Large Truck–Involved Crashes: Exploratory Injury Severity Analysis

Mouyid Islam[1] and Salvador Hernandez, Ph.D.[2]

Abstract: In recent years, a growing concern related to large truck accidents has increased owing to the level of injury severity that can be sustained and to the related potential economic impact. Current studies related to large truck–involved crashes are scarce and do not address the human factors that can greatly influence accident outcomes. This study presents an analysis of data from the fusion of several national data sets addressing injury severity related to large truck–involved crashes. This is accomplished by considering human, road environment, and vehicular factors in large truck–involved crashes on U.S. interstates. A random-parameter ordered-probit model was estimated to predict the likelihood of five injury severity outcomes—fatality, incapacitating, nonincapacitating, possible injury, and no injury. The modeling approach accounts for possible unobserved effects relating to human, vehicular, and road environment factors not present in the data. Estimation findings indicate that the level of injury severity is highly influenced by a number of complex interactions between factors, and the effects of some factors can vary across observations. **DOI: 10.1061/(ASCE)TE.1943-5436.0000539.** *© 2013 American Society of Civil Engineers.*

CE Database subject headings: Freight transportation; Trucks; Injuries; Parameters; Traffic accidents.

Author keywords: Freight movement; Large trucks; Ordered probit; Random parameter; Safety; Injury severity.

Downloaded from ascelibrary.org by UTEP LIBRARY-SERIALS on 05/28/13. Copyright ASCE. For personal use only; all rights reserved.

Introduction

Trucking is a vital component of any prospering and growing economy. It is the backbone of many logistic and supply-chain systems. Growing concerns related to large truck [gross vehicle weight rating (GVWR) greater than 4,535.9 kg (10,000 pounds)] crashes have increased in recent years owing to the potential level of injury severity and economic impact. Recent statistical data indicate that large trucks have a higher rate of crash involvement than passenger vehicles in the United States controlling for the number of registered vehicles and vehicle miles traveled (VMT) [Federal Highway Administration (FHWA) 2010; National Highway Traffic Safety Administration (NHTSA) 2008]. Although large trucks accounted for 4% of registered vehicles and 8% of VMT in 2008, 11% of motor vehicle deaths in 2008 were a result of large truck crashes (FHWA 2010). Large trucks impact the national economy heavily through daily freight movements. However, large truck–involved crashes also impact the level of injury severity of collision partners and incur high societal cost associated with fatalities, injuries, and property damages.

The cost associated with these large truck–involved crashes is of great concern and can be substantial. Based on 2005 dollars, the estimated cost of a police-reported crash involving a large truck, considering all truck-tractor with trailer configurations, averaged $91,112 (Zaloshnja and Miller 2006). In addition, this study estimated the average cost per fatality, nonfatality, and property damage only as $3,604,518, $195,258, and $15,114, respectively. An earlier study by Zaloshnja and Miller (2004) estimated the cost associated with different configurations of large trucks involved in crashes. According to this study, of all configurations of truck-tractor carrying a different number of trailers and multiple combination trucks (i.e., large truck carrying two or three trailers) had the highest cost at $88,483 per crash based on Year 2000 dollars. The crash costs based on Year 2000 dollars per 1,000 truck miles were $157 for single unit trucks, $131 for single combination trucks, and $63 for multiple combinations (Zaloshnja and Miller 2004). These costs illustrate the potential monetary impacts large truck crashes have on society. Hence, any increase in the number or severity of these types of crashes is of great concern to organizations that operate, maintain, and construct the transportation system as well as to trucking companies.

With this in mind, this study aims to analyze the injury severity of large truck–involved crashes through an econometric modeling approach. The random-parameters ordered-probit model is utilized to shed light on the factors contributing to large truck crashes. To achieve this, the fusion of three data sets from the National Automotive Sampling System General Estimates System (NASS-GES) crash database was used. This fused data set is hoped to provide an improved understanding of the complex interactions between contributing factors influencing large truck crash results. The three fused data sets pertain to human, vehicle, and road-environment factors. To capture these complexities using the NASS-GES database, consideration of random parameters provides a mechanism to account for any unobserved heterogeneity. To the best of the authors' knowledge, this study is one of the first attempts at modeling large truck injury severity focusing on the U.S. interstate system by utilizing the NASS-GES data set. Although the random-parameters ordered-probit model has been applied to large truck crash severity from different modeling perspectives, these studies use limited data sets and do not consider the potential effect of unobserved factors on crash severity outcomes exclusively (see the next section). By contrast, our research extends the current literature and introduces

[1]Graduate Research Assistant, Dept. of Civil Engineering, 500 West University Ave., Univ. of Texas at El Paso, El Paso, TX 79968. E-mail: mbislam@miners.utep.edu

[2]Assistant Professor, Dept. of Civil Engineering, 500 West University Ave., Univ. of Texas at El Paso, El Paso, TX 79968 (corresponding author). E-mail: shernandez43@utep.edu

Note. This manuscript was submitted on June 14, 2012; approved on January 9, 2013; published online on January 11, 2013. Discussion period open until November 1, 2013; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Transportation Engineering***, Vol. 139, No. 6, June 1, 2013. © ASCE, ISSN 0733-947X/2013/6-596-604/$25.00.

additional significant variables related to human factors in regard to large truck crashes.

Literature Review

This section presents a synthesis of previous research with special attention given to the methodological approaches that establish any links between crash characteristics and injury severity with human, vehicle, and road environment factors.

A recent study by Lemp et al. (2011) introduced a heteroskedastic ordered-probit (HOP) model to analyze the injury severity in crashes involving at least one large truck. The analysis of large trucks in this study was limited to long-combination trucks (LVCs) of two or more trailers with a GVWR of 36,287 kg (80,000 lb). They utilized a HOP model specification for greater flexibility in parameter estimation over the standard ordered-probit (OP) model to address the issue of heteroskedasticity (i.e., nonconstant variance) across the observations. Their model results indicated that in an injurious large truck crash, the likelihood of an injury of lesser severity was greatly increased if a crash occurred at curved sections of a roadway, if a crash occurred on a roadway sag, if the trucks were overweight, if a driver was under the influence of illegal drugs, and/or if a driver exhibited aggressive driving behavior other than speeding. Their study was limited to data provided from the Large Truck Crash Causation Study (LTCCS) collected between 2001 and 2003. Moreover, the modeling approach did not explicitly account for any unobserved factors (i.e., factors not captured in the data set but that may be contributing to the injury severity outcomes).

Zhu and Srinivasan (2011) applied an ordered-probit model using the data from large truck–involved crashes. The aim of the study was to address the need for research regarding large truck safety in addition to contributions to transportation policy, improvement of motor carrier operations, and incident cost reductions. The study found that head-on collisions and collisions at intersections were the most serious, whereas crashes on multilane highways were less severe. Their estimation results indicated that particular attention must be paid to truck corridors near major tourist spots because of network (route) unfamiliarity issues of passenger car drivers. Namely, distracted driving, driving under the influence, or emotional distraction increased the likelihood of severe crashes. Other factors such as truck-driver fatigue, aggression, and seat belt usage turned out to be statistically insignificant. This study was based on a small data set extracted from the LTCCS study.

