Modeling Injury Outcomes of Crashes Involving Heavy Vehicles on Texas Highways

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Concern related to crashes that involve large trucks has increased in Texas recently because of the potential economic impacts and level of injury severity that can be sustained. However, detailed studies on large truck crashes that highlight the contributing factors leading to injury severity have not been conducted in Texas, especially for its Interstate system. The contributing factors related to injury severity were analyzed with Texas crash data based on a discrete outcome-based model that accounts for possible unobserved heterogeneity related to human, vehicle, and road–environment factors. A random parameter logit (i.e., mixed logit) model was estimated to predict the likelihood of five standard injury severity scales commonly used in the Crash Records Information System in Texas: fatal, incapacitating, nonincapacitating, possible, and none (i.e., property damage only). Estimation results indicated that the level of injury severity outcomes was highly influenced by several complex interactions between factors and that the effects of some factors could vary across observations. The contributing factors include driver demographics, traffic flow, roadway geometric features, land use, time characteristics, weather, and lighting conditions.

Concern related to crashes that involve large trucks has increased in Texas (and globally) recently because of the potential economic impacts and level of injury severity that can be sustained (*1*). These concerns are well founded because the total economic losses due to vehicular crashes in the United States between 2006 and 2010 are estimated to be $107.4 billion, and in 2008, Texas faced the greatest economic losses of any state at $22.9 billion (*2–6*). Statistically, crash data indicate that in 2010, Texas experienced 3,023 deaths, 59,660 crashes that resulted in serious injury, and a total of 82,685 persons sustaining serious injuries (*3*). Consequently, any increase in the number and level of crash injury severity is of great concern to trucking companies as well as to transportation organizations that operate, maintain, and construct the Texas transportation system (*7–9*).

To understand better the safety impacts related to large trucks on the Texas highway system, tools must be developed that can help transportation safety professionals and trucking industry operations managers avoid and mitigate large truck crashes. Severity prediction models still are regarded as the primary tools to understand and estimate factors involving vehicular crashes (*9*). However, few studies have investigated the injury severity associated with large truck crashes, especially using state-specific crash databases (*10, 11*).

Therefore, the main objective of this study is to analyze the contributing factors related to injury severity by using Texas's crash database and applying the data to a discrete outcome model. This discrete outcome model accounts for possible unobserved heterogeneity (i.e., unobserved factors that may influence an injury outcome) related to human, vehicle, and road–environment factors. A random parameter logit model (i.e., mixed logit) is estimated to predict the likelihood of five levels of injury severity commonly used in the Crash Records Information System (CRIS) in Texas: fatal, incapacitating, nonincapacitating, possible, and none [i.e., property damage only (PDO)]. To the best of the authors' knowledge, these attempts at modeling injury severity in large truck crashes with the CRIS data set are the first of their kind. Even though the mixed logit model has been applied to the severity of large truck crashes from different modeling perspectives, this research extends the current literature and introduces additional significant variables related to crashes that involve large trucks.

The remainder of this paper is organized as follows. First, the literature is reviewed related to crash models in general and the mixed logit model with respect to large truck crashes. Next, the empirical setting and descriptive statistics are discussed, followed by a description of the methodological approach. Then, insights from the empirical results are summarized and discussed, and some concluding comments are presented.

BACKGROUND: CRASH MODELS

General

Crash frequency, likelihood, and severity modeling approaches have been used widely in traffic safety analyses. The most frequently applied models relate to crash frequency models such as negative binomial and Poisson models (*12–15*), zero-inflated Poisson and zero-inflated negative binomial models (*16–18*), random parameter negative binomial models (*19–21*), Markov switching of two states of crash occurrence (*22*), and Bayesian statistics on negative binomial models (*23*). Crash likelihood and severity models also have been studied, but the literature is relatively sparse when it comes to analyzing large truck crashes (*9, 24–31*).

Mixed Logit Model

The modeling of crash frequency and injury severity conditioned on crash occurrence is not new. However, research efforts have focused mainly on modeling crash frequency by considering the severity

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at each specific severity level simultaneously (*32*). This modeling approach significantly introduces potential estimation error because of the correlation among the numbers of crashes by specific severity level: fatal, incapacitating, nonincapacitating, possible injury, or none (*32, 33*). To overcome such limitations in the modeling approach, Milton et al. applied a mixed logit model in which the proportion of crashes of each severity level was analyzed on a specific roadway segment over a specified period (*32*).

The mixed logit approach has been successfully applied in traffic safety, where data limitations could be a potential hindrance to other modeling approaches, to determine the likelihood of seat belt usage by passengers in single and multioccupant vehicles (*34*). Additionally, this approach has been promising in the modeling of pedestrian injury severity for pedestrian–vehicle interactions (*27*). The flexibility of this modeling approach makes it attractive because it accounts for variation over the observations known as unobserved heterogeneity, indicating that units of observation are more different than the descriptive variables that may be present in limited data, such as roadway geometric features, pavement condition, and general weather and traffic characteristics (*27, 33*).

Anastasopoulos and Mannering applied a mixed logit model to injury categories; however, they combined the intermediate injury categories (incapacitating, nonincapacitating, and possible injury) as injury and considered the fatal and noninjury categories separately, resulting in three injury levels: fatal, injury, and none (*33*). Likewise, Chen and Chen applied a mixed logit model to injury severity for truck drivers in single- and multivehicle collisions separately, rather than combined, in rural Illinois settings over 10 years (1991 through 2000) (*6*). They also combined possible and nonincapacitating injuries in one category, combined incapacitating and fatal injuries in another category, and considered no injury separately, resulting in three response outcome variables. However, the current study considers each of the five levels of injury severity (fatal, incapacitating, nonincapacitating, possible, and none) separately as response outcome variables in the mixed logit formulation.

EMPIRICAL SETTINGS

The data used in this study were collected from the Texas Peace Officers' Crash Reports, commonly known as the CRIS database. To investigate human, vehicle, and road–environment factors, a sample of 20,495 data observations were extracted from the CRIS database by filtering crashes that involved large trucks on the Texas Interstate system over 5 years from 2006 to 2010. In the data-processing stage, the vehicle body style was set to truck, truck tractor, semi-trailer, and highway facility type and processed with SAS statistical software (*35*). Each observation in the sample is a crash that represents the maximum level of injury sustained by the drivers and involves at least one large truck in the Interstate system. The crash data set was linked to vehicle and person data sets through appropriate linking variables (i.e., crash number), and the vehicle and person data sets were linked through the vehicle and crash number with SAS statistical software. The linkage of the three data components (i.e., crash, vehicle, and person) was processed to yield a single observation with a maximum injury level sustained by the drivers involved in the crash (done with the crash number).

The descriptive statistics of the variables used in the model (i.e., dependent variable and all the independent variables) are presented in Table 1, in which the dependent variable has five injury severity outcomes: fatal, incapacitating, nonincapacitating, possible, and none (i.e., PDO), which accounted for about 0.38% ($N = 78$), 2.26% ($N = 463$), 2.93% ($N = 601$), 5.46% ($N = 1{,}120$), and 88.96% ($N = 18{,}223$), respectively, of total observations ($N = 20{,}495$). By not grouping injury severity categories, additional insights can be gained regarding the contributing factors that influence each injury outcome sustained in large truck crashes.

