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Multi-Vehicle Crashes Involving Large Trucks: A Random Parameter Discrete Outcome Modeling Approach

by Mouyid Islam

A growing concern on large-truck crashes increased over the years due to the potential economic impacts and level of injury severity. This study aims to analyze the injury severities of multi-vehicle large-trucks crashes on national highways. To capture and understand the complexities of contributing factors, two random parameter discrete outcome models – random parameter ordered probit and mixed logit – were estimated to predict the likelihood of five injury severity outcomes: fatal, incapacitating, non-incapacitating, possible injury, and no-injury. Estimation findings indicate that the level of injury severity is highly influenced by a number of complex interactions of factors, namely, human, vehicular, road-environmental, and crash dynamics that can vary across the observations.

INTRODUCTION

Very few studies have addressed freight transport safety with regard to injury analysis of crashes involving large trucks from an econometric modeling standpoint (Islam and Hernandez 2011, Islam and Hernandez 2012, Chen and Chen 2011, Zhu and Srinivasan 2011, Lemp et al. 2011), specifically, multi-vehicle crashes in which large trucks are involved. A more recent safety fact by NHTSA (2011) indicated that 81% of fatal crashes involving large trucks are multi-vehicle crashes in contrast with 58% for crashes involving passenger vehicles. A clear evidence of large trucks being more likely to be involved in a fatal multi-vehicle crash compared to a fatal single-vehicle crash (NHTSA 2011), is a growing concern for highway safety engineers, trucking companies, policy makers, and overall public due to the magnitude and devastation associated with these crashes.

Numerous studies have been conducted on crash frequency (Ivan et al. 1999, Ivan et al. 2000, Geedipally and Lord 2010) models rather than severity likelihood models. Those studies focusing on severity models indicated that multi-vehicle crashes are more severe than single-vehicle crashes in particular conditions (Viano et al. 1990) but not with regard to large trucks (Viano et al. 1990, Jung et al. 2012, Savolainen and Mannering 2007). A study by Viano (1990) emphasized the injury severities in multi-vehicle crashes mostly occurred on dry surface, daylight hours and non-alcohol involvement, from side-impacts based on the National Crash Severity Study. Moreover, Jung et al. (2012) modeled injury severity for multi-vehicle crashes which occur more frequently than single-vehicle crashes in rainy weather, using time of day, rainfall intensity, water film depth, and deficiency of car-following distance. Ivan et al. (1999) developed a Poisson regression model and found that multiple vehicle crashes are highly related with increase of traffic intensity, shoulder width, truck percentage, and traffic signals based on studies of two-lane rural highways in Connecticut. Considering injury mechanism involving large trucks with other vehicles, the contributing factors in multi-vehicle crashes are quite different in nature from single-vehicle crashes because of the differences in driving behavior, vehicle operating characteristics, and maneuverability by different groups of vehicles (Ivan et al. 1999, Chen and Chen 2011, Geedipally and Lord 2010). Since the vehicular form and mass incompatibility between large trucks and passenger vehicles are high in multi-vehicle crashes, the level of severity sustained is significant as is the associated societal cost.

Departing from traditional modeling approaches such as fixed parameter models focusing on the injury severities, advanced econometric modeling approach was explored by emphasizing the unobserved factors hidden in the process of crash reporting by the investigating police officers at the crash scene, and data sampling scheme within the stored database. Mixed logit and random parameter ordered probit models were developed to shed light on the contributing factors leading to multi-vehicle crashes involving large trucks. Fusing three datasets of the National Automotive Sampling System – General Estimated System (NASS-GES) from 2005 to 2008 to obtain a crash sample, this study aims at providing a better understanding of the complex interactions of contributing factors influencing injury outcomes (i.e., fatal, incapacitating injury, non-incapacitating injury, possible injury, and no-injury) in crashes involving large trucks. To capture these complexities using NASS-GES, consideration of random parameters provides a mechanism to account for any unobserved heterogeneity that may exist, indicating unobserved factors that may vary across observations. This unobserved heterogeneity can be explained in such a way that each observation in the dataset vary from each other in the entire sample (Kim et al. 2010) and there may be cases of limited data such as roadway geometrics, pavement condition, and general weather and traffic characteristics (Anastasopolus and Mannering 2010).

Although both of the models (i.e., mixed logit and random parameter ordered probit models) have been applied to large truck crash severity analysis from different modeling perspectives, this research extends the current literature by introducing additional significant variables related to human factors in regard to multi-vehicle large truck crashes on US Interstate 1. From the standpoint of practical applications, the models indicating any critical factors such as human, vehicular, and road-environment should be considered for the implementation of possible countermeasures by the safety engineers, policy makers, trucking companies, and other stakeholders. The statistical models based on the comprehensive historical crash data focusing on multi-vehicle crashes involving large trucks on the interstates can be used as an analytical tool to identify the factors for possible countermeasures. A specific countermeasure against severe injury crashes involving large trucks related to fatigued drivers can be undertaken by installing new and increasing efficiency of existing parking spaces and installing rumble strips in new and existing roadways (NCHRP 500 2004). The paper focuses on the sample size and descriptive statistics of the important variables in the Empirical Setting section as well as modeling techniques in the Methodology section and model results in the Empirical Results section. Then, the model results are discussed in terms of contributing factors leading to multi-vehicle crashes involving large trucks with marginal effect estimates from both models. A conclusion was drawn from the results and future work to be done to improve the sample and model results is discussed.

EMPIRICAL SETTINGS

The data for crashes involving large trucks were obtained from the nationwide NASS-GES crash database maintained by National Highway Traffic Safety Administration (NHTSA). A large truck is commonly classified as a tractor-trailer, single-unit truck, or cargo van having a Gross Vehicle Weight Rating (GVWR) greater than 10,000 pounds (IIHS 2009). The GES database is based on a nationally representative probability sample selected from the estimated 5.8 million police-reported crashes resulting in a fatality or injury and those involving major property damage annually (NASS-GES 2008). It is traditional to analyze injury severity utilizing police reported crash data. However, this police reported crash data are generally subjected to under reporting in the case of minor or no personal injury, as evidenced from a technical report by NHTSA (2009) that 25% of minor injury crashes and 50% of no injury crashes are unreported (Savolainen et al. 2011). In this study, a subset of 6,588 observations was used for large truck involved crashes over a period of four years (i.e., 2005 to 2008) from an annual average of 56,970 total crashes over this time period (also includes truck-truck crashes). Despite the issues of under reporting for minor and no personal injury crashes along with the multi-stage sampling scheme in the GES database, GES focuses on the crashes of greatest concern to the highway safety community and general public (NASS-GES 2008). As a result, GES is a representative sample of the crashes from the police reports all over the United States and it is fairly common practice in the modeling approach to assume that sample data selected from the population have equal likelihood of being considered in the sample (Savolainen et al. 2011).

To investigate contributing human, vehicle, and road-environment factors, a sample of 6,588 data observations representing crashes involving at least a large truck and other vehicles (i.e., number of vehicles involved is two or more than two) on the interstate highway system from 2005 to 2008 were extracted from the NASS-GES database. The maximum level of injury severity recorded in the vehicle or person dataset was aggregated to represent a crash. Each observation in the sample is a crash representing the maximum level of injury of the occupants, involving at least one large truck with one or more vehicles on interstate highways. The crash dataset was fused to the vehicle and person datasets through appropriate linking variables such as crash number; while the vehicle and person dataset were linked through the vehicle and crash number using the Statistical Analysis System (SAS). The mixed logit and ordered probit frameworks were modeled in Limdep (NLOGIT 4.0).