As with the present work, Chistoforou et al. (2010) applied a random-parameter ordered-probit framework to large truck crashes, but it was applied to road users to address the challenge of external cost estimation and roadway safety. The data they utilized for their analysis period is not continuous (2000–2002 and then 2006 were considered). This discontinuity in the analysis period could lead to estimation errors; that is, some observed and unobserved factors may vary from year-to-year. For example, weather may vary from year-to-year, geometry (e.g., widening shoulder or median or installing a roadside barrier), or policy-related factors (e.g., change in posted speed limit). These variations could lead to variations in the injury severities that are experienced from year-to-year and could lead to erroneous estimates (Tarko et al. 2011).

Duncan et al. (1998) applied an ordered-probit model for rear-end collisions between truck and passenger car. The authors found when a rear-end crash outcome occurs between a passenger car and truck, factors related to darkness, high speed differentials, high speed limits, grades (especially when wet), being in a car struck from the rear, driving while drunk, and being female increase the likelihood of a high severity of injury for passenger vehicle occupants. The study also found car rollovers and the situation in which a car is rear-ended by a truck at a high speed differential to be significant. Driving on snowy, icy, or congested roads; the use of a child restraint in passenger vehicles; and being in a rear-ended station wagon as opposed to a sedan are likely to reduce the severity outcome of the crashes. This study was limited to the inadequate traffic data on certain segments of highway at the time of crash. That is to say, unavailable road inventory data, such as the number of lanes and traffic flow data, not present in the crash data set could lead to unobserved factors influencing injury severity outcomes, thus leading to biased estimates of the parameters. For instance, the number of directional lanes indirectly related to the ease or tendency of lane-changing behavior of the passenger and heavy vehicle drivers. Similarly, the traffic flow is related to time of day, types of crashes such as single- and multivehicle (Qin et al. 2006) as well as speed and injury severities of the involved vehicles. To limit biased estimates, a comprehensive database should be considered. This study considers the GES system because it is a nationally representative sampled crash database.

From a logit-based approach, Chang and Mannering (1999) applied a nested logit structure to model injury severity based on vehicle occupancy in terms of exposure effects to address the issue of severe injury caused by large trucks (i.e., nesting structure was based on vehicle occupancy). Their results indicate that the effects of trucks on crash injury severity are greater for multioccupant vehicles over single-occupant vehicles, although the multioccupant vehicle crash data set was limited in the number of observations. The authors considered nonincapacitating injury, incapacitating injury, and fatal injury into one single group, which could be separated and addressed in different modeling approaches, such as ordered-probit models where all five categories—fatality, incapacitating, no-incapacitating, possible injury, and property damage only (no injury)—could be addressed. However, considering disaggregate injury outcomes (i.e., considering nonincapacitating injury, incapacitating injury, and fatal separately rather than combined) could be challenging in the model estimation that depends on data regarding those injury outcomes in the sample.

Khorashadi et al. (2005) investigated injury severity through the use of a multinomial logit model to address large truck crashes and fatalities and the limitations of other studies regarding crash frequencies. Although not incorporated in their study, they identify the urgency of additional research regarding human factors such as perceptual, cognitive, and response demands of drivers to explain the complex interaction of factors in crashes. Their study was focused on the exclusive use of crash data from California.

A mixed logit framework was implemented by Milton et al. (2008) to capture injury severities of crashes involving all vehicles—not explicitly focusing on large truck crashes—on roadway segments to address the challenges of methodological approaches related to count models. Their model results indicate that the average daily traffic (ADT) per lane (in thousands of vehicles) for slightly less than half of the roadway segments in the sample result in a decrease in property damage only (PDO) crashes, which implies an increase in more severe injury outcomes. They found that increasing pavement friction decreases the likelihood of possible injury and increases the likelihood of PDO and injury; whereas a greater snowfall increases the likelihood of PDO and consequently decreases the likelihood of more severe injury outcomes. The number of horizontal curves and the number of grade breaks, both used as a fixed parameter, and the number of interchanges per mile in the roadway segment reduces the likelihood of injury crashes. Their work was limited to an aggregated data set to avoid missing event specific information.

J. Transp. Eng. 2013.139:596-604.

Downloaded from ascelibrary.org by UTEP LIBRARY-SERIALS on 05/28/13. Copyright ASCE. For personal use only; all rights reserved.

From the perspective of large truck–involved crashes, Vadlamani et al. (2011) conducted a hot spot analysis of high-risk sites through both a negative binomial regression model and a proposed methodology that utilized property damage only equivalents (PDOEs). The authors found that the hot spots identified by the negative binomial model exhibited low fatalities and major injuries but large minor injuries and PDOs and presented large annual average daily traffic (AADTs) in contrast to the PDOE methodology. In addition, site investigations at the hot spots indicated the potential risk factors such, as weaving activities near freeway junctions and ramps, absence of acceleration lanes near on-ramps, small shoulders to accommodate large trucks, narrow lane widths, inadequate signage, and poor lighting conditions within a tunnel, suggest inadequate road design and inefficient and unsafe traffic operation. Their work provides a methodology for screening large truck–involved crashes and provides a way to quantify the societal impacts of such crashes.

The current literature related to the modeling of large truck crash severity is wide and extensive in nature. However, various aspects of the problem have not been addressed with particular emphasis, for instance, on human factors focusing on precrash driving behaviors over the U.S. interstate system. It is evident through the presented works that data sample age and size is an issue. The present research differentiates itself from the presented works through the use of a comprehensive nationally representative sampled crash database that incorporates human-related factors, vehicle factors, and road environment variables. This study considers additional human-related factors that are not only limited to the driving behavior in the precrash phase but also include drivers' demographics into the modeling framework. Furthermore, it utilizes a large database to minimize the effects of unaccounted for factors dealing with human behavior. Also, large trucks are defined to be greater than 4,536 kg (10,000 lb) as defined by the Insurance Institute for Highway Safety (IIHS).

Empirical Setting

The data for large truck crashes was collected from the National Automotive Sampling System General Estimated System (NASS-GES) crash database maintained by the National Highway Traffic Safety Administration (NHTSA). A large truck, as defined by the IIHS and for this study, can be classified as a tractor-trailer, single-unit truck, or cargo van having gross vehicle weight rating (GVWR) greater than 4,536 kg (10,000 lb). According to the *Analytical Users' Manual* (NASS-GES 2005), the GES database is based on a nationally representative probability sample selected from an estimated 5.8 million police-reported crashes that occur annually, resulting in a fatality or injury and those involving major property damage.