Of spatial characteristics, rural and urban settings accounted for about 26.8% and 56.4%, respectively, of the total observations. Of temporal characteristics, time of day accounted for 20.3% and 15.9% of the total observations for 3 to 7 p.m. and midnight to 6 a.m., respectively, and season accounted for 25.6%, 31.8%, and 42.5% of the total observations for summer (June to August), fall (September to December), and spring (January to May), respectively. However, the summer and fall months' variables were the only statistically significant variables in the model. Exposure variables addressing traffic flow in terms of average daily traffic (ADT) had a mean value of 15,397 vehicles per day per lane, and the variable for an ADT of more than 2,000 vehicles per day per lane was statistically significant and accounted for 98.5% of the total observations.

The highway geometry of a 19.7-ft-wide average right (i.e., outer) shoulder and four lanes in both directions accounted for about 42.8% of the total observations. Environmental aspects at the time of a crash were 81.0%, 68.2%, and 11.9% of the total observations for dry surface, clear weather, and dark highway sections (lighted outside), respectively. Of driver demographics, male drivers accounted for 94.4% of the total observations, and the 25- to 35- and 45- to 55-year-old age groups accounted for 17.8%, and 23.9% of the total observations, respectively. These variables also were statistically significant in the model. The 35- to 45- and 55- to 65-year-old age groups accounted for 26.0% and 12.7% of the total observations, respectively, but were not statistically significant.

METHODOLOGICAL APPROACH

Past research studies have used numerous methodological approaches, including multinomial logit, ordered probit and Bayesian ordered probit, nested logit, and mixed logit models to model injury severity (*32, 34, 36–43*). In this study, the mixed logit model is developed for the injury severity of large truck crashes by considering random parameters in the developed model according to a logical research framework similar to that of past research studies (*6, 32, 34*).

The level of injury is discrete in nature, as coded in the KABCO injury scale (where K = fatal, A = incapacitating injury, B = nonincapacitating injury, C = possible injury, and O = PDO), and the mixed logit model has been widely accepted to model the effects of several contributory factors on injury severity levels. Research studies conducted by Revelt and Train (*44, 45*), Train (*46*), Brownstone and Train (*47*), McFadden and Train (*48*), and Bhat (*49*) clearly demonstrate the effectiveness of this methodological approach. Even though discrete outcome severity could be modeled by a multinomial logit model, heterogeneous effects and correlation in unobserved factors still could be a potential limitation in the assumption behind using this model for injury severity (*50*). A mixed logit model overcomes all of these limitations by generalizing the multinomial logit structure, allowing for the parameters $\boldsymbol{\beta}_i$ (a vector of estimable parameters) to vary across crash observations (*51*). The assumption regarding independent and identically distributed errors, independence of irrelevant alternatives, and unobserved heterogeneity associated with observations in a multinomial logit model is completely relaxed through the introduction of the mixed logit approach (*52*).

TABLE 1 Descriptive Statistics of Key Variables, by Injury Severity Outcome (N = 20,495)

Meaning of Variable	Mean	SD
Fatal		
Terrain of roadway (1 if level roadway surface, 0 otherwise)	0.764	0.425
Time of day (1 if between 3 and 7 p.m., 0 otherwise)	0.203	0.402
Weather condition (1 if clear weather, 0 otherwise)	0.682	0.466
Land use pattern at crash location (1 if rural, 0 otherwise)	0.268	0.443
Traffic flow at time of crash [ADT per lane in each direction (vpdpl)]	15,397.3	8,845.23
Incapacitating		
Month [1 if summer (June to August), 0 otherwise]	0.257	0.437
Weather condition (1 if clear weather, 0 otherwise)	0.682	0.466
Shoulder width [right shoulder width (ft)]	19.727	3.555
Time of day (1 if between 3 and 7 p.m., 0 otherwise)	0.203	0.402
Land use pattern at crash location (1 if urban, 0 otherwise)	0.564	0.496
Nonincapacitating		
Number of lanes on highway (1 if 4 lanes in both directions, 0 otherwise)	0.428	0.495
Time of day (1 if between midnight and 6 a.m., 0 otherwise)	0.159	0.366
Month [1 if fall (September to December), 0 otherwise]	0.318	0.428
Land use pattern at crash location (1 if rural, 0 otherwise)	0.268	0.443
Possible		
Gender of driver (1 if male, 0 otherwise)	0.944	0.229
Time of day (1 if between 3 and 7 p.m., 0 otherwise)	0.203	0.402
Traffic flow at time of crash [ADT per lane in each direction (vpdpl)] (1 if vpdpl > 2,000, 0 otherwise)	0.985	0.122
Surface condition at time of crash (1 if dry surface, 0 otherwise)	0.810	0.392
Age group (1 if age between 25 and 35, 0 otherwise)	0.178	0.382
None (PDO)		
Weather condition at time of crash (1 if clear weather condition, 0 otherwise)	0.682	0.466
Light condition of street (1 if surrounding area is dark but outside is lighted, 0 otherwise)	0.119	0.324
Land use pattern at crash location (1 if urban, 0 otherwise)	0.564	0.496
Age group of driver (1 if age between 45 and 55, 0 otherwise)	0.239	0.427
Surface condition at time of crash (1 if dry surface, 0 otherwise)	0.810	0.392
Traffic flow at time of crash [ADT per lane in each direction (vpdpl)]	15,397.3	8,845.23

NOTE: SD = standard deviation; ADT = average daily traffic; vpdpl = vehicles per day per lane.

To better understand the injury severity of large truck crashes on the Texas Interstate system, an econometric model is used to determine the contributing factors that influence the likelihood of severity outcomes in large truck crashes. A discrete choice modeling framework in Limdep is applied (*53*). To start, a linear function is used to determine the discrete injury severity outcome (i.e., fatal, incapacitating, nonincapacitating, possible, or PDO) for large truck crashes:

$$S_{in} = \boldsymbol{\beta}_i \mathbf{X}_{in} + \varepsilon_{in} \tag{1}$$

where $\mathbf{X}_{in}$ is the vector of explanatory variables (e.g., driver, vehicle, road, and environment variables) and ε_{in} is the error term (*54*). If ε_{in} values are assumed to be generalized extreme value distributed, then McFadden has shown the multinomial logit results such that

$$P_n(i) = \frac{\exp[\boldsymbol{\beta}_i \mathbf{X}_{in}]}{\sum_I \exp[\boldsymbol{\beta}_i \mathbf{X}_{in}]} \tag{2}$$

where $P_n(i)$ is probability of a large truck incident (n) with a severity outcome i (where $i \in I$, which denotes all possible injury severity outcomes presented thus far) (*55*).

The CRIS data probably have a significant level of unobserved heterogeneity because CRIS crash data are based on the CR-3 law enforcement form (commonly known as the Texas Peace Officer's Crash Report), and no information is provided regarding the individuals recorded in the report or any unobserved factors related to the roadway, vehicle, and driver that may have influenced the crash outcome. Therefore, the possibility that elements of the parameter vector $\boldsymbol{\beta}_i$ may vary across observations of each large truck crash is considered by using a random parameter logit (also known as mixed logit) model to account for unobserved heterogeneity.

