	
Wet grade (1 if wet with a grade more than 5%; otherwise 0)	Negative		
Driver info			
Alcohol (1 if under influence of alcohol or drug, otherwise 0)	Positive	Positive	Positive
Asleep (1 if apparently asleep; otherwise 0)	Positive	Positive	N.E.
Inattention (1 if reported inattention, otherwise 0)			N.E.
Driver action (1 going straight, otherwise 0)	Positive	Negative	Positive
Collision info			
Head-on (front side) (1 if head-on collision; otherwise 0)	Positive	Positive	Positive
Rear-end (back side) (1 if rear-end collision; otherwise 0)	Negative	Positive	Negative
Left-side (1 if left-side impact; otherwise 0)		Positive	
Right-side (1 if right-side impact; otherwise 0)	Negative	Positive	
Rollover (1 if rollover; otherwise 0)	Positive	Positive	N.E.
Object (1 if collision with roadside objects; otherwise 0)		Positive	
Animal (1 if collision with an animal; otherwise 0)	Negative	Negative	Negative

Note: N.E. stands for not examined (there were too few crashes to draw conclusive results for these variables in the dark-lighted dataset.

roadway segments. Limited sight distance in darkness may delay driver's reaction at the impending collision with another vehicle at intersections; therefore, due to higher impact speeds, the injury severity of crashes increase in these locations on two-lane rural roads. However, the other two models could not find any significant correlation between crash locations and injury severity in daylight or dark-lighted conditions. Some studies (such as Huang, Chin, & Haque, 2008) also found that darkness increases the probability of severe crashes at intersections. However, this result is in contrast to the findings of Theofilatos, Graham, and Yannis (2012), which indicated that non-intersection-related crashes are 1.77 times more likely to be fatal or severe than those of at intersections. It is noted, unlike the present study, that their research did not consider intersection-related crashes under different lighting conditions. Therefore, this paper highlights the importance of deploying street lights at intersections or access points on two-lane, two-way rural roads.

Quite interestingly, the dark-lighted condition model suggests that shoulder width is positively associated with the increased levels of injury severity. However, in the daylight and dark lighting condition models, the variable of shoulder width was not statistically significant. As mentioned before, intersections include 65.2% of crash locations in the dark-lighted condition dataset. Therefore, one possible explanation for this finding could be that wide shoulders may promote improper use of the additional space by encouraging drivers to inappropriately use the shoulder for merging or lane-changing maneuvers at and near intersections or access points, resulting in increasing the probability of severe crashes during nighttime periods. Also, several studies have found partially similar results that shoulder width is positively associated with injury severity (Gårder, 2006; Haleem & Abdel-Aty, 2010; Hosseinpour, Yahaya, & Sadullah, 2014). It should be noted that, since prior studies proved that shoulder width has a negative effect on crash frequency, further research in this domain should be performed to evaluate the efficiency of different measures (e.g., installing shoulder rumble strips, improving delineation) for decreasing both frequency and severity of intersection-related crashes during nighttime periods.

The estimation results indicate that speed limit is a statistically significant variable in the daylight and dark-lighted condition models but not for the dark condition one. In both daylight and dark-lighted models, this variable is positively associated with the increased levels of injury severity. However, its significance for the daylight condition is remarkably higher than that for the dark-lighted condition model. This finding implies that drivers in roadways with higher speed limits are more likely to experience higher impact of collision at daytime periods but not significantly at nighttime. This is likely because drivers are more cautious and tend to travel at lower speeds in limited lighting conditions. The increasing pattern of injury severity by increasing speed limit also conforms to the studies done by Aarts and Van Schagen (2006) and Dee and Sela (2003), which investigated the effects of speed limit on injury severity. Nevertheless, this study highlights the significance of speed limit only in daylight conditions.