According to a technical report by NHTSA (2009), 25% of minor injury crashes and half no-injury crashes are unreported (Savolainen et al. 2011). This study considered the GES sample data over a period of 4 years from 2005 to 2008 for large truck–involved crashes. Despite the issues of underreporting for minor and no personal injury along with the multistage sampling scheme in the GES database, the GES focuses on crashes of greatest concern to the highway safety community and the general public (NASS-GES 2005).

To investigate human, vehicle, and road environment factors, a sample of 8,291 data observations is used in which each observation is a crash representing the most severely injured occupants (i.e., the worst injury level) involving at least a large truck on the interstate system from 2005 to 2008. The nontruck vehicles are broadly classified as passenger cars and their derivatives and light trucks [having GVWR less than 4,536 kg (10,000 lb)] and comprises approximately 71 and 21%, respectively, of the vehicles involved with large trucks in this sample. The statistics clearly indicate that quite a large number of passenger vehicles are involved in large truck crashes. This truck-involved data sample (i.e., 8,291 observations) was extracted from the GES crash data set with an average of 56,970 crashes (i.e., truck and non-truck–involved crashes) reported each year from 2005 to 2008. The crash data set was fused to the vehicle and person data set through the appropriate linking variable and crash number, whereas vehicle and person data sets were linked through vehicle and crash number using the Statistical Analysis System (SAS 2011). The random-parameter ordered-probit modeling framework was modeled in Limdep (NLOGIT 4.0) (Greene 2007).

Descriptive statistics of key variables used in the model (i.e., all independent variables) are presented in Table 1. The dependent variable has five levels of injury categories—fatality (K), incapacitating (A), nonincapacitating (B), possible injuries (C), and noninjury (O) or property damage only (PDO), which represent 56 (0.06%), 258 (3.1%), 527 (6.3%), 593 (7.1%), and 6,857 (82.7%) of the sample size considered in this study, respectively.

Human factors cover occupant's demographics, driving behavior, restraint usage, and driving or living area vicinity. Turning to

Table 1. Descriptive Statistics of Key Variables in the Model

Variable	Meaning of variables in the model	Mean	Standard deviation
CURVE	Alignment of highway section (1 for curved section, 0 otherwise)	0.1353	0.3421
WEEKEND	Day of the week (1 if weekend, 0 otherwise)	0.1455	0.3526
SUMMER	Months of the year [1 if summer months (June–August), 0 otherwise]	0.2387	0.4263
DARK	Light condition of street (1 if dark, 0 otherwise)	0.1341	0.3408
VEH_INVL	Number of vehicles involved in the crash	2.0526	0.8034
TRAIL1	Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	0.7523	0.4317
PASSIVE	Vehicle role (1 if struck by other vehicle, 0 otherwise)	0.3711	0.4831
RLOVER	The most harmful event (1 if rollover, 0 otherwise)	0.8019	0.3985
LRRDDEP	Vehicle maneuver during precrash situation (1 if left- or right-side departure, 0 otherwise)	0.1354	0.3422
SSWIPESD	Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	0.2632	0.4404
LANECHNG	Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	0.0988	0.2984
GOSTRGHT	Vehicle maneuver just before impending crash (1 if going straight, 0 otherwise)	0.6490	0.4773
SPEEDFAC	Factor of crash identified in the investigation (1 if speed, 0 otherwise)	0.1438	0.351
TEXAS1	Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	0.1019	0.3026
LAPSHLD	Occupants' use of available vehicle restraints (1 if lap and shoulder belt used, 0 otherwise)	0.8229	0.3817
MALE	Gender of the occupants (1 if male, 0 otherwise)	0.9388	0.2396
AGE5565	Age of occupants (1 if age group is 55–65, 0 otherwise)	0.1271	0.3331

J. Transp. Eng. 2013.139:596-604.

Downloaded from ascelibrary.org by UTEP LIBRARY-SERIALS on 05/28/13. Copyright ASCE. For personal use only; all rights reserved.

Table 1 demographics, males make up approximately 93.8% of the sample and age between 55 and 65 accounts for approximately 12.7% of the sample. Speed as a contributing factor in the crash identified through the investigation process accounts for 14.4% of the sample. Restraint usage (i.e., lap and shoulder belt) accounts for approximately 82.2% of the sample. Drivers residing in the state of Texas account for approximately 10.2% of the sample. Turning to vehicular characteristics, trucks carrying single trailing unit account for approximately 75.2% of sample. On average, there are two vehicles involved in the crashes in this study. Vehicular role being passive in crashes (i.e., being struck by another vehicle in the crash) accounts for approximately 37.1% of the sample. Then, road and environmental characteristics, such as curved sections of the highways, account for approximately 13.5% of the sample. Lighting condition at the time of the crash, such as darkness, represents approximately 13.4% of the sample. Temporal characteristics, such as weekend (i.e., Saturdays and Sundays) and summer months (i.e., June to August), account for approximately 14.5 and 23.9% of the sample, respectively. Finally, crash mechanism such as rollover, departing the roadway, sideswipe in the same direction, lane changing, and going straight in the lane accounts for approximately 80.2, 13.5, 26.3, 9.8, and 64.9% of the sample, respectively.

The correlation matrix for the ordered-probit model was performed and indicated that none of the variables of interest have a correlation value of more than ± 0.50. The correlation matrix shows the maximum correlation between departing the roadway and the number of vehicles involved is -0.477. Similarly, the crash mechanism, such as lane changing and going straight, shows a correlation of -0.450. However, these two situations show logical relationship in terms of their signs (i.e., they are negatively correlated). This is possibly due to a single vehicle running off the road rather than multiple vehicles. Similarly, lane changing and going straight (i.e., lane keeping) deal with dissimilar characteristics with respect to driving maneuvers and in reality may not indicate any degree of multi-colinearity.

Methodology

To obtain a better understanding of the factors associated with large truck–involved crashes, a random-parameters ordered-probit–modeling approach is proposed to capture the injury severity experienced and to account for any unobserved heterogeneity (Zhu and Srinivasan 2011; Chistoforou et al. 2010; McKelvey and Zavoina 1975). Since the level of injury is ordinal in nature, the KABCO scale [fatality (K), incapacitating (A), nonincapacitating (B), possible injuries (C), and noninjury (O) or property damage only (PDO)] is followed. To reduce the bias and variability in the parameters estimation resulting from any underreporting tendency in the crash data reporting system, a descending order of injury severity level 0 for K (fatality), 1 for A (incapacitating injury), 2 for B (nonincapacitating injury), 3 for C (possible injury), and 4 for O (property damage only) is considered. Ye and Lord (2011) showed that by formulating in descending order of injury severity (KABCO) rather than ascending order (OCBAK) reduced the bias and variability of the estimated parameters for the ordered-probit model. Ye and Lord (2011) tested this under different simulation scenarios.

