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While there have been several efforts to understand large-truck crashes, the relationship between crash factors, crash severity and collision type is not clearly understood. Past studies have utilized different statistical or econometric models to predict the manner of collision at intersections, yet not much attention has been paid to the factors that lead to injury severity by different types of collisions on state and interstate highways. Studying collision types is crucial when identifying potential safety improvements for state and interstate systems. In this study six collision types are explored they are: angled collisions, fixed object collisions, rear end collision both vehicles moving forward, rear end collisions on moving vehicle, sideswipe collision same direction and sideswipe collisions different directions. With these in mind, the aim of this research is to perform exploratory analyses of large truck-involved crashes through the use of advanced econometric techniques that can shed insights on the factors influencing crashes by collision type. Namely, this research utilizes the mixed multinomial logit model to uncover the effects of unobservable factors (unobserved heterogeneity) across crash observations underlying the data generating process. The results of this thesis indicate that complex interactions of various human, vehicle, and road–environment factors due in fact contribute and that some of the model variables varied across observations, validating the choice of the mixed multinomial logit model and separation of data by collision type.

Evaluating Contributing Factors to Collision Types through Discrete Choice Analysis: An Application to Large-Truck Crashes in Washington State

by
Dejan Dudich

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APPROVED:

Major Professor, representing Civil Engineering

Head of the School of Civil and Construction Engineering

Dean of the Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Dejan Dudich, Author

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Chapter 1: Introduction

1.1 Motivation

The increased growth in over-the-road freight volume (e.g., via truck) poses numerous challenges for transportation organizations that plan, design, construct, operate, and maintain the transportation system. For example, problems stemming from passing sight distance conflict due to truck size and height, and increased loads on roadways. These and other concerns have drawn significant attention from safety professionals, policy makers, and the general public. One reason for these concerns stem from the cost associated with large truck-involved crashes that can be substantial, specifically in the case of a fatality. The estimated cost of police-reported crashes involving large trucks with a gross vehicle weight rating (GVWR) higher than 10,000 pounds was on average $91,112 based on 2005 dollars (Zaloshnja and Miller, 2006). Further, Zaloshnja and Miller (2006) estimated the average cost per fatality, injury and no injury crashes to be $3,604,518, $195,258, and $15,114, respectively. Subsequently, any increase in the level of crash severity and in number is of great concern to transportation organizations.

While there have been several efforts to understand large-truck crashes, the relationship between crash factors, crash severity and collision type is not clearly understood. One possible reason for this is that typically disaggregate crash analysis models focus on holistic[1] injury severity models where collision types are treated as indicator variables. Although studies have developed different statistical or econometric models to predict the manner of collision at intersections (Abdel-aty and Nawathe, 2006; Abdel-aty et al., 2006; Kim et al., 2007; Ye et al., 2009) not much attention has been paid to the factors that lead to injury severity by different types of collisions on state and interstate highways (Romo et al., 2014). Studying collision types is crucial when identifying potential safety improvements for state and interstate systems. Collision type analysis is implemented in the Highway Safety Improvement Program (HSIP) Manual to quantify the actual or expected safety of a roadway in

[1] Models that include all crash data and are not subdivide or partitioned into subgroups. For example, by collision type, time of day, weather, season, etc.

addition to identifying high-risk facilities for potential safety improvement (Herbel et al., 2010).

With this in mind, the aim of this research is to perform exploratory analyses of large truck-involved crashes through the use of advanced econometric techniques[2] that can shed insights on the factors influencing crashes by collision type. Compared to basic econometric techniques (e.g., linear regression), this exploratory analysis seeks to determine if the mixed multinomial logit modelling framework is an appropriate method to establish the validity of analyzing large truck crash injury severity by collision type. To achieve this, large truck crashes from 2007 to 2013 from the State of Washington are utilized. The advantage of utilizing the mixed multinomial logit-modeling framework in this context is that it allows accounting and correcting for heterogeneity that can arise from factors related to 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. In addition, it addresses the weaknesses that can result in erroneous parameter estimates if underlying assumptions of the multinomial logit model (MNL) are not met. That is, the mixed multinomial logit-modeling framework addresses the shortcomings of the MNL framework by allowing parameter values to vary across observations (Washington et al., 2010). To the best of our knowledge, these are the first attempts to better understand injury severity of large truck crashes by collision type utilizing the mixed multinomial logit model to uncover the effects of unobservable factors (unobserved heterogeneity) across crash observations underlying the data generating process (Washington et al., 2010).

Through this methodology, the work performed in this thesis seeks to answer the following question—how do factors (observed and/or unobserved) that contribute to large truck-involved crashes effect the injury severity sustained by collision type?

Hence, this thesis attempts to fill the gap in current injury severity analyses of large truck-involved crash literature through addressing the above question.

[2] Advanced treatment of econometric principles for cross-sectional, panel and time-series data sets in comparison to basic techniques such as linear regression, see Washington et al. (2010)

Additionally, the results of this thesis can provide valuable insight for the improvement of safety planning tools and safety analysis tools. For example, the results of this thesis can help agencies track potential factors that contribute to a particular collision type, which is currently missing.

Finally, this thesis provides a foundation for future research. As stated in chapter five, a future study could expand this to a more comprehensive and extensive dataset that spanned several states. In summary, this thesis involves original research that expands the literature and provides a new foundation to analyze large truck-involved crashes.

1.2 Organization of the Thesis

This thesis is organized into six chapters. Chapter 2 presents a discussion of the current body of literature related to this research. Chapter 3 presents the data used for this thesis. The methodological framework and the explanation of the modeling approach utilized is presented in Chapter 4. Chapter 5 presents the collision type models and the statistical inference that was made. Finally, conclusions and recommendations are found in Chapter 6. Individual model results separated by collision type can be found in the appendices.

Chapter 2: Literature Review

2.1 Collision type analysis

Past research has focused on the assessment and modeling of the relationship(s) between total, fatal, and injuries in crashes. Granted, this research is extremely useful for understanding these relationships in a general sense, it does not reveal a disaggregate picture of these crash events. It has been suggested that collision types are associated with different pre-crash conditions and that modeling total crash frequency may not be helpful in identifying specific countermeasures (Kim et al., 2006). The purpose of this research is to investigate the effects that different collision types may have on injury severity and the factors that may be influencing those injury severity outcomes. Four general collision types are investigated in this research; angled, fixed object, rear-end, and sideswipe collisions.

2.2 Crash Injury Severity Modeling and Analysis

The availability of econometric and statistical models with which crash injury severity and collision type may be modeled is extremely vast. Researchers have applied several different types of models to crash severity analysis. In a general sense, crash severity has been analyzed via logistic regression models (Al-Ghamdi, 2002; M. Bin Islam and Hernandez, 2013; Kononen et al., 2011), probit models (Islam et al., 2013; Jiang et al., 2013; Kockelman and Kweon, 2002; Lemp et al., 2011a; Xie et al., 2009), and bivariate models (Yamamoto and Shankar, 2004). Taking a refined and closer look at the crash severity analyses that have been performed for large truck crashes we find again an extensive collection (Chang and Mannering, 1999; M. Islam and Hernandez, 2013; Khorashadi et al., 2005; Lemp et al., 2011; Zhu and Srinivasan, 2011b). Of those papers referenced above, the latter set for large truck analyses follow the more common consideration, which is that crash severity outcomes are discrete variables rather than continuous or ordered. This thesis also follows this commonly held consideration.

2.3 Discrete Choice Methods

When modeling crash injury severity as a discrete outcome it is often considered best to use the reported injury severity of the occupants as the discrete outcome. In this thesis the discrete outcome was taken to be the reported maximum injury severity of the driver involved in the collision. For example, in this thesis, three discrete injury severity outcomes were identified: first, a severe injury, which includes any fatal or incapacitating injury. Second, a minor injury, which was comprised of minor and non-incapacitating injuries; and lastly, the third category was property damage only (PDO).

A common modeling approach for injury severity would be to use an ordinal framework. This is done by considering the three previously laid out injury severity categories as being ordered, such that the severe injury category is of a more serious nature than the minor injury category, which in turn is more serious than the property damage only category. In order to take this ordinal nature there are a few models that could be applied though namely the ordered probit model is used more often (Jiang et al., 2013; Kockelman and Kweon, 2002; Lemp et al., 2011a; Xie et al., 2009). The drawback to this methodology is the ordered models do not account for unobserved heterogeneity in the data that, if it exists, may lead to biased parameter estimates. An additional limitation is that the ordered probit model does not account for the effects of the interior categorical probabilities. To solve these flaws another modeling structure known as the multinomial logit model is required.

An alternate approach to crash injury severity analysis is to predict and evaluate severity outcomes while considering the data to be unordered in nature. When three or more distinct outcomes are being considered for the injury severity analysis then a multinomial probability framework may be applicable. The application of multinomial models has grown in popularity for crash severity analysis, the prevailing two types include the Multinomial Logit model (L. Chang and Mannering, 1999; Khorashadi et al., 2005; Zhu and Srinivasan, 2011b) and the Mixed Multinomial Logit model (Chen and Chen, 2011; Islam et al., 2013; Mathew et al., 2014; Pahukula, 2015; Romo et al., 2014). The Mixed Multinomial Logit model (MML) has been shown to be more useful for modeling as it relaxes the independence of irrelevant alternatives (IIA) assumption that the Multinomial logit model has to contend with (Washington et al., 2010).

The Mixed Multinomial Logit model allows for the parameters to vary across all observations. The properties and specifications of the MML can be found in chapter 4 of this thesis. The MML methodology has been applied to various crash injury severity studies (Chen and Chen, 2011; Islam et al., 2013; Mathew et al., 2014; Pahukula, 2015; Romo et al., 2014). For additional discussion of the model readers are directed to Washington et al. (Washington et al., 2010) and Ortúzar and Willumsen (de Dios Ortúzar and Willumsen, 2011). It should be noted that another modeling approach would be appropriate here as well, which is the Latent Class Model. The latent class model allows for the modeler to account for any unobserved heterogeneity without having to assume a particular distribution for the parameters. The latent class model instead assumes that the parameters come from specific classes based on similar characteristics. It has been identified by Xiong and Mannering (Kang et al., 2013) that the latent class model suffers from a drawback similar to that of the ordered probit model in that it does not account for potential variations within each distinct class. Another potential drawback is in determining the number and size of the classes used for the model. Thus, the mixed multinomial logit-modeling framework will be used for this research.

2.4 Effects of Collision Type

The previous sections dealt with and presented the literature on the application of various econometric models on crash severity analysis. One of the drawbacks to the existing literature is the lack of understanding of what factors affect collision types. A common practice is to consider collision type as an indicator variable that may affect the crash injury severity. This is normally done by creating the indicator variable such as “Angle” which can be defined as 1 if the vehicles were involved in an angled collision and 0 if otherwise. The resulting parameter estimates may be found to show either an increasing or decreasing effect for the probability of whichever crash injury severity was being tested. This approach does not shed light on why angled collisions happen or why they affect severity.

The research that has been done in regards to collision type is limited to studies exploring a single dominant collision type. Several studies have looked directly at a single type of collision type (Abdel-Aty and Abdelwahab, 2004a, 2004b; Farmer et al., 1997; Harb et al., 2008; Lee and Mannering, 2002; Yamamoto and Shankar, 2004; Yan et al., 2005). A drawback to these works is that they investigate a single collision type.

In contrast, the research in this thesis explores the factors that affect multiple collision types and their impact on crash injury severity for an extensive database centered in Washington State.

Abdel-Aty and Abdelwahab (Abdel-Aty and Abdelwahab, 2004a) examined the interaction of light trucks and passenger cars during angled collisions. Through the use of time series ARIMA models, based on the Fatality Analysis Reporting System (FARS) data, it was found that the coefficient of light truck vehicle (LTV) percentage in the system of regression equations was significant because of the instantaneous effect (time lag equals to zero) of LTVs on the annual fatalities resulting from angle collisions. Abdel-Aty and Wang (Harb et al., 2008) used a partial proportional odds model to investigate left turn crashes at intersections in the Central Florida area. They looked at 197 intersections over a span of 6 years and found that traffic volume was the most significant factor attributing to crash occurrence. These studies, while shedding light on the factors associated with angled crashes, fail to capture a statewide understanding of the factors and neither study was focused on large trucks whose crash patterns are different than those of passenger cars and light trucks.

Shankar and Yamamoto (Yamamoto and Shankar, 2004) used a bivariate ordered-response probit model to investigate the injury severity of both drivers and passengers who had collided with fixed objects in Washington State. They looked at data that spanned 4 years and found that there was a significant shift in injury severity patterns along the dimensions of vehicle occupancy and space. Lee and Mannering (Lee and Mannering, 2002) looked at the frequency and severity of run-off-roadway accidents. They looked at state route 3 in Washington State and found that run-off-roadway accident severity is a complex interaction of roadside features such as the presence of guardrails, miscellaneous fixed objects, sign supports, tree groups, and utility poles along the roadway.

Yan et al. (Yan et al., 2005) developed a multiple logistic regression model to examine accident characteristics of rear-end accidents at signalized intersections in Florida during 2001. The results showed that environmental, striking role, and struck role factors are significantly associated with the risks of rear-end accidents. Abdel-Aty and Abdelwahab (Abdel-Aty and Abdelwahab, 2004b) developed a nested logit model which modeled rear-end collisions of light truck vehicles using the general estimates system database. Their results showed that driver inattention and visibility were the largest contributing factors to rear-end collision risks. Yan et al. looked at a single year of data while Abdel-Aty and Abdelwahab looked at a significantly more robust set of data. However both only looked at a single collision type without looking to see if other types could be captured and examined by their models.

The relationship of vehicle and crash characteristics as related to side-impact crashes was evaluated by Farmer et al. (Farmer et al., 1997). The study used data pulled from the United States National Accident Sampling System Crashworthiness Data System and was analyzed using logistic regression. They found that elderly occupants as well as occupants that sat on the struck side of the vehicle were most severely injured. However, this study focused on a national sample and only returns a broad overview of this crash type. Also, this study was limited to the crashes experienced by passenger vehicles whose crash patterns and profiles are different than those of large trucks.

2.5 Summary

The existing literature, while robust and extensive in nature, provides a foundation for the understanding of factors that affect crash injury severity. This research seeks to expand the current body of literature by looking at a disaggregate picture of crash severity through collision types, to best of our knowledge has not been addressed. Also, the variables that affect each of the collision types are explored to see their effects on both collision type and driver injury.

Chapter 3: Data

This study utilizes data collected from state and local governments and by police responding to vehicle crashes in the State of Washington. This information is collected and reported annually for all crashes across the State. The data was provided by the Washington State Department of Transportation and encompasses the years 2007 until 2013. The data used was selected because it was the most recent and because it had the highest quality. The data provided encompassed all crashes in the state of Washington between those years and as such was filtered to show only large truck involved crashes and was then further filtered by collision type; this is shown in the process diagram in Figure 3 below.

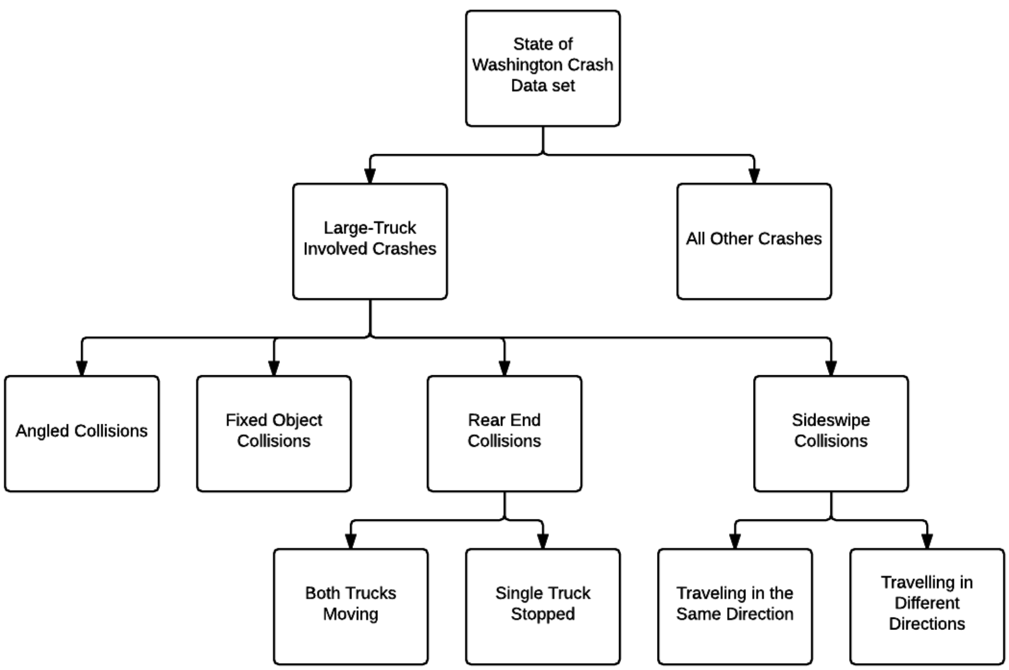

Figure 3: Study Data Structure

3.1 Vehicle Types

This study considered crashes' involving large trucks exclusively; in this context a large truck is a vehicle whose gross vehicle weight is greater than 10,000 lbs as defined by Insurance Institute for Highway Safety (IIHS). In order to remove some bias from the model estimates, crashes involving small vehicles such as bicycles, motorcycles, and those involving passenger vehicles were not considered in the models. The

Washington State data set while robust and extensive does lack a particular amount of specificity when looking at the weight of the vehicles involved in the collisions. For this research all trucks with a weight above 10,000 lb were considered. The mixed multinomial logit modeling approach provides a mechanism to account for any unobserved heterogeneity related to the difference in vehicular mass of large trucks through random parameters.