The expected and modeled effects of the explanatory variables are shown in Table 1 for Ordered Probit model and in Table 2 for Mixed Logit model. The expected effects for the variables are based on the previous safety studies and the analyst's (i.e., author's) general understanding on the outcomes of the crashes under given conditions (such as wet surface, time of day, month of year, curved section, distraction, crash types, etc.). In the perspective of multi-vehicle large truck involved crashes, the collision partners range from single passenger vehicles to multiple passenger vehicles or trucks. The expected effects of the variable follows the general trend in term of injury outcomes of large truck involved crashes.

Out of 15 variables, only four were found to have opposite than expected effects in random parameter ordered probit model. Similarly, out of 22 variables, only three were found to have opposite than expected effects.

1. Single-unit trucks are found to be involved in less severe crashes. However, the expectation is opposite – more severe crashes. This is because single-unit trucks are comparatively easier to maneuver than double-unit trucks. As such, the drivers of single-unit trucks are less cautious than those of double-unit trucks. The chances are single-unit trucks would be highly involved in more severe crashes because of flexibility of maneuvering in higher speed than double-unit trucks.
2. In the event of rollover, the likelihood of being severely injured is higher. However, that likelihood of being severely injured is only the case for passenger vehicle occupants, when being struck by large trucks coupled with not being properly restrained by seat-belts. However, that may not be true for large truck occupants. And this is reflected in the sign of the variable – decreasing effect.
3. The presence of passengers in the vehicles increases the chances of being severely injured for passenger vehicle being struck by large trucks. Higher occupancy increases the likelihood of being severely injured for passenger vehicles compared with large trucks.
4. In the event of rollover, the likelihood of having incapacitating injury (A-type) is higher. However, that likelihood of having A-type injury is the case for passenger vehicle occupants, when being struck by large trucks coupled with not being properly restrained by seat-belts. However, that may not be true for large truck occupants. And this is reflected in the sign of the variable – decreasing effect.
5. When the road surface is wet, drivers tend to slow down to adjust to the ambient environmental conditions. So, the likelihood of possible injury to passenger vehicle occupants should be less. However, the chances of other injury levels can increase as well. On the other hand, multi-vehicle collisions between large trucks and passenger vehicles

Table 1: Expectation on Signs of Explanatory Variables of Random Parameter Ordered Probit Model

Variables	Modeled Effect	Expected Effect	Basis of Expectation
Weather condition (1 if snow, 0 otherwise)	Decreasing effect	Decreasing effect	In snowy weather drivers would be more cautious.
Months of the year (1 if summer months (June - August), 0 otherwise)	Increasing effect	Increasing effect	Because of better weather, there is a tendency to travel more and thus exposure level increases.
Light condition of street (1 if dark, 0 otherwise)	Increasing effect	Increasing effect	In dark condition, drivers face difficulty is terms of visibility.
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	Decreasing effect	Increasing effect	See the explanation above.
Vehicle role (1 if struck by other vehicle, 0 otherwise)	Decreasing effect	Decreasing effect	If large truck is struck by other vehicles, there will less of energy absorption by the trucks than by the passenger vehicles because of momentum.
The most harmful event (1 if rollover, 0 otherwise)	Decreasing effect	Increasing effect	See the explanation above.
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	Decreasing effect	Decreasing effect	Same direction side swipe may not results in serious injury than opposite direction.
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	Decreasing effect	Decreasing effect	Lane changing maneuver may not result in serious injury because of vehicles are changing between lanes.
Vehicle maneuver just prior to impending crash (1 if going straight, 0 otherwise)	Decreasing effect	Decreasing effect	One of the two or multiple vehicles involved in the crashes, is keeping the lane (i.e., going straight) while other vehicles are changing lanes. This maneuver results in low severe crashes.
Factor of crash identified in the investigation (1 if speed, 0 otherwise)	Increasing effect	Increasing effect	Speeding for the conditions very likely result in serious injury crashes.
Driver's attention level at the time of impending crash (1 if distraction or inattention, 0 otherwise)	Increasing effect	Increasing effect	Driver's distraction can very likely lead to serious injury crashes because of not paying required level of attention to drive and maintain safe distance between vehicles.

(Table 1 continued)

Variables	Modeled Effect	Expected Effect	Basis of Expectation
Occupants' use of available vehicle restraints (1 if no restraint used, 0 otherwise)	Increasing effect	Increasing effect	Not using seat-belt can lead to serious injury crashes because of unbelted occupants can eject from the vehicles and secondary impacts of occupants' body inside the vehicle compartment can cause serious injuries.
Location of the occupants in the vehicle (1 if for passenger position, 0 otherwise)	Decreasing effect	Increasing effect	See the explanation above.
Gender of the occupants (1 if male, 0 otherwise)	Decreasing effect	Decreasing effect	Male drivers/occupants are less likely to be involved in severe crashes than female counter parts because of different body tolerance against the sustained injury levels.
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	Increasing effect	Increasing effect	Because of border state and wide landscape of rural and urban interstate system in Texas, drivers drive relatively relaxed with higher speeds. Also, drivers from border regions may not be familiar with road network and driving behavior is very different.

Table 2: Expectation on Signs of Explanatory Variables of Mixed Logit Model

Variables	Modeled Effect	Expected Effect	Basis of Expectation
Fatal Outcome			
Vehicle maneuver during pre-crash situation (1 if left or right side departure, 0 otherwise)	Increasing effect	Increasing effect	Getting departed from the roadway increases in the risk of getting hit by the roadside fixed objects as well as the rollover (because of steep slope and tipping point and speed).
Light condition of street (1 if dark, 0 otherwise)	Increasing effect	Increasing effect	Dark roadway condition clearly poses more risk if terms of visibility for the drivers in the high speed roadway.
Orientation of vehicle at the time of crash (1 if head-on, 0 otherwise)	Increasing effect	Increasing effect	Head-on collision increases the risk of crashes result in severe injuries.
Time of the day (1 if 2 pm in the afternoon, 0 otherwise)	Increasing effect	Increasing effect	This relates the fatigue/sleepy driving condition (after lunch time) during the day.
Incapacitating Injury Outcome			
Driver's attention level at the time of impending crash (1 if distraction or in attention, 0 otherwise)	Increasing effect	Increasing effect	Distracted driving obviously increases the risk of crashes that results in severe crashes.
Vehicular factors (1 if tire-related malfunction, 0 otherwise)	Increasing effect	Increasing effect	Tire-related malfunctions increase the instability of keeping the vehicle on the road and increases the crashes resulting in severe injuries.
The most harmful event in crash consequences (1 if rollover, 0 otherwise)	Decreasing effect	Increasing effect	See the explanation below
Orientation of vehicle at the time of crash (1 if rear-end, 0 otherwise)	Increasing effect	Increasing effect	Rear-end crashes increases the severe injuries crashes – passenger vehicles hitting the rear of large trucks, where the height of large truck with its form and mass incompatibility force intrudes into the passenger vehicle and same is true for otherwise (large truck hitting passenger vehicles).