Regarding driver condition variables, there is a noteworthy finding about the effects of driver action on injury severity in the different lighting conditions. The indicator variable of driver action, representing driving straight before the impending crash, is statistically significant in every model. This variable is positively associated with the increased injury severity levels in daylight and dark-lighted conditions, while in the case of darkness, driving straight decreases the probability of severe crashes. One possible explanation for this finding may be that increased sight distance, as a result of going straight in suitable lighting conditions, provides additional confidence for the driver and promotes higher speeds leading to more severe injury crashes. On the other hand, due to the restriction of drivers' sight distance in dark lighting conditions, drivers are more likely to be faced with unexpected events such as sudden turning vehicles or other vehicles involved in the roadside activity. Therefore, the probability of occupants being involved in severe crashes decreases when drivers go straight compared to the situations that they do the other actions. Also, in prior studies, Islam and Hernandez (2013) found driving straight leads to less severe injury for large truck-involved crashes. However, it is noted that, unlike the current study, their research focused on only truck-related crashes and did not study lighting conditions separately.

Regarding collision type variables, head-on collision was found to be significant in every models and it increases the likelihood of more severe crashes. Also, rollover is statistically significant in both daylight and dark conditions. The sign of its coefficients indicate it is positively associated with the increased levels of injury severity. Examining the sizes of the marginal effects imply the effects of rollover on the injury categories are almost similar in daylight and dark lighting conditions. However, the marginal effects of head-on collision indicate this collision is much more likely to be severe in darkness. This is likely because drivers may have less reaction time and perception ability on crash risk of head-on collisions in dark conditions compared to the sufficient lighting conditions. Also, these results are consistent with prior studies (Khattak, Schneider, & Targa, 2003; Kockelman & Kweon, 2002; Lee & Li, 2014) that they have found rollover and head-on crashes lead to more severe injuries.

In contrast to head-on and rollover crashes, animal-involved crashes consistently decrease the possibility of occupants being involved in severe crashes in every lighting conditions.

Right-side impact collision type decreases the probability of severe crashes in daylight conditions but increases this probability for dark conditions. As previously mentioned, increased impact speed under insufficient lighting conditions may be the reason for increasing the probability of occupants (especially passengers) being involved in severe crashes for the right-side impact collisions related to the vehicles coming from opposite direction on two-lane rural roads. Also, the left-side impact variable was found to be statistically significant only in dark conditions. Left-side impact collisions are positively associated with the increased levels of injury severity only in dark conditions. Also, partially consistent results can be found in past studies (Theofilatos et al., 2012; Islam & Hernandez, 2013; Zhu & Srinivasan, 2011), which suggested sideswipe collisions decrease the probability of severe crashes. However, none of them have not considered the effects darkness on these collisions.

A key finding is the change of signs of the rear-end collisions between the lighting condition models. Rear-end collisions decrease the probability of severe crashes in daylight and dark-lighted conditions; however, darkness reduces the available reaction distance and increases the closing speed which results in increasing the likelihood of severe crashes in dark conditions for two-lane rural roads. Similar to these results, Duncan et al. (1998) found that darkness causes more severe rear-end crashes and street lighting eliminates the effects of darkness on injury severity of these crashes.

Finally, hitting fixed objects was found to be significant only in the dark condition model, which increases the probability of severe crashes on two-lane rural roads. Low visibility of roadside objects in darkness may delay the driver's reaction at the impending collision; therefore, the collision impact is high due to the high impact speed. A consistent result also can be found in the study by Holdridge, Shankar, and Ulfarsson (2005), which suggested the severity of this collision type increases in dark lighting conditions. Moreover, they demonstrated that streetlights can decrease the probability of fatal or disabling injury level of fixed object-related crashes.

7. Conclusions

In this paper, the fixed-effects ordered probit model was employed to investigate lighting condition differences in the injury severity of crashes for two-lane rural roads. Using the data from the state of Washington, separate models for three lighting conditions were developed: daylight, dark, and dark-lighted. A series of likelihood ratio tests were conducted to determine that these lighting condition models were justified. The estimation results suggest that the crash injury severity levels in different lighting conditions are associated with contributing factors in different ways, and such differences cannot be uncovered by estimating merely one aggregate model.

The evidence shows striking and significant differences among the three lighting condition models. These differences are in terms of the sign, size, and significance of the explanatory variables in each model. Key differences include crash location, speed limit, shoulder width, driver action, head-on collision, rear-end collision, and right-side impact collision. For example, it was found that increasing speed limits causes an increase of the probability of sustaining severe injuries in daylight conditions, but it does not have a significant effect on crash severity in the nighttime lighting conditions.