3.2 Injury Types

In this study, each large truck-involved crash (observation) used represents the maximum level injury severity sustained by the driver. The level of injury severity is discrete in nature and is typically coded using the KABCO injury scale (e.g., K = fatal, A = incapacitating, B = non-incapacitating, C = possible injury, and O = property damage only). For this study, injury categories are grouped due to low observations in the "K" or fatal category. Following Pahukula et al. (2015) categories are grouped into three distinct groupings—these are, serious injury (K and A), minor injury (B and C), and no injury (O). For this study, any recorded incidents that showed an injury severity of not reported, unknown, or refused were rejected, because the severity of those injuries could not be satisfactorily determined. Figure 3.1 below shows the considered injury severity outcomes for this study.

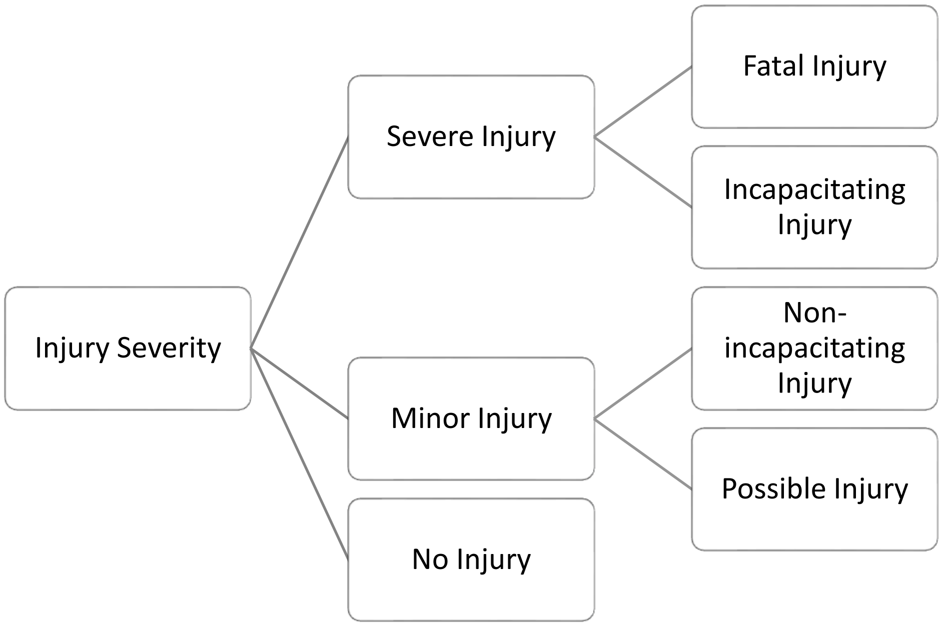

Figure 3.1 Structure of Injury Severity Outcomes

3.3 Collision Types

This study focused on what factors influence different collision types. In the beginning the provided crash data was filtered twice. The first filtration condensed the data to look at large truck involved crashes exclusively. The second round of filtering was to separate the total data set and gather the large truck crashes into individual data sets representing six different collision types. Figure 3.2 below shows a histogram of the chosen collision types and how many observations each type included. The collision type data sets were initially capped at four types that included: angled collisions, fixed object collisions, rear end collisions, and sideswipe collisions. After looking at the data it was decided that both rear end collisions and sideswipe collisions should be split into two different categories each to better illustrate and explore the factors that affect those collisions types. As seen from Figure 3.2 these collision types are angled collisions, fixed object collisions, rear end collision both vehicles moving forward, rear end collisions on moving vehicle, sideswipe collision same direction and sideswipe collisions different directions.

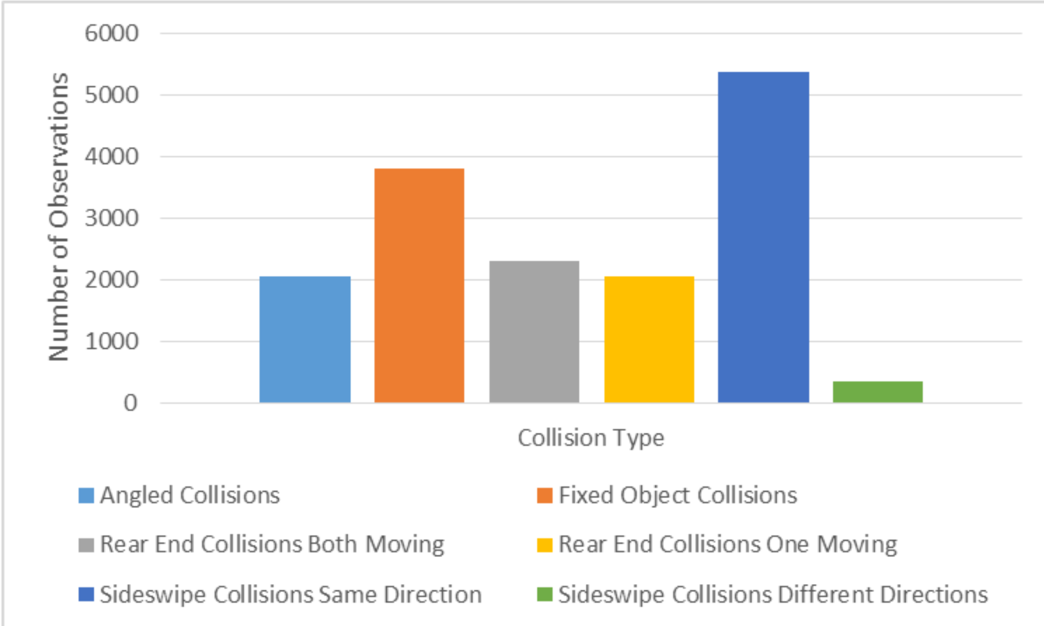

Figure 3.2: Histogram of Collision Type vs Number of Observations

3.4 Model Variables

The crash data used in this study was collected by state and local agencies in Washington State and is quite extensive in nature. This section explains and highlights the process behind variable selection for the six models used.

Data collected for this study was collected directly at the scene of the crash by the responders, or after the fact by insurance companies and follow up investigations done by police. Information collected includes when and where the crash occurred, roadway and vehicle characteristics, contributing circumstances, vehicle damage locations, occupant injuries, and crash severities. Crash severities were determined by injury reports filed by police using the KABCO scale. The reported information was converted, where appropriate, into indicator variables that represented possible outcomes for each data category. When creating the indicator variables three cases were encountered. The first case was when a specific data category had an insufficient number of observations making any conclusions drawn from the indicator variable statistically insignificant (e.g. whether the vehicle was in a hit and run, or drug test types). The first case could be dealt with if the second case was present as well. The second case was when a data category had more values than would be practical to consider individually. For the Contributing Circumstances data category there were at times over twenty five different variables to test, so instead groups were put together to be tested (e.g. driver-related, environmental-related, or distracted-drivers). The third and final case was where a data category had a large number of observations; in this case an indicator for that specific variable was created.

3.5 Model Data Sets

As was shown above in Figures 3 and 3.2, the data received was filtered and sorted several times in order to put together separate datasets that represented distinct collision types for large trucks. Table 1 below displays the frequency and percentage distribution of injury severity organized by the collision type. The frequency of property damage only was found to be nearly double than that of the other injury severities regardless of collision type. The number of observations and the disparity in size for sideswipe collisions made the modeling slightly difficult, however there was little that could been done to resolve those modeling issues.

Table 3: Driver Injury Frequency and Percentage Distribution by Collision Type

Collision Type	Severe Injury		Minor Injury		Property Damage Only		Total
Angled	22	1.06%	567	27.42%	1479	71.52%	2068
Fixed Object	25	0.65%	492	12.89%	3300	86.46%	3817
Rear End Both Moving	15	0.65%	917	39.70%	1378	59.65%	2310
Rear End One Moving	11	0.53%	802	38.84%	1252	60.63%	2065
Sideswipe Same Direction	6	0.11%	833	15.50%	4534	84.39%	5374
Sideswipe Different Directions	16	4.56%	130	37.04%	205	58.40%	351
Total	95	0.59%	3741	23.40%	12148	76.01%	15985

Chapter 4: Methodology

The standard methodology for typical roadway safety analysis studies is to look at the factors that may influence the frequency and/or the injury severity experienced during vehicle crashes. The research presented here looks to interpret the factors that affect each of the selected collision types as well as the affects those factors have on large truck driver injury severity. As previously mentioned, this study utilizes data collected from Washington State from 2007 until 2013 and has been separated to look solely at large truck crashes.

This chapter discusses the modeling structure and framework used for this research. For this research the modeling software NLOGIT5 was utilized for the analysis, which provides a foundation to analyze data on multinomial choice (Greene, 2012). Figure 4.1 in the following section gives an overview of the modeling framework that was utilized and is followed by a discussion of that framework.

4.1 Large-Truck Collision Type Modeling Framework

The initial step for the framework was to postulate that a relationship between collision type and injury severity existed for the data from Washington State. Following this idea the data was initially split into two distinct databases, one that was limited to large trucks and the other that encompassed all other forms of vehicle. From there the large truck database was organized into four distinct collisions types, namely: angled, fixed object, rear-end, and sideswipe. The latter two databases were further separated to account for rear-end collisions in which a single vehicle was stopped or both were moving. The sideswipe collision category was also spilt to account for sideswipe collisions in which vehicles were traveling in opposite directions and sideswipe collisions that occurred when vehicles were travelling in the same direction. Figure 4.1 on the following page shows a quick overview of the framework's structure and is followed by an explanation of its components.

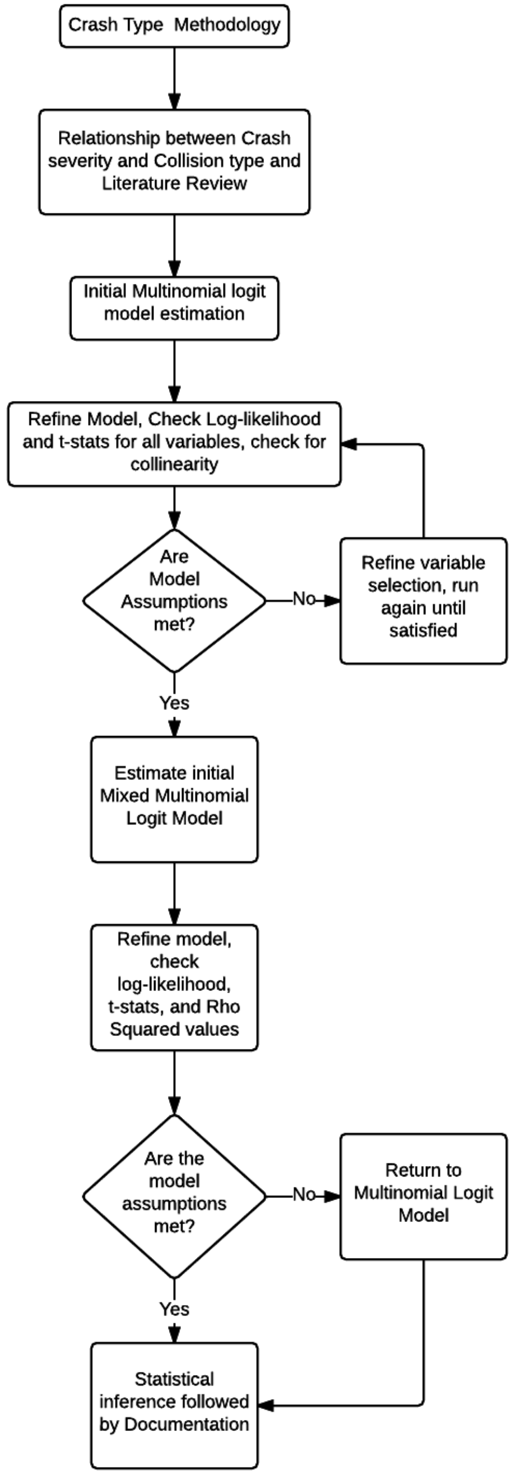

Figure 4.1: Large-Truck Involved Crash Modeling Framework

For each of the now six models, an initial multinomial logit model was developed and run. The model was then evaluated based on the model log-likelihood value at convergence and the individual parameter t-statistic (t-stats) significance. Once an initial model was developed, the models were modified by the addition of other variables from the data set. Each time a variable was added to one of the injury severity utility equations the model was rerun and evaluated to see if there was any improvement. If new variables were found to have significant t-stats, in this case the variable needed to exceed either -1.96 or 1.96 (or the 95% level of significance[3]) to be significant and improve the log-likelihood of the model, they were kept in the utility equations and documented. In some cases variables found to be significant at the 90% level of significance were kept in the model (although these variables are not significant at the 95%, these variables are known to be contributing factors). Once all of the variables had been run and evaluated the final multinomial logit model was specified and the variables utilized were run through a correlation matrix to ensure that the significance of the variables was not being bolstered and biased.

Once the final multinomial logit model was specified, the variables chosen had to be examined to see if they were fixed parameters or if they varied significantly across the observations. The initial step was to choose one of the constants in the model and run a mixed multinomial logit model with 200 Halton[4] draws to determine if the variable was random and significant[5]. Any variable that was found to be random and significant was kept in the varying parameter equation for the mixed multinomial logit model and additional variables were added and tested one at a time. Once all of the variables in the model were tested for significance the new mixed multinomial logit model was documented.

After all of the collision types had been run, and the random and significant variables found, the marginal effects of each of the variables were found. In the cases that no random parameters were found, at the appropriate significance level, the model

[3] Some variables with t-stats lower than +/- 1.96 or 95% were kept in the model. The reason is that some of these variables are known to be contributing factors.

[4] See section 4.2

[5] At the +/- 1.96 or 95% level of significance, also see section 4.2

was reverted to its final multinomial logit model and documented. With the models finalized and the marginal effects determined, statistical inference were drawn and the results were documented in this thesis. Results and statistical inference for each of the models can be found in the following chapter.

4.2 Discrete Choice Models

As mentioned in the previous section, to better understand the injury severity of crashes involving large trucks on major freight corridors in Washington State, an econometric framework was used to determine the factors that influence the likelihood of severity outcomes by collision type through the application of a discrete choice analysis. More specifically, this thesis utilized a mixed multinomial logit modeling approach. The mixed multinomial logit model has been shown by previous studies to be an appropriate method in capturing the ordered nature of injury severity data in addition to accounting for any unobserved heterogeneity (unobserved factors) influencing the data and/or subjectivity of the crash reporting by police officers. For a complete review of crash-injury severity models and methodological approaches readers are directed to Savolainen et al., Islam and Hernandez, and Pahukula et al. (M. Bin Islam and Hernandez, 2013; Pahukula et al., 2015; Savolainen et al., 2011).

Multinomial Logit Model

The level of injury severity is discrete in nature and is typically coded using the KABCO injury scale (where K = fatal, A = incapacitating, B = non-incapacitating, C = possible injury, and O = property damage only). For this study, injury categories were grouped due to low observations in the “K” category, as was explained and shown in the previous chapter.

To start, the deterministic component of the utility value of discrete injury outcome *i* (KABCO) for crashes *n* involving large trucks can be presented by a linear function as (Washington et al., 2010):

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

where U_{in} is the dependent variable of each driver-injury outcome *i* in crash n, $\mathbf{X}_{in}$ is vector of explanatory variables (e.g., driver, vehicle, road, and environment variables), $\boldsymbol{\beta}_i$ represents the vector of estimable parameters and ε_{in} represent the error term. If ε_{in} values are assumed to be generalized extreme value distributed, McFadden has shown that the multinomial logit formulation can be presented as (McFadden, 1981):

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

where $P_n(i)$ is the probability of large-truck-involved crashes *n* having driver severity outcome *i* ($i \in I$ with *I* denoting severe injury (K and A), minor injury (B and C), and no injury (O)).

Mixed Logit Model Extension

The Washington State data is not completely free from unobserved heterogeneity, therefore to account for the possibility that elements for parameter vector $\boldsymbol{\beta}_i$ may vary across observations of each large-truck-involved crash, a mixed multinomial logit model (also known as the mixed logit model) is utilized. As previously mentioned this is due to the subjectivity of the crash reporting by police officers and randomness associated to some factors influencing the data. Equation 2 is extended and the following is the resulting mixed multinomial logit model (Mcfadden and Train, 2000; Train, 2003) :

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

where P_{in} is probability of large-truck-involved crashes *n* having driver maximum severity outcome *i* ($i \in I$ with *I* denoting all possible injury severity outcomes as hereunto presented), $f(\boldsymbol{\beta}_i|\varphi)$ represents 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 account for severity outcome-specific variations of the effect of $\mathbf{X}_{in}$ probabilities on crashes involving large trucks in the State of Washington, with the density function $f(\boldsymbol{\beta}_i|\boldsymbol{\varphi})$ used to determine $\boldsymbol{\beta}_i$. The mixed multinomial logit probabilities are a weighted average for different values of $\boldsymbol{\beta}_i$ across the observations where some elements of the vector $\boldsymbol{\beta}_i$ can be fixed and some randomly distributed. If the parameters are random, the weights can be determined by the density function $f(\boldsymbol{\beta}_i|\boldsymbol{\varphi})$ (Washington et al., 2010).