(Table 2 continued)

Variables	Modeled Effect	Expected Effect	Basis of Expectation
Time of the day (1 if 5 am in the morning, 0 otherwise)	Increasing effect	Increasing effect	Its early morning traffic in high speed facility which increases the severe injury crashes.
Non-incapacitating Injury Outcome			
Occupants' use of available vehicle restraints (1 if no restraint used, 0 otherwise)	Increasing effect	Increasing effect	Not using seat-belt can lead to serious injury crashes because of unbelted occupants can eject from the vehicles and secondary impacts of occupants' body inside the vehicle compartment can cause serious injuries.
Time of the day (1 if 4 am in the morning, 0 otherwise)	Increasing effect	Increasing effect	Its early morning traffic in high speed facility which increases the severe injury crashes.
Months of the year (1 if summer months (June to August), 0 otherwise)	Increasing effect	Increasing effect	Because of better weather, there is a tendency to travel more on roads and thus exposure level increases.
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	Decreasing effect	Decreasing effect	Side-swipe (same direction) increases the likelihood of property-damage-only or lower severity crashes. But, that does not results in severe injury crashes.
Possible Injury Outcome			
Gender of the occupants (1 if male, 0 otherwise)	Decreasing effect	Decreasing effect	Male drivers/occupants are less likely to be involved in severe crashes than female counter parts because of different body tolerance against the sustained injury levels.
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	Increasing effect	Increasing effect	Because of border state and wide landscape of rural and urban interstate system in Texas, drivers drive relatively relaxed with higher speeds. Also, drivers from border regions may not be familiar with road network and driving behavior is very different.
Speed-related factor in crash (1 if speed as a factor, 0 otherwise)	Increasing effect	Increasing effect	Speeding for the conditions very likely result in serious injury crashes.

(Table 2 continued)

Variables	Modeled Effect	Expected Effect	Basis of Expectation
Number of vehicles involved in the crash	Increasing effect	Increasing effect	Higher the number of vehicles involved in the large truck involved crashes, the higher likelihood of being injured.
Road surface condition (1 if wet, 0 otherwise)	Increasing effect	Decreasing effect	See the explanation below.
Non-injury Outcome (Property-Damage-Only)			
Alignment of highway section (1 for curved section, 0 otherwise)	Decreasing effect	Decreasing effect	Driving along the curve under the unfavorable weather, lighting, and distraction makes drivers aware of the risk associated in driving along that segment.
Orientation of vehicle at the time of crash (1 if rear-end, 0 otherwise)	Decreasing effect	Increasing effect	See the explanation below.
Light condition of street (1 if the surrounding area is dark but outside is lighted, 0 otherwise)	Increasing effect	Increasing effect	Some section of high speed roadways may have lighting but some places lacks proper lighting and the surrounding place providing lighting to the high-speed motorist is not enough to avoid the risk at night time driving.
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	Increasing effect	Increasing effect	Lane changing maneuver may not result in serious injury because of vehicles are changing between lanes. But, it can results in lower to no-injury crashes.
Driver's attention level at the time of pre-crash (1 if sleepy, 0 otherwise)	Decreasing effect	Decreasing effect	Sleepy or fatigued driving obviously increases the risk of crashes that results in severe crashes (alternatively decreases the likelihood of lower severity crashes)
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	Increasing effect	Increasing effect	Single-unit trucks comparatively easier to maneuver than double-unit trucks. As such, the drivers of single-unit trucks are less cautious than those of double-unit trucks. The chances are single-unit trucks would be highly involved in non-severe crashes because of flexibility of maneuvering in higher speed than double-unit trucks.

could possibly result in some level of injury given at lower speed, and may still have higher potential for possible injury.

6. In the case of rear-end collision, there is higher likelihood of property-damage-only crashes but it also may cause higher chances of other injury levels such as A-, B-, and C-injury levels.

In summary, the variables are defined from data sources and they are found to be statistically significant in large truck modeling.

Table 3 and Table 4 show the descriptive statistics of key variables in the models[2]. Although some of the variables are common in both models, the data description of some important variables is presented here. With regard to random parameter ordered probit model, Table 3 illustrates about 33% of the observations related to side-swipes in the same directions, 81% related to rollover crashes. Additionally, as seen from Table 3, lane changing maneuvers account for 12% of the total observations compared with 65.2% regarding going straight. Another key observation is that dark conditions and summer months (i.e., June to August) account for 11% and 23.5% of the multi-vehicle crashes, respectively. The statistics further illustrate that speeding and being struck by other vehicles account for about 8% and 46.6% of the total observations in multi-vehicle crashes, respectively.

Table 3: Descriptive Statistics of Key Variables in Ordered Probit Model

Meaning of Variables in the Model	Mean	Std. Dev.
Vehicle maneuver during pre-crash situation (1 if left or right side departure, 0 otherwise)	0.041	0.199
Light condition of street (1 if dark, 0 otherwise)	0.109	0.312
Passenger role (1 if passenger is present, 0 otherwise)	0.977	0.146
Vehicle maneuver during pre-crash situation (1 if going straight, 0 otherwise)	0.652	0.476
Driver's attention level at the time of impending crash (1 if distraction or in attention, 0 otherwise)	0.041	0.197
Role as crash partner (1 if struck, 0 otherwise)	0.466	0.498
The most harmful event in crash consequences (1 if rollover, 0 otherwise)	0.809	0.392
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	0.331	0.471
Occupants' use of available vehicle restraints (1 if no restraint used, 0 otherwise)	0.018	0.133
Months of the year (1 if summer months (June to August), 0 otherwise)	0.235	0.424
Gender of the occupants (1 if male, 0 otherwise)	0.938	0.240
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	0.100	0.300
Speed-related factor in crash (1 if speed as a factor, 0 otherwise)	0.079	0.270
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	0.118	0.323
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	0.750	0.432

Table 4 shows that about 42.4% of the total crash observations related to rear-end crashes and on average more than two (2.3) vehicles were involved in multiple vehicle crashes. The statistics as seen in Table 4 illustrate that lane changing, inattentive driving, and dark conditions account for

11.8%, 4.1%, and 11% of the total crash observations, respectively. Curved sections of highways and wet pavement account for 8.1% and 15.2% of total crash observations, respectively. The time specific variables such as summer month (i.e., June to August) and time of day (2 pm and 5 am) on average account for 23.5%, 5.5%, and 12.3% of total crash observations, respectively.

Table 4: Descriptive Statistics of Key Variables in Mixed Logit Model

Meaning of Variables in the Model	Mean	Std. Dev.	Outcome
Vehicle maneuver during pre-crash situation (1 if left or right side departure, 0 otherwise)	0.009	0.098	Fatal (K)
Light condition of street (1 if dark, 0 otherwise)	0.109	0.312	
Orientation of vehicle at the time of crash (1 if head-on, 0 otherwise)	0.008	0.093	
Time of the day (1 if 2 pm in the afternoon, 0 otherwise)	0.055	0.228	
Driver's attention level at the time of impending crash (1 if distraction or in attention, 0 otherwise)	0.041	0.197	Incapacitating Injury Crash (A)
Time of the day (1 if 5 am in the morning, 0 otherwise)	0.123	0.328	
Vehicular factors (1 if tire-related malfunction, 0 otherwise)	0.007	0.085	
Orientation of vehicle at the time of crash (1 if rear-end, 0 otherwise)	0.424	0.494	
The most harmful event in crash consequences (1 if rollover, 0 otherwise)	0.809	0.392	
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	0.331	0.470	Non-Incapaci-tating Injury Crash (B)
Occupants' use of available vehicle restraints (1 if no restraint used, 0 otherwise)	0.018	0.133	
Time of the day (1 if 4 am in the morning, 0 otherwise)	0.020	0.141	
Months of the year (1 if summer months (June to August), 0 otherwise)	0.235	0.424	
Gender of the occupants (1 if male, 0 otherwise)	0.938	0.240	Possible Injury (C)
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	0.100	0.300	
Number of vehicles involved in the crash	2.324	0.672	
Speed-related factor in crash (1 if speed as a factor, 0 otherwise)	0.079	0.270	
Road surface condition (1 if wet, 0 otherwise)	0.152	0.359	
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	0.118	0.323	No-injury (PDO)
Light condition of street (1 if the surrounding area is dark but outside is lighted, 0 otherwise)	0.157	0.364	
Driver's attention level at the time of impending crash (1 if sleepy, 0 otherwise)	0.002	0.042	
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	0.751	0.432	
Orientation of vehicle at the time of crash (1 if rear-end, 0 otherwise)	0.424	0.494	
Alignment of highway section (1 for curved section, 0 otherwise)	0.081	0.274	