Previous studies by McFadden and Ruud (*56*), Geweke et al. (*57*), Revelt and Train (*44, 45*), Train (*46*), Stern (*58*), Brownstone and Train (*47*), McFadden and Train (*48*), and Bhat (*49*) have shown the development and effectiveness of the mixed logit approach which can explicitly account for the variations (across crash observations) of the effects that variables have on the severity outcomes (or choices) considered in this study. With respect to this work, the mixed logit model is represented by

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

where $f(\boldsymbol{\beta}_i|\boldsymbol{\varphi})$ is the density function of $\boldsymbol{\beta}_i$ and $\boldsymbol{\varphi}$ is a vector of parameters of the density function (mean and variance) (*59*). This model now can account for variations of the effect of $\mathbf{X}_{in}$ specific to severity outcome on the probabilities of large truck crashes, with $f(\boldsymbol{\beta}_i|\boldsymbol{\varphi})$ used to determine $\boldsymbol{\beta}_i$. The mixed logit probabilities then are a weighted average for different $\boldsymbol{\beta}_i$ values across observations, where some elements of $\boldsymbol{\beta}_i$ could be fixed and some randomly distributed. If the parameters are random, then the mixed logit weights can be determined by $f(\boldsymbol{\beta}_i|\boldsymbol{\varphi})$ (*32, 54*).

Maximum likelihood of the mixed logit model shown in Equation 3 is estimated with a simulation-based approach because of difficulty in computing the probabilities. The most widely accepted simulation approach uses Halton draws, which is a technique developed to generate a systematic nonrandom sequence of numbers (*60*). Halton draws provide a more efficient distribution of the draws for numerical integration than purely random draws (*61, 62*).

To apply the mixed logit, the size of the data sample must be considered. Ye and Lord show the influence of sample size on the three most commonly used models of injury severity with a simulation-driven analysis, the findings of which can be generalized for mixed logit models (*63*). They find that crash severity models with sample sizes of less than 1,000 should not be estimated. The sample size must be greater than 1,000 for an ordered probit model and at least 2,000 for a multinomial logit model; a mixed logit model (the most demanding) requires more than 5,000 observations. The sample size in this work is 20,495, which is greater than the safe threshold (i.e., 5,000) identified by Ye and Lord (*63*).

To estimate the impact of a particular variable on the injury outcome likelihood, elasticities (or direct pseudo-elasticities) are computed. Because most of the variables are indicators in nature in the current study, direct pseudo-elasticities are estimated to measure the marginal effects when any particular indicator variable switches from 0 to 1 or vice versa (*54*). It is translated to a percentage change in the likelihood of injury outcomes while the indicator variables switch between 0 and 1 or 1 and 0. For binary indicator variables, the direct pseudo-elasticity is estimated as

$$E_{x_{nk(i)}}^{P_{in}} = \frac{P_{in}[\text{given } x_{nk(i)} = 1] - P_{in}[\text{given } x_{nk(i)} = 0]}{P_{in}[\text{given } x_{nk(i)} = 0]} \tag{4}$$

where P_{in} (from Equation 3) is simulated as in Equation 6 and $x_{nk(i)}$ is the kth independent variable associated with injury severity i for observation n (*27*).

In contrast, direct average elasticities are estimated for any continuous variable with Equation 5, which measures the percentage change in the likelihood of injury outcome when the continuous variable changes one unit (*54*):

$$E_{x_{nk(i)}}^{P_n(i)} = \frac{\dfrac{\partial P_n(i)}{P_n(i)}}{\dfrac{\partial x_{nk(i)}}{x_{nk(i)}}} = \frac{\partial P_n(i)}{P_n(i)} \cdot \frac{x_{nk(i)}}{\partial x_{nk(i)}} \tag{5}$$

An unbiased and smooth simulator estimates unconditional probability in Equation 3, which can be computed as

$$\hat{P}_{in} = \frac{1}{R}\sum_{r=1}^{R} P_{in} = \frac{1}{R}\sum_{r=1}^{R} \int \frac{\exp[\boldsymbol{\beta}_i \mathbf{X}_{in}]}{\sum_I \exp[\boldsymbol{\beta}_i \mathbf{X}_{in}]} f(\boldsymbol{\beta}_i|\boldsymbol{\varphi}) d\boldsymbol{\beta}_i \tag{6}$$

where R is the total number of draws (*26, 48, 64*). Because the direct pseudo-elasticity is calculated for each observation, it usually is reported as the average (over the sample) direct pseudo-elasticity as a measure of the marginal effect of an indicator variable on the likelihood of a particular injury severity outcome (*27*).

With the simulator in Equation 6, maximum simulated likelihood estimation can be used to estimate the parameters, and this estimator is asymptotically normal and consistent:

$$\max \boldsymbol{\beta}_{in} \sum_{n=1}^{N} \sum_{i=1}^{I} y_{in} \ln \hat{P}_{in} \tag{7}$$

where

$\boldsymbol{\beta}_{in}$ = vector of parameters that can be estimated of each driver–injury outcome i in crash n,
N = total number of observations (i.e., crashes in the sample), and
y_{in} = 1 if individual n suffers from injury severity i, 0 otherwise (*65*).

EMPIRICAL RESULTS AND DISCUSSION

Maximum likelihood and simulation-based maximum likelihood methods are used to estimate the parameter vector $\boldsymbol{\beta}_i$ for fixed- and random-parameter logit models, respectively. Normal, lognormal, triangular, and uniform distributions are considered for the distribution of random parameters in this analysis, but the normal distribution was statistically significant. Two hundred Halton draws were empirically shown to produce accurate parameter estimates that were used for the simulation-based maximum likelihood estimation (*32, 61*).

The estimated variables in both models were statistically significant within a 95% confidence level. A likelihood ratio test was performed with the multinomial logit (i.e., fixed parameter) and mixed logit (i.e., random parameter) models to test the null hypothesis that the two models are statistically equivalent; this procedure is as follows:

$$\chi^2 = -2\left[\mathrm{LL}_{\mathrm{MNL}}(\beta^{\mathrm{MNL}}) - \mathrm{LL}_{\mathrm{ML}}(\beta^{\mathrm{ML}})\right] \tag{8}$$

where $\mathrm{LL}_{\mathrm{MNL}}(\beta^{\mathrm{MNL}})$ is the log likelihood at convergence of the multinomial logit model (–9,231.729) and $\mathrm{LL}_{\mathrm{ML}}(\beta^{\mathrm{ML}})$ is the log likelihood at convergence of the mixed logit model (–9,200.257) (*52*). The chi-square statistic for the likelihood ratio test with six degrees of freedom gave a value greater than the 99.99% confidence limit ($\chi^2 = 62.944$), indicating that the mixed logit (i.e., random-parameter) model is statistically superior to the corresponding multinomial (fixed-parameter) model. Therefore, the null hypothesis is rejected; the random-parameter model estimates are no better than the compared fixed-parameter model estimates.

The model results are discussed in the following subsections, along with the elasticities (direct pseudo and average direct) as presented in Tables 2 and 3.