To estimate the mixed multinomial logit, as seen from Equation 3, maximum likelihood estimation is performed through a simulation-based approach that utilizes Halton draws to address the complexity of computing the outcome probabilities. Halton draws have been shown to provide a more efficient distribution of draws for numerical integration than purely random draws (Bhat, 2003; Halton, 1960; Train, 1999). In this study, the normal, lognormal, triangular and uniform distributions for the mixing distributions for the random parameters were used. However, only the normal distribution (with corresponding mean and standard deviation parameters) was found to be statistically significant.

4.3 Marginal Effects

In the discrete choice model, the effect of a change in an attribute "*k*" of alternative "*j*" on the probability that individual *i* would chose alternative "*m*" (where *m* may or may not be equal to *j*) is known as a marginal effect and is shown below. Marginal effects are computed to show the effect of a one unit change in variable, $\mathbf{X}_{in}$, on the driver severity outcome I (see Washington et al. for marginal effects computations) (Washington et al., 2010).

$$\delta_{im}(k|j) = \frac{\partial Prob[y_i = m]}{\partial x_i(k|j)} = \left[1(j = m) - P_{ij}\right] P_{im}\beta_k \tag{4}$$

The average marginal effect (averaged over all observations) is reported herein.

4.4 Goodness of Fit

In order to determine the goodness of fit for the developed models several measures of goodness of fit were considered. The main techniques used were the t-statistic, the log likelihood ratio test, and finally a prediction rate using the *;crosstab* function in NLOGIT5.

The t-statistic is a ratio of the departure of an estimated parameter from its notional value and its standard error which is used in hypothesis testing. T-statistics are calculated as follows with $\hat{\beta}$ being an estimator of the parameter β:

$$t_{\hat{\beta}} = \frac{\hat{\beta} - \beta_0}{s.e.(\hat{\beta})} \tag{5}$$

where β_0 is a non-random known constant and s.e.($\hat{\beta}$) is the standard error of the estimator $\hat{\beta}$. For this research, a confidence level of 95% was used when determining if a t-statistic and variable were statistically significant in the model and accurately depicted the data. The t-statistic is applicable only on the individual parameter basis while the log likelihood ratio test was used for individual parameters and the overall models.

Likelihood ratio tests, or transferability tests, are preformed to determine if there is a difference between any two given models. In this research a log likelihood ratio test was performed after each model iteration to ensure proper variable and model selection. To run the likelihood ratio test, a mixed logit model is created where all of the estimated parameters are restricted to zero. Then the same model is run again with unrestricted parameters. The resulting difference and χ^2 values are used to determine the significance of the models. For the likelihood ratio test, the χ^2 is defined as (Washington et al., 2010):

$$\chi^2 = -2[LL(\beta_R) - LL(\beta_U)] \tag{6}$$

where χ^2 is a chi-squared distributed parameter with degrees of freedom equal to the total number of estimated parameters in the restricted model minus the number of estimated parameters in the unrestricted model. This test is repeated not only for each modeling iteration within the collision type models but also against the different types of collision type models to ensure that they are statistically different. The final goodness of fit measure used was the rate of prediction.

The rate of prediction can be calculated using the output from the *;crosstab* command in the modeling software NLOGIT5. The *;crosstab* function provides a contingency table that shows the distribution of actual observations, observed injury severity outcomes in this case, and shows the number of predicted observations, predicted injury severity outcomes. The rate of prediction is determined using the following equation (Hensher A. et al., 2015):

$$Rate\ of\ Prediction\ (\%) = \frac{Total\ Predicted\ Values}{Total\ Actual\ Values} \times 100 \tag{7}$$

The total predicted and total actual values are provided by NLOGIT5 in the *;crosstab* tables. An example of this calculation can be found in the model accuracy section of Chapter 5.

Chapter 5: Collision Type Models

The results for the six models are presented in this chapter. The first four models are mixed multinomial logit models while the final two having no significant and random parameters are presented in their multinomial logit structure. Each modeling section presents the descriptive statistics on the variables used by the model as well as the particular model results and the effects the variables have on the injury outcomes. Provided below in Table 5 is an overview of the variables included in each model.

Table 5: Variables included in each model.

	Angled	Fixed Object	Rear End Both Moving	Rear End One Stopped	Sideswipe Different Directions	Sideswipe Same Direction
Restraint use (1 if not used, 0 otherwise)	X					
Driver registration origin (1 if from pacific Northwest, 0 otherwise)	X	X			X	
Posted speed limit (1 if greater than 55 mph, 0 otherwise)	X			X	X	
Airbag status (1 if not equipped, 0 otherwise)	X	X		X	X	
Traffic control device type (1 if signal, 0 otherwise)	X	X				
Lighting Condition (1 if daylight, 0 otherwise)	X		X			X
Posted speed limit (1 if between 0 and 35mph, 0 otherwise)	X		X			
Driver registration origin (1 if from U.S.A but not Pacific Northwest, 0 otherwise)	X					X
Contributing Circumstance(1 if Driver Disregards other drivers and signs, 0 otherwise)	X					
Ejection status of driver(1 if driver was not ejected, 0 otherwise)	X					
Weather Condition (1 if clear weather, 0 otherwise)	X	X				
First Object Struck (1 if utility pole or box, 0 otherwise)		X				
Contributing Circumstance(1 if Driver was distracted, 0 otherwise)		X				
Traffic control device type (1 if uncontrolled, 0 otherwise)		X				X
First Object Struck (1 if bridge support or component, 0 otherwise)		X				
Road surface characteristic (1 if road surface was wet, 0 otherwise)		X			X	
Contributing Circumstance(1 if Driver was speeding, 0 otherwise)		X	X	X		
Roadway Type (1 if designated Main Line roadway, 0 otherwise)		X				
Road surface characteristic (1 if road surface was dry, 0 otherwise)		X				
Gender Variable (1 if male, 0 otherwise)			X			
Age Variable (1 if driver is between 45 and 55 years old, 0 otherwise)			X	X		
Airbag status (1 if not deployed, 0 otherwise)			X			
Contributing Circumstance(1 if vehicle has a defect, 0 otherwise)			X			
Road type(1 if collision occurred on rural roadway, 0 otherwise)			X	X		
Sobriety indicator (1 if sober at time of collision, 0 otherwise)			X	X		
Age Variable (1 if driver is between 25 and 35 years old, 0 otherwise)			X			
Road type(1 if collision occurred on urban roadway, 0 otherwise)			X			
Intersection indicator (1 if Collision related to intersection, 0 otherwise)				X	X	X
Roadway characteristic (1 if straight segment, 0 otherwise)				X		
Age Variable (1 if driver is between 35 and 45 years old, 0 otherwise)				X		
Weekday indicator (1 if collision occurred during the weekend, 0 otherwise)				X		
Season indicator (1 if Collision occurred between September and the end of November, 0 otherwise)					X	X
Season indicator (1 if Collision occurred between December and the end of February, 0 otherwise)						X

As presented in Table 5, no two models are exactly alike and no variable is found to be shared across all collisions types (an indication that collision types should be considered separately). The closest shared variable is related to Airbags, indicating that the truck is not airbag equipped, which appears in four of the six collision type models. Daylight, speeding, high speeds, Pacific Northwest origin, and intersections were variables found to be significant in three of the models. It should be noted that the variable that indicates the posted speed limit was split to investigate whether higher posted speed limits, those posted at 55 mph or greater, and lower posted speed limits, those lower than 35 mph, had an explicit effect on injury severity for different collision types.

A comprehensive look at the individual models and the variables is presented in the following subsections. For all of the models a 95% confidence level was used to determine if the variables were significant for the injury outcomes. Random variables were evaluated at the 95% confidence level as well. As mentioned earlier, some variables with less significance were left in the models since they are known to be contributing factors (Savolainen et al., 2011). The variables effects are presented in the form of marginal effects for all models.

The results for the analysis are presented in a combined format in Section 5.5 and are split by driver, environmental/roadway, vehicle and collision factors. The effects of the random variables and their meaning however are discussed in the models appropriate section. The marginal effects presented in the following sections provide additional insights regarding what occurs with large-truck involved crash injury severity categories, their probabilities, and the magnitude of change for these categories. A positive coefficient in the marginal effects tables represents increased impact on the respective injury severity probability. For example, in the context of marginal effects and angled collisions, the variable indicating High Posted speed limit (1 if greater than 55 mph, 0 otherwise) for severe injury with the negative sign (-0.0166) indicates that on average the probability of severe injuries occurring is lower given the crashes that occurred in areas with speed limits greater than 55 mph. On the other hand, the minor injury and property damage only effects are positive and suggest that on average their probabilities are higher. For the sideswipe collisions models the elasticities can be interpreted in a similar, yet different way. For example, in the context of elasticities and sideswipe collisions where trucks are travelling in different directions, the variable indicating High Posted speed limit (1 if greater than 55 mph, 0 otherwise) for severe injury with the negative sign (-0.2635) indicates that for a 1% increase in speed that there is a 0.26% decrease in the likelihood of a severe injury outcome.

5.1 Angle Collision Model

Angled collisions where defined as a collision that occurred as the vehicles were entering the roadway at an angle. The model for angled collisions was found to have three significant and random parameters. The descriptive statistics of the model variables can be found in Table 5.1 while the modeling results and the marginal effects can be seen in Tables 5.2 and 5.3, respectively.

Table 5.1: Angled Collision Descriptive Statistics

Variable Meaning	Mean	Std.Dev.
Restraint use (1 if not used, 0 otherwise)	0.007	0.082
Driver registration origin (1 if from pacific Northwest, 0 otherwise)	0.736	0.441
Posted speed limit (1 if greater than 55 mph, 0 otherwise)	0.109	0.312
Airbag status (1 if not equipped, 0 otherwise)	0.449	0.497
Traffic control device type (1 if signal, 0 otherwise)	0.333	0.471
Lighting Condition (1 if daylight, 0 otherwise)	0.803	0.398
Posted speed limit (1 if between 0 and 35mph, 0 otherwise)	0.533	0.499
Driver registration origin (1 if from U.S.A but not Pacific Northwest, 0 otherwise)	0.202	0.401
Contributing Circumstance(1 if Driver Disregards other drivers and signs, 0 otherwise)	0.059	0.237
Ejection status of driver(1 if driver was not ejected, 0 otherwise)	0.923	0.267
Weather Condition (1 if clear weather, 0 otherwise)	0.655	0.475

Table 5.2: Mixed Multinomial Logit Model Results for Angled Collisions

Variable	Coefficient	t-statistic
Severe Injury		
Constant	1.37	4.05
Restraint use (1 if not used, 0 otherwise)	-1.64	-2.27
Driver registration origin (1 if from pacific Northwest, 0 otherwise)	-0.78	-2.50
Posted speed limit (1 if greater than 55 mph, 0 otherwise)	-0.68	-3.86
Airbag status (1 if not equipped, 0 otherwise)	-0.49	-3.45
Traffic control device type (1 if signal, 0 otherwise)	0.84	2.00
(Standard error of parameter distribution)	(1.86)	(2.09)
Lighting Condition (1 if daylight, 0 otherwise)	0.64	3.68
Minor Injury		
Posted speed limit (1 if between 0 and 35mph, 0 otherwise)	-1.49	-1.62
(Standard error of parameter distribution)	(3.08)	(2.01)
Driver registration origin (1 if from U.S.A but not Pacific Northwest, 0 otherwise)	0.47	1.38
Contributing Circumstance (1 if Driver Disregards other drivers and signs, 0 otherwise)	1.54	4.16
No Injury		
Constant	-3.22	-3.87
Ejection status of driver (1 if driver was not ejected, 0 otherwise)	-4.00	-1.82
(Standard error of parameter distribution)	(2.48)	(2.12)
Weather Condition (1 if clear weather, 0 otherwise)	1.51	1.99
Model Statistics		
Number of Observations	2068	
Restricted log-likelihood	-2271.93021	
Log-likelihood at convergence	-1267.63978	
McFadden pseudo-R-squared (ρ^2)	.4420428	

Table 5.3: Marginal Effects of Angled Model Variables

	Marginal effects		
	Severe Injury	Minor Injury	No Injury
Severe Injury			
Constant			
Restraint use (1 if not used, 0 otherwise)	-0.0019	0.0018	0.0001
Driver registration origin (1 if from pacific Northwest, 0 otherwise)	-0.0799	0.0762	0.0037
Posted speed limit (1 if greater than 55 mph, 0 otherwise)	-0.0166	0.0162	0.0004
Airbag status (1 if not equipped, 0 otherwise)	-0.0332	0.0319	0.0013
Traffic control device type (1 if signal, 0 otherwise)	0.0025	-0.0034	0.0009
Lighting Condition (1 if daylight, 0 otherwise)	0.0665	-0.0634	-0.003
Minor Injury			
Posted speed limit (1 if between 0 and 35mph, 0 otherwise)	0.399	-0.3988	-0.0001
Driver registration origin (1 if from U.S.A but not Pacific Northwest, 0 otherwise)	-0.0108	0.0109	-0.0001
Contributing Circumstance (1 if Driver Disregards other drivers and signs, 0 otherwise)	-0.012	0.0122	-0.0002
No Injury			
Constant			
Ejection status of driver (1 if driver was not ejected, 0 otherwise)	-0.0015	-0.0005	0.002
Weather Condition (1 if clear weather, 0 otherwise)	-0.0077	-0.0029	0.0106

For the angled collisions model three variables were found to be both significant and random. The first of these variables was the indicator variable for Signals, which was found to be significant with a random parameter that is normally distributed, with a mean of 1.86 and a standard deviation of 2.09. Given these values, this variable is less than 0 for 51.91% of large truck crashes that result in severe injuries. That is, on average, about 48% of large truck crashes are more likely to experience severe injury outcomes for angled collisions when signals are present, and for roughly 52% the opposite. The second indicator variable for low speeds was found to be significant and a random parameter that is normally distributed, with a mean of 3.08 and a standard deviation of 2.01. These values indicate that this variable is greater than zero for 71.13% of large truck collisions which means for 71.13% of large trucks that low speeds were estimated to increase the likelihood of a minor injury, while for 28.87% the opposite was true. The third and final variable found to be significant and random with a normal distribution was the indicator variable for drivers that were not ejected from the vehicle. This indicator variable had a mean of 2.48 and a standard deviation of 2.12 which indicates that for 59.69% of the population this variable is greater than

0.This means that for 60% of the population, not being eject from the vehicle was estimated to increase the possibility of a collision being a property damage only crash while for 40% of the population the opposite was true.

5.2 Fixed Object Collision Model

Fixed Object Collisions were defined as any collisions where a large truck struck a fixed object. This could include a vehicle leaving the roadway and striking a tree or if a vehicle crossed into a median and struck a bridge support. The descriptive statistics of the model variables can be found in Table 5.4 while the modeling results and the marginal effects can be seen in Tables 5.5 and 5.6, respectively.