The correlation matrix for both of the injury severity models was computed. The correlation matrix for the random parameter ordered probit model indicates that lane changing maneuver has a correlation coefficient of 0.501 and 0.329 with going straight and side-swipe crashes, respectively. On the other hand, the correlation matrix for mixed logit model indicate that rear-end collision has a correlation coefficient of 0.604 with side-swipe crashes, and time – four o'clock has correlation coefficient of 0.385 with five o'clock. Although the magnitude of the coefficients might pose some multicollinearity issues, the lane changing maneuver and crashes are not seriously correlated in the models. For the random parameter ordered probit model, a lane changing maneuver might result in subsequent actions of going straight and side-swipe in the same direction in a multi-vehicle collision. The same is true for the mixed logit model where rear-end collision might be the outcome of some subsequent actions of a side-swipe collision. Also, the early morning hours from four to five o'clock account for severe injuries for multi-vehicle crashes.

METHODOLOGY

In order to achieve a better understanding of the injury severity of large trucks involved in multi-vehicle crashes with discrete outcome models, random parameter ordered probit and mixed logit models were developed.

Ordered Probit Framework

A random parameter ordered probit model was developed to capture the injury severity experienced while accounting for unobserved heterogeneity (McKelvey and Zavoina 1975, Chistoforou et al. 2010, Zhu and Srinivasan 2011) because of the ordinal nature of injury according to the KABCO scale (i.e., 'K' for Fatal, 'A' for Incapacitating injury, 'B' for Non-incapacitating injury, 'C' for Possible injury, and 'O' for Property-Damage-Only). In this study, the descending order (i.e., 0 for K , 1 for A, 2 for B, 3 for C, and 4 for O) (Islam and Hernandez 2012) was followed rather than ascending order in the previous studies (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 2002) to account for any bias resulting from under-reporting tendency in the crash and variability of parameter estimation (Ye and Lord 2011).

In the formulation of the model, an unobserved variable is a modeling basis of ordinal ranking of the data, with specified as a latent and continuous measure of injury severity of each observation (Washington et al. 2011):

(1) $y^* = \boldsymbol{\beta X} + \varepsilon$

where:

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

Using Equation 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):

$$(2)\quad \begin{array}{ll} y = 0 & if\ \infty \leq y^* \leq \mu_0 \\ y = 1 & if\ \mu_0 \leq y^* \leq \mu_1 \\ y = 2 & if\ \mu_1 \leq y^* \leq \mu_2 \\ y = I-1 & if\ \mu_{I-2} \leq y^* \leq \mu_{I-1} \\ y = I & if\ \mu_{I-1} \leq y^* \leq \infty \end{array}$$

where:

μ : are estimable parameters (i.e., thresholds) that define y and are estimated jointly with the model parameters $\boldsymbol{\beta}$, which corresponds to integer ordering, and I is the highest integer ordered response (e.g., PDO which is 4).

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

$$(3)\quad \begin{array}{l} P_n(y=0) = \Phi(-\boldsymbol{\beta X}) \\ P_n(y=1) = \Phi(\mu_1 - \boldsymbol{\beta X}) - \Phi(-\boldsymbol{\beta X}) \\ P_n(y=2) = \Phi(\mu_2 - \boldsymbol{\beta X}) - \Phi(\mu_1 - \boldsymbol{\beta X}) \\ P_n(y=3) = \Phi(\mu_3 - \boldsymbol{\beta X}) - \Phi(\mu_2 - \boldsymbol{\beta X}) \\ P_n(y=4) = \Phi(\mu_4 - \boldsymbol{\beta X}) - \Phi(\mu_3 - \boldsymbol{\beta X}) \\ P_n(y=I) = 1 - \Phi(\mu_{I-1} - \boldsymbol{\beta X}) \end{array}$$

where:

$P_n(y = I)$: is the probability that observation has as the highest ordered-response index (in our case PDO being 4 is the highest)

$\Phi(\cdot)$: is the standard normal cumulative distribution function

Marginal effects are computed at the sample mean for each category (Greene 2007, Washington et al. 2010):

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

where:

$\phi(\cdot)$: is the probability mass function of the standard normal distribution

Greene (2007) developed an estimation procedure that utilizes simulated maximum likelihood estimation to incorporate random parameters in the ordered probit modeling scheme. 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 Equation 1), which translates the individual heterogeneity into parameter heterogeneity,[3] as follows (Greene 2007):

$$(5)\quad \beta_{in} = \beta + \gamma_{in}$$

where:

β_{in} : is vector of parameters that can be estimated of each driver–injury outcome i in observation n.

γ_{in} : is randomly distributed term (for example a normally distributed term with mean zero and variance σ^2).

This parameter heterogeneity results from the uncertainty of β_{in} for a number of factors. These include the data collection process by the investigating police officers at the crash scene, objective information of a particular parameter as opposed to incomplete and qualitative information gathered or inferred from the secondary sources.

Mixed Logit Framework

In terms of utility functions and other methodological flexibility, a mixed logit model was developed that can be used to determine the contributing factors that influence the likelihood of severity outcomes in large truck involved crashes.

S_{in} is a linear function that determines discrete outcome i as injury severity outcome such as fatality, incapacitating injury, non-incapacitating injury, possible injury, and no-injury (property-damage-only) for observation n such that: (Washington et al. 2011):

(6) $$S_{in} = \boldsymbol{\beta}_i \mathbf{X}_{in} + \varepsilon_{in}$$

where:

$\boldsymbol{X_{in}}$: is vector of explanatory variables covering driver, vehicle, and road and environmental factors that determine injury outcome (i),

β_i : is vector of estimable parameters,

ε_{in} : is random error.

If ε_{in}'s are assumed to be generalized extreme value distributed (or Gumble distributed) with a possible limit distribution of properly normalized maxima of a sequence of independent and identically distributed random variables, McFadden (1981) has shown that the multinomial logit results such that

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

where:

$P_n(i)$: is probability of observation n having severity outcome i (such as fatality, incapacitating injury, non-incapacitating injury, possible injury, PDO) ($\in I$ with I denoting all possible outcomes of injury severity for observation n).

The NASS-GES crash database is likely to have a significant amount of unobserved heterogeneity. As the investigating police officers report factors influencing the injury severity outcome differently due to officers' discretion when reporting estimates of the representative crash data sample all over the United States. The possibility that elements of the parameter vector may vary across observations of each crash was considered by using a random parameters logit model (also known as the mixed logit model). Previous works by McFadden and Rudd (1994), Geweke et al. (1994), Revelt and Train (1997, 1999), Train (1997), Stern (1997), Brownstone and Train (1999), McFadden and Train (2000), and Bhat (2001) have shown the development and effectiveness of the mixed logit model approach can account for the variations across crash observations of the effects that variables have on the injury severity outcomes considered in this study. The mixed logit model is written as (Train 2003),

(8) $$P_n(i) = \int \frac{EXP[\boldsymbol{\beta}_i \mathbf{X}_{in}]}{\sum_I EXP[\boldsymbol{\beta}_i \mathbf{X}_{in}]} f(\boldsymbol{\beta}_i|\boldsymbol{\varphi}) d\boldsymbol{\beta}_i$$

where:

$f(\boldsymbol{\beta}i|\boldsymbol{\varphi})$: is the density function of $\boldsymbol{\beta}i$, $\boldsymbol{\varphi}$ is a vector of parameters of the density function (mean and variance), and all other terms are as previously defined.