Model Constants

The constant term for the fatal injury outcome is random and normally distributed, with a mean of –6.911 and a standard deviation of 1.691. Given these values, this constant is less than 0 for 99.9% of large truck

TABLE 2 Model Estimates for Injury Severity Model

Meaning of Variable	Estimate	*t*-Statistic	*P*-Value
Fatal			
Constant (standard error of parameter distribution)	−6.911 (1.691)	−6.209 (2.458)	.000
Terrain of roadway (1 if level roadway surface, 0 otherwise)	−1.032	−3.840	.000
Time of day (1 if between 3 and 7 p.m., 0 otherwise)	−0.803	−1.998	.045
Land use pattern at crash location (1 if rural, 0 otherwise)	0.986	2.937	.003
Traffic flow at time of crash [ADT per lane in each direction (vpdpl)]	-0.468×10^{-4}	−2.050	.040
Weather condition (1 if clear weather, 0 otherwise)	0.901	2.499	.013
Incapacitating			
Constant	−3.567	−11.406	.000
Month [1 if summer (June to August), 0 otherwise]	0.224	2.043	.041
Weather condition (1 if clear weather, 0 otherwise)	−1.045	−5.436	.000
Shoulder width [right shoulder width (ft)]	0.028	1.953	.050
Time of day (1 if between 3 and 7 p.m., 0 otherwise)	−0.365	−2.627	.008
Land use pattern at crash location (1 if urban, 0 otherwise)	−1.159	−6.924	.000
Nonincapacitating			
Constant (standard error of parameter distribution)	−14.403 (6.924)	−4.683 (4.494)	.000
Number of lanes on highway (1 if 4 lanes in both directions, 0 otherwise)	1.295	3.185	.001
Time of day (1 if between midnight and 6 a.m., 0 otherwise)	1.978	3.804	.000
Month [1 if fall (September to December), 0 otherwise]	−0.680	−1.920	.054
Land use pattern at crash location (1 if rural, 0 otherwise)	1.908	3.474	.000
Possible			
Constant (standard error of parameter distribution)	−0.939 (3.083)	−1.731 (3.289)	.083
Gender of driver (1 if male, 0 otherwise) (standard error of parameter distribution)	−3.936 (1.622)	−4.417 (2.353)	.000
Time of day (1 if between 3 and 7 p.m., 0 otherwise)	−0.542	−2.881	.0040
Traffic flow at time of crash [ADT per lane in each direction (vpdpl)] (1 if vpdpl > 2,000, 0 otherwise)	−0.889	−1.879	.060
Surface condition at time of crash (1 if dry surface, 0 otherwise)	−1.112	−5.010	.000
Age group of driver (1 if age between 25 and 35, 0 otherwise)	−0.388	−2.115	.034
None (PDO)			
Weather condition at time of crash (1 if clear weather condition, 0 otherwise)	0.379	2.337	.019
Light condition of street (1 if surrounding area is dark but outside is lighted, 0 otherwise)	−0.564	−5.631	.000
Land use pattern at crash location (1 if urban, 0 otherwise)	−0.377	−2.633	.008
Age group of driver (1 if age between 45 and 55, 0 otherwise) (standard error of parameter distribution)	1.097 (1.866)	4.194 (6.800)	.000
Surface condition at time of crash (1 if dry surface, 0 otherwise)	−0.783	−6.264	.000
Traffic flow at time of crash [ADT per lane in each direction (vpdpl)] (standard error of parameter distribution)	0.249×10^{-4} 0.294×10^{-4}	2.347 (2.049)	.018

NOTE: Number of observations = 20,495; restricted log likelihood = −32,985.43; log likelihood at convergence = −9,231.729; chi-squared value = 47,570.35; McFadden pseudo-*R*-squared (ρ^2) = .721.

crashes that result in fatal injuries. That is, on average, about 99% of large truck crashes are less likely to result in fatal injury outcomes. Similarly, the constant for nonincapacitating injury outcome is random and normally distributed, with a mean of −14.404 and a standard deviation of 6.924. Therefore, the constant is less than 0 for 98.1% of large truck crashes for this injury severity category and, on average, about 98.1% of large truck crashes were less likely to result in nonincapacitating injury outcomes. Finally, the constant for the possible injury outcome also was random and normally distributed, with a mean of −0.938 and a standard deviation of 3.083. Given these estimates, this constant is less than 0 for 62% of large truck crashes and implies that, on average, about 62% of large truck crashes were less likely to result in possible injuries.

Driver Characteristics

In Table 2, the male indicator is negative, which means that male drivers are less likely than female drivers to be involved in possible injuries. This parameter was random and normally distributed, with a

TABLE 3 Average Direct Pseudo-Elasticities, by Injury Severity Outcome

Variable	Elasticity (%) None (PDO)	Possible	Nonincapacitating	Incapacitating	Fatal
Terrain of roadway (1 if level roadway surface, 0 otherwise) [F]	0.21	0.15	0.11	0.50	–54.10
Time of day (1 if between 3 and 7 p.m., 0 otherwise) [F]	0.03	0.02	0.01	0.06	–7.60
Weather condition (1 if clear weather, 0 otherwise) [F]	–0.26	–0.18	–0.13	–0.48	66.86
Land use pattern at crash location (1 if rural, 0 otherwise) [F]	–0.19	–0.14	–0.13	–0.52	49.65
Traffic flow at time of crash [ADT in each direction (vpd)] [F]	0.17	0.13	0.07	0.36	–44.35
Month [1 if summer (June to August), 0 otherwise] [INCAP]	–0.14	–0.11	–0.07	6.00	–0.31
Weather condition (1 if clear weather, 0 otherwise) [INCAP]	1.03	0.71	0.43	–43.48	3.26
Shoulder width [right shoulder width (ft)] [INCAP]	–1.22	–0.93	–0.61	51.73	–2.66
Time of day (1 if between 3 and 7 p.m., 0 otherwise) [INCAP]	0.12	0.08	0.05	–5.10	0.15
Land use pattern at crash location (1 if urban, 0 otherwise) [INCAP]	0.89	0.73	0.31	–37.58	1.23
Number of lanes on highway (1 if 4 lanes in both directions, 0 otherwise) [NONINCAP]	–0.70	–0.64	23.02	–1.35	–1.48
Time of day (1 if between midnight and 6 a.m., 0 otherwise) [NONINCAP]	–0.47	–0.49	15.61	–0.95	–1.06
Month [1 if fall (September to December), 0 otherwise] [NONINCAP]	0.13	0.12	–4.38	0.20	0.22
Land use pattern at crash location (1 if rural, 0 otherwise) [NONINCAP]	–0.76	–0.71	25.08	–1.64	–1.98
Weather condition (1 if clear weather, 0 otherwise) [NONINCAP]	0.61	0.49	–19.50	0.58	1.17
Gender of driver (1 if male, 0 otherwise) [POSS]	6.58	–113.33	3.35	10.39	9.18
Time of day (1 if between 3 and 7 p.m., 0 otherwise) [POSS]	0.26	–4.44	0.12	0.29	0.17
Traffic flow at time of crash [ADT per lane in each direction (vpdpl)] (1 if vpdpl > 2,000, 0 otherwise) [POSS]	2.43	–41.68	1.30	3.48	3.03
Surface condition at time of crash (1 if dry surface, 0 otherwise) [POSS]	2.39	–41.06	1.24	3.38	3.52
Age group of driver (1 if age between 25 and 35, 0 otherwise) [POSS]	0.17	–2.95	0.09	0.19	0.18
Weather condition at time of crash (1 if clear weather condition, 0 otherwise) [PDO]	1.38	–11.02	–6.53	–14.71	–25.39
Light condition of street (1 if surrounding area is dark but outside is lighted, 0 otherwise) [PDO]	–0.63	3.48	3.02	10.37	11.48
Land use pattern at crash location (1 if urban, 0 otherwise) [PDO]	–1.10	9.93	4.50	11.45	10.35
Age group of driver (1 if age between 45 and 55, 0 otherwise) [PDO]	–0.45	–0.41	–2.87	19.97	15.21
Surface condition at time of crash (1 if dry surface, 0 otherwise) [PDO]	–3.83	27.29	16.95	52.28	56.66
Traffic flow at time of crash [ADT per lane in each direction (vpdpl)] [PDO]	1.47	–13.11	–7.90	–13.41	–12.37