Table 5.4: Fixed Object Collision Variable Descriptive Statistics

Variable Meaning	Mean	Std.Dev.
Posted speed limit (1 if greater than 55 mph, 0 otherwise)	0.329	0.469
First Object Struck (1 if utility pole or box, 0 otherwise)	0.149	0.356
Contributing Circumstance (1 if Driver was distracted, 0 otherwise)	0.207	0.406
Traffic control device type (1 if uncontrolled, 0 otherwise)	0.684	0.465
First Object Struck (1 if bridge support or component, 0 otherwise)	0.097	0.296
Driver registration origin (1 if from pacific Northwest, 0 otherwise)	0.618	0.486
Road surface characteristic (1 if road surface was wet, 0 otherwise)	0.205	0.404
Airbag status (1 if not equipped, 0 otherwise)	0.434	0.496
Traffic control device type (1 if signal, 0 otherwise)	0.149	0.357
Contributing Circumstance (1 if Driver was speeding, 0 otherwise)	0.124	0.33
Weather Condition (1 if clear weather, 0 otherwise)	0.611	0.488
Roadway Type (1 if designated Main Line roadway, 0 otherwise)	0.491	0.499
Road surface characteristic (1 if road surface was dry, 0 otherwise)	0.662	0.473

Table 5.5: Fixed Object Collision Model Results

Variable	**Coefficient**	**t-statistic**
Severe Injury		
Constant	3.54	13.33
Posted speed limit (1 if greater than 55 mph, 0 otherwise)	-1.49	-8.17
First Object Struck (1 if utility pole or box, 0 otherwise)	2.11	5.22
Contributing Circumstance (1 if Driver was distracted, 0 otherwise)	0.07	0.19
(Standard error of parameter distribution)	(1.40)	(2.16)
Traffic control device type (1 if uncontrolled, 0 otherwise)	-0.57	-2.61
Minor Injury		
First Object Struck (1 if bridge support or component, 0 otherwise)	-0.77	-3.04
Driver registration origin (1 if from pacific Northwest, 0 otherwise)	0.36	2.31
Road surface characteristic (1 if road surface was wet, 0 otherwise)	-0.002	-0.01
(Standard error of parameter distribution)	(1.40)	(2.02)
Airbag status (1 if not equipped, 0 otherwise)	-0.30	-0.79
(Standard error of parameter distribution)	(2.31)	(4.17)
Traffic control device type (1 if signal, 0 otherwise)	-2.69	-4.19
Contributing Circumstance (1 if Driver was speeding, 0 otherwise)	0.33	1.79
No Injury		
Constant	-3.62	-4.58
Weather Condition (1 if clear weather, 0 otherwise)	-1.19	-2.35
Roadway Type (1 if designated Main Line roadway, 0 otherwise)	1.38	1.83
Road surface characteristic (1 if road surface was dry, 0 otherwise)	0.81	1.62
Model Statistics		
Number of Observations	3817	
Restricted log-likelihood	-4193.40311	
Log-likelihood at convergence	-1363.13180	
McFadden pseudo-R-squared (ρ^2)	.6749342	

Table 5.6: Marginal Effects of Fixed Object Model Variables

	Marginal effects		
	Severe Injury	Minor Injury	No Injury
Severe Injury			
Constant			
Posted speed limit (1 if greater than 55 mph, 0 otherwise)	-0.0671	0.0611	0.006
First Object Struck (1 if utility pole or box, 0 otherwise)	0.0059	-0.0058	-0.0001
Contributing Circumstance (1 if Driver was distracted, 0 otherwise)	-0.0097	0.0083	0.0014
Traffic control device type (1 if uncontrolled, 0 otherwise)	-0.0364	0.0339	0.0025
Minor Injury			
First Object Struck (1 if bridge support or component, 0 otherwise)	0.0168	-0.0207	0.004
Driver registration origin (1 if from pacific Northwest, 0 otherwise)	-0.0166	0.0169	-0.0003
Road surface characteristic (1 if road surface was wet, 0 otherwise)	-0.0103	0.0104	-0.0001
Airbag status (1 if not equipped, 0 otherwise)	-0.0378	0.038	-0.0002
Traffic control device type (1 if signal, 0 otherwise)	0.0027	-0.0027	0
Contributing Circumstance (1 if Driver was speeding, 0 otherwise)	-0.0047	0.0048	-0.0001
No Injury			
Constant			
Weather Condition (1 if clear weather, 0 otherwise)	0.0022	0.0006	-0.0028
Roadway Type (1 if designated Main Line roadway, 0 otherwise)	-0.0063	-0.0017	0.008
Road surface characteristic (1 if road surface was dry, 0 otherwise)	-0.0024	-0.0006	0.0031

Three variables were found to be significant and random at 95% confidence for the fixed object collision model. The first variable found to be significant and random was the indicator variable for driver distraction, with a mean of 1.40 and a standard deviation of 2.16. Given these values it is estimated that for 60.23% of large truck collisions this variable is less than zero. This would indicate that for an estimated 39.77% of large truck drivers being distracted drastically increased the chances of being involved in a serious injury crash, while for 60.23% it had little effect. The second variable was wet roadway surfaces, which had a mean of 1.40 and a standard deviation of 2.02. These values indicate that for 39.08% of collisions this variable was greater than zero which means that for 39.08% of truck drivers wet roadways increased the probability of being involved in a minor injury collisions while for 60.92% it had the opposite effect. The final significant and random variable was the indicator for when a truck was not airbag equipped, the variable had a mean of 2.31 and a standard deviation of 4.17, given these values it is estimated that for 53.34% of collisions this variable is greater than zero. These values suggested that for an estimated 53.34% of the population of large truck drivers that traveling in a truck without airbags increases the probabilities of obtaining a minor injury during a collision, while for 46.66% the opposite is true.

5.3 Rear End Collision Model

The Rear-End collision model was more simple to put together as the data was easily identifiable. However, in the course of separating the data it was found that a record was kept of when a rear-end collision involved two moving vehicles and when it involved a single stopped vehicle. To test if there were any significant differences the rear-end collision data set was split into two distinct sets and modeled.

5.3.1 Rear-End Collisions where Both Trucks are Moving

The descriptive statistics of the model variables can be found in Table 5.7 while the modeling results and the marginal effects can be seen in Tables 5.8 and 5.9, respectively.

Table 5.7: Descriptive Statistics of Rear-End Collision variables when both Trucks are Moving

Variable Meaning	Mean	Std.Dev.
Gender Variable (1 if male, 0 otherwise)	0.919	0.271
Contributing Circumstance (1 if Driver was speeding, 0 otherwise)	0.161	0.367
Age Variable (1 if driver is between 45 and 55 years old, 0 otherwise)	0.281	0.449
Airbag status (1 if not deployed, 0 otherwise)	0.473	0.499
Lighting Condition (1 if daylight, 0 otherwise)	0.737	0.44
Contributing Circumstance (1 if vehicle has a defect, 0 otherwise)	0.013	0.115
Posted speed limit (1 if between 0 and 35mph, 0 otherwise)	0.087	0.282
Road type (1 if collision occurred on rural roadway, 0 otherwise)	0.227	0.419
Sobriety indicator (1 if sober at time of collision, 0 otherwise)	0.906	0.292
Age Variable (1 if driver is between 25 and 35 years old, 0 otherwise)	0.15	0.357
Road type (1 if collision occurred on urban roadway, 0 otherwise)	0.674	0.469

Table 5.8: Rear-End Collisions where Both Trucks are Moving Model Results

Variable	Coefficient	t-statistic
Severe Injury		
Constant	0.58	3.26
Gender Variable (1 if male, 0 otherwise)	-0.39	-2.31
Contributing Circumstance (1 if Driver was speeding, 0 otherwise)	-0.51	-4.39
Age Variable (1 if driver is between 45 and 55 years old, 0 otherwise)	-0.26	-2.68
Airbag status (1 if not deployed, 0 otherwise)	0.36	4.03
Lighting Condition (1 if daylight, 0 otherwise)	0.30	3.04
Minor Injury		
Contributing Circumstance(1 if vehicle has a defect, 0 otherwise)	1.16	2.95
Posted speed limit (1 if between 0 and 35mph, 0 otherwise)	-0.38	-2.31
Road type (1 if collision occurred on rural roadway, 0 otherwise)	0.22	2.14
No Injury		
Constant	-6.05	-1.80
(Standard error of parameter distribution)	(3.19)	(1.67)
Sobriety indicator (1 if sober at time of collision, 0 otherwise)	-2.01	-1.72
Age Variable (1 if driver is between 25 and 35 years old, 0 otherwise)	1.54	1.67
Road type (1 if collision occurred on urban roadway, 0 otherwise)	-1.49	-1.81
Model Statistics		
Number of Observations	2310	
Restricted log-likelihood	-2537.79439	
Log-likelihood at convergence	-1587.66114	
McFadden pseudo-R-squared (ρ^2)	.3743933	

Table 5.9: Marginal Effects of Rear-End Collisions where Both Trucks are Moving Model Variables

	Marginal effects		
	Severe Injury	Minor Injury	No Injury
Severe Injury			
Constant			
Gender Variable (1 if male, 0 otherwise)	-0.083	0.0821	0.0009
Contributing Circumstance (1 if Driver was speeding, 0 otherwise)	-0.02	0.0199	0.0002
Age Variable (1 if driver is between 45 and 55 years old, 0 otherwise)	-0.0172	0.0171	0.0001
Airbag status (1 if not deployed, 0 otherwise)	0.0376	-0.0372	-0.0004
Lighting Condition (1 if daylight, 0 otherwise)	0.0503	-0.0497	-0.0006
Minor Injury			
Contributing Circumstance (1 if vehicle has a defect, 0 otherwise)	-0.1964	0.2005	-0.0041
Posted speed limit (1 if between 0 and 35mph, 0 otherwise)	0.0066	-0.0067	0.0001
Road type (1 if collision occurred on rural roadway, 0 otherwise)	-0.0119	0.0121	-0.0002
No Injury			
Constant			
Sobriety indicator (1 if sober at time of collision, 0 otherwise)	0.004	0.0028	-0.0068
Age Variable (1 if driver is between 25 and 35 years old, 0 otherwise)	-0.0012	-0.0008	0.002
Road type (1 if collision occurred on urban roadway, 0 otherwise)	0.0018	0.0011	-0.0029

For rear-end collisions where both vehicles are moving only the constant term for the no injury category was found to be significant with a random parameter that is normally distributed, with a mean of 3.19 and a standard deviation of 1.67. Given these values, this constant is greater than 0 for 76.93% for large truck crashes that result in severe injuries. That is, on average, about 77% of large truck crashes are more likely to result in property damage only injury outcomes, and for roughly 23% the opposite.

5.3.2 Rear-End Collisions where a Single Truck is Stopped

The descriptive statistics of the model variables can be found in Table 5.10 while the modeling results and the marginal effects can be seen in Tables 5.11 and 5.12, respectively.

Table 5.10: Descriptive Statistics of Rear-End Collisions Variables when One Truck was Stopped

Variable Meaning	Mean	Std.Dev.
Intersection indicator (1 if Collision related to intersection, 0 otherwise)	0.378	0.485
Roadway characteristic (1 if straight segment, 0 otherwise)	0.898	0.302
Age Variable (1 if driver is between 35 and 45 years old, 0 otherwise)	0.252	0.434
Airbag status (1 if not equipped, 0 otherwise)	0.446	0.497
Contributing Circumstance (1 if Driver was speeding, 0 otherwise)	0.161	0.368
Sobriety indicator (1 if sober at time of collision, 0 otherwise)	0.875	0.331
Road type (1 if collision occurred on rural roadway, 0 otherwise)	0.106	0.307
Age Variable (1 if driver is between 45 and 55 years old, 0 otherwise)	0.286	0.452
Posted speed limit (1 if greater than 55 mph, 0 otherwise)	0.373	0.484
Weekday indicator (1 if collision occurred during the weekend, 0 otherwise)	0.068	0.252

Table 5.11: Rear-End Collisions when One Truck was Stopped Model Results

Variables	Coefficient	t-statistic
Severe Injury		
Constant	0.99	3.03
Intersection indicator (1 if Collision related to intersection, 0 otherwise)	0.39	2.00
Roadway characteristic (1 if straight segment, 0 otherwise)	-0.68	-2.04
Age Variable (1 if driver is between 35 and 45 years old, 0 otherwise)	-0.26	-1.39
Minor Injury		
Airbag status (1 if not equipped, 0 otherwise)	0.39	1.90
Contributing Circumstance (1 if Driver was speeding, 0 otherwise)	1.15	3.10
Sobriety indicator (1 if sober at time of collision, 0 otherwise)	-0.91	-1.95
(Standard error of parameter distribution)	(2.88)	(2.09)
No Injury		
Constant	-6.71	-7.71
Road type (1 if collision occurred on rural roadway, 0 otherwise)	2.50	3.82
Age Variable (1 if driver is between 45 and 55 years old, 0 otherwise)	1.26	1.98
Posted speed limit (1 if greater than 55 mph, 0 otherwise)	1.44	1.77
Weekday indicator (1 if collision occurred during the weekend, 0 otherwise)	1.47	2.00
Model Statistics		
Number of Observations	2065	
Restricted log-likelihood	-2268.63438	
Log-likelihood at convergence	-1404.13009	
McFadden pseudo-R-squared (ρ^2)	.3810681	

Table 5.12: Marginal effects of Rear-End Collisions where One Truck was Stopped Variables

	Marginal effects		
	Severe Injury	Minor Injury	No Injury
Severe Injury			
Constant			
Intersection indicator (1 if Collision related to intersection, 0 otherwise)	0.019	-0.0187	-0.0003
Roadway characteristic (1 if straight segment, 0 otherwise)	-0.0791	0.0768	0.0023
Age Variable (1 if driver is between 35 and 45 years old, 0 otherwise)	-0.0083	0.0081	0.0002
Minor Injury			
Airbag status (1 if not equipped, 0 otherwise)	-0.1521	0.1521	0
Contributing Circumstance (1 if Driver was speeding, 0 otherwise)	-0.0224	0.0226	-0.0003
Sobriety indicator (1 if sober at time of collision, 0 otherwise)	0.0195	-0.0198	0.0002
No Injury			
Constant			
Road type (1 if collision occurred on rural roadway, 0 otherwise)	-0.006	-0.0016	0.0075
Age Variable (1 if driver is between 45 and 55 years old, 0 otherwise)	-0.0026	-0.0007	0.0033
Posted speed limit (1 if greater than 55 mph, 0 otherwise)	-0.0045	-0.0012	0.0057
Weekday indicator (1 if collision occurred during the weekend, 0 otherwise)	-0.0014	-0.0004	0.0018

For rear-end collisions where both vehicles are moving, only the indicator variable for Sobriety in the Minor Injury utility equation was found to be significant with a random parameter that is normally distributed, with a mean of 2.88 and a standard deviation of 2.09. Given these values, this variable is greater than 0 for 67.01% for large truck crashes that result in minor injuries. That is, on average, about 67% of large truck crashes where the driver was sober the crash resulted in a minor injury outcome, and for roughly 33% the opposite.

5.4 Sideswipe Collision Model

In a similar fashion to the rear-end collision datasets, the sideswipe datasets were also split. The Sideswipe collision datasets were split into trucks traveling in different directions and those traveling in the same direction. These models were also found to have no significant and random parameters and are thus reported as multinomial logit models.

5.4.1 Sideswipe Collisions of Trucks Traveling in Different Directions

The descriptive statistics of the model variables can be found in Table 5.13 while the modeling results and the marginal effects can be seen in Tables 5.14 and 5.15, respectively.

Table 5.13: Descriptive Statistics for Sideswipe Collisions of Trucks Traveling in Different Directions

Variable Meaning	Mean	Std.Dev.
Posted speed limit (1 if greater than 55 mph, 0 otherwise)	0.413	0.493
Airbag status (1 if not equipped, 0 otherwise)	0.456	0.498
Road surface characteristic (1 if road surface was wet, 0 otherwise)	0.177	0.382
Driver registration origin (1 if from pacific Northwest, 0 otherwise)	0.701	0.458
Intersection indicator (1 if Collision related to intersection, 0 otherwise)	0.037	0.189
Season indicator (1 if Collision occurred between September and the end of November, 0 otherwise)	0.242	0.429

Table 5.14: Sideswipe Collisions of Trucks Traveling in Different Directions Model Results

Variables	Coefficient	t-statistic
Severe Injury		
Constant	1.77	6.11
Posted speed limit (1 if greater than 55 mph, 0 otherwise)	-1.11	-4.68
Airbag status (1 if not equipped, 0 otherwise)	-0.51	-2.17
Road surface characteristic (1 if road surface was wet, 0 otherwise)	-0.57	-1.90
Minor Injury		
Driver registration origin (1 if from pacific Northwest, 0 otherwise)	0.74	2.76
Intersection indicator (1 if Collision related to intersection, 0 otherwise)	-1.89	-1.77
No Injury		
Constant	-1.90	-4.79
Season indicator (1 if Collision occurred between September and the end of November, 0 otherwise)	0.88	1.69
Model Statistics		
Number of Observations	351	
Log-likelihood at Constants	-288.7780	
Log-likelihood at convergence	-263.63178	
McFadden pseudo-R-squared (ρ^2)	.0871	

Table 5.15: Marginal Effects of Sideswipe Collisions of Trucks Traveling in Different Directions Model Variables

	Marginal Effects		
	Severe Injury	Minor Injury	No Injury
Severe Injury			
Constant			
Posted speed limit (1 if greater than 55 mph, 0 otherwise)	-0.2373	0.2106	0.0267
Airbag status (1 if not equipped, 0 otherwise)	-0.1080	0.0958	0.0122
Road surface characteristic (1 if road surface was wet, 0 otherwise)	-0.1224	0.1086	0.0138
Minor Injury			
Driver registration origin (1 if from pacific Northwest, 0 otherwise)	-0.2629	0.2630	-0.0001
Intersection indicator (1 if Collision related to intersection, 0 otherwise)	0.3568	-0.3921	0.0353
No Injury			
Constant			
Season indicator (1 if Collision occurred between September and the end of November, 0 otherwise)	-0.0212	-0.0165	0.0377

An example inference that can be drawn from Table 5.15 above, is that for a

1 unit change in the number of trucks not equipped with airbags a 0.108% decrease in severe injury crash outcomes is estimated.

5.4.2 Sideswipe Collisions of Trucks Traveling in the Same Direction

The descriptive statistics of the model variables can be found in Table 5.16 while the modeling results and the marginal effects can be seen in Tables 5.17 and 5.18, respectively.