This model can now account for the injury severity outcome of specific variations of the effect of $\mathbf{X}_{in}$ on injury severity outcome probabilities, with the density function $f(\boldsymbol{\beta}\mathbf{i}|\boldsymbol{\varphi})$ used to determine $\boldsymbol{\beta}_i$. Mixed logit probabilities are then a weighted average for different values of $\boldsymbol{\beta}_i$ across crash observations where some elements of the vector $\boldsymbol{\beta}_i$ may be fixed and some randomly distributed. If the parameters are random, the mixed logit weights are determined by the density function $f(\boldsymbol{\beta}i|\boldsymbol{\varphi})$ (Milton et al. 2008, Washington et al. 2011).

In order to estimate the impact of particular variables on the injury-outcome likelihood, elasticities (or direct-pseudo elasticity) are computed. In the context of the current injury severity model, most of the variables are indicator (i.e., 1 or 0) in nature. Direct-pseudo elasticities are estimated to measure the marginal effects of indicator variables when any particular indicator variable switches from 0 to 1 or vice versa (Washington et al. 2011). This is translated to a percentage change of the injury-outcome likelihood when the indicator variable switches between 0 and 1 or 1 to 0. For binary indicator variables, the direct-pseudo elasticity is estimated as shown in Equation (10) (Kim et al. 2010):

$$(9)\quad E_{x_{nk}(i)}^{P_n(i)} = \frac{P_n(i)[given\ x_{nk}(i) = 1] - P_n(i)[given\ x_{nk}(i) = 0]}{P_n(i)[given\ x_{nk}(i) = 0]}$$

where:

$P_n(i)$: is given the Equation (8) and simulated as shown in Equation (11).
$x_{nk}(i)$: is the k-th independent variable associated with injury severity i for observation n.

Direct average elasticities of any continuous variable are estimated using Equation 10. This measures the percentage change is injury outcome likelihood when the continuous variable changes one unit (Washington et al. 2011).

$$(10)\quad E_{x_{nki}}^{P_n(i)} = \frac{\frac{\partial P_n(i)}{P_n(i)}}{\frac{\partial x_{nk(i)}}{x_{nk(i)}}} = \frac{\partial P_n(i)}{P_n(i)} \cdot \frac{x_{nk(i)}}{\partial x_{nk(i)}}$$

where:

$P_n(i)$: is given the Equation (8) and simulated as shown in Equation (11).
$x_{nk}(i)$: the k-th independent variable associated with injury severity i for observation n.

The unconditional probability in Equation (8) (Kim et al. 2010) can be estimated with an unbiased and smooth simulator (McFadden and Train 2000) that is computed as (Walker and Ben-Akiva 2002, Kim et al. 2010):

$$(11)\quad \hat{P}_n(i) = \frac{1}{R}\sum_{r=1}^{R} P_{in} = \frac{1}{R}\sum_{r=1}^{R} \int \frac{EXP[\boldsymbol{\beta}_i\mathbf{X}_{in}]}{\sum_I EXP[\boldsymbol{\beta}_i\mathbf{X}_{in}]} f(\boldsymbol{\beta}_i|\boldsymbol{\varphi})d\boldsymbol{\beta}_i$$

where:

R : is the total number of draws (systematic non-random sequence of numbers – Halton draws).

Since the direct pseudo-elasticity is calculated for each observation, it is usually reported as the average direct pseudo-elasticity (taking average over the sample) as a measure of the marginal effect of an indicator variable on the likelihood of a particular injury severity outcome (Kim et al. 2010).

With the simulator in Equation (11), Maximum Simulated Likelihood Estimation (MSLE) can be used to estimate parameters, and this MSLE estimator is asymptotically normal and consistent (Lee 1992, Kim et al. 2010):

(12) $max_{\boldsymbol{\beta}_{in}} \sum_{n=1}^{N} \sum_{i=1}^{I} y_{in} ln\widehat{P}_n(i)$

where:

N : is the total number of observations (i.e., crashes in the sample)

y_{in} : is 1 if individual n suffers from injury severity i, 0 otherwise.

Maximum likelihood estimation with random parameters of both mixed logit and random parameter ordered probit models is undertaken with simulation approaches due to the difficulty in computing the probabilities (Halton 1960, Train 1999, Bhat 2003, Milton et al. 2008, Anastasopoulos and Mannering 2009). The most widely accepted simulation approach utilizes Halton draws, which is a technique developed by Halton (1960) to generate a systematic non-random sequence of numbers. Halton draws have been shown to provide a more efficient distribution of the draws for numerical integration than purely random draws (Bhat 2003, Train 1999, Christoforou et al. 2010). In both of the random parameter models, 200 Halton draws were applied to estimate parameters using maximum simulated likelihood estimation.

EMPIRICAL RESULTS

The variables in both estimated models were found to be statistically significant within a 95% and 90% confidence level for random parameter ordered probit and mixed logit models, respectively.

A random parameter ordered probit and mixed logit model was developed based on fixed parameter ordered probit and initial multinomial logit model, respectively. The random parameter ordered probit model and mixed logit model were found to be statistically superior models (i.e., fixed parameter ordered probit model and multinomial logit model) as evidenced from the following hypothesis and likelihood ratio test.

(13) $\chi^2 = -2 * [LL_{FIX}(\beta^{FIX}) - LL_{RAN}(\beta^{RAN})]$

where:

$LL_{FIX}(\beta^{FIX})$: is the log-likelihood at convergence of the fixed parameters model (-3032.560)

$LL_{RAN}(\beta^{RAN})$: is the log-likelihood at convergence of the random parameters model (-3022.542)

χ^2 = 20.036 (5 degree of freedom)

The Chi-square statistic for the likelihood ratio test with five degrees of freedom gave a value greater than the 99.88% (χ^2 = 20.036) confidence interval. This confidence interval indicates that the random parameter model is statistically superior to the corresponding fixed parameter models.

(14) $\chi^2 = -2 * [LL_{MNL}(\beta^{MNL}) - LL_{ML}(\beta^{ML})]$

where:

$LL_{MNL}(\beta^{MNL})$: is the log-likelihood at convergence of the multinomial logit model (-3087.115)

$LL_{ML}(\beta^{ML})$: is the log-likelihood at convergence of the mixed logit model (-3081.050)

χ^2 = 12.13 (with 3 degree of freedom)

The Chi-square statistic for the likelihood ratio test with three degrees of freedom gave a value greater than the 99.31% (χ^2 = 12.13) confidence interval. This confidence interval indicates that the random parameter model is statistically superior to the corresponding fixed parameter model (i.e., multinomial model). In both cases above, this means that the null hypothesis of the random parameter models (i.e., mixed logit and random parameter ordered probit) are no better than the fixed models (i.e., multinomial and ordered probit model) is rejected.

The human, vehicle, and road-environment contributing factors as well as crash mechanisms in the multi-vehicle large truck involved crashes are described below as found in the model results shown in Table 5 and Table 6.