NOTE: Variables that were significant in the mixed logit model are indicated with the injury severity level in brackets. F = fatal; INCAP = incapacitating; NONINCAP = nonincapacitating; POSS = possible; PDO = property damage only; vpd = vehicles per day.

mean of –3.936 and a standard deviation of 1.622 for possible injuries. Given these estimates, this parameter is greater than 0 for 0.7% of large truck crashes. This suggests that, on average, about 0.7% of crashes that involved both a large truck and a male driver were more likely to result in possible injuries. Usually, the injury tolerance of the male body is higher than that of female body. Chen and Chen find a similar result, because females are more likely to be involved in fatal or incapacitating injuries in single- and multivehicle collisions (*6*). This evidence also is supported by Abdelwahab and Abdel-Aty (*66*).

The 45- to 55-year-old drivers are more likely to be involved in noninjury (i.e., PDO) crashes. The elasticity estimate indicates that this age group is 15.21% and 19.97% more likely to be involved in crashes with fatal and incapacitating injuries, respectively. One possible explanation is that this age group may be more experienced in driving and handling large trucks but may have slower reaction times when maneuvering to avoid a crash. This parameter also was random for the PDO outcome and normally distributed, with a mean of 1.097 and a standard deviation of 1.866. Given these values, this parameter is less than 0 for 72.2% of large truck crashes, which implies that, on average, about 72.2% of large truck crashes in this age group are less likely to result in PDO.

Driscoll et al. report that about 70% of traffic fatalities are of people between 25 and 54 years old and that the largest proportion of these deaths occur in Australia, New Zealand, and the United States (*67*). The model results also indicate that the 25- to 35-year-old age group is 2.9% (as indicated by the elasticity) less likely to be involved in possible injury crashes. This finding may be due to possibly faster reaction times than the older age groups when maneuvering to avoid a crash. Stamatiadis and Deacon indicate that, on average, 25- to 35-year-old motorists are more likely to be involved in crashes than 45- to 55-year-old motorists (*68*). Younger drivers also perform relatively poorly because of factors related to driving experience, risk-taking behaviors, and attitude, particularly at night, which all led to the significant finding that the middle-aged drivers are safer than the younger ones.

Land Use Characteristics

For crashes that occurred in rural areas (population < 5,000 persons), the likelihoods of fatal and nonincapacitating injuries were 49.6% and 25.2%, respectively. These findings result from rural areas having higher speed limits, longer stretches of roads with less traffic, and less enforcement than urban settings. Khorashadi et al. report similar findings for a detailed study of rural settings in which the probability of drivers' injuries in crashes involving excessive speeds, improper lane passing, and single-vehicle collisions increased the likelihood of severe or fatal injuries (*42*). Khattak et al. report similar findings (*69*).

In contrast, crashes that occurred in an urban area (population > 200,000 persons) reduced the likelihood of incapacitating injuries by 37.6%. This decrease may be a result of drivers driving more slowly in urban settings as a result of lower speed limits and congestion effects. This variable also may reflect the existence of higher enforcement levels. Khorashadi et al. report a similar finding, that the likelihood of noninjury crashes is greater in an urban setting because of improper lane passing and multivehicle collisions (*41*).

Time Characteristics

When crashes occurred between 3 and 7 p.m., the likelihood of fatal, incapacitating, and possible injuries was reduced by 7.6%, 5.1%, and 4.4%, respectively. This period captures the afternoon peak and may reflect the congestion effect. In this study, the likelihood of nonincapacitating injuries increased by 15.6% during the period from midnight to 6 a.m. This increase may be a result of drivers of large trucks operating while drowsy or fatigued. Similarly, Lenné et al. report that reaction time varies across time of day and that reaction times are prolonged at 2 a.m., 6 a.m., and 2 p.m. (*70*), and Doherty et al. demonstrate that crash rates for all severity levels increases in the evening (8:00 to 11:59 p.m.) and from late night to early morning (midnight to 4:59 a.m.) (*71*). Otmani et al. offer an additional explanation, indicating that a physiological decline in alertness occurs at two periods of the day: in the afternoon (1 to 4 p.m.) and the early morning (4 to 6 a.m.) (*72*). These findings are in line with the findings of the present study regarding the time of day.

The likelihood of nonincapacitating injuries decreased by 4.4% in the fall (September to December). This decrease may be caused by more cautious driving precipitated by changes in climate and traffic patterns. For example, traffic volumes tend to decrease in the fall after being relatively high during the summer. However, a 6% increased likelihood of incapacitating injuries was observed during the summer (June to August). This finding could reflect increased traffic interactions between passenger vehicles and large trucks on highways. Brown and Baass report similar results for the same seasons (*73*). Ulfarsson and Mannering also report an increase of incapacitating injuries among female drivers of sport utility vehicles and minivans in single-vehicle collisions during the summer months (*31*).

Traffic Characteristics

Greater traffic flow, as measured by ADT per lane in each direction, reduces the likelihood of fatal injuries by 44.3%. This reduction could be a result of higher traffic volumes and more periods of traffic congestion. Furthermore, average traffic flow greater than 2,000 vehicles per lane in each direction also reduces the likelihood of possible injuries by 41.7%. Again, this reduction may be a result of higher traffic volume and the presence of traffic congestion. A similar study shows that low annual ADT (AADT; defined as traffic volume less than 2,000 AADT per lane) increases the possibility of nonincapacitating injuries for single- and multivehicle collisions (*6*). This parameter was random and normally distributed, with a mean of 0.249×10^{-4} and a standard deviation of 0.294×10^{-4} for noninjury (i.e., PDO) outcomes. Given these estimates, this parameter is greater than 0 for 19.8% of large truck crashes, which suggests that, on average, about 19.8% of large truck crashes were more likely to result in PDO crashes with increased traffic flow.

Weather Characteristics

Clear weather increases the likelihood of fatal outcomes by 66.9%. One possible explanation may be that drivers are more relaxed and possibly choose riskier behaviors as a result of better driving visibility; Edwards reports a similar result (*74*). However, clear weather reduces the likelihood of incapacitating injuries by 43.5%.