The modeling results indicate that the severity of crashes highly increases when the crashes occur at intersections in dark conditions. Whereas in sufficient lighting conditions, the crash location variable was not found to be statistically significant at the 0.05 level. In addition, shoulder width was found to be positively associated with the increased levels of injury severity in dark-lighted conditions on two-lane rural roads. This finding implies the importance of shoulder width near intersections or access points at nighttime periods.

As regards collision types and their effects on injury severity, a head-on collision is much more likely to be severe in darkness compared to the sufficient lighting conditions. Moreover, the effects of rear-end collisions on injury severity were found opposite between daylight, dark-lighted, and dark lighting conditions, so that darkness increases the probability of occupants being involved in severe crashes when rear-end collisions occur.

The development of three separate injury models based on lighting conditions for crashes in two-lane rural roads has yielded some new information not present in the existing literature. However, similar to most past studies, the current study also has some limitations, such as it used a single database from a single state so that there were few crashes to draw conclusive estimates for several variables.

For future studies, an extension of this research can be proposed. In this way, depending on different research purposes, a more in-depth form of lighting condition analysis can be conducted by regarding different categories of data such as region, crash type, environmental conditions, and so forth. For example, it would be worthwhile to analyze the interaction of separate lighting conditions in different roadway surfaces with the injury severity of specific types of crashes.

Acknowledgments

This research was supported, in part, by the Highway Safety Information System (HSIS) through the contribution of data. The authors would like to thank Ms. Anushapatel Nujjetty at HSIS. Opinions expressed in this report are those of the authors and may not necessarily reflect the views and policies of HSIS.

References

Aarts, L., & Van Schagen, I. (2006). Driving speed and the risk of road crashes: A review. *Accident Analysis and Prevention*, *38*(2), 215–224.

Abdel-Aty, M., & Keller, J. (2005). Exploring the overall and specific crash severity levels at signalized intersections. *Accident Analysis and Prevention*, *37*(3), 417–425.

Bedard, M., Guyatt, G. H., Stones, M. J., & Hirdes, J. P. (2002). The independent contribution of driver, crash, and vehicle characteristics to driver fatalities. *Accident Analysis and Prevention*, *34*(6), 717–727.

Borooah, V. K. (Ed.). (2002). *Logit and probit: Ordered and multinomial models (No. 138)*. Sage.

Chen, F., & Chen, S. (2011). Injury severities of truck drivers in single-and multi-vehicle accidents on rural highways. *Accident Analysis and Prevention*, *43*(5), 1677–1688.

Dee, T. S., & Sela, R. J. (2003). The fatality effects of highway speed limits by gender and age. *Economics Letters*, *79*(3), 401–408.

Dong, C., Richards, S. H., Huang, B., & Jiang, X. (2013). Identifying the factors contributing to the severity of truck-involved crashes. *International Journal of Injury Control and Safety Promotion*, 1–11 (ahead-of-print).

Duncan, C. S., Khattak, A. J., & Council, F. M. (1998). Applying the ordered probit model to injury severity in truck-passenger car rear-end collisions. *Transportation Research Record: Journal of the Transportation Research Board*, *1635*(1), 63–71.

Gårder, P. (2006). Segment characteristics and severity of head-on crashes on two-lane rural highways in Maine. *Accident Analysis and Prevention*, *38*(4), 652–661.

Gelman, A., & Hill, J. (2006). *Data analysis using regression and multilevel/hierarchical models*. Cambridge University Press.

Greene, W. H., & Hensher, D. A. (2010). *Modeling ordered choices: A primer*. Cambridge University Press.

Haleem, K., & Abdel-Aty, M. (2010). Examining traffic crash injury severity at unsignalized intersections. *Journal of Safety Research*, *41*(4), 347–357.

Holdridge, J. M., Shankar, V. N., & Ulfarsson, G. F. (2005). The crash severity impacts of fixed roadside objects. *Journal of Safety Research*, *36*(2), 139–147.

Hosseinpour, M., Yahaya, A. S., & Sadullah, A. F. (2014). Exploring the effects of roadway characteristics on the frequency and severity of head-on crashes: Case studies from Malaysian federal roads. *Accident Analysis and Prevention*, *62*, 209–222.