There are five parameters found to be random in the random parameter ordered probit model. These five random parameters are constant, dark condition, side-swipe collision (same direction), lane changing maneuver, and being male occupants. The first parameter – constant, having mean of 6.088 and standard deviation of 3.672, has 4.87% observations below zero (i.e., 91.13% above zero). This captures significant unobserved heterogeneity present in sample data. The second parameter – dark condition, having mean of -0.269 and standard deviation of 2.223, has 54.82% observations below zero (i.e., 45.18% above zero). This indicates that 54.8% multiple vehicle large truck crashes in the dark condition resulted in severe injuries. The third parameter – side-swipe collision (same direction), having mean of 1.251 and standard deviation of 1.004, has 10.64% of observations below zero (i.e., 89.36% above zero). This indicates that 89.4% of multiple vehicle large truck collision as side-swipe (same direction) resulted in less severe injuries. The fourth parameter – lane changing maneuver, having mean of 2.617 and standard deviation of 3.119, has 20.1% observations below zero (i.e., 79.9% above zero). This indicates that 79.9% of multiple vehicle large truck crashes as consequences of lane changing maneuver resulted in less severe injuries. The fifth parameter – male occupants, having mean of 0.719 and standard deviation of 0.546, has 9.4% observations below zero (i.e., 89.6% above zero). This indicates that 89.6% of multi-vehicle large truck crashes involving male occupants experienced less severe injuries. The estimated model results are presented in Table 5.

Since no-injury (i.e., PDO) is a base condition in the mixed logit model, the estimated results presented in Table 6 are the difference between the target injury outcomes (i.e., fatal, incapacitating, non-incapacitating, and possible injury outcome) with respect to base condition (i.e., PDO). There are three random parameters found statistically significant in mixed logit model. The constant specific to fatality, having a mean of -8.729 and standard deviation of 2.663, has 99.95% of observations below zero. This captures some unobserved heterogeneity present in the fatal outcome in multiple vehicle large truck involved crashes.

Table 5: Multi-Vehicle Random Parameter Ordered Probit Model Results

Injury Severity – Random Parameter Ordered Probit	Random Parameters Model		
	Coeff.	***t*-stat**	***P*-value**
Constant	6.088	18.889	0.000
Standard Deviation of parameter distribution	*3.672*	*34.078*	*0.000*
Weather condition (1 if snow, 0 otherwise)	0.861	4.344	0.000
Months of the year (1 if summer months (June - August), 0 otherwise)	-0.580	-7.484[	0.000
Light condition of street (1 if dark, 0 otherwise)	-0.269	-2.137	0.033
Standard Deviation of parameter distribution	*2.223*	*17.636*	*0.000*
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	1.402	17.427	0.000
Vehicle role (1 if struck by other vehicle, 0 otherwise)	1.522	17.311	0.000
The most harmful event (1 if rollover, 0 otherwise)	1.691	19.231	0.000
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	1.251	12.857	0.000
Standard Deviation of parameter distribution	*1.004*	*12.524*	*0.000*
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	2.617	11.868	0.000
Standard Deviation of parameter distribution	*3.119*	*18.117*	*0.000*
Vehicle maneuver just prior to impending crash (1 if going straight, 0 otherwise)	0.457	5.427	0.000
Factor of crash identified in the investigation (1 if speed, 0 otherwise)	-0.846	-7.868	0.000
Driver's attention level at the time of impending crash (1 if distraction or inattention, 0 otherwise)	-1.158	-7.733	0.000
Occupants' use of available vehicle restraints (1 if no restraint used, 0 otherwise)	-3.250	-17.810	0.000
Location of the occupants in the vehicle (1 if for passenger position, 0 otherwise)	1.018	5.533	0.000
Gender of the occupants (1 if male, 0 otherwise)	0.719	5.598	0.000
Standard Deviation of parameter distribution	*0.546*	*13.735*	*0.000*
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	-0.789	-7.864	0.000
Threshold 1, $\mu1$	2.845	14.047	0.000
Threshold 2, $\mu2$	4.708	21.307	0.000
Threshold 3, $\mu3$	6.280	25.969	0.000
Log-likelihood at zero, LL(0)	-3258.341		
Log-likelihood at convergence, LL(β)	-3022.542		
Chi-squared value (χ^2)	471.598		
McFadden's pseudo, R^2	0.072		
Number of observations, N	6,588		

Table 6: Multi-Vehicle Mixed Logit Model Results

Injury Severity - Mixed Logit	Random Parameters Model		
	Coeff.	*t*-stat	*P*-value
Fatal Outcome			
Constant	-8.729	-4.047	0.000
Standard Deviation of parameter distribution	*2.663*	*2.618*	*0.009*
Vehicle maneuver during pre-crash situation (1 if left or right side departure, 0 otherwise)	2.939	2.272	0.023
Light condition of street (1 if dark, 0 otherwise)	2.065	3.298	0.001
Orientation of vehicle at the time of crash (1 if head-on, 0 otherwise)	2.804	2.278	0.023
Time of the day (1 if 2 pm in the afternoon, 0 otherwise)	2.224	3.066	0.002
Incapacitating Injury Outcome			
Constant	-3.027	-14.942	0.000
Driver's attention level at the time of impending crash (1 if distraction or in attention, 0 otherwise)	1.279	2.550	0.018
Vehicular factors (1 if tire-related malfunction, 0 otherwise)	2.276	2.927	0.003
The most harmful event in crash consequences (1 if rollover, 0 otherwise)	-3.233	-1.956	0.051
Standard Deviation of parameter distribution	*2.195*	*2.126*	*0.033*
Orientation of vehicle at the time of crash (1 if rear-end, 0 otherwise)	0.495	2.159	0.031
Time of the day (1 if 5 am in the morning, 0 otherwise)	1.235	4.381	0.000
Non-incapacitating Injury Outcome			
Constant	-8.233	-2.176	0.029
Standard Deviation of parameter distribution	*4.522*	*1.993*	*0.046*
Occupants' use of available vehicle restraints (1 if no restraint used,0 otherwise)	4.320	2.219	0.026
Time of the day (1 if 4 am in the morning, 0 otherwise)	2.119	1.831	0.067
Months of the year (1 if summer months (June to August), 0 otherwise)	0.852	1.756	0.079
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	-1.396	-1.816	0.069
Possible Injury Outcome			
Constant	-2.678	-10.091	0.000
Gender of the occupants (1 if male, 0 otherwise)	-0.455	-2.311	0.021
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	0.790	5.510	0.000
Speed-related factor in crash (1 if speed as a factor, 0 otherwise)	0.346	1.994	0.046
Number of vehicles involved in the crash	0.245	3.767	0.000
Road surface condition (1 if wet, 0 otherwise)	0.504	3.696	0.037
Non-Injury Outcome (Property-Damage-Only)			
Alignment of highway section (1 for curved section, 0 otherwise)	-0.339	-2.162	0.031
Orientation of vehicle at the time of crash (1 if rear-end, 0 otherwise)	-0.232	-2.161	0.031
Light condition of street (1 if the surrounding area is dark but outside is lighted, 0 otherwise)	0.512	2.940	0.003
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	0.371	2.086	0.037
Driver's attention level at the time of pre-crash (1 if sleepy, 0 otherwise)	-2.188	-3.357	0.001
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	0.741	7.510	0.000
Log-likelihood at zero, LL(0)		-10602.98	
Log-likelihood at convergence, , LL(β)		-3081.050	
Chi-squared value (χ^2)		15043.85	
McFadden pseudo-R^2		0.709	
Number of observations, N		6,588	

The second parameter – rollover, having a mean of -3.233 and standard deviation of 2.195, has 92.9% of observations below zero. This fact indicates that 92.6% of multiple vehicle crashes associated with rollover resulted in a decrease in incapacitating injuries. The third parameter – constant specific to non-incapacitating injury, having a mean of -8.233 and standard deviation of 4.522, has 96.6% of observations below zero. This captures some unobserved heterogeneity present in the non-incapacitating injury category in the multiple vehicle large truck involved crashes.