Road Geometry Characteristics

The road geometry indicator for four lanes in both directions increases the likelihood of nonincapacitating injuries by 23%. This variable may capture the effects of the rightmost lane of the highway, that is, a slow lane with a high percentage of truck traffic. Furthermore, the existence of a wide right shoulder indicator increases the likelihood of incapacitating injuries by 51.7%, which may reflect risk-compensating behavior because drivers feel comfortable having increased driving space.

The presence of a level surface increases the likelihood of nonfatal injuries by 54.1%. One possible explanation may be that level surfaces may increase driver awareness as a result of favorable driving visibility. Crashes that occur on dry pavement reduce the likelihood of possible injuries by 41.1%. Evasive actions (such as skidding of tires) are more effective on dry surfaces than on wet surfaces.

Lighting Characteristics

Crashes that occur under dark highway sections increase the likelihood of fatal and incapacitating injuries by 11.5% and 10.4%, respectively. Similar results are reported by Morgan and Mannering for single-vehicle crashes by female drivers younger than 45 years old on dry surfaces and by male drivers younger than 45 years old on wet surfaces (*43*); Malyshkina and Mannering for single-vehicle collisions on Indiana Interstates (*22*); and Anastasopoulos and Mannering for rural Interstates in Indiana (*33*).

In summary, the results provide insight into the complex interactions of various human, vehicle, and road–environment factors. They also indicate that some of the model variables varied across observations, validating the choice of the mixed logit model.

CONCLUSIONS AND FUTURE RESEARCH

This study develops and demonstrates the use of a mixed logit model for studying injury severity caused by large truck crashes on the Texas Interstate system with five distinct injury severity outcomes: fatal, incapacitating, nonincapacitating, possible, and none (i.e., PDO). The mixed logit model was developed from 5 years of crash data from 2006 to 2010. The mixed logit modeling framework is an important approach because it allows accounting and correcting for heterogeneity that can arise from factors such as individuals (i.e., drivers and passengers), vehicles, road–environment factors, weather, variations in police reporting, and temporal and other unobserved factors not captured in the data set. The 2006 to 2010 data used in this study were obtained from the CRIS database, which is, to the best of the authors' knowledge, a first with respect to explicitly modeling large truck injury severity.

The model results indicate that temporal characteristics such as time of day (3 to 7 p.m., midnight to 6 a.m.), season (summer and fall), and spatial characteristics (rural versus urban settings) as well as traffic conditions (expressed as directional AADT per lane) significantly affect injury severity outcomes at different levels of injury severity. Other factors contributing to injury severity outcomes include highway geometry (terrain of roadway, shoulder width, and surface condition) and demographic characteristics (driver gender and age group).

Variables that represent the contributing factors in a mixed logit model influence the likelihood of each injury outcome with increasing or decreasing effects. As shown in this study, higher traffic flow (as measured by ADT per lane) reduces the likelihood of fatal injuries but increases the likelihood of PDO crashes. Still, directional traffic flow exceeding a threshold of 2,000 vehicles per day per lane decreases the likelihood of possible injuries.

Crashes that occur in rural settings result in a higher likelihood of fatal and nonincapacitating injuries; however, crashes that occur in urban settings result in a lower likelihood of incapacitating and PDO crashes. Spatial characteristics are fixed across observations. Time of day between 3 and 7 p.m. results in a lower likelihood of fatal, incapacitating, and possible injuries. Additionally, time of day between midnight and 6 a.m. results in a higher likelihood of nonincapacitating injuries. Summer is more likely to increase the likelihood of incapacitating injuries, and fall is more likely to decrease the likelihood of nonincapacitating injuries. Both summer and fall seasons are fixed across observations.

Increased right shoulder width increases the likelihood of incapacitating injuries; four lanes in both directions increase the likelihood of nonincapacitating injuries. The 25- to 35-year-old age group is less likely to be involved in possible injury crashes, and the 45- to 55-year-old age group is more likely to be involved in noninjury crashes, where this age group was random for possible injury outcomes. Male drivers are more likely to be involved in possible injury crashes, which was a random parameter that varied across observations. A dry surface condition reduces the likelihood of possible and PDO crashes and is fixed across observations.

Even though this study is exploratory in nature, the modeling approach presented offers a method for analyzing the injury severity of large truck crashes while accounting for unobserved factors. In future work, the authors will explore the effects of splitting the model by setting (urban or rural) and by time of day.