Table 5.16: Descriptive Statistics of Sideswipe Collisions of Trucks Traveling in the Same Direction

Variable Meaning	**Mean**	**Std.Dev.**
Lighting Condition (1 if daylight, 0 otherwise)	0.715	0.452
Driver registration origin (1 if from U.S.A but not Pacific Northwest, 0 otherwise)	0.727	0.446
Season indicator (1 if Collision occurred between December and the end of February, 0 otherwise)	0.251	0.434
Intersection indicator (1 if Collision related to intersection, 0 otherwise)	0.148	0.355
Traffic control device type (1 if uncontrolled, 0 otherwise)	0.874	0.332
Season indicator (1 if Collision occurred between September and the end of November, 0 otherwise)	0.269	0.443

Table 5.17: Sideswipe Collisions of Trucks Traveling in the Same Direction Model Results

Variables	Coefficient	t-statistic
Severe Injury		
Constant	2.17	13.10
Lighting Condition (1 if daylight, 0 otherwise)	0.38	4.63
Driver registration origin (1 if from U.S.A but not Pacific Northwest, 0 otherwise)	-0.63	-5.94
Season indicator (1 if Collision occurred between December and the end of February, 0 otherwise)	0.16	1.77
Minor Injury		
Intersection indicator (1 if Collision related to intersection, 0 otherwise)	-0.52	-3.83
Traffic control device type (1 if uncontrolled, 0 otherwise)	0.38	2.49
No Injury		
Constant	-5.42	-7.50
Season indicator (1 if Collision occurred between September and the end of November, 0 otherwise)	1.64	1.89
Model Statistics		
Number of Observations	5374	
Log-likelihood at Constants	-2363.5470	
Log-likelihood at convergence	-2298.97584	
McFadden pseudo-R-squared (ρ^2)	.0273	

Table 5.18: Marginal Effects of Sideswipe Collisions of Trucks Traveling in the Same Direction Model Variables

	Marginal Effects		
	Severe Injury	Minor Injury	No Injury
Severe Injury			
Constant			
Lighting Condition (1 if daylight, 0 otherwise)	0.0491	-0.0487	-0.0004
Driver registration origin (1 if from U.S.A but not Pacific Northwest, 0 otherwise)	-0.0812	0.0807	0.0006
Season indicator (1 if Collision occurred between December and the end of February, 0 otherwise)	0.0207	-0.0206	-0.0001
Minor Injury			
Intersection indicator (1 if Collision related to intersection, 0 otherwise)	0.0866	-0.0866	-0.0001
Traffic control device type (1 if uncontrolled, 0 otherwise)	-0.0481	0.0482	-0.0001
No Injury			
Constant			
Season indicator (1 if Collision occurred between September and the end of November, 0 otherwise)	-0.0015	-0.0003	0.0018

An example inference that can be drawn from table 5.18 above is that for a

1 unit change in the number of trucks driving during the winter months a 0.0207% increase in severe injury crash outcomes is estimated.

5.5 Modeling Results

To simplify the discussion and explanation of the modeling results the variables found to be significant for the six models are categorized based on the characteristics of the drivers, roadway/environment, vehicle and collision. Of the six collision types modeled for the Washington dataset, four were found to be random parameters models and the other two were found to contain no significant and random variables so they were estimated as multinomial logit models.

Driver Characteristics

In all of the models, except for the sideswipe model for vehicles travelling in the same direction, variables dealing with speed (High speed indicator, Low speed indicator, and the Speeding indicator variables) were significant for the injury severity categories they appear in. Of these speed indicator variables, the low speed variable in angle collisions was found to be a variable that varied across observations for minor injury collisions.

This may indicate that when a large truck was traveling at a low speed, in this case 35 mph or lower, the probability of the truck driver experiencing a minor injury during an angled crash is increased for an estimated 71%.

In terms of the Severe Injury Collision Equations, the angle model found that high speed, no restraint used, and Pacific Northwest origin indicators were related to an increase in serious injury outcomes. These three variables were all found to lower the likelihood of a serious injury outcome for angled collisions. This may be explained by drivers being more cautious if they are not already wearing a restraint. It is likely that at high speeds the number of opportunities to get into a situation that would result in an angled collision are lessened than when a driver is driving at a relatively lower speed. The final variable relating to the origin of the driver lessening the likelihood of this injury outcome can be attributed to driver expectancy and familiarity with the roadway environment. The fixed model revealed that high speed and the distraction indicator variables were contributing factors. Taken either together or separately, these two factors for the fixed object model make sense. Higher speeds could contribute to loss of control around corners and contribute to the truck subsequently leaving the roadway surface to strike an object on the side of the roadway. Distracted driving has been found to increase the likelihood of crashes, as can be seen in Chen and Chen (2011). The rear end model for when both trucks are moving found that the variables indicating male, speeding, and age between 45 and 55 years old were contributing factors. For these types of rear end collisions it was found that male drivers were less likely to experience severe injury outcomes which corresponds with findings by both Islam and Hernandez (2013) and Chen and Chen (2011), this is generally attributed to the higher injury tolerance some male bodies have over their female counterparts. The age category between 45 and 55 years of age was found to decrease the possibility of severe injury outcomes which may be explained by the experience of the driver but their longer perception reaction time. The model for rear ends where a single truck was moving found that only ages between 35 and 45 were significant. The two sideswipe models each had a single driver characteristic variable that contributed to the model. For sideswipe collisions where trucks are going in different directions the variable indicating high speeds was significant, while for the sideswipe collisions of trucks going in the same direction found that drivers that were from the US but not the Pacific Northwest were significant. For sideswipe collisions in different directions the presences of higher posted speeds reduced the probability of a severe injury outcome which may be explained by the placement of high speed zones. Higher speeds are ideally used on flat and straight roadway segments where there is less of a chance for vehicles to cross over any medians or barriers. For sideswipe collisions travelling in the same direction the origin of the driver lessened the likelihood of a severe injury outcome, which may be attributed to the driver driving more cautiously in an unfamiliar environment.

For the minor injury utility equations the angled model found low speeds, drivers disregarding other vehicles and signs, and drivers who didn't originate from the Pacific Northwest to be statistically important. Drivers disregarding other drivers and signs was found by Islam and Hernandez (2013) to be likely to contribute to an increase in injury severity which is similar to what was found in this research. The fixed model determined that drivers who originated from the Pacific Northwest and those who were speeding at the time of the collision were significant for minor injury collisions. Both of these variables were found to increase the probability of minor injury crash outcomes. While it may be expected that drivers from the Pacific Northwest would've have had a smaller probability to experience a collision due to their familiarity with the road environment, this familiarity may be attributing to the increase in minor injury outcomes found in this research. The rear end model for both trucks moving found that only low speeds were significant for minor injury collisions. The read end model, where a single truck was stopped, found that drivers being sober, and drivers speeding were significant for minor injury collisions. Romo et al. (2014) also found that a driver's tendency to drive in excess of the posted speed limit was a significant contributing factors to rear end collisions. Of the two remaining models only the sideswipe model for trucks traveling in different directions had a significant variable for minor collisions and that was drivers who originated from the Pacific Northwest. This variable is new to this research, to the best of the author's knowledge, and could be explained by a driver's familiarity with the roadway environment and subsequent over confidence in driving along the local highways and state routes.

For property damage only collisions only four driver characteristic variables were found to be significant between two of the models. For rear end collisions where both trucks were moving the age increment between 25 and 35 was found to be significant as well as the sober variable, which was found to be both a contributing factor and have a varying affect across the data sample. The age increment of 25 to 35 years old was found to increase the likelihood of a PDO outcome which may reflect the driver's inexperience with handling such large vehicles. For rear end collisions where only one of the trucks was moving the variables for high speeds and the age increment between 45 and 55 were found to be significant. A similar result was found by Islam and Hernandez (2013). The combination of higher speeds and drivers being in the 45 to 55 year old age group were found to increase the likelihood of a property damage only injury outcome. A possible explanation is that the drivers experience in handling such a large vehicle but then having a slower reaction time due to age making an accident unavoidable but not as serious as it may have been were the driver less experienced.

Roadway/Environmental Factors

Across all six of the collision types only two roadway/environmental variables were found to vary across the observations and to be considered contributing factors. In the Angle model the presence of signals was found to have a variable effect on large trucks for severe injury collisions. In the fixed object model the variable indicating whether the roadway surface was wet or not was found to have a significant and variable effect on minor injury collisions.

For the Severe Injury Severity Utility Equation of the angled model it was found that the presence of daylight was a contributing factor and that signals, as shown before had both a significant and variable effect. Romo et al. (2014) found that daylight decreased the likelihood of rear end collisions, while in this research it was found that daylight conditions were contributing to an increase in serious injury collisions for large trucks. For the fixed object model collisions with utility poles and boxes were found to be of importance as well as those collisions that occurred where there were no control devices. For rear end collisions daylight was found to be significant for cases where both trucks involved were moving. In this research unlike in Romo et al. (2014) the presence of daylight increased the probability of a rear end collisions, this is most likely explained by the types of vehicles used in the study. Romo et al. looked at large truck and passenger vehicle interactions while this study focuses only on large truck collisions. In cases where only a single truck was moving, straight road segments and intersections were found to be contributing factors. The factor indicating an intersection was expected to be significant since this is the area where most rear end collisions where a single truck is stopped are likely to occur. The presence of straight road segments was found to lower the probability of a serious injury outcome which probably accounts for other drivers having better visibility of the vehicle in front of them and having sufficient area to slow down. For sideswipe collisions, the variable for wet roadway surfaces was found to be significant for cases where the trucks were heading in opposite directions. Wet roadway surfaces were determined to decrease the likelihood of a serious injury outcome, and is likely due to drivers driving more cautiously to compensate for the slick roadway surface. For events where the involved trucks were heading in the same direction the variables for daylight and for the winter months were found to be significant. Both of these variables were found to increase the likelihood of serious injury outcomes in same direction sideswipe collisions. This is likely do to winter months having an increased likelihood of ice on the roadways making driving a bit more perilous. And daylight could be either reflecting or directly blinding drivers making it difficult for them to find safe gaps when to merge.

In terms of the minor injury utility equations no roadway/environmental variables were found to be significant for the angled model. For the Fixed object model the variables for signals and collisions with bridges were found to be significant while the variable for wet roadway surfaces was found to be both significant and to vary across the data observations. Collisions with bridges were defined as a truck striking any component of a bridge during its collision, and was found to decrease the probability of minor injury outcomes. This could be due to the fact that these types of collisions are generally counting the times large trucks driver under a bridge whose clearance isn’t quite enough thus causing damage to the truck but not necessarily the driver. For rear end crashes the rural variable was found to be significant for cases where both trucks were moving. For sideswipe collisions the variable for intersections was found to be significant for both cases while the variable for no control devices being present was significant for only cases where both trucks were heading in the same direction. Intersections were found to decrease the likelihood of minor injury outcomes for both types of sideswipe collisions which can be explained by the path of travel large trucks take trough intersections and the probability that drivers are paying more attention at the intersections and are less likely to hit one another.

For property damage only utility equations for this data set it was found that the presence of clear weather was a contributing factor for both angled collisions and fixed object collisions. Clear weather was found to increase the chances of a property damage only outcome for angled collisions and may be explained by driver's thinking they have enough of a gap to turn but misjudge the gap timing. For fixed object collisions mainline roadways and dry surface conditions were also found to be significant for property damage only collisions. It was found that dry roadway surfaces were increasing the probability of property damage only injury outcomes, which is likely explained by drivers having enough traction to slow their vehicles to reasonable speeds before striking a fixed object which would be significantly harder if the road way were slick. In rear end crashes the variable for urban roadways was significant for cases where both trucks were moving, while conversely, the variable for rural roadways was significant for cases where only a single truck was moving. For all sideswipe collisions the indicator variable for the fall season was found to be significant. The fall season was found to be significant for sideswipe collisions and was found to increase the likelihood of a property damage only collision. This can be explained by the increase in truck traffic in fall months as the holiday shopping seasons get closer and drivers are dispatched in higher numbers to distribute goods.

Vehicle and Collision Factors

For the Washington data set the variable for trucks not being equipped with airbags (NAB) was found to be a contributing factor for four of the six collision models. NAB was significant for severe injuries for both the angle model as well as the sideswipe model. NAB was significant for minor injury collisions for the one truck moving rear end model and was found to be a contributing and variable factor for the fixed object collision model. Large trucks are normally not equipped with airbags due to their large mass and the positioning of the driver in the truck cab not requiring airbags. In most cases where airbags were not equipped the likelihood of the injury outcome was decreased. It was only for rear end collisions where a single truck was stopped that the probability of a minor injury outcome was increased.

Three other variables were found to be significant for this category. The first was the variable accounting for airbags that did not deploy, which was a contributing factor for severe injury collisions in the rear end model with both trucks moving. Similarly for that model the variable describing if the truck had a defect at the time of the collision was found to be significant for minor injury collisions. This factor was expected to be a contributing variable, though it was surprising and a relief that it was only a contributing factor in this type of collisions and not others. The final variable was the collision factor determining whether or not the injured party was ejected from the car. It was found that those not ejected from the vehicle were found to have a decreased the likelihood of suffering property damage only injury outcomes during angles collisions.

Model Accuracy

In order to check the validity of the developed models the probability share for each injury category for each modeled collision type was found. The predicted versus actual probability share can be seen in Table 5.19 below. From this table it can be seen that the differences between the predicted and actual values are consistent across all of the models. It has been shown that the models developed unanimously under predict the injury severity outcomes for the data. While under prediction on an individual injury severity category basis is noted the overall rate of prediction is within acceptable limits for three of the models. In general a prediction rate of at least 70% is considered a fair rate of prediction. The three models whose rate of prediction falls under this threshold include the rear end collision models and the different direction sideswipe model. The low rate of prediction for the rear end collision models could be explained by the need to split the rear end collision data into two distinct data sets for the models. The sideswipe model on the other hand has a low rate of prediction that is most likely cause by its low sample observation size which stems from the data being collected from highways which are mainly divided making it less likely for this collision type to occur. To show how the rate of prediction was determined the following example using the angled collision models numbers is provided.

Rate of prediction for Angled Collision Model example:

$$Rate\ of\ Prediction = \frac{Total\ Predicted\ Values}{Total\ Actual\ Values} \times 100 = \frac{1453 + 53 + 0}{1479 + 567 + 22} \times 100$$
$$= 72.8\%$$

Table 5.19: Predicted vs Actual Probability Share of Models

	Predicted			Actual			Rate of Prediction
Collision Type	PDO	Minor Injury	Severe Injury	PDO	Minor Injury	Severe Injury	
Angled	1453	53	0	1479	567	22	72.8%
Fixed Object	3100	200	0	3300	492	25	86.5%
Rear-End Both Moving	1226	193	0	1378	917	15	57.1%
Rear-End One Stopped	1178	97	0	1252	802	11	61.7%
Sideswipe Different Direction	165	61	0	205	130	16	64.4%
Sideswipe Same Direction	4535	0	0	4535	833	6	84.4%

As this is an exploratory analysis, the results of Table 5.1.9 are encouraging given the amount of data for each of the collision type models developed in this thesis. 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 multinomial logit model.

Chapter 6: Conclusions and Recommendations

This Chapter presents a summary of the findings developed by this research. This thesis aimed to explore distinct collision types through the application of a discrete choice analysis framework. The application of a mixed multinomial logit model was successful for four out of the six models, while the latter two models were modeled as multinomial logit models. The remainder of this chapter serves to highlight the summary of findings, the practical use of this research, and finally the implications it has on future research.

6.1 Summary of Findings

In this thesis, large-truck involved crashes by collision types were analyzed through a mixed multinomial logit-modeling framework. The mixed multinomial logit model is an important approach because it provides a mechanism to account and correct for unobserved heterogeneity that can arise from factors related to the driver, vehicle, road-environment, weather, variations in police reporting, temporal and other unobserved factors not captured. The data used in this study was the crash reports taken from the State of Washington database for the years of 2007 to 2013, and to the best of our knowledge a first with respect to explicitly modeling large-truck injury severity by collision types.

The results of the analyses performed in this thesis provided some interesting findings. First, a majority of trucks are not airbag equipped (as expressed in the crash data) and that while for the majority of collision type models this was a factor that decreased the likelihood of an minor injury outcome for more than 50% of individuals involved in fixed object collisions; it also increased the chances of a minor injury. Second, it was also discovered that driver origin plays a factor in collision type and crash severity whether the driver is from the Pacific Northwest or from the rest of the U.S. It was seen that the presence of high posted speed limits and drivers actively speeding were significant to crash severity, as was expected. Third, an unexpected discovery was the importance of sobriety and the inclusion of utility poles and bridge components. Sobriety was found to be both significant and random for rear end collisions where one of the vehicles was stopped. Lastly, utility poles and bridge components had a significant impact on crash severity for fixed object collisions. It was also shown that separating the dataset by collision type was warranted, as none of the developed models were sufficiently similar to be considered the same.

Although the research performed in this thesis is exploratory in nature, the mixed multinomial logit-modeling framework presented in this work offers a flexible methodology to analyze large-truck crashes by collision type while at the same time accounting for unobserved heterogeneity. Using this same approach with an expanded sample of large truck crashes could provide important new insights into large truck driving behavior. For example, datasets with driver skill and other cognitive processing information, car-following dynamics, and human response can greatly improve parameter estimates as well as help improve truck driver training for collision avoidance.

6.2 Practical Applications

This thesis provides several interesting practical applications. The first application is that the examination and modeling of collisions types can lead to the identification of cost effective countermeasures to these types of collisions. One such example is the removal of obstacles and utility equipment from the immediate roadside. While clear zones have been used since the 1960s, there are occasions when the required area is not enough to allow for an appropriate clear zone. As well in more urban areas utility boxes and poles are not always pulled sufficiently far from the roadside. While it may seem impractical to remove utility poles from all areas it may be acceptable to use sunken cables in some areas or to secure poles next to areas with high crash rates with sheer bolts to facilitate less severe crash outcomes. Another countermeasure and suggestion that has been pulled from this research is that it may possibly be a good idea to start requiring the equipment of airbags to large trucks. It was shown that while trucks not being airbag equipped did not lead to an increase in injury severity for all the collision types, it did lead to an increase for minor injury severity when experiencing a fixed object collision for more than 50% of the large truck population modeled.