Statistical goodness-of-fit of both discrete choice models are presented in Table 5, where the random parameter ordered probit model was first considered as base model and then mixed logit was estimated progressively from the base model. The reported pseudo-R^2 is 0.709 for the mixed logit model, in contrast to 0.072 for the random parameter ordered probit model, implying the mixed logit model fits the data better, predicting the multi-vehicle crashes for all five injury outcomes. It is clearly found that log-likelihood at convergence is much better for the mixed logit model over the random parameter ordered probit model. The Chi-squared values support the mixed logit model as well.

With regard to under reporting issues of less severe crashes compared to more severe crashes, the estimated model could lead to erroneous inferences (Savolainen et al. 2011; Washington et al. 2011). Model estimation, particularly for the ordered probit model, resulting from such data sample leads to non-randomness in its dependent variable with a violation of fundamentals of econometric model derivations (Savolainen et al. 2011). However, mixed logit accounts for limited data by considering a mixing distribution in the estimation process with a flexibility of varying the coefficient for each observation in the data sample (Gkritza and Mannering 2008).

Table 7: Model Results of Discrete Outcome Models

Items related to Goodness-of-fit	Mixed Logit Model	Random Parameter Ordered Probit Model
Number of observations	6,588	6,588
Restricted log-likelihood	-10602.980	-3258.341
Log-likelihood at convergence	-3081.050	-3022.542
Chi-squared value	15,043.85	471.598
McFadden Pseudo R^2	0.709	0.072
Number of random parameters	3	5
Number of parameters	31	24

Considering the better goodness-of-fit by the mixed logit model (Table 7), only the marginal effects in terms of average direct pseudo-elasticities were considered to be reported and computed to measure the impact of respective variables for the mixed logit model on the corresponding injury outcomes. The average direct pseudo-elasticities of the mixed logit model are presented in Table 8.[4]

Table 8: Marginal Effects of Multi-Vehicle Mixed Logit Model

Variables	Elasticity (%)				
	PDO/No Injury	Possible Injury	Non-incapac-itating	Incapacitating	Fatal
Human factors					
Gender of the occupants (1 if male, 0 otherwise)	2.33	-38.28	1.17	2.56	2.15
Driver's attention level at the time of impending crash (1 if distraction or in attention, 0 otherwise)	-0.16	-0.19	-0.10	7.75	-0.15
Driver's attention level at the time of impending crash (1 if sleepy, 0 otherwise)	-0.09	0.92	0.21	1.04	0.81
Drivers' working/residing place according to license record (1 if Texas, 0 otherwise)	-0.78	12.80	-0.41	-0.92	-0.67
Speed-related factor in crash (1 if speed as a factor, 0 otherwise)	-0.22	3.67	-0.13	-0.31	-0.24
Occupants' use of available vehicle restraints (1 if no restraint used, 0 otherwise)	-0.42	-0.55	11.48	-0.63	-0.58
Road and Environmental Factors					
Light condition of street (1 if dark, 0 otherwise)	-0.23	-0.26	-0.13	-0.36	50.26
Time of the day (1 if 2 pm in the afternoon, 0 otherwise)	-0.14	-0.17	-0.08	-0.13	30.06
Time of the day (1 if 5 am in the morning, 0 otherwise)	-0.49	-0.54	-0.32	23.86	-0.83
Time of the day (1 if 4 am in the morning, 0 otherwise)	-0.13	-0.12	3.49	-0.33	-0.18
Months of year (1 if summer months (June to August), 0 otherwise)	-0.41	-0.48	10.96	-0.49	-0.40
Road surface condition (1 if wet, 0 otherwise)	-0.57	9.43	-0.29	-0.62	-0.55
Alignment of highway section (1 for curved section, 0 otherwise)	-0.31	2.99	1.14	2.41	2.44
Vehicular Factors					
Vehicular factors (1 if tire-related malfunction, 0 otherwise)	-0.11	-0.11	-0.08	5.24	-0.11
Trailing unit when the crash occurred (1 if one trailer, 0 otherwise)	4.39	-39.80	-20.37	-36.19	-35.30
Number of vehicles involved in the crash	-3.37	55.42	-1.72	-4.06	-3.05
Crash Mechanism					
Vehicle maneuver during pre-crash situation (1 if left or right side departure, 0 otherwise)	-0.05	-0.07	-0.05	-0.12	12.15
Orientation of vehicle at the time of crash (1 if head-on, 0 otherwise)	-0.05	-0.06	-0.03	-0.04	11.47
Orientation of vehicle at the time of crash (1 if rear-end, 0 otherwise)	-0.44	-0.66	-0.30	22.17	-0.46
The most harmful event in crash consequences (1 if rollover, 0 otherwise)	-0.20	-0.10	-0.19	9.60	-0.13
Orientation of vehicle at the time of crash (1 if sideswipe in the same direction, 0 otherwise)	0.47	0.41	-12.37	0.32	0.37
Vehicle maneuver just prior to impending crash (1 if changing lane, 0 otherwise)	0.27	-2.57	-1.19	-1.99	-2.24

Human Factors

Male occupants are 38.3% less likely to be involved in possible injuries compared with females as supported in a study by Chen and Chen (2011) that male occupants are less likely to be involved in fatal or incapacitating and non-incapacitating or possible injuries[5]. Distracted driving is 7.7% more likely to result in incapacitating injuries because of multiple vehicular interactive dynamics. Not wearing a seatbelt results in 11.5% more likelihood to be involved in a crash with non-incapacitating injury outcomes. This might indicate the unbelted occupants to be involved in non-incapacitating injuries rather than drivers. Similar findings by Chen and Chen (2011) also indicated this is true for fatal or incapacitating and non-incapacitating or possible injuries. Drivers residing or registered to work in the state of Texas are 12.8% more likely to be involved with possible injuries. Sleepy drivers are more likely to be not involved with non-injury which indirectly shows them more likely to be involved with serious injuries. As found in the random parameter ordered probit model, the presence of passengers reduces the likelihood of severe injuries, which might indicate the passengers keep the drivers alert on long drives. Also, speeding as a factor of crashes increases the likelihood of possible injuries by 3.7%, although choice of driving speed might be also influenced by geometric features of the roadway segment and drivers' behavior. Geometric features may include number of travel lanes, vertical grade, inside and outside shoulder, horizontal curvatures, and rumble strips presence (Amarasingha and Dissanayake 2013). Thus, although the magnitude of the two studies in terms of variables are different due to different estimation methods, most of the explanatory variables have the same sign.

Road and Environmental Factors

Dark conditions lead to a 50.3% greater likelihood of fatalities since other vehicles might be completely blinded by such unfavorable driving conditions. This fact is supported with a similar study by Chen and Chen (2011) where dark condition increases both fatal or incapacitating injuries and non-incapacitating or possible injuries. Similarly, wet road surface increases possible injuries by 9.4%. Time of day and month of the year implies the traffic condition on the highway. Time of day is a significant factor. Driving at 2 pm increases the likelihood of fatalities by 30.1%, which may indicate that drowsy driving after lunch affects by vehicles other than trucks. Driving between 4 and 5 am increases the likelihood of a non-incapacitating injury crash by 3.5% and an incapacitating injury crash by 23.9%, respectively, which indicates sleepy or drowsy driving. Sleepy or fatigue driving could also lead to run-off-road crashes and result in severe injury crashes (Roy and Dissanayake 2011). Summer months (from June to August) increases the likelihood of non-incapacitating injury crashes by 11% because of more traffic on the highways and greater chances of interaction between vehicles leading to crashes. Wet pavement condition increases by 9.4% the likelihood of possible injuries because of unfavorable driving and braking on slippery road conditions for other vehicles and the braking characteristics of large trucks. Curved segments of the highways decrease the likelihood of non-injury crashes, which indirectly points toward serious injuries.