REFERENCES

1. *Resolution Adopted by the United Nations General Assembly: 64/255. Improving Global Road Safety.* A/RES/64/255. United Nations, New York, March 2, 2010. http://www.un.org/ga/search/view_doc.asp?symbol=A/RES/64/255. Accessed May 21, 2012.
2. *2009 Traffic Fatalities by State and Percent Change from 2008. State: USA.* National Highway Traffic Safety Administration, Washington, D.C. http://www-fars.nhtsa.dot.gov/States/StatesCrashesAndAllVictims.aspx. Accessed Mar. 21, 2012.
3. *Texas Motor Vehicle Traffic Crash Highlights: Calendar Year 2011.* Texas Department of Transportation, Austin, 2011. http://ftp.dot.state.tx.us/pub/txdot-info/trf/crash_statistics/2011/01_2011.pdf. Accessed Feb. 21, 2012.
4. *Traffic Safety Facts: 2008 Data—State Traffic Data.* DOT HS 811 168. National Highway Traffic Safety Administration, Washington, D.C. http://www-nrd.nhtsa.dot.gov/Pubs/811168.pdf. Accessed Mar. 5, 2012.
5. *Fatality Facts 2010, Large Trucks.* Insurance Institute for Highway Safety. http://www.iihs.org/research/fatality.aspx?topicName=Largetrucks. Accessed Jan. 5, 2012.
6. Chen, F., and S. Chen. Injury Severities of Truck Drivers in Single- and Multi-Vehicle Accidents on Rural Highways. *Accident Analysis and Prevention,* Vol. 43, No. 5, 2011, pp. 1677–1688.
7. *Truck Driver Occupational Safety and Health: 2003 Conference Report and Selective Literature Review.* Department of Health and Human Services, Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health, Atlanta, Ga., 2007.
8. *Report to Congress on the Large Truck Crash Causation Study.* Federal Motor Carrier Safety Administration, U.S. Department of Transportation, 2005.
9. Geedipally, S. R., and D. Lord. Investigating the Effect of Modeling Single-Vehicle and Multi-Vehicle Accidents Separately on Confidence Intervals of Poisson–Gamma Models. *Accident Analysis and Prevention,* Vol. 42, No. 4, 2010, pp. 1273–1282.
10. Islam, M. B., and S. Hernandez. An Empirical Analysis of Fatality Rates for Large Truck Involved Crashes on Interstate Highways. In *3rd International Conference on Road Safety and Simulation,* Indianapolis, Ind., Sept. 14–16, 2011.
11. Islam, M. B., and S. Hernandez. Large Truck–Involved Crashes: Exploratory Injury Severity Analysis. *Journal of Transportation Engineering,* Vol. 139, No. 6, 2013, pp. 596–604.
12. Shankar, V. N., F. L. Mannering, and W. Barfield. Effect of Roadway Geometrics and Environmental Factors on Rural Accident Frequencies. *Accident Analysis and Prevention,* Vol. 27, No. 3, 1995, pp. 371–389.
13. Poch, M., and F. L. Mannering. Negative Binomial Analysis of Intersection Accident Frequencies, *Journal of Transportation Engineering,* Vol. 122, No. 2, 1996, pp. 105–113.
14. Abdel-Aty, M., and A. E. Radwan. Modeling Traffic Accident Occurrence and Involvement. *Accident Analysis and Prevention,* Vol. 32, No. 5, 2000, pp. 633–642.
15. Savolainen, P. T., and A. P. Tarko. Safety Impacts at Intersections on Curved Segments. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1908,* Transportation Research Board of the National Academies, Washington, D.C., 2005, pp. 130–140.
16. Shankar, V. N., J. Milton, and F. L. Mannering. Modeling Accident Frequencies as Zero-Altered Probability Processes: An Empirical Inquiry. *Accident Analysis and Prevention* Vol. 29, No. 6, 1997, pp. 829–837.
17. Carson, J., and F. L. Mannering. The Effect of Ice Warning Signs on Accident Frequencies and Severities. *Accident Analysis and Prevention,* Vol. 33, No. 1, 2001, pp. 99–109.
18. Lee, J., and F. L. Mannering. Impact of Roadside Features on the Frequency and Severity of Run-Off-Roadway Accidents: An Empirical Analysis. *Accident Analysis and Prevention,* Vol. 34, No. 2, 2002, pp. 149–161.
19. Shankar, V. N., R. B. Albin, J. C. Milton, and F. L. Mannering. Evaluating Median Crossover Likelihoods with Clustered Accident Counts: An Empirical Inquiry Using the Random Effects Negative Binomial Model. In *Transportation Research Record 1635,* TRB, National Research Council, Washington, D.C., 1998, pp. 44–48.
20. Chin, H. C., and M. A. Quddus. Applying the Random Effect Negative Binomial Model to Examine Traffic Accident Occurrence at Signalized Intersections. *Accident Analysis and Prevention,* Vol. 35, No. 2, 2003, pp. 253–259.
21. Anastasopoulos, P. C., and F. L. Mannering. A Note on Modeling Vehicle Accident Frequencies with Random-Parameters Count Models. *Accident Analysis and Prevention,* Vol. 41, No. 1, 2009, pp. 153–159.
22. Malyshkina, N. V., and F. L. Mannering. Markov Switching Multinomial Logit Model: An Application to Accident-Injury Severities. *Accident Analysis and Prevention,* Vol. 41, No. 4, 2009, pp. 829–838.
23. Park, B. J., D. Lord, and J. D. Hart. Bias Properties of Bayesian Statistics in Finite Mixture of Negative Binomial Regression Models in Crash Data Analysis. *Accident Analysis and Prevention,* Vol. 42, No. 2, 2010, pp. 741–749.
24. Patil, S., S. R. Geedipally, and D. Lord. Analysis of Crash Severities Using Nested Logit Model—Accounting for the Underreporting of Crashes. *Accident Analysis and Prevention,* Vol. 45, No. 1, 2012, pp. 646–653.
25. Golob, T., W. Recker, and J. Leonard. An Analysis of the Severity and Incident Duration of Truck-Involved Freeway Accidents. *Accident Analysis and Prevention,* Vol. 19, No. 5, 1987, pp. 375–396.
26. Islam, S., and F. L. Mannering. Driver Aging and Its Effect on Male and Female Single-Vehicle Accident Injuries: Some Additional Evidence. *Journal of Safety Research,* Vol. 37, No. 3, 2006, pp. 267–276.
27. Kim, J.-K., G. Ulfarsson, V. N. Shankar, and F. L. Mannering. A Note on Modeling Pedestrian Injury Severity in Motor Vehicle Crashes with