The trucking industry could benefit from this research by applying the methodology outlined in this research to determine the effectiveness of their driver training programs and to evaluate the safety of their vehicle fleets. Truck drivers of national chains are often required to travel for several weeks and occasional across country or international borders. This research has found that the origin of a driver can influence the collision type and injury severity experienced by the driver. This finding can be explained by expectancy, in terms of local drivers knowing what to expect from the driving environment while those that are not local can be blindsided by the driving environment in the Pacific Northwest. The clearest indication of this can be seen in angled collisions where both the indicators for Pacific Northwest residents and domestic drivers not from the Pacific Northwest were significant. In this model residents of the Pacific Northwest were estimated to be less likely to experience a serious injury outcome, while those domestic drivers that were from other parts of the country had an increased likelihood to experience minor injury outcomes.

In summary, there are various practical implications for this research that could be directly applied to improve transportation safety. The results of this research could benefit transportation safety professional and the trucking industry throughout the decision making process.

6.3 Future Research

This research has shown the potential for future avenues of research. First, this thesis builds a foundation for examining various collision types across a state specific database. Second, it also prompts an investigation into a regional collision type model. And finally the research shows a need for a more standardized national truck driving education program.

The thesis has shown that there is promise and reason to examine crash injury outcomes for distinct collision types. It has also shown that multiple collision types should be tested for a given vehicular population. This research encourages future studies to do one of two things. The first is to expand the data sets used to include several states and see if there are commonalties in the factors that affect collision types. The second avenue of research would be to move the methodology to a different set of vehicles or to even look exclusively at two vehicle's interaction during collisions.

Finally this thesis has shown that the origin of the driver may play a bigger role in collision types than was previously thought. It should be noted that any data on this would need to be normalized across the data set since there is likely to be a substantial number of drivers from Washington in comparison to the rest of the country because of businesses and locale drivers staying within local boundaries. This prompts an investigation into the current state of truck driver training and regulations, as well as shining a spot light on the need for a more standardized and nationally utilized driver training program.

Overall, this thesis explored and presented original research that aims to extend the current state of literature regarding large truck-involved crash severity analysis. The results were based on exploratory studies, but they highlight the importance and the potential usefulness of analyzing large truck-involved crashes based on collision type. This thesis provides a foundation to analyze large truck-involved crashes in a new light.

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APPENDICES

Chapter 8: Appendices

Presented in this section are the code and output for each of the collision type's models from the Modeling Software NLOGIT.

8.1 Nlogit Code and Output for Angled Collision Model

```
nlogit;lhs=x86
           ;choices=sinj,inj,ninj
           ;model:
           u(sinj) = sev    +bNR*NR + bPNW*PNW + bhigh*high +bNAB*NAB
+ bSgnl*Sgnl +bDylght*Dylght /
    u(inj) =           blow*low + bNPNW*NPNW +bDsrgrd*Dsrgrd   /
    u(ninj) = noinj  + bNeject*Neject +bClear*Clear
           ;rpl;pts=200;halton;fcn= bSgnl(n), blow(n),
bNeject(n);effects:NR[*]/PNW[*]/high[*]/NAB[*]/Sgnl[*]/Dylght[*]/low[
*]/NPNW[*]/Dsrgrd[*]/Neject[*]/C
Normal exit:   6 iterations. Status=0, F=    1272.827

-----------------------------------------------------------------------
--------
Start values obtained using MNL model
Dependent variable                Choice
Log likelihood function     -1272.82735
Estimation based on N =   2068, K =  13
Inf.Cr.AIC  =   2571.7 AIC/N =    1.244
Model estimated: Nov 10, 2015, 13:07:06
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only  -1329.4221  .0426 .0389
Chi-squared[11]          =    113.18951
Prob [ chi squared > value ] =   .00000
Response data are given as ind. choices
Number of obs.=  2068, skipped    0 obs
--------+--------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
     X86|  Coefficient       Error        z    |z|>Z*          Interval
--------+--------------------------------------------------------------
--------
   BSGNL|     .24983**       .11257      2.22  .0265       .02920
.47046
    BLOW|    -.21032*        .11004     -1.91  .0560     -.42600
.00535
 BNEJECT|   -1.30155**       .56327     -2.31  .0208    -2.40554    -
.19756
     SEV|    1.33528***      .25767      5.18  .0000       .83025
1.84030
     BNR|   -1.00306*        .55244     -1.82  .0694    -2.08583
.07970
    BPNW|    -.64169***      .23131     -2.77  .0055    -1.09505    -
.18833
   BHIGH|    -.64122***      .16035     -4.00  .0001     -.95550    -
.32693
    BNAB|    -.37304***      .10185     -3.66  .0002     -.57266    -
.17342
 BDYLGHT|     .42338***      .12098      3.50  .0005      .18627
.66050
   BNPNW|     .45075*        .25235      1.79  .0741     -.04384
.94533
```

```
 BDSRGRD|     .91618***      .19717     4.65  .0000      .52973
1.30262
   NOINJ|   -3.02401***      .73183    -4.13  .0000    -4.45836  -
1.58966
  BCLEAR|    1.24101**       .62439     1.99  .0469      .01723
2.46478
--------+----------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-------------------------------------------------------------------
--------

Normal exit:  34 iterations. Status=0, F=    1267.640

-------------------------------------------------------------------
--------
Random Parameters Logit Model
Dependent variable                  X86
Log likelihood function     -1267.63978
Restricted log likelihood   -2271.93021
Chi squared [  16 d.f.]      2008.58087
Significance level               .00000
McFadden Pseudo R-squared      .4420428
Estimation based on N =   2068, K =  16
Inf.Cr.AIC  =   2567.3 AIC/N =    1.241
Model estimated: Nov 10, 2015, 13:10:23
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
No coefficients -2271.9302  .4420 .4399
Constants only  -1329.4221  .0465 .0428
At start values -1272.8273  .0041 .0002
Response data are given as ind. choices
Replications for simulated probs. = 200
Used Halton sequences in simulations.
Number of obs.=  2068, skipped    0 obs
--------+----------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
     X86|  Coefficient       Error       z    |z|>Z*          Interval
--------+----------------------------------------------------------
--------
        |Random parameters in utility functions
   BSGNL|     .84312**       .42244     2.00  .0460      .01514
1.67109
    BLOW|   -1.48714         .92015    -1.62  .1061    -3.29060
.31632
 BNEJECT|   -4.00245*       2.19936    -1.82  .0688    -8.31312
.30822
        |Nonrandom parameters in utility functions
     SEV|    1.36872***      .33822     4.05  .0001      .70581
2.03162
     BNR|   -1.63513**       .72042    -2.27  .0232    -3.04713   -
.22313
    BPNW|    -.77672**       .31054    -2.50  .0124    -1.38536   -
.16809
   BHIGH|    -.68405***      .17707    -3.86  .0001    -1.03110   -
.33701
    BNAB|    -.49594***      .14382    -3.45  .0006     -.77782   -
.21406
 BDYLGHT|     .64277***      .17463     3.68  .0002      .30051
.98504
   BNPNW|     .47434         .34423     1.38  .1682     -.20033
1.14901
```

```
 BDSRGRD|    1.54131***      .37053     4.16  .0000      .81508
2.26754
   NOINJ|   -3.22466***      .83282    -3.87  .0001    -4.85697  -
1.59236
  BCLEAR|    1.51473**       .76110     1.99  .0466      .02301
3.00645
        |Distns. of RPs. Std.Devs or limits of triangular
 NsBSGNL|    1.85590**       .88674     2.09  .0364      .11792
3.59389
  NsBLOW|    3.08233**      1.53002     2.01  .0440      .08354
6.08111
NsBNEJEC|    2.47822**      1.16624     2.12  .0336      .19243
4.76401
--------+------------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------
--------

+--------------------------------------------------------+
| Cross tabulation of actual choice vs. predicted P(j)   |
| Row indicator is actual, column is predicted.          |
| Predicted total is F(k,j,i)=Sum(i=1,...,N) P(k,j,i).   |
| Column totals may be subject to rounding error.        |
+--------------------------------------------------------+

--------+------------------------------------------------------
NLOGIT Cross Tabulation for 3 outcome Multinomial Choice Model
XTab_Prb|         SINJ           INJ          NINJ          Total
--------+------------------------------------------------------
    SINJ|      1082.00       383.000       14.0000       1479.00
     INJ|      384.000       177.000       6.00000       567.000
    NINJ|      13.0000       9.00000       .000000       22.0000
   Total|      1478.00       569.000       21.0000       2068.00

+--------------------------------------------------------+
| Cross tabulation of actual y(ij) vs. predicted y(ij)   |
| Row indicator is actual, column is predicted.          |
| Predicted total is N(k,j,i)=Sum(i=1,...,N) Y(k,j,i).   |
| Predicted y(ij)=1 is the j with largest probability.   |
+--------------------------------------------------------+

--------+------------------------------------------------------
NLOGIT Cross Tabulation for 3 outcome Multinomial Choice Model
XTab_Frq|         SINJ           INJ          NINJ          Total
--------+------------------------------------------------------
    SINJ|      1453.00       26.0000       .000000       1479.00
     INJ|      514.000       53.0000       .000000       567.000
    NINJ|      17.0000       5.00000       .000000       22.0000
   Total|      1984.00       84.0000       .000000       2068.00

+----------------------------------------------------+
| Derivative            averaged over observations.|
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.    |
+----------------------------------------------------+

---------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt NR       in SINJ
--------+------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
```

```
  Choice|  Coefficient       Error       z     |z|>Z*         Interval
--------+-------------------------------------------------------------
--------
    SINJ|    -.00192***      .00053    -3.63  .0003     -.00295   -
.00088
     INJ|     .00182***      .00051     3.58  .0003      .00082
.00282
    NINJ| .95373D-04***   .3438D-04     2.77  .0055   .27989D-04
.16276D-03
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------



----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt PNW      in SINJ
--------+-------------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z     |z|>Z*         Interval
--------+-------------------------------------------------------------
--------
    SINJ|    -.07988***      .00139   -57.58  .0000     -.08260   -
.07716
     INJ|     .07622***      .00135    56.36  .0000      .07357
.07887
    NINJ|     .00366***   .9333D-04    39.20  .0000      .00348
.00384
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------



----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt HIGH     in SINJ
--------+-------------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z     |z|>Z*         Interval
--------+-------------------------------------------------------------
--------
    SINJ|    -.01662***      .00106   -15.67  .0000     -.01870   -
.01454
     INJ|     .01621***      .00103    15.67  .0000      .01418
.01824
    NINJ|     .00041***   .3266D-04    12.44  .0000      .00034
.00047
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
```

```
----------------------------------------------------------------------
--------


----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt NAB      in SINJ
--------+-------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+-------------------------------------------------------------
--------
    SINJ|    -.03319***      .00094   -35.34  .0000     -.03503    -
.03135
     INJ|     .03192***      .00091    34.94  .0000      .03013
.03372
    NINJ|     .00126***   .4065D-04    31.11  .0000      .00119
.00134
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------


----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt SGNL     in SINJ
--------+-------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+-------------------------------------------------------------
--------
    SINJ|     .00251***      .00048     5.23  .0000      .00157
.00346
     INJ|    -.00337***      .00048    -7.00  .0000     -.00431    -
.00242
    NINJ|     .00085***   .5999D-04    14.20  .0000      .00073
.00097
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------


----------------------------------------------------------------------
--------
Average partial effect  on choice probabilities with respect to LOW
--------+-------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
```

```
--------+-------------------------------------------------------------
--------
    SINJ|     .39895         .00149   267.99  .0000      .39604
.40187
     INJ|    -.39881         .00153  -259.89  .0000     -.40182    -
.39580
    NINJ|    -.00015      .7759D-04    -1.87  .0615     -.00030
.00001
--------+-------------------------------------------------------------
--------
----------------------------------------------------------------------
--------

----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt NPNW     in INJ
--------+-------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+-------------------------------------------------------------
--------
    SINJ|    -.01082***      .00054   -20.22  .0000     -.01187    -
.00977
     INJ|     .01094***      .00054    20.22  .0000      .00988
.01200
    NINJ|    -.00012***   .8106D-05   -14.40  .0000     -.00013    -
.00010
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------



----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt DSRGRD   in INJ
--------+-------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+-------------------------------------------------------------
--------
    SINJ|    -.01199***      .00112   -10.67  .0000     -.01419    -
.00979
     INJ|     .01221***      .00114    10.68  .0000      .00997
.01445
    NINJ|    -.00022***   .2715D-04    -7.93  .0000     -.00027    -
.00016
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------
```

Average partial effect on prob(alt) wrt NEJECT in NINJ

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval
SINJ	-.00146***	.4777D-04	-30.65	.0000	-.00156 - .00137
INJ	-.00054***	.2155D-04	-25.00	.0000	-.00058 - .00050
NINJ	.00200***	.6081D-04	32.94	.0000	.00188 .00212

Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

Average partial effect on prob(alt) wrt CLEAR in NINJ

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval
SINJ	-.00769***	.00019	-39.71	.0000	-.00807 - .00731
INJ	-.00288***	.9091D-04	-31.69	.0000	-.00306 - .00270
NINJ	.01057***	.00026	40.78	.0000	.01006 .01108

Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

Derivative wrt change of X in row choice on Prob[column choice]

NR	SINJ	INJ	NINJ
SINJ	-.0019	.0018	.0001

Derivative wrt change of X in row choice on Prob[column choice]

PNW	SINJ	INJ	NINJ
SINJ	-.0799	.0762	.0037

```
Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
HIGH    |    SINJ      INJ     NINJ
--------+--------------------------
    SINJ|  -.0166    .0162    .0004

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
NAB     |    SINJ      INJ     NINJ
--------+--------------------------
    SINJ|  -.0332    .0319    .0013

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
SGNL    |    SINJ      INJ     NINJ
--------+--------------------------
    SINJ|   .0025   -.0034    .0009

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
SGNL    |    SINJ      INJ     NINJ
--------+--------------------------
    SINJ|   .0025   -.0034    .0009

Derivative of Choice Probabilities with Respect to LOW
--------+--------------------------
        |    SINJ      INJ     NINJ
--------+--------------------------
     LOW|   .3990   -.3988   -.0001

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
NPNW    |    SINJ      INJ     NINJ
--------+--------------------------
     INJ|  -.0108    .0109   -.0001

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
DSRGRD  |    SINJ      INJ     NINJ
--------+--------------------------
     INJ|  -.0120    .0122   -.0002

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
NEJECT  |    SINJ      INJ     NINJ
--------+--------------------------
    NINJ|  -.0015   -.0005    .0020

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
CLEAR   |    SINJ      INJ     NINJ
--------+--------------------------
    NINJ|  -.0077   -.0029    .0106
```