With this in mind, the ordered-probit models have been widely applied to model the marginal probability effects of several contributory factors on injury severity by considering 0 for no injury/PDO, 1 for possible injuries, 2 for nonincapacitating injury, 3 for incapacitating injury, and 4 for fatality (Chistoforou et al. 2010; Abdel-Aty 2003; Gray et al. 2008; Kockelman and Kweon 2002; Lee and Abdel-Aty 2005; O'Donnell and Connor 1996; Pai and Saleh 2008; Quddus et al. 2002; Xie et al. 2009; Zajac and Ivan 2003). However, this study models the level of injuries as five levels of ordinal categories of the dependent variable and is as follows: 0 for fatality, 1 for incapacitating injury, 2 for nonincapacitating injury, 3 for possible injury, and 4 for property damage only.

The model is formulated by defining an unobserved variable y^* as a modeling basis of ordinal ranking of the data, with y^* specified as a latent and continuous measure of injury severity of each observation (Washington et al. 2011)

$$y^* = \boldsymbol{\beta}\mathbf{X} + \varepsilon \tag{1}$$

where y^* = dependent variable (specified as a latent and continuous measure of injury severity of each observation n); $\boldsymbol{\beta}$ = vector of estimable parameters; $\mathbf{X}$ = vector of explanatory variables (e.g., human, roadway segment, vehicle, and crash mechanism characteristics); and ε = random error term (assumed to be normally distributed with 0 mean and a variance of 1).

By using Eq. (1) and under the order probit framework, the observed ordinal data y (e.g., injury severity) for each observation can be represented as (Washington et al. 2011)

$$\begin{array}{ll} y = 0 \quad \text{if } \infty \le y^* \le \mu_0 & y = 1 \quad \text{if } \mu_0 \le y^* < \mu_1 \\ y = 2 \quad \text{if } \mu_1 \le y^* < \mu_2 & y = \cdots \\ y = I-1 \quad \text{if } \mu_{I-2} \le y^* < \mu_{I-1} & y = I \quad \text{if } \mu_{I-1} \le y^* < \infty \end{array} \tag{2}$$

where μ = estimable parameters or thresholds between two adjacent injury categories that define y and are estimated jointly with the model parameters $\boldsymbol{\beta}$, which corresponds to integer ordering; and I = highest integer ordered response (e.g., for PDO, this is 4).

To estimate the probabilities of I specific ordered response for each observation n, ε is assumed to be normally distributed with 0 mean and variance 1. The ordered-probit model with ordered selection probabilities is defined as follows:

$$\begin{aligned} P_n(y=0) &= \Phi(-\boldsymbol{\beta}\mathbf{X}) \\ P_n(y=1) &= \Phi(\mu_1 - \boldsymbol{\beta}\mathbf{X}) - \Phi(-\boldsymbol{\beta}\mathbf{X}) \\ P_n(y=2) &= \Phi(\mu_2 - \boldsymbol{\beta}\mathbf{X}) - \Phi(\mu_1 - \boldsymbol{\beta}\mathbf{X}) \\ &\cdots \\ P_n(y=1) &= 1 - \Phi(\mu_{I-1} - \boldsymbol{\beta}\mathbf{X}) \end{aligned} \tag{3}$$

where $P_n(y=1)$ is the probability that observation n has I as the highest ordered response index (for instance, injury outcomes, in our case PDO), given a crash occurred; and $\Phi(\cdot)$ = standard normal cumulative distribution function.

Marginal effects are computed at the sample mean for each category (Washington et al. 2011; Greene 1997)

$$\frac{P_n(y=1)}{\partial \mathbf{X}} = [\phi(\mu_{I-2} - \boldsymbol{\beta}\mathbf{X}) - \phi(\mu_{I-1} - \boldsymbol{\beta}\mathbf{X})]\boldsymbol{\beta} \tag{4}$$

where $\Phi(\cdot)$ = probability mass function of the standard normal distribution.

To accommodate any unaccounted factors that may vary across observations, this study extends the standard ordered-probit model to account for random parameters (Chistoforou et al. 2010; Train 1997; Revelt and Train 1998; Brownstone and Train 1999; McFadden and Train 2000; Bhat 2001; Eluru et al. 2008; Anastasopoulos and Mannering 2009; Anastasopoulos et al. 2009a, b). The inclusion of random parameters provides a mechanism to minimalize inconsistent, inefficient, and biased parameter

J. Transp. Eng. 2013.139:596-604.

Downloaded from ascelibrary.org by UTEP LIBRARY-SERIALS on 05/28/13. Copyright ASCE. For personal use only; all rights reserved.

estimates (Washington et al. 2011). By contrast, the fixed-parameters ordered-probit model would lead to bias estimates while neglecting the unobserved heterogeneity as shown by Chistoforou et al. (2010). This would be the case because (1) some assumptions regarding the standard probit model limits its applicability; (2) the marginal probability effects change their sign while moving from the smallest to the largest outcome; and (3) possible unobserved factors are not properly addressed. The assumptions made in the standard fixed-parameters ordered-probit model (Chistoforou et al. 2010) are (1) independent variables $\boldsymbol{\beta}$ are fixed over the observations; (2) threshold μ's are fixed across observations; (3) probability functions shown in Eq. (3) are single indexed (i.e., fixed in single direction); and (4) the error terms are normally distributed. Furthermore, there are limitations in the applicability of the fixed-parameter probit model. For example, an air bag very likely decreases the likelihood of fatalities and increases the likelihood of no-injury crashes (i.e., PDO). However, air bag deployment, in reality, decreases fatalities but increases minor injuries (i.e., interior categories). As such, the practical flexibility of fixed-parameter ordered probit is limited (Washington et al. 2011).

Greene (2007) developed an estimation procedure that utilized simulated maximum likelihood estimation to incorporate random parameters in the ordered-probit modeling scheme (Greene 2007). The random-parameter ordered-probit model is formulated by taking into account an error term being correlated with the unobserved factors in ε_i [as shown in Eq. (1)], which translates the individual heterogeneity into parameter heterogeneity as follows (Greene 1997):

$$\beta_{in} = \beta + \gamma_{in} \tag{5}$$

where γ_{in} = randomly distributed term (for example, a normally distributed term with mean 0 and variance σ^2).

Estimation of the random-parameters model is done using a Halton sequence approach (Milton et al. 2008; Anastasopoulos and Mannering 2009; Halton 1960; Train 1997; Bhat 2003). Two hundred Halton draws are used to estimate the parameters that maximize the simulated log-likelihood function (Chistoforou et al. 2010). As with previous studies, this study considered the normal, lognormal, triangular, and uniform distributions for the functional form of the parameter density function (Gkritza and Mannering 2008; Anastasopoulos and Mannering 2009).

Empirical Results and Discussions

Fixed- and random-parameters ordered-probit models are estimated using maximum likelihood and simulation-based maximum likelihood methods for parameter vector β, respectively. With regard to the distribution of the random parameters in this analysis, consideration was given to the normal, lognormal, triangular, and uniform distributions. Only the normal distribution was found to be statistically significant. Two hundred Halton draws were used for the simulation-based maximum likelihood estimate. This number of draws has been empirically shown to produce accurate parameter estimates (Milton et al. 2008; Bhat 2003).