Huang, H., Chin, H. C., & Haque, M. M. (2008). Severity of driver injury and vehicle damage in traffic crashes at intersections: A Bayesian hierarchical analysis. *Accident Analysis and Prevention*, *40*(1), 45–54.

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

Islam, S., Jones, S. L., & Dye, D. (2014). Comprehensive analysis of single-and multi-vehicle large truck at-fault crashes on rural and urban roadways in Alabama. *Accident Analysis and Prevention*, *67*, 148–158.

Khattak, A. J., Schneider, R. J., & Targa, F. (2003). Risk factors in large truck rollovers and injury severity: analysis of single-vehicle collisions. *Transportation Research Record*.

Khorashadi, A., Niemeier, D., Shankar, V., & Mannering, F. (2005). Differences in rural and urban driver-injury severities in accidents involving large-trucks: An exploratory analysis. *Accident Analysis and Prevention*, *37*(5), 910–921.

Kockelman, K. M., & Kweon, Y. J. (2002). Driver injury severity: An application of ordered probit models. *Accident Analysis and Prevention*, *34*(3), 313–321.

Lee, C., & Li, X. (2014). Analysis of injury severity of drivers involved in single-and two-vehicle crashes on highways in Ontario. *Accident Analysis and Prevention*, *71*, 286–295.

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

Mujalli, R. O., & de Oña, J. (2013). *Injury severity models for motor vehicle accidents: A review*.

Obeng, K. (2011). Gender differences in injury severity risks in crashes at signalized intersections. *Accident Analysis and Prevention*, *43*(4), 1521–1531.

Pahukula, J., Hernandez, S., & Unnikrishnan, A. (2015). A time of day analysis of crashes involving large trucks in urban areas. *Accident Analysis and Prevention*, *75*, 155–163.

Pai, C. W., & Saleh, W. (2008). Modelling motorcyclist injury severity by various crash types at T-junctions in the UK. *Safety Science*, *46*(8), 1234–1247.

Rana, T. A., Sikder, S., & Pinjari, A. R. (2010). Copula-based method for addressing endogeneity in models of severity of traffic crash injuries. *Transportation Research Record: Journal of the Transportation Research Board*, *2147*(1), 75–87.

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

Theofilatos, A., Graham, D., & Yannis, G. (2012). Factors affecting accident severity inside and outside urban areas in Greece. *Traffic Injury Prevention*, *13*(5), 458–467.

Wang, X., & Abdel-Aty, M. (2008). Analysis of left-turn crash injury severity by conflicting pattern using partial proportional odds models. *Accident Analysis and Prevention*, *40*(5), 1674–1682.

Washington, S. P., Karlaftis, M. G., & Mannering, F. L. (2012). *Statistical and econometric methods for transportation data analysis*. CRC press.

Wood, D. P., & Simms, C. K. (2002). Car size and injury risk: A model for injury risk in frontal collisions. *Accident Analysis and Prevention*, *34*(1), 93–99.

World Health Organization (2013). *WHO global status report on road safety 2013: Supporting a decade of action*. World Health Organization.

Xie, Y., Zhao, K., & Huynh, N. (2012). Analysis of driver injury severity in rural single-vehicle crashes. *Accident Analysis and Prevention*, *47*, 36–44.

Zhu, X., & Srinivasan, S. (2011). A comprehensive analysis of factors influencing the injury severity of large-truck crashes. *Accident Analysis and Prevention*, *43*(1), 49–57.

M. Hadji Hosseinlou received his B.E. degree in civil engineering from the University of Tabriz, Tabriz, Iran, in 1987, and M.Sc. and Ph.D. degrees in traffic and transportation engineering from Hokkaido University, Sopporo, Japan, in 1995 and 1998, respectively. In 2002, he joined the Department of Civil Engineering, K. N. Toosi University of Technology, as an Assistant Professor. His current research interests include traffic safety and transportation planning.

A. Jafari Anarkooli earned his B.E. degree in Civil Engineering from the University of Ardebil, Ardebil, Iran, in 2011, and his M.Sc. degree in Traffic and Transportation Engineering from K. N. Toosi University of Technology, in 2014. He also achieved rank of 4 in the National PhD entrance exam in 2014.