Vehicular Factors

Tire related malfunction increases the likelihood of incapacitating injury by 5.2%, which indicates the lack of vehicle maintenance of commercial vehicles resulted in weight imbalance and uncontrolled driving situations. This situation could lead to severe injuries if run-off-road crashes can be imminent of this tire malfunction. A study by Roy and Dissanayake (2011) indicated that tired-related factors can be very dangerous, resulting in run-off-road crashes. However, this fact is contradicted by a similar study by Chen and Chen (2011) where tire defects decrease the likelihood of f non-incapacitating injuries. A single trailing unit decreases the major injury categories (i.e., fatality, incapacitating injuries, non-incapacitating injuries, and possible injuries by 35.3%, 36.2%, 20.4%, and 39.8%, respectively).

Crash Mechanism

Departing the roadway (by left or right side of roadway) increases the likelihood of fatalities by 12.2%, which is also supported in a study by Chen and Chen (2011). Head-on collision also increases the likelihood of fatalities by 11.5%. This fact is supported by Chen and Chen (2011) through the variables such as driving on the wrong side or wrong way, which might indicate a head-on impact with oncoming vehicles. Vehicle rollover situations increase the likelihood of incapacitating injuries 9.6%, which are complex in nature for multi-vehicle crashes. This fact is contradicted by Chen and Chen (2011) findings on truck overturn crashes. Rear-end crashes increase the likelihood of incapacitating injuries by 22.2% and decreases the likelihood of non-injury crashes. Sideswipe in the same direction decreases the likelihood of non-incapacitating injuries by 12.4%. As the number of vehicles involved in multiple vehicle crashes increases, the likelihood of possible injuries increases by 55.4%, which is supported in a similar study by Chen and Chen (2011) that more than three vehicles involved in the collision increases fatal, incapacitating, non-incapacitating, or possible injuries. Speed-related factor, which is speeding for the existing driving condition, increases the likelihood of possible injuries, which is supported by the fact that exceeding the speed limit increases the likelihood of possible or non-incapacitating injuries in a study by Chen and Chen (2011). Lane changing behavior increases the likelihood of non-injury crashes (i.e., property-damage-only) which results from multi-vehicle interactions. As found in the random parameter ordered probit model, vehicles struck by other vehicles as consequences of vehicular interaction reduces the likelihood of severe injuries. Likewise, driving on the lane or going straight keeping the lane, which indicates no lane changing behavior, also reduces the likelihood of severe injuries.

CONCLUSION

Utilizing the nationwide GES crash database, two discrete outcome random parameter models were investigated. These models made it possible to minimize the possible bias and erroneous inferences by considering the estimated coefficients to vary across the crash observations (McFadden and Train 2000, Train 2009). The random parameter ordered probit model was used because of the ordinal characteristics of the injury scale (the KABCO scale was followed), and the mixed logit model used for methodological flexibility such as each injury outcome has individual utility functions and independent of irrelevant alternatives (IIA). The IIA property in the mixed logit model provides the flexibility of variables within each of the particular injury outcomes being independent on the utility function as well as between the outcomes (Jones and Hensher 2007). The random parameter ordered probit model provides the indication of more and less severe injury outcomes based on the sign of the variables. On the other hand, the mixed logit model characterizes more or less severe injury outcomes with individual injury outcome through utility function set-up. The results of both models are presented here (Table 3 and Table 4) as well as their statistical performance. The parameter estimates and statistical goodness-of-fit clearly indicate that mixed logit model is superior to random parameter ordered probit model. However, a tradeoff is made in model selection between ordered response variable in ordered probability models as opposed to unordered probability models (Washington et al. 2011).

Several crucial factors from the human aspect were identified in this study. Distracted and sleepy driving, male occupants (driver or passengers), drivers residing or working in the state of Texas, and not using a seatbelt are listed in the Empirical Results section as showing the increased risk of being seriously injured in a multi-vehicle collision with a large truck.

Road and environmental factors such as dark driving conditions and time of day can increase severe injuries. On the other hand, curved road segments and wet surface conditions only increase minor injuries. Vehicular factors such as tire related defects increase severe injury; whereas, single trailing unit such as semi-trailer involved in multi-vehicle crashes increases non-injury (i.e., PDO crashes) crashes.

Factors that are part of the human response are the maneuvers which are mainly executed by drivers at the impending or pre-crash situations. Actions such as departing roadway, rear-end collision, head-on collision, and vehicle rollover increases the severity of injuries. On the other hand, sideswipe (same direction), the number of vehicles involved in the crashes, speeding for the condition such as unfavorable weather or heavy traffic, increases minor injuries in multi-vehicle large truck crashes.

The variables that explained multi-vehicle crashes involving large trucks include human (i.e., sleepy driving), road and environmental factors (i.e., 2 pm, 4 to 5 am, wet surface, curved segments, dark but illuminated condition), vehicular factors (i.e., tire related defects), and crash mechanism (i.e., head-on and rear-end collision, number of vehicles involved in the crashes).

Although the GES dataset does not contain any traffic information (such as average annual daily traffic or vehicle-miles travelled), proxy variables such as time of day (2 pm, 4 to 5 am), and month of year (June to August) were considered in the mixed logit and random parameter ordered probit models to capture traffic conditions at the time of crash. It is worth investigating the contributing factors for single and multiple vehicle crashes involving large trucks and understand their role and differences in leading to large truck crashes on U.S. highways, for instance, an interstate facility. From the practical application of the models, the contributing factors related to human, such as distraction/inattention, driving speed, vehicular such as the tire related malfunction, and road-environment, such as light and surface condition, clearly indicate the importance of drivers' education and training as well as the installation of roadside lights and roadside warning signs on wet surfaces along the critical segments. Also, policy related decisions, including routine inspection of tires for the large trucks prior to long haul trips, should be implemented.

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Endnotes

1. If the database contains all the various function classes (i.e., interstates, arterials, collectors, and local streets) it is difficult to separate the effects of variables coming from different functional classes on injury outcomes. Thus, splitting the database containing only crashes on interstate highways will produce better parameter estimates and marginal effects on injury outcomes.

2. Analysis began with the same set of explanatory variables for both models. However, after model estimation, the mixed logit model had more statistically significant variables than the random parameter ordered probit model.

   Also, it is desirable to include traffic in the models but the GES database does not have AADT (annual average daily traffic).

3. Random parameter probit and mixed logit models capture the variation of the variables across the observations that influence the dependent variable, resulting in parameter heterogeneity.

4. Other variables such as speed limit at the crash locations, age of the drivers, and rural/urban nature of the crashes were not included. Speed limit is not in the GES database and age of the driver and rural/rural location could be correlated with other variables in the models. Further research involving these variables is planned.

5. Each observation in the sample is a crash with maximum injury levels of the occupants, which can be either the driver or passengers. In the case of multiple vehicle crashes, a vehicle with an occupant that sustained the maximum injury severity among all the occupants in the crash involved vehicles was considered in the model.

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