The estimated variables in both models were found to be statistically significant within a 95% confidence level. A likelihood ratio test comparing the fixed- and random-parameters ordered-probit models was performed to test the null hypothesis that the fixed-parameter model is statistically equivalent to the random-parameters model and the procedure is as follows (Washington et al. 2011):

$$\chi^2 = -2[\mathrm{LL}_{\mathrm{FIX}}(\beta^{\mathrm{FIX}}) - \mathrm{LL}_{\mathrm{RAN}}(\beta^{\mathrm{RAN}})] \tag{6}$$

where $\mathrm{LL}_{\mathrm{FIX}}(\beta^{\mathrm{FIX}})$ = log-likelihood at convergence of the fixed-parameters model (−4,933.841); and $\mathrm{LL}_{\mathrm{RAN}}(\beta^{\mathrm{RAN}})$ = log-likelihood at convergence of the random-parameters model (−4,908.552).

The chi-square statistic for the likelihood ratio test with six degrees of freedom gave a value greater than the 99.99% ($\chi^2 = 55.578$) confidence limit based on one-tailed p-value, indicating that the random-parameter model is statistically superior to the corresponding fixed-parameter model. This means that the null hypothesis, that the random-parameters model not being better than the fixed-parameter model, is rejected. Tables 2 and 3 present the details of the fixed- and random-parameters models and marginal effects of the random-parameters model, respectively.

The marginal effects illustrated in Table 3 provide additional information regarding what occurs with interior injury severity categories, their corresponding probabilities, and the magnitude of change across these categories. A negative coefficient (Table 2) represents an increased impact on injury severity probabilities. For example, in the context of marginal effects (Table 3), the variable indicating alignment of highway section (1 for curved section, 0 otherwise) for PDO ($Y = 4$) with the negative sign (−0.023) indicates that on average the probability of severe injuries is higher given the crashes that occurred on curved sections. By contrast, the other categories are positive and on average their probabilities are lower.

Six parameters were found to be random with statistically significant standard deviations under the assumed distribution (normal in this case); the constant term, dark conditions, lane changing, one-trailer trucks, left- or right-side departure, and the number of vehicles involved in the crashes. For the parameters whose standard deviations were not statistically different from zero, the parameters were fixed to be constant across the observations in the model.

Turning to the results found in Table 2, the constant term was found to be significant with a random parameter that is normally distributed, with mean 1.425 and standard deviation of 0.207. The variability in the constant term is likely capturing the unobserved heterogeneity in large truck–involved crashes, for example, the underreporting of the level of crash severity by police officers.

In addition to the constant term, other explanatory variables were found to be significant. These variables are related to the fused data sets from GES and pertain to human, vehicle, and road-environmental factors.

Human-Related Factors

Previous work related to large truck injury severity lacked variables related to human factors. As Table 2 shows, males are more likely to experience less severe injuries. A possible explanation is the greater physiological strength and injury-sustaining capability of males over that of females (O'Donnell and Connor 1996). Also, Abdel-Aty (2003) found that female drivers are more likely to be involved in more severe crashes. Another demographic characteristic related to the occupants (i.e., both drivers and passengers) is the age group between 55 and 65, who are also more likely to be severely injured. This might also be related to the physiological strength and injury-sustaining capability of older individuals.

The indicator variable for speed was significant. High-speed crashes involving large trucks may lead to greater injury severity levels owing to larger kinetic forces, especially when objects of substantial mass are involved. Khattak et al. (2003) also found speeding to be a significant factor that impacts the level of injury severity experienced by the vehicle's occupants.

The proper use of in-vehicle restraints is proven to save lives. As shown in Table 2, vehicle occupants that were restrained by

J. Transp. Eng. 2013.139:596-604.

Downloaded from ascelibrary.org by UTEP LIBRARY-SERIALS on 05/28/13. Copyright ASCE. For personal use only; all rights reserved.

Table 2. Large Truck–Involved Injury Severity Model Results

Variable	Fixed-parameters model		Random-parameters model	
	Coefficient	t-stat	Coefficient (standard deviation)	t-stat
Constant	1.512	13.653	1.425 (0.207)	10.126
Alignment of highway section (1 for curved section, 0 otherwise)	−0.149	−2.795	−0.167	−2.761
Day of the week (1 if weekend, 0 otherwise)	0.102	2.107	0.150	2.763
Months of the year [1 if summer months (June–August), 0 otherwise]	−0.171	−4.543	−0.201	−4.706
Light condition of street (1 if dark, 0 otherwise)	−0.137	−2.857	0.227 (1.084)	3.433
Number of vehicles involved in the crash	0.050	2.175	0.341 (0.333)	12.068
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	0.336	9.220	0.552 (0.501)	13.183
Vehicle role (1 if struck by other vehicle, 0 otherwise)	0.469	10.712	0.621	11.912
The most harmful event (1 if rollover, 0 otherwise)	0.412	10.345	0.578	13.017
Vehicle maneuver during precrash situation (1 if left- or right-side departure, 0 otherwise)	−0.481	−9.626	−0.441 (0.473)	−8.227
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	0.357	7.110	0.480	8.158
Vehicle maneuver just before impending crash (1 if changing lane, 0 otherwise)	0.232	2.942	0.658 (0.816)	6.114
Vehicle maneuver just before impending crash (1 if going straight, 0 otherwise)	0.116	2.600	0.168	3.230
Factor of crash identified in the investigation (1 if speed, 0 otherwise)	−0.098	−2.179	−0.094	−1.905
Occupants' use of available vehicle restraints (1 if lap and shoulder restraint used, 0 otherwise)	0.305	7.531	0.401	8.809
Age of the occupants (1 if for age group of 55–65 years, 0 otherwise)	−0.114	−2.299	−0.161	−2.836
Gender of the occupants (1 if male, 0 otherwise)	0.182	2.790	0.254	3.455
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	−0.140	−2.698	−0.202	−3.296
Threshold 1, $\mu 1$	0.772	27.782	1.1062	15.992
Threshold 2, $\mu 2$	1.350	59.431	1.906	26.086
Threshold 3, $\mu 3$	1.738	73.697	2.439	32.790
Log-likelihood at zero, LL(0)	−5493.706		−5493.706	
Log-likelihood at convergence, LL(β)	−4933.841		−4908.552	
Chi-square	1119.728		1170.308	
Number of observations, N	8,291		8,291	