the Mixed Logit Model. *Accident Analysis and Prevention,* Vol. 42, No. 6, 2010, pp. 1751–1758.
28. Moore, D. N., W. Schneider, P. T. Savolainen, and M. Farzaneh. Mixed Logit Analysis of Bicyclist Injury Severity Resulting from Motor Vehicle Crashes at Intersection and Non-Intersection Locations. *Accident Analysis and Prevention,* Vol. 43, No. 3, 2011, pp. 621–630.
29. Malyshkina, N. V., and F. L. Mannering. Empirical Assessment of the Impact of Highway Design Exceptions on the Frequency and Severity of Vehicle Accidents. *Analysis, Accident Analysis and Prevention,* Vol. 42, No. 1, 2010, pp. 131–139.
30. Shankar, V. N., and F. L. Mannering. An Exploratory Multinomial Logit Analysis of Single-Vehicle Motorcycle Accident Severity. *Journal of Safety Research,* Vol. 27, No. 3, 1996, pp. 183–194.
31. Ulfarsson, G., and F. L. Mannering. Differences in Male and Female Injury Severities in Sport-Utility Vehicle, Minivan, Pickup and Passenger Car Accidents. *Accident Analysis and Prevention,* Vol. 36, No. 2, 2004, pp. 135–147.
32. Milton, J. C., V. N. Shankar, and F. L. Mannering. Highway Accident Severities and the Mixed Logit Model: An Exploratory Empirical Analysis. *Accident Analysis and Prevention,* Vol. 40, No. 1, 2008, pp. 260–266.
33. Anastasopoulos, P. C., and F. L. Mannering. An Empirical Assessment of Fixed and Random Parameter Logit Models Using Crash- and Non-Crash-Specific Injury Data. *Accident Analysis and Prevention,* Vol. 43, No. 3, 2001, pp. 1140–1147.
34. Gkritza, K., and F. L. Mannering. Mixed Logit Analysis of Seat-Belt Use in Single- and Multi-Occupant Vehicles. *Accident Analysis and Prevention,* Vol. 40, No. 2, 2008, pp. 443–451.
35. *SAS 9.2 for Windows.* SAS Institute, Inc., Cary, N.C., 2009.
36. Chistoforou, Z., S. Cohen, and M. G. Karlaftis. Vehicle Occupant Injury Severity on Highways: An Empirical Investigation. *Accident Analysis and Prevention,* Vol. 42, No. 6, 2010, pp. 1606–1620.
37. Lemp, J. D., K. M. Kockelman, and A. Unnikrishnan, Analysis of Large Truck Crash Severity Using Heteroskedastic Ordered Probit Models. *Accident Analysis and Prevention,* Vol. 43, No. 1, 2011, pp. 370–380.
38. Zhu, X., and S. Srinivasan. A Comprehensive Analysis of Factors Influencing the Injury Severity of Large Truck Crashes. *Accident Analysis and Prevention,* Vol. 43, No. 1, 2011, pp. 49–57.
39. Duncan, C. S., A. J. Khattak, and F. M. Council. Applying the Ordered Probit Model to Injury Severity in Truck–Passenger Car Rear-End Collisions. In *Transportation Research Record 1635,* TRB, National Research Council, Washington, D.C., 1998, pp. 63–71.
40. Xie, Y., Y. Zhang, and F. Liang. Crash Injury Severity Analysis Using Bayesian Ordered Probit Models. *Journal of Transportation Engineering,* Vol. 135, No. 1, 2009, pp. 18–25.
41. Khorashadi, A., D. Niemeier, V. N. Shankar, and F. L. Mannering. Differences in Rural and Urban Driver-Injury Severities in Accidents Involving Large Trucks: An Exploratory Analysis. *Accident Analysis and Prevention,* Vol. 37, No. 5, 2005, pp. 910–921.
42. Chang, L.-Y., and F. L. Mannering. Analysis of Injury Severity and Vehicle Occupancy in Truck- and Non-Truck Involved Accidents. *Accident Analysis and Prevention,* Vol. 31, No. 5, 1999, pp. 579–592.
43. Morgan, A., and F. L. Mannering. The Effects of Road Surface Conditions, Age, and Gender on Driver Injury Severities. *Accident Analysis and Prevention,* Vol. 43, No. 5, 2011, pp. 1852–1863.
44. Revelt, D., and K. Train. Mixed Logit with Repeated Choices: Households' Choice of Appliance Efficiency Level. *Review of Economics and Statistics,* Vol. 80, No. 4, 1997, pp. 647–657.
45. Revelt, D., and K. Train. Customer Specific Taste Parameters and Mixed Logit. Working paper. Department of Economics, University of California, Berkeley, 1999.
46. Train, K. Mixed Logit Models for Recreation Demand. In *Valuing the Environment Using Recreation Demand Models* (C. Kling and J. Herriges, eds.). Elgar Press, New York, 1997.
47. Brownstone, D., and K. Train. Forecasting New Product Penetration with Flexible Substitution Patterns. *Journal of Econometrics,* Vol. 89, No. 1–2, 1999, pp. 109–129.
48. McFadden, D., and K. Train. Mixed MNL Models for Discrete Response. *Journal of Applied Econometrics,* Vol. 15, No. 5, 2000, pp. 447–470.
49. Bhat, C. Quasi-Random Maximum Simulated Likelihood Estimation of the Mixed Multinomial Logit Model. *Transportation Research Part B,* Vol. 17, No. 1, 2001, pp. 677–693.
50. Train, K. *Discrete Choice Methods with Simulation.* Cambridge University Press, New York, 2009.
51. Savolainen, P. T., F. L. Mannering, D. Lord, M. A. Quddus. The Statistical Analysis of Highway Crash-Injury Severities: A Review and Assessment of Methodological Alternatives. *Accident Analysis and Prevention,* Vol. 43, No. 5, 2011, pp. 1666–1676.
52. Jones, S., and D. Hensher. Evaluating the Behavioural Performance of Alternative Logit Models: An Application to Corporate Takeovers Research. *Journal of Business Finance Accounting,* Vol. 34, 2007, pp. 1193–1220.
53. *NLOGIT 4.0.* Econometric Software, Plainview, N.Y., 2007.
54. Washington, S., M. Karlaftis, and F. L. Mannering. *Statistical and Econometric Methods for Transportation Data Analysis,* 2nd ed. Chapman and Hall/CRC, Boca Raton, Fla., 2011.
55. McFadden, D. Econometric Models of Probabilistic Choice. In *A Structural Analysis of Discrete Data with Econometric Applications* (C. F. Manski and D. McFadden, eds.). MIT Press, Cambridge, Mass., 1981.
56. McFadden, D., and P. Ruud. Estimation by Simulation. *Review of Economics and Statistics,* Vol. 76, No. 4, 1994, pp. 591–608.
57. Geweke, J., M. Keane, and D. Runkle. Alternative Computational Approaches to Inference in the Multinomial Probit Model. *Review of Economics and Statistics,* Vol. 76, No. 4, 1994, pp. 609–632.
58. Stern, S. Simulation-Based Estimation. *Journal of Economic Literature,* Vol. 35, No. 4, 1997, pp. 2006–2039.
59. Train, K. *Discrete Choice Methods with Simulation.* Cambridge University Press, Cambridge, United Kingdom, 2003.
60. Halton, J. On the Efficiency of Evaluating Certain Quasi-Random Sequences of Points in Evaluating Multi-Dimensional Integrals. *Numerische Mathematik,* Vol. 2, 1960, pp. 84–90.
61. Bhat, C. Simulation Estimation of Mixed Discrete Choice Models Using Randomized and Scrambled Halton Sequences. *Transportation Research Part B,* Vol. 37, No. 1, 2003, pp. 837–855.
62. Train, K. Halton Sequences for Mixed Logit. Working paper. Department of Economics, University of California, Berkeley, 1999.
63. Ye, F., and D. Lord. Comparing Three Commonly Used Crash Severity Models on Sample Size Requirements: Multinomial Logit, Ordered Probit and Mixed Logit Models. Presented at 90th Annual Meeting of the Transportation Research Board, Washington, D.C., 2011.
64. Walker, J., and M. Ben-Akiva. Generalized Random Utility Model. *Mathematical Social Sciences,* Vol. 43, No. 3, 2002, pp. 303–343.
65. Lee, L. On Efficiency of Method of Simulated Moments and Maximum Simulated Maximum Estimation of Discrete Response Models. *Econometric Theory,* Vol. 8, No. 3, 1992, pp. 518–552.
66. Abdelwahab, H. T., and M. A. Abdel-Aty. Development of Artificial Neural Network Models to Predict Driver Injury Severity in Traffic Accidents at Signalized Intersections. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1746,* TRB, National Research Council, Washington, D.C., 2001, pp. 6–13.
67. Driscoll, T., S. Marsh, B. McNoe, J. Langley, N. Stout, A.-M. Feyer, and A. Williamson. Comparison of Fatalities from Work Related Motor Vehicle Traffic Incidents in Australia, New Zealand, and the United States. *Journal of Injury Prevention,* Vol. 11, No. 5, 2005, pp. 294–299.
68. Stamatiadis, N., and J. A. Deacon. Trends in Highway Safety: Effects of an Aging Population on Accident Propensity. *Accident Analysis and Prevention,* Vol. 27, No. 4, 1995, pp. 443–459.
69. Khattak, A. J., M. D. Pawlovich, R. R. Souleyrette, and S. L. Hallmark. Factors Related to More Severe Older Driver Traffic Crash Injuries. *Journal of Transportation Engineering,* Vol. 128, No. 3, 2002, pp. 243–249.
70. Lenné, M. G., T. J. Triggs, and J. R. Redman. Time of Day Variation in Driving Performance. *Accident Analysis and Prevention,* Vol. 29, No. 4, 1997, pp. 431–437.
71. Doherty, S. T., J. C. Andrey, and C. MacGregor. The Situational Risks of Young Drivers: The Influence of Passengers, Time of Day and Day of Week on Accident Rates. *Accident Analysis and Prevention,* Vol. 30, No. 1, 1998, pp. 45–52.
72. Otmani, S., J. Rogé, and A. Muzet. Sleepiness in Professional Drivers: Effect of Age and Time of Day. *Accident Analysis and Prevention,* Vol. 37, No. 5, 2005, pp. 930–937.
73. Brown, B., and K. Baass. Seasonal Variation in Frequencies and Rates of Highway Accidents as Function of Severity. In *Transportation Research Record 1581,* TRB, National Research Council, Washington, D.C., 1997, pp. 59–65.
74. Edwards, J. B. The Relationship Between Road Accident Severity and Recorded Weather. *Journal of Safety Research,* Vol. 29, No. 4, 1998, pp. 249–262.

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