8.2 Nlogit Code and Output for Fixed Object Collision Model

```
nlogit;lhs=x92
           ;choices=sinj,inj,ninj
           ;model:
           u(sinj) = sev    +bhigh*high   + bUtlty*Utlty +
bDstrct*Dstrct +bNcntrl*Ncntrl/
    u(inj) =       bBrdg*Brdg +  bPNW*PNW + bWet*Wet + bNAB*NAB +
bSgnl*Sgnl +bSpdng*Spdng /
    u(ninj) = noinj   + bClear*Clear + bMLine*MLine + bDry*Dry
    ;rpl;pts=200;halton;fcn=  bDstrct(n), bWet(n),
bNAB(n);effects:high[*]/Utlty[*]/Dstrct[*]/Ncntrl[*]/Brdg[*]/PNW[*]/W
et[*]/NAB[*]/Sgnl[*]/Spdng[*]/
Normal exit:   7 iterations. Status=0, F=    1372.798

---------------------------------------------------------------------
--------
Start values obtained using MNL model
Dependent variable                Choice
Log likelihood function     -1372.79795
Estimation based on N =   3817, K =  15
Inf.Cr.AIC  =   2775.6 AIC/N =     .727
Model estimated: Nov 10, 2015, 13:28:41
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only  -1613.9790  .1494 .1474
Chi-squared[13]          =    482.36200
Prob [ chi squared > value ] =   .00000
Response data are given as ind. choices
Number of obs.=  3817, skipped    0 obs
--------+------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
     X92|  Coefficient       Error        z    |z|>Z*          Interval
--------+------------------------------------------------------------
--------
 BDSTRCT|    -.23090*         .12146    -1.90  .0573     -.46896
.00715
    BWET|     .26190**        .11922     2.20  .0280      .02823
.49558
    BNAB|     .51979***       .10631     4.89  .0000      .31142
.72816
     SEV|    3.07750***       .18210    16.90  .0000     2.72058
3.43441
   BHIGH|   -1.03210***       .11071    -9.32  .0000    -1.24908   -
.81512
  BUTLTY|    1.51235***       .26646     5.68  .0000      .99009
2.03461
 BNCNTRL|    -.46900***       .16309    -2.88  .0040     -.78865   -
.14935
   BBRDG|    -.58002***       .18525    -3.13  .0017     -.94310   -
.21694
    BPNW|     .28454**        .11188     2.54  .0110      .06525
.50382
   BSGNL|   -2.08006***       .47520    -4.38  .0000    -3.01144  -
1.14867
  BSPDNG|     .28652**        .13618     2.10  .0354      .01961
.55343
   NOINJ|   -3.83689***       .77873    -4.93  .0000    -5.36317  -
2.31061
  BCLEAR|   -1.21962**        .49752    -2.45  .0142    -2.19475   -
.24450
  BMLINE|    1.68581**        .74346     2.27  .0234      .22866
3.14296
```

```
    BDRY|     .81582*        .48966     1.67  .0957     -.14389
1.77552
--------+------------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------
--------

Line search at iteration   29 does not improve fn. Exiting
optimization.

---------------------------------------------------------------------
--------
Random Parameters Logit Model
Dependent variable                   X92
Log likelihood function     -1363.13180
Restricted log likelihood   -4193.40311
Chi squared [  18 d.f.]      5660.54262
Significance level               .00000
McFadden Pseudo R-squared      .6749342
Estimation based on N =   3817, K =  18
Inf.Cr.AIC  =   2762.3 AIC/N =     .724
Model estimated: Nov 10, 2015, 13:36:20
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
No coefficients -4193.4031  .6749 .6742
Constants only  -1613.9790  .1554 .1534
At start values -1372.7980  .0070 .0047
Response data are given as ind. choices
Replications for simulated probs. = 200
Used Halton sequences in simulations.
Number of obs.=  3817, skipped    0 obs
--------+------------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
     X92|  Coefficient       Error       z    |z|>Z*         Interval
--------+------------------------------------------------------------
--------
        |Random parameters in utility functions
 BDSTRCT|     .06989         .36140      .19  .8466     -.63843
.77822
    BWET|    -.00201         .38412     -.01  .9958     -.75487
.75084
    BNAB|    -.30176         .38397     -.79  .4319    -1.05433
.45082
        |Nonrandom parameters in utility functions
     SEV|    3.53709***      .26535    13.33  .0000     3.01702
4.05716
   BHIGH|   -1.49423***      .18298    -8.17  .0000    -1.85287  -
1.13559
  BUTLTY|    2.10542***      .40333     5.22  .0000     1.31490
2.89594
 BNCNTRL|    -.57152***      .21882    -2.61  .0090    -1.00040   -
.14264
   BBRDG|    -.77049***      .25313    -3.04  .0023    -1.26661   -
.27437
    BPNW|     .35715**       .15438     2.31  .0207      .05457
.65973
   BSGNL|   -2.69021***      .64262    -4.19  .0000    -3.94972  -
1.43071
  BSPDNG|     .33262*        .18568     1.79  .0732     -.03130
.69654
   NOINJ|   -3.61575***      .78918    -4.58  .0000    -5.16251  -
2.06900
```

```
  BCLEAR|   -1.19664**       .50826    -2.35  .0186    -2.19281   -
.20048
  BMLINE|    1.37776*        .75324     1.83  .0674     -.09856
2.85408
    BDRY|     .81404         .50114     1.62  .1043     -.16818
1.79625
        |Distns. of RPs. Std.Devs or limits of triangular
NsBDSTRC|    1.39562**       .64636     2.16  .0308      .12878
2.66247
  NsBWET|    1.40000**       .69295     2.02  .0433      .04185
2.75816
  NsBNAB|    2.30857***      .55340     4.17  .0000     1.22393
3.39320
--------+----------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-------------------------------------------------------------------
--------

+-------------------------------------------------------+
| Cross tabulation of actual choice vs. predicted P(j)  |
| Row indicator is actual, column is predicted.         |
| Predicted total is F(k,j,i)=Sum(i=1,...,N) P(k,j,i).  |
| Column totals may be subject to rounding error.       |
+-------------------------------------------------------+

--------+------------------------------------------------------
NLOGIT Cross Tabulation for 3 outcome Multinomial Choice Model
XTab_Prb|         SINJ           INJ          NINJ          Total
--------+------------------------------------------------------
    SINJ|      2905.00       377.000       19.0000       3300.00
     INJ|      376.000       110.000       6.00000       492.000
    NINJ|      19.0000       6.00000       .000000       25.0000
   Total|      3300.00       492.000       25.0000       3817.00

+-------------------------------------------------------+
| Cross tabulation of actual y(ij) vs. predicted y(ij)  |
| Row indicator is actual, column is predicted.         |
| Predicted total is N(k,j,i)=Sum(i=1,...,N) Y(k,j,i).  |
| Predicted y(ij)=1 is the j with largest probability.  |
+-------------------------------------------------------+

--------+------------------------------------------------------
NLOGIT Cross Tabulation for 3 outcome Multinomial Choice Model
XTab_Frq|         SINJ           INJ          NINJ          Total
--------+------------------------------------------------------
    SINJ|      3300.00       .000000       .000000       3300.00
     INJ|      492.000       .000000       .000000       492.000
    NINJ|      25.0000       .000000       .000000       25.0000
   Total|      3817.00       .000000       .000000       3817.00

+---------------------------------------------------+
| Derivative             averaged over observations.|
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.    |
+---------------------------------------------------+

-------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt HIGH     in SINJ
--------+----------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
```

Choice	Coefficient	Error	z	|z|>Z*	Interval	
SINJ	-.06705***	.00162	-41.35	.0000	-.07023	-.06388
INJ	.06107***	.00149	40.99	.0000	.05815	.06399
NINJ	.00598***	.00017	35.30	.0000	.00565	.00632

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

Average partial effect on prob(alt) wrt UTLTY in SINJ

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
SINJ	.00592***	.00031	19.17	.0000	.00531	.00652
INJ	-.00580***	.00030	-19.23	.0000	-.00639	-.00521
NINJ	-.00012***	.1242D-04	-9.69	.0000	-.00014	-.00010

Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

Average partial effect on prob(alt) wrt DSTRCT in SINJ

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
SINJ	-.00973***	.00035	-28.03	.0000	-.01041	-.00905
INJ	.00832***	.00032	26.36	.0000	.00770	.00894
NINJ	.00141***	.6715D-04	21.02	.0000	.00128	.00154

Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

```
-----------------------------------------------------------------------
--------
Average partial effect  on choice probabilities with respect to BRDG
--------+--------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+--------------------------------------------------------------
--------
    SINJ|     .01676          .00021    79.66  .0000       .01635
.01718
     INJ|    -.02074          .00026   -78.37  .0000      -.02126    -
.02022
    NINJ|     .00398      .9163D-04    43.40  .0000       .00380
.00416
--------+--------------------------------------------------------------
--------
-----------------------------------------------------------------------
--------

-----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt PNW      in INJ
--------+--------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+--------------------------------------------------------------
--------
    SINJ|    -.01664***       .00031   -53.48  .0000      -.01725    -
.01603
     INJ|     .01693***       .00032    53.19  .0000       .01631
.01756
    NINJ|    -.00029***   .1092D-04   -27.01  .0000      -.00032    -
.00027
--------+--------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------
--------


-----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt WET      in INJ
--------+--------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+--------------------------------------------------------------
--------
    SINJ|    -.01029***       .00038   -26.90  .0000      -.01103    -
.00954
     INJ|     .01037***       .00039    26.89  .0000       .00961
.01112
```

```
    NINJ|-.80357D-04***   .5388D-05   -14.91  .0000 -.90917D-04  -
.69797D-04
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------
```

```
----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt NAB      in INJ
--------+-------------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+-------------------------------------------------------------
--------
    SINJ|    -.03776***      .00077   -49.20  .0000     -.03927   -
.03626
     INJ|     .03796***      .00077    49.20  .0000      .03645
.03947
    NINJ|    -.00020***   .1207D-04   -16.29  .0000     -.00022   -
.00017
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------
```

```
----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt SGNL     in INJ
--------+-------------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+-------------------------------------------------------------
--------
    SINJ|     .00273***      .00016    17.28  .0000      .00242
.00304
     INJ|    -.00274***      .00016   -17.23  .0000     -.00306   -
.00243
    NINJ| .13045D-04***   .2186D-05     5.97  .0000  .87611D-05
.17329D-04
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------
```

```
----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt SPDNG    in INJ
```

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
SINJ	-.00472***	.00022	-21.32	.0000	-.00515	-.00428
INJ	.00479***	.00023	21.27	.0000	.00435	.00523
NINJ	-.72157D-04***	.4406D-05	-16.38	.0000	-.80792D-04	-.63522D-04

Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

Average partial effect on prob(alt) wrt CLEAR in NINJ

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
SINJ	.00220***	.6506D-04	33.85	.0000	.00207	.00233
INJ	.00059***	.2452D-04	24.01	.0000	.00054	.00064
NINJ	-.00279***	.8673D-04	-32.18	.0000	-.00296	-.00262

Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

Average partial effect on prob(alt) wrt MLINE in NINJ

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
SINJ	-.00627***	.00015	-40.86	.0000	-.00657	-.00597
INJ	-.00170***	.5278D-04	-32.25	.0000	-.00181	-.00160
NINJ	.00798***	.00020	39.74	.0000	.00758	.00837

```
--------+------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------
--------
```

```
---------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt DRY      in NINJ
--------+------------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z     |z|>Z*          Interval
--------+------------------------------------------------------------
--------
    SINJ|    -.00243***   .7964D-04   -30.46  .0000     -.00258    -
.00227
     INJ|    -.00064***   .2822D-04   -22.77  .0000     -.00070    -
.00059
    NINJ|     .00307***      .00010    29.27  .0000      .00286
.00327
--------+------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------
--------
```

```
Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
HIGH    |     SINJ       INJ      NINJ
--------+--------------------------
    SINJ|  -.0671     .0611     .0060
```

```
Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
UTLTY   |     SINJ       INJ      NINJ
--------+--------------------------
    SINJ|   .0059    -.0058    -.0001
```

```
Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
DSTRCT  |     SINJ       INJ      NINJ
--------+--------------------------
    SINJ|  -.0097     .0083     .0014
```


```
Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
DSTRCT  |     SINJ       INJ      NINJ
--------+--------------------------
    SINJ|  -.0097     .0083     .0014
```


```
Elasticity of Choice Probabilities with Respect to BRDG
```

```
--------+--------------------------
        |    SINJ      INJ     NINJ
--------+--------------------------
    BRDG|   .0168   -.0207    .0040

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
PNW     |    SINJ      INJ     NINJ
--------+--------------------------
     INJ|  -.0166    .0169   -.0003

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
WET     |    SINJ      INJ     NINJ
--------+--------------------------
     INJ|  -.0103    .0104   -.0001

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
NAB     |    SINJ      INJ     NINJ
--------+--------------------------
     INJ|  -.0378    .0380   -.0002

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
SGNL    |    SINJ      INJ     NINJ
--------+--------------------------
     INJ|   .0027   -.0027    .0000

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
SPDNG   |    SINJ      INJ     NINJ
--------+--------------------------
     INJ|  -.0047    .0048   -.0001

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
CLEAR   |    SINJ      INJ     NINJ
--------+--------------------------
    NINJ|   .0022    .0006   -.0028

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
MLINE   |    SINJ      INJ     NINJ
--------+--------------------------
    NINJ|  -.0063   -.0017    .0080

Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
DRY     |    SINJ      INJ     NINJ
--------+--------------------------
    NINJ|  -.0024   -.0006    .0031
```

8.3 Nlogit Code and Output for Rear-End Collisions Model Where Both Trucks are Moving

```
nlogit;lhs=x88
           ;choices=sinj,inj,ninj
           ;model:
           u(sinj) = sev     + bmale*male + bSpdng*Spdng + bage4*age4
+ bNdplyd*Ndplyd + bDylght*Dylght/
    u(inj) =            bDfct*Dfct + blow*low  + bRural*Rural/
    u(ninj) = noinj   +bSober*Sober +bage2*age2 + bUrban*Urban
           ;rpl;pts=200;halton;fcn=
noinj(n);effects:male[*]/Spdng[*]/age4[*]/Ndplyd[*]/Dylght[*]/Dfct[*]
/low[*]/Rural[*]/Sober[*]/age2[*]/Urban[*];crosstab
Normal exit:   7 iterations. Status=0, F=    1588.384

-----------------------------------------------------------------------
--------
Start values obtained using MNL model
Dependent variable                Choice
Log likelihood function     -1588.38391
Estimation based on N =    2310, K =  13
Inf.Cr.AIC  =    3202.8 AIC/N =    1.386
Model estimated: Nov 10, 2015, 13:37:39
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only  -1634.6609  .0283 .0254
Chi-squared[11]           =     92.55395
Prob [ chi squared > value ] =    .00000
Response data are given as ind. choices
Number of obs.=  2310, skipped    0 obs
--------+--------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
     X88|  Coefficient       Error         z     |z|>Z*          Interval
--------+--------------------------------------------------------------
--------
   NOINJ|   -2.58497***      .55939     -4.62  .0000     -3.68135  -
1.48859
     SEV|     .57710***      .17583      3.28  .0010       .23249
.92172
   BMALE|    -.38772**       .16689     -2.32  .0202      -.71481   -
.06063
  BSPDNG|    -.50663***      .11656     -4.35  .0000      -.73507   -
.27818
   BAGE4|    -.25446***      .09561     -2.66  .0078      -.44185   -
.06707
 BNDPLYD|     .35074***      .08788      3.99  .0001       .17850
.52298
 BDYLGHT|     .29664***      .09791      3.03  .0024       .10474
.48854
   BDFCT|    1.16433***      .39415      2.95  .0031       .39181
1.93686
    BLOW|    -.37813**       .16507     -2.29  .0220      -.70166   -
.05460
  BRURAL|     .21937**       .10365      2.12  .0343       .01622
.42251
  BSOBER|   -1.38941**       .60092     -2.31  .0208     -2.56719   -
.21163
   BAGE2|    1.19090**       .56053      2.12  .0336       .09228
2.28952
  BURBAN|   -1.10805**       .53303     -2.08  .0376     -2.15277   -
.06332
--------+--------------------------------------------------------------
--------
```

```
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------
--------

Normal exit:  29 iterations. Status=0, F=    1587.661

---------------------------------------------------------------------
--------
Random Parameters Logit Model
Dependent variable                   X88
Log likelihood function     -1587.66114
Restricted log likelihood   -2537.79439
Chi squared [  14 d.f.]      1900.26650
Significance level               .00000
McFadden Pseudo R-squared      .3743933
Estimation based on N =   2310, K =  14
Inf.Cr.AIC  =   3203.3 AIC/N =    1.387
Model estimated: Nov 10, 2015, 13:39:06
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
No coefficients -2537.7944  .3744 .3725
Constants only  -1634.6609  .0288 .0258
At start values -1588.3839  .0005-.0026
Response data are given as ind. choices
Replications for simulated probs. = 200
Used Halton sequences in simulations.
Number of obs.=  2310, skipped    0 obs
--------+------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
     X88|  Coefficient       Error       z    |z|>Z*         Interval
--------+------------------------------------------------------------
--------
        |Random parameters in utility functions
   NOINJ|   -6.05035*      3.35423    -1.80  .0713   -12.62452
.52383
        |Nonrandom parameters in utility functions
     SEV|     .57530***      .17636     3.26  .0011      .22965
.92096
   BMALE|    -.38733**       .16743    -2.31  .0207     -.71548   -
.05917
  BSPDNG|    -.51246***      .11681    -4.39  .0000     -.74141   -
.28352
   BAGE4|    -.25666***      .09578    -2.68  .0074     -.44439   -
.06893
 BNDPLYD|     .35535***      .08818     4.03  .0001      .18252
.52818
 BDYLGHT|     .29872***      .09823     3.04  .0024      .10619
.49124
   BDFCT|    1.16309***      .39463     2.95  .0032      .38963
1.93654
    BLOW|    -.38144**       .16529    -2.31  .0210     -.70541   -
.05747
  BRURAL|     .22179**       .10387     2.14  .0327      .01821
.42537
  BSOBER|   -2.00517*      1.16342    -1.72  .0848    -4.28543
.27509
   BAGE2|    1.54492*        .92683     1.67  .0955     -.27164
3.36148
  BURBAN|   -1.48550*        .82106    -1.81  .0704    -3.09475
.12374
        |Distns. of RPs. Std.Devs or limits of triangular
 NsNOINJ|    3.18858*      1.91139     1.67  .0953     -.55768
6.93483
```

```
--------+-------------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------

+--------------------------------------------------------+
| Cross tabulation of actual choice vs. predicted P(j)   |
| Row indicator is actual, column is predicted.          |
| Predicted total is F(k,j,i)=Sum(i=1,...,N) P(k,j,i).   |
| Column totals may be subject to rounding error.        |
+--------------------------------------------------------+

--------+-----------------------------------------------------------
NLOGIT Cross Tabulation for 3 outcome Multinomial Choice Model
XTab_Prb|           SINJ           INJ           NINJ          Total
--------+-----------------------------------------------------------
    SINJ|       842.000       528.000       9.00000       1378.00
     INJ|       528.000       384.000       6.00000       917.000
    NINJ|       9.00000       6.00000       .000000       15.0000
   Total|       1378.00       917.000       15.0000       2310.00

+--------------------------------------------------------+
| Cross tabulation of actual y(ij) vs. predicted y(ij)   |
| Row indicator is actual, column is predicted.          |
| Predicted total is N(k,j,i)=Sum(i=1,...,N) Y(k,j,i).   |
| Predicted y(ij)=1 is the j with largest probability.   |
+--------------------------------------------------------+

--------+-----------------------------------------------------------
NLOGIT Cross Tabulation for 3 outcome Multinomial Choice Model
XTab_Frq|           SINJ           INJ           NINJ          Total
--------+-----------------------------------------------------------
    SINJ|       1226.00       152.000       .000000       1378.00
     INJ|       724.000       193.000       .000000       917.000
    NINJ|       13.0000       2.00000       .000000       15.0000
   Total|       1963.00       347.000       .000000       2310.00

+----------------------------------------------------+
| Derivative             averaged over observations.|
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.    |
+----------------------------------------------------+

----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt MALE     in SINJ
--------+-------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+-------------------------------------------------------------
--------
    SINJ|    -.08303***      .00053  -157.91  .0000     -.08406   -
.08200
     INJ|     .08212***      .00052   157.57  .0000      .08110
.08314
    NINJ|     .00091***   .1966D-04    46.09  .0000      .00087
.00094
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
```

```
----------------------------------------------------------------------
--------


----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt SPDNG    in SINJ
--------+-------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*         Interval
--------+-------------------------------------------------------------
--------
    SINJ|    -.02004***      .00095   -20.99  .0000     -.02191   -
.01817
     INJ|     .01986***      .00095    20.99  .0000      .01801
.02171
    NINJ|     .00018***   .1198D-04    15.14  .0000      .00016
.00020
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------


----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt AGE4     in SINJ
--------+-------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*         Interval
--------+-------------------------------------------------------------
--------
    SINJ|    -.01720***      .00057   -29.96  .0000     -.01832   -
.01607
     INJ|     .01705***      .00057    29.96  .0000      .01594
.01817
    NINJ|     .00014***   .6648D-05    21.57  .0000      .00013
.00016
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------


----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt NDPLYD   in SINJ
--------+-------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*         Interval
```

```
--------+------------------------------------------------------------
--------
    SINJ|     .03763***      .00083    45.24  .0000      .03600
.03926
     INJ|    -.03722***      .00082   -45.22  .0000     -.03883   -
.03560
    NINJ|    -.00041***   .1544D-04   -26.52  .0000     -.00044   -
.00038
--------+------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------
--------
```

```
---------------------------------------------------------------------
--------
Average partial effect  on choice probabilities with respect to DFCT
--------+------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error        z    |z|>Z*          Interval
--------+------------------------------------------------------------
--------
    SINJ|    -.19637         .00034  -576.49  .0000     -.19704   -
.19570
     INJ|     .20050         .00034   589.31  .0000      .19983
.20117
    NINJ|    -.00413      .9076D-04   -45.50  .0000     -.00431   -
.00395
--------+------------------------------------------------------------
--------
---------------------------------------------------------------------
--------
```

```
---------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt LOW      in INJ
--------+------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error        z    |z|>Z*          Interval
--------+------------------------------------------------------------
--------
    SINJ|     .00665***      .00045    14.73  .0000      .00576
.00753
     INJ|    -.00672***      .00046   -14.72  .0000     -.00762   -
.00583
    NINJ| .75052D-04***   .7043D-05    10.66  .0000  .61247D-04
.88856D-04
--------+------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------
--------
```

```
----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt RURAL    in INJ
--------+-------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*         Interval
--------+-------------------------------------------------------------
--------
    SINJ|    -.01193***      .00046   -26.00  .0000     -.01283   -
.01103
     INJ|     .01209***      .00047    26.00  .0000      .01118
.01300
    NINJ|    -.00016***   .7890D-05   -20.77  .0000     -.00018   -
.00015
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------
```

```
----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt SOBER    in NINJ
--------+-------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*         Interval
--------+-------------------------------------------------------------
--------
    SINJ|     .00401***   .7140D-04    56.23  .0000      .00387
.00415
     INJ|     .00283***   .5407D-04    52.27  .0000      .00272
.00293
    NINJ|    -.00684***      .00012   -56.80  .0000     -.00708   -
.00660
--------+-------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------
```

```
----------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt AGE2     in NINJ
--------+-------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*         Interval
--------+-------------------------------------------------------------
--------
    SINJ|    -.00123***   .7596D-04   -16.24  .0000     -.00138   -
.00108
     INJ|    -.00079***   .4939D-04   -15.94  .0000     -.00088   -
.00069
```

```
    NINJ|     .00202***      .00012    16.46  .0000      .00178
.00226
--------+------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------
--------
```

```
---------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt URBAN    in NINJ
--------+------------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+------------------------------------------------------------
--------
    SINJ|     .00179***   .4207D-04    42.55  .0000      .00171
.00187
     INJ|     .00115***   .2740D-04    41.80  .0000      .00109
.00120
    NINJ|    -.00293***   .6789D-04   -43.23  .0000     -.00307    -
.00280
--------+------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------
--------
```

```
Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
MALE    |     SINJ       INJ      NINJ
--------+--------------------------
    SINJ|  -.0830     .0821     .0009
```

```
Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
SPDNG   |     SINJ       INJ      NINJ
--------+--------------------------
    SINJ|  -.0200     .0199     .0002
```

```
Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
AGE4    |     SINJ       INJ      NINJ
--------+--------------------------
    SINJ|  -.0172     .0171     .0001
```

```
Derivative wrt change of X in row choice on Prob[column choice]
--------+--------------------------
NDPLYD  |     SINJ       INJ      NINJ
--------+--------------------------
    SINJ|   .0376    -.0372    -.0004
```

```
Derivative wrt change of X in row choice on Prob[column choice]
--------+-------------------------
NDPLYD  |    SINJ      INJ     NINJ
--------+-------------------------
    SINJ|   .0376   -.0372   -.0004


Elasticity of Choice Probabilities with Respect to DFCT
--------+-------------------------
        |    SINJ      INJ     NINJ
--------+-------------------------
    DFCT|  -.1964    .2005   -.0041


Derivative wrt change of X in row choice on Prob[column choice]
--------+-------------------------
LOW     |    SINJ      INJ     NINJ
--------+-------------------------
     INJ|   .0066   -.0067    .0001


Derivative wrt change of X in row choice on Prob[column choice]
--------+-------------------------
RURAL   |    SINJ      INJ     NINJ
--------+-------------------------
     INJ|  -.0119    .0121   -.0002


Derivative wrt change of X in row choice on Prob[column choice]
--------+-------------------------
SOBER   |    SINJ      INJ     NINJ
--------+-------------------------
    NINJ|   .0040    .0028   -.0068


Derivative wrt change of X in row choice on Prob[column choice]
--------+-------------------------
AGE2    |    SINJ      INJ     NINJ
--------+-------------------------
    NINJ|  -.0012   -.0008    .0020


Derivative wrt change of X in row choice on Prob[column choice]
--------+-------------------------
URBAN   |    SINJ      INJ     NINJ
--------+-------------------------
    NINJ|   .0018    .0011   -.0029
```