Table 3. Marginal Effects Associated to the Random-Parameters Model

Variable	Marginal Effects (Random-parameters model)				
	$Y = 0$	$Y = 1$	$Y = 2$	$Y = 3$	$Y = 4$
Alignment of highway section (1 for curved section, 0 otherwise)	0.000	0.001	0.008	0.013	−0.023
Day of the week (1 if weekend, 0 otherwise)	0.000	−0.000	−0.005	−0.011	0.017
Months of the year [1 if summer months (June–August), 0 otherwise]	0.000	0.002	0.009	0.016	−0.027
Light condition of street (1 if dark, 0 otherwise)	0.000	−0.001	−0.008	−0.016	0.025
Number of vehicles involved in the crash	−0.000	−0.002	−0.014	−0.026	0.042
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	−0.000	−0.005	−0.029	−0.049	0.084
Vehicle role (1 if struck by other vehicle, 0 otherwise)	−0.000	−0.003	−0.023	−0.043	0.069
The most harmful event (1 if rollover, 0 otherwise)	−0.000	−0.006	−0.033	−0.052	0.093
Vehicle maneuver during precrash situation (1 if left- or right-side departure, 0 otherwise)	0.000	0.005	0.024	0.039	−0.069
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	−0.000	−0.002	−0.016	−0.032	0.050
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	0.000	−0.002	−0.016	−0.035	0.054
Vehicle maneuver just before impending crash (1 if going straight, 0 otherwise)	0.000	−0.001	−0.007	−0.013	0.022
Factor of crash identified in the investigation (1 if speed, 0 otherwise)	0.000	0.001	0.004	0.007	−0.012
Occupants' use of available vehicle restraints (1 if lap and shoulder restraint used, 0 otherwise)	−0.000	−0.004	−0.021	−0.035	0.060
Age of the occupants (1 if for age group of 55–65 years, 0 otherwise)	0.000	0.001	0.007	0.013	−0.022
Gender of the occupants (1 if male, 0 otherwise)	−0.000	−0.002	−0.013	−0.022	0.037
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	0.000	0.002	0.009	0.017	−0.028

lap/shoulder belts were less prone to being severely injured. One possible explanation is that the components inside the passenger compartment such as the dashboard, wheel, steering column, console, head-rest, A-pillar, and windshield may inflict greater damage to unrestrained individuals as they hurl toward these objects inside the vehicles during the crash phase as opposed to properly restrained individuals. In addition, occupants may be ejected from the vehicles leading to increased levels of injury severity. Both Abdel-Aty (2003) and Boufous et al. (2008) identified through their studies that not wearing a seat belt is a leading risk factor and may lead to higher injury severities suffered by vehicle occupants. The findings of this variable are also substantiated by Gkritza and Mannering (2008).

The indicator variable representing licensed drivers working or residing in the state of Texas was found to be significant in the model. When the drivers are licensed and registered in Texas they

J. Transp. Eng. 2013.139:596-604.

Downloaded from ascelibrary.org by UTEP LIBRARY-SERIALS on 05/28/13. Copyright ASCE. For personal use only; all rights reserved.

are more likely to be involved in more severe injury crashes. This variable may be capturing the driving complexities related to the diverse geographical nature of the state of Texas.

Vehicle-Related Factors

As with the influential aspects of human-related factors on large truck–involved crashes, factors associated with the vehicle are presented in this study. The indicator variable for a trailing unit (i.e., a truck is hauling a trailer) was found to be statistically significant with a random parameter that is normally distributed, with mean 0.553 and standard deviation of 0.510. This indicates that 82.0% (less than zero) of the crash occurrences involving a truck with a trailing unit will experience a lower level of injury severity, whereas 18.0% experience more severe injury. This variable may be capturing the varying degree of driving experience and training with hauling a trailing unit. The randomness in the coefficient may be accounting for driver experience levels of trucks with trailing units.

Considering the vehicle role, when large trucks are struck by other vehicles, the likelihood of the injury outcome is less severe. A possible explanation is that large trucks when struck by other vehicles (such as passenger cars) may sustain less damage because of their structural design integrity and size difference. By contrast, Duncan et al. (1998) found that passenger vehicles being rear-ended by high velocity trucks resulted in higher injury outcomes. Additionally, this variable may be capturing other vehicular dynamics specific to large trucks (e.g., damage sustainability potential).

When the number of vehicles involved in a crash increases, the level of injury severity decreases. This continuous variable is statistically significant with a random parameter that is normally distributed, with mean 0.341 and standard deviation of 0.333. This indicates that for 97.6% (less than zero) of the crash occurrences, as the number of vehicles in the crash increases, the resultant outcome is lower levels of injury severity, whereas 2.4% experience more severe injuries. A possible explanation for this finding is that crashes with many vehicles, such as pile-ups, lessen injury severity resulting from some unforeseen dynamics and preventive technologies present in vehicles (Chakravarthy et al. 2009).

Road and Environmental-Related Factors

This section discusses road and environmental factors that are significant. As shown in Table 2, the indicator variable representing curved road sections leads to more severe injury categories. Consequently, the drivers of large trucks often deal with a higher level of difficulty in negotiating curved sections, especially when considering the weight and size of the vehicle. In addition, this variable may be capturing the influence of locational factors related to curve sections as well as the skill level of drivers.

Regarding street lighting conditions, dark conditions (i.e., no lighting) are significant with a random parameter that is normally distributed, with mean 0.227 and standard deviation of 1.084. This implies that for roughly 76.2% (less than zero) of the crash occurrences in which street lighting conditions is classified as dark, a lower level of injury severity is a possible outcome, whereas the opposite is true for approximately 23.8%. Several studies have found that dark or limited lighting conditions could increase injury severity outcomes (Xie et al. 2009; Chimba and Sando 2009; Helai et al. 2008). Also, this variable may be capturing varying nighttime driving behavior in addition to visibility and sight distance-related factors not reported. Truck drivers are usually more cautious in dark conditions on highways than passenger vehicle drivers.

Although not explicitly related to road and environmental factors, the indicator variable for weekend driving is significant. If crashes occur on the weekend, the injury severity sustained by the occupants of large trucks is less severe. This variable might be capturing the effect of weekend driving patterns, density, and frequency of truck trips. Moreover, the indicator variable representing the summer months was also significant and increased the possibility of injury severity. This may be the case because in the summer months there is a higher number of vehicles on the road, which increases the exposure of passenger vehicles on the highways. This exposure clearly indicates greater interaction of passenger vehicles with large trucks, resulting in increasing likelihood of severe crashes. A similar result was found by Malyshkina and Mannering (2009).

Crash Mechanism-Related Factors

Lastly, variables related to crash mechanism are presented next. As illustrated in Table 2, the indicator variable representing truck rollovers is significant and more likely to lead to crashes that are less severe. The significance of this variable may stem from vehicular compartment rigidness and properly working restraint systems. The variable may also be capturing driver skill level as well as rollover locational factors. A study by Khattak et al. (2003) and Cate and Richards (2001) found that rollovers cause increased injury severities of occupants in large trucks. In addition, their study associated greater injury severity with curves of 5 degrees or more. The randomness of the variable coefficient may be accounting for these types of crashes.

Sideswipe in the same direction is significant and likely to lead to less severe large truck crashes. A possible explanation may be that truck drivers' skill level and training in regard to steering control in the same direction is possibly minimizing the injury severity outcomes under sideswipe scenarios.

When large trucks depart from the traveled roadway either to the left or right side of the travel direction is significant with a random parameter that is normally distributed, with mean −0.441 and standard deviation of 0.473. This indicates that 99.9% (less than zero) of the crash occurrences in which a large truck departs from the roadway will experience a higher level of injury severity, whereas 0.1% will less-severe injuries. The increased level of severity for veering off the road may stem from the possibility of collisions with stationary objects or other dangers present on the traveled roadway. The wide range of variability may be attributable to the factors related to driver skill level and training. A study performed by Yamamoto and Shankar (2004) also found that running off the roadway may lead to increased injury severities sustained by vehicle occupants.

Lane changing as an evasive maneuver before an impending crash is significant with a random parameter that is normally distributed, with mean 0.659 and standard deviation of 0.816. This implies that approximately 66.2% (less than zero) of the crash occurrences in which lane changing was an evasive maneuver observed a lower level of injury severity, whereas for approximately 33.8% a higher level of injury severity may result. A possible explanation for the variability of this estimate may stem from unforeseen factors related to oncoming traffic, median types, or secondary crashes influencing the reported severity. Lane changing as a crash risk factor was also found to be significant by Gray et al. (2008) and Khattak et al. (2003). Similarly, driving straight as an evasive maneuver to avoid a crash is found to be fixed and resulted in less-severe injuries possibilities. This could be due to driver alertness and crash anticipation because drivers can more successfully brace themselves for impact if they are holding a straight trajectory.

J. Transp. Eng. 2013.139:596-604.

Downloaded from ascelibrary.org by UTEP LIBRARY-SERIALS on 05/28/13. Copyright ASCE. For personal use only; all rights reserved.

Summary and Future Work

This paper analyzed large truck injury severity through a random-parameters ordered-probit modeling framework. The random-parameters ordered probit is an important approach because it allows an accounting and correction for unobserved heterogeneity that can arise from factors such as human (i.e., drivers and passengers), vehicle, road-environment, weather, underreporting, temporal, and other unobserved factors not captured. The data used in this study was from NASS-GES database for the years of 2005 to 2008 and, to the best of the authors' knowledge, is one of first studies to explicitly use this database for the modeling of large truck injury outcomes.

The results of the analyses provide some interesting findings. First, human-related factors from the fused GES data set are found to be significant in the model. Of these, the estimate for the factor of crash identified in the investigation "speed" indicator variable was fixed. However, lane-changing behavior and departing the roadway during pre-crash stages are random and vary across observations in contrast with variables related to gender, age of occupants, in-vehicle restraint usage, and Texas truck drivers' parameter estimates that are fixed. Second, in terms of vehicle-related variables from the fused data set, the estimates for a trailing unit and the number of vehicles involved are random, whereas variables related to vehicle role in a collision, orientation of vehicle at the time of crash, and vehicle maneuvering during precrash are also fixed. Third, the dark indicator variables for road and environment-related factors are random. In addition, indicator variables related to highway alignment, day of the week, and summer months (serves as a proxy for traffic conditions) are also fixed across large truck crash occurrences.

A key finding is the change of signs from the dark condition observed between the fixed- and random-parameters models. Under the fixed model, this variable would increase the likelihood of severe injuries. By contrast, the random-parameters model identified the variable coefficient to be random, accounting for unobserved factors that lead to cases of severe injuries (i.e., above zero) or less severe cases (i.e., below zero).

Although this study is exploratory in nature, the modeling approach presented in this paper offers a methodology to analyze large truck injury severity and at the same time to account for unobserved factors. Applying this approach to state-specific data sets with available AADT data, car-following dynamics, and human response over a longer time period could potentially provide additional information in regard to large truck crashes. In addition, data sets with driver skill and other cognitive processing information can greatly improve parameter estimates as well as help in the development and improvement of truck driver training.

Concerning future research, current work is focusing on a random-parameters (mixed) logit modeling framework to investigate whether better coefficient estimates can be obtained in addition to finding more statistically significant variables. Furthermore, local trucking companies are cooperating on truck driver training to identify variables of interest for simulation-based safety analyses.

References

Abdel-Aty, M. (2003). "Analysis of driver injury severity levels at multiple locations using ordered probit models." *J. Safety Res.*, 34(5), 597–603.

Anastasopoulos, P. C., Labi, S., Karlaftis, M. G., and Mannering, F. L. (2009a). "Exploring relationships between aggregate pavement performance, and surface geology, climate, and expenditure: An econometric analysis of state-level data." *88th Annual Meeting of Transportation Research Board*, Washington, DC.

Anastasopoulos, P. C., Labi, S., and McCullouch, B. (2009b). "Analyzing duration and prolongation of performance-based contracts using hazard-based duration and zero-inflated random parameters poisson models." *Transportation Research Record 2136*, Transportation Research Board, Washington, DC, 11–19.

Anastasopoulos, P. C., and Mannering, F. L. (2009). "A note on modeling vehicle-accident frequencies with random parameter count models." *Accid. Anal. Prev.*, 41(1), 153–159.

Bhat, C. (2001). "Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model." *Transp. Res. Part B: Methodol.*, 35(7), 677–693.

Bhat, C. (2003). "Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences." *Transp. Res. Part B: Methodol.*, 37(9), 837–855.

Boufous, S., Finch, C., Hayen, A., and Williamson, A. (2008). "The impact of environmental, vehicle and driver characteristics on injury severity in older drivers hospitalized as a result of a traffic crash." *J. Safety Res.*, 39(1), 65–72.

Brownstone, D., and Train, K. (1999). "Forecasting new product penetration with flexible substitution patterns." *Econometrica*, 89(1–2), 109–129.

Cate, M. A., and Richards, S. H. (2001). "An evaluation of large truck rollover crashes on Tennessee interstate highways." *80th Annual Meeting of Transportation Research Board*, Washington, DC.

Chakravarthy, A., Song, K., and Feron, E. (2009). "Preventing automotive pileup crashes in mixed-communications environments." *IEEE Trans. Intell. Transp. Syst.*, 10(2), 211–225.

Chang, L.-Y., and Mannering, F. L. (1999). "Analysis of injury severity and vehicle occupancy in truck- and non-truck-involved accidents." *Accid. Anal. Prev.*, 31(5), 579–592.

Chimba, D., and Sando, T. (2009). "Neuromorphic prediction of highway injury severity." *Adv. Transp. Stud.*, 19(1), 17–26.

Chistoforou, Z., Cohen, S., and Karlaftis, M. G. (2010). "Vehicle occupant injury severity on highways: An empirical investigation." *Accid. Anal. Prev.*, 42(6), 1606 –1620.

Duncan, C. S., Khattak, A. J., and Council, F. M. (1998). "Applying the ordered probit model to injury severity in truck–passenger car rear-end collisions." *Transportation Research Recor1635*, Transportation Research Board, Washington, DC, 63–71.

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

Federal Highway Administration (FHWA). (2010). "Highway statistics, 2008." U.S. Dept. of Transportation, Washington, DC.

Gkritza, K., and Mannering, F. L. (2008). "Mixed logit analysis of safety-belt use in single- and multi-occupant vehicles." *Accid. Anal. Prev.*, 40(2), 443–451.

Gray, R. C., Quddus, M. A., and Evans, A. (2008). "Injury severity analysis of accidents involving young male drivers in Great Britain." *J. Safety Res.*, 39(5), 483–495.

Greene, W. (1997). *Econometric analysis*, 3rd Ed., Macmillan, New York.

Greene, W. (2007). *Limdep, Version 9.0*. [Computer software]. Econometric Software, Inc., Plainview, NY.

Halton, J. (1960). "On the efficiency of certain quasi-random sequences of points in evaluating multi-dimensional integrals." *Numerische Mathematik*, 2(1), 84–90.

Helai, H., Chor, C. H., and Haque, M. M. (2008). "Severity of driver injury and vehicle damage in traffic crashes at intersections: A Bayesian hierarchical analysis." *Accid. Anal. Prev.*, 40(1), 45–54.

Khattak, A. J., Schneider, R. J., and Targa, F. (2003). "Risk factors in large truck rollovers and injury severity: Analysis of single-vehicle collisions." *82nd Annual Meeting of the Transportation Research Board Meeting*, Washington, DC.

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

Kockelman, K. M., and Kweon, Y.-J. (2002). "Driver injury severity: An application of ordered probit models." *Accid. Anal. Prev.*, 34(3), 313–321.

J. Transp. Eng. 2013.139:596-604.

Downloaded from ascelibrary.org by UTEP LIBRARY-SERIALS on 05/28/13. Copyright ASCE. For personal use only; all rights reserved.

Lee, C., and Abdel-Aty, M. (2005). "Comprehensive analysis of vehicle–pedestrian crashes at intersections in Florida." *Accid. Anal. Prev.*, 37(4), 775–786.

Lemp, J. D., Kockelman, K. M., and Unnikrishnan, A. (2011). "Analysis of large truck crash severity using heteroskedastic ordered probit models." *Accid. Anal. Prev.*, 43(1), 370–380.

Malyshkina, N. V., and Mannering, F. L. (2009). "Markov switching multinomial logit model: An application to accident-injury severities." *Accid. Anal. Prev.*, 41(4), 829–838.

McFadden, D., and Train, K. (2000). "Mixed MNL models for discrete response." *J. Appl. Econometrics*, 15(5), 447–470.

McKelvey, W., and Zavoina, T. A. (1975). "Statistical model for analysis of ordinal level dependent variables." *J. Math. Sociol.*, 4(1), 103–120.

Milton, J. C., Shanker, V. N., and Mannering, F. L. (2008). "Highway accident severities and the mixed logit model: An exploratory empirical analysis." *Accid. Anal. Prev.*, 40(1), 260–266.

National Automotive Sampling System (NASS) General Estimates System (GES). (2005). "Analytical user's manual 1988–2005." ⟨http://www-nrd.nhtsa.dot.gov/Pubs/AUM05.pdf⟩ (Sep. 10, 2010).

National Highway Traffic Safety Administration (NHTSA). (2008). "Traffic safety facts 2007: Large trucks." *DOT HS 810 805*, ⟨http://www-nrd.nhtsa.dot.gov/Pubs/810989.PDF⟩ (Sep. 5, 2010).

National Highway Traffic Safety Administration (NHTSA). (2009). "Traffic safety facts: Motorcycles." DOT HS 811 159, ⟨http://www-nrd.nhtsa.dot.gov/Pubs/811172.pdf⟩ (May 14, 2012).

O'Donnell, C. J., and Connor, D. H. (1996). "Predicting the severity using models of ordered multiple choice." *Accid. Anal. Prev.*, 28(6), 739–753.

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

Qin, X., Ivan, J. N., Ravishanker, N., Liu, J., and Tepas, D. (2006). "Bayesian estimation of hourly exposure functions by crash type and time of day." *Accid. Anal. Prev.*, 38(6), 1071–1080.

Quddus, M. A., Noland, R. B., and Chor, C. H. (2002). "An analysis of motorcycle injury and vehicle damage using ordered probit models." *J. Safety Res.*, 33(4), 445–462.

Revelt, D., and Train, K. (1998). "Mixed logit with repeated choices: Households' choice of appliance efficiency level." *Rev. Econ. Stat.*, 80(4), 647–657.

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

Statistical Analysis System (SAS) 9.2 for Windows [Computer software]. (2011). SAS Institute, Inc., Cary, NC.

Tarko, A. P., Islam, M. B., and Thomaz, J. E. (2011). "Improving safety in high-speed work zones: A super 70 study." *Rep. SPR-3249*, Joint Transportation Research Program Technical Report Series, Indiana Dept. of Transportation and Purdue Univ., West Lafayette, IN.

Train, K. (1997). "Mixed logit models for recreation demand." *Valuing the environment using recreation demand models*, C. Kling and J. Herriges, eds., Elgar Press, New York.

Vadlamani, S., Erdong, C., Ahn, S., and Washington, S. (2011). "Identifying large truck hot spots using crash counts and PDOEs." *J. Transp. Eng.*, 137(1), 11–21.

Washington, S. P., Karlaftis, M. G., and Mannering, F. L. (2011). *Statistical and econometric methods for transportation data analysis*, 2nd Ed., Chapman and Hall/CRC, Boca Raton, FL.

Xie, Y., Zhang, Y., and Liang, F. (2009). "Crash injury severity analysis using Bayesian ordered probit models." *J. Transp. Eng.*, 135(1), 18–25.

Yamamoto, T., and Shankar, V. N. (2004). "Bivariate ordered-response probit model of driver's and passenger's injury severities in collisions with fixed objects." *Accid. Anal. Prev.*, 36(5), 869–876.

Ye, F., and Lord, D. (2011). "Investigating the effects of underreporting of crash data on three commonly used traffic crash severity models: Multinomial logit, ordered probit and mixed logit models." *90th Annual Meeting of the Transportation Research Board*, Washington, DC.

Zajac, S., and Ivan, J. N. (2003). "Factors influencing injury severity of motor vehicle-crossing pedestrian crashes in rural Connecticut." *Accid. Anal. Prev.*, 35(3), 369–379.

Zaloshnja, E., and Miller, T. R. (2004). "Costs of large truck-involved crashes in the United States." *Accid. Anal. Prev.*, 36(5), 801–808.

Zaloshnja, E., and Miller, T. R. (2006). "Unit costs of medium and heavy truck crashes." *Final Rep.*, Federal Motor Carrier Safety Administration and Federal Highway Administration, Washington, DC.

Zhu, X., and Srinivasan, S. (2011). "A comprehensive analysis of factors influencing the injury severity of large truck crashes." *Accid. Anal. Prev.*, 43(1), 49–57.

Downloaded from ascelibrary.org by UTEP LIBRARY-SERIALS on 05/28/13. Copyright ASCE. For personal use only; all rights reserved.

J. Transp. Eng. 2013.139:596-604.