8.4 Nlogit Code and Output for Rear-End Collisions Model Where One Truck is Stopped

```
nlogit;lhs=x89
           ;choices=sinj,inj,ninj
           ;model:
           u(sinj) = sev     + bInsct*Insct +bStrght*Strght +
bage3*age3  /
    u(inj) =         bNAB*NAB +bSpdng*Spdng +bSober*Sober  /
    u(ninj) = noinj +   bRural*Rural + bage4*age4 +bhigh*high
+bWknd*Wknd

           ;rpl;pts=200;halton;fcn=bSober(n);effects:Insct[*]/Strght[
```

```
*]/age3[*]/NAB[*]/Spdng[*]/Sober[*]/Rural[*]/age4[*]/high[*]/wknd[*];
crosstab;full $
Normal exit:   9 iterations. Status=0, F=    1405.590

----------------------------------------------------------------------
--------
Start values obtained using MNL model
Dependent variable                Choice
Log likelihood function     -1405.59024
Estimation based on N =   2065, K =  12
Inf.Cr.AIC  =   2835.2 AIC/N =    1.373
Model estimated: Nov 10, 2015, 13:40:51
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only  -1442.5837  .0256 .0226
Chi-squared[10]          =     73.98689
Prob [ chi squared > value ] =   .00000
Response data are given as ind. choices
Number of obs.=  2065, skipped    0 obs
--------+-------------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
     X89|  Coefficient       Error       z    |z|>Z*          Interval
--------+-------------------------------------------------------------
--------
  BSOBER|    -.24507*        .14170    -1.73  .0837     -.52279
.03265
     SEV|     .68313***      .19320     3.54  .0004      .30447
1.06179
  BINSCT|     .19476**       .09580     2.03  .0420      .00701
.38252
 BSTRGHT|    -.31373**       .15547    -2.02  .0436     -.61843    -
.00902
   BAGE3|    -.18682*        .10422    -1.79  .0730     -.39108
.01744
    BNAB|     .19848**       .09383     2.12  .0344      .01457
.38239
  BSPDNG|     .62157***      .12255     5.07  .0000      .38138
.86176
   NOINJ|   -6.69990***      .85150    -7.87  .0000    -8.36880   -
5.03100
  BRURAL|    2.43516***      .65052     3.74  .0002     1.16016
3.71016
   BAGE4|    1.21224*        .62302     1.95  .0517     -.00886
2.43333
   BHIGH|    1.48448*        .80863     1.84  .0664     -.10040
3.06936
   BWKND|    1.40265*        .71996     1.95  .0514     -.00845
2.81375
--------+-------------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------

Normal exit:  23 iterations. Status=0, F=    1404.130

----------------------------------------------------------------------
--------
Random Parameters Logit Model
Dependent variable                   X89
Log likelihood function     -1404.13009
Restricted log likelihood   -2268.63438
Chi squared [  13 d.f.]      1729.00857
```

```
Significance level                .00000
McFadden Pseudo R-squared       .3810681
Estimation based on N =    2065, K =  13
Inf.Cr.AIC  =   2834.3 AIC/N =     1.373
Model estimated: Nov 10, 2015, 13:41:54
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
No coefficients -2268.6344  .3811 .3791
Constants only  -1442.5837  .0267 .0236
At start values -1405.5902  .0010-.0021
Response data are given as ind. choices
Replications for simulated probs. = 200
Used Halton sequences in simulations.
Number of obs.=  2065, skipped    0 obs
--------+------------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
     X89|  Coefficient       Error       z    |z|>Z*         Interval
--------+------------------------------------------------------------
--------
        |Random parameters in utility functions
  BSOBER|    -.91415*         .46803    -1.95  .0508    -1.83148
.00317
        |Nonrandom parameters in utility functions
     SEV|     .99081***       .32654     3.03  .0024      .35080
1.63082
  BINSCT|     .38847**        .19407     2.00  .0453      .00810
.76884
 BSTRGHT|    -.67628**        .33190    -2.04  .0416    -1.32679   -
.02577
   BAGE3|    -.25917          .18582    -1.39  .1631     -.62337
.10503
    BNAB|     .39798*         .20976     1.90  .0578     -.01315
.80911
  BSPDNG|    1.14867***       .37111     3.10  .0020      .42130
1.87604
   NOINJ|   -6.71413***       .87105    -7.71  .0000    -8.42136  -
5.00689
  BRURAL|    2.50442***       .65494     3.82  .0001     1.22077
3.78807
   BAGE4|    1.25979**        .63474     1.98  .0472      .01573
2.50385
   BHIGH|    1.43856*         .81117     1.77  .0762     -.15130
3.02842
   BWKND|    1.47114**        .73559     2.00  .0455      .02940
2.91288
        |Distns. of RPs. Std.Devs or limits of triangular
NsBSOBER|    2.87656**       1.37827     2.09  .0369      .17520
5.57791
--------+------------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------
--------

+--------------------------------------------------------+
| Cross tabulation of actual choice vs. predicted P(j)   |
| Row indicator is actual, column is predicted.          |
| Predicted total is F(k,j,i)=Sum(i=1,...,N) P(k,j,i).   |
| Column totals may be subject to rounding error.        |
+--------------------------------------------------------+

--------+-------------------------------------------------------
NLOGIT Cross Tabulation for 3 outcome Multinomial Choice Model
```

```
XTab_Prb|         SINJ          INJ          NINJ          Total
--------+-------------------------------------------------------
    SINJ|      770.000      476.000      6.00000       1252.00
     INJ|      476.000      322.000      4.00000       802.000
    NINJ|      6.00000      4.00000      1.00000       11.0000
   Total|      1252.00      802.000      11.0000       2065.00

+--------------------------------------------------------+
| Cross tabulation of actual y(ij) vs. predicted y(ij)   |
| Row indicator is actual, column is predicted.          |
| Predicted total is N(k,j,i)=Sum(i=1,...,N) Y(k,j,i).   |
| Predicted y(ij)=1 is the j with largest probability.   |
+--------------------------------------------------------+

--------+-------------------------------------------------------
NLOGIT Cross Tabulation for 3 outcome Multinomial Choice Model
XTab_Frq|         SINJ          INJ          NINJ          Total
--------+-------------------------------------------------------
    SINJ|      1178.00      74.0000      .000000       1252.00
     INJ|      705.000      97.0000      .000000       802.000
    NINJ|      11.0000      .000000      .000000       11.0000
   Total|      1894.00      171.000      .000000       2065.00

+----------------------------------------------------+
| Derivative             averaged over observations.|
| Effects on probabilities of all choices in model: |
| * = Direct Derivative effect of the attribute.    |
+----------------------------------------------------+

--------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt INSCT    in SINJ
--------+-----------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error        z    |z|>Z*          Interval
--------+-----------------------------------------------------------
--------
    SINJ|     .01900***      .00058    32.62  .0000      .01786
.02014
     INJ|    -.01874***      .00058   -32.52  .0000     -.01987   -
.01761
    NINJ|    -.00026***   .2784D-04    -9.20  .0000     -.00031   -
.00020
--------+-----------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
--------------------------------------------------------------------
--------


--------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt STRGHT   in SINJ
--------+-----------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error        z    |z|>Z*          Interval
--------+-----------------------------------------------------------
--------
```

```
    SINJ|    -.07911***      .00081   -97.37  .0000     -.08070   -
.07752
     INJ|     .07677***      .00081    95.34  .0000      .07519
.07835
    NINJ|     .00234***      .00015    15.70  .0000      .00205
.00263
--------+-----------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
--------------------------------------------------------------------
--------
```

```
--------------------------------------------------------------------
--------
Average partial effect  on choice probabilities with respect to NAB
--------+-----------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+-----------------------------------------------------------
--------
    SINJ|    -.15212         .00020  -746.97  .0000     -.15252   -
.15172
     INJ|     .15217         .00020   745.82  .0000      .15177
.15257
    NINJ|-.43649D-04      .2010D-04    -2.17  .0299 -.83042D-04  -
.42558D-05
--------+-----------------------------------------------------------
--------
--------------------------------------------------------------------
--------
```

```
--------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt SPDNG    in INJ
--------+-----------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+-----------------------------------------------------------
--------
    SINJ|    -.02236***      .00114   -19.62  .0000     -.02460   -
.02013
     INJ|     .02262***      .00115    19.63  .0000      .02036
.02487
    NINJ|    -.00025***   .4442D-04    -5.65  .0000     -.00034   -
.00016
--------+-----------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
--------------------------------------------------------------------
--------
```

```
--------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt SOBER    in INJ
```

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
SINJ	.01955***	.00100	19.57	.0000	.01759	.02151
INJ	-.01976***	.00101	-19.59	.0000	-.02174	-.01778
NINJ	.00021***	.3366D-04	6.20	.0000	.00014	.00027

Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

Average partial effect on prob(alt) wrt RURAL in NINJ

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
SINJ	-.00595***	.00058	-10.31	.0000	-.00709	-.00482
INJ	-.00159***	.00017	-9.25	.0000	-.00192	-.00125
NINJ	.00754***	.00074	10.15	.0000	.00608	.00900

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

Average partial effect on prob(alt) wrt AGE4 in NINJ

Choice	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
SINJ	-.00259***	.00026	-10.11	.0000	-.00310	-.00209
INJ	-.00069***	.7899D-04	-8.78	.0000	-.00085	-.00054
NINJ	.00329***	.00033	9.87	.0000	.00264	.00394

```
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------
--------


---------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt HIGH     in NINJ
--------+------------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+------------------------------------------------------------
--------
    SINJ|    -.00453***      .00033   -13.74  .0000     -.00518   -
.00389
     INJ|    -.00120***   .9786D-04   -12.27  .0000     -.00139   -
.00101
    NINJ|     .00573***      .00042    13.51  .0000      .00490
.00656
--------+------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------
--------


---------------------------------------------------------------------
--------
Average partial effect  on prob(alt) wrt WKND     in NINJ
--------+------------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+------------------------------------------------------------
--------
    SINJ|    -.00139***      .00025    -5.62  .0000     -.00188   -
.00091
     INJ|    -.00042***   .8302D-04    -5.09  .0000     -.00059   -
.00026
    NINJ|     .00181***      .00033     5.53  .0000      .00117
.00246
--------+------------------------------------------------------------
--------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
---------------------------------------------------------------------
--------


Derivative wrt change of X in row choice on Prob[column choice]
--------+-------------------------
INSCT   |    SINJ      INJ     NINJ
--------+-------------------------
    SINJ|   .0190   -.0187   -.0003
```

Derivative wrt change of X in row choice on Prob[column choice]

STRGHT	SINJ	INJ	NINJ
SINJ	-.0791	.0768	.0023

Derivative wrt change of X in row choice on Prob[column choice]

STRGHT	SINJ	INJ	NINJ
SINJ	-.0791	.0768	.0023

Elasticity of Choice Probabilities with Respect to NAB

	SINJ	INJ	NINJ
NAB	-.1521	.1522	.0000

Derivative wrt change of X in row choice on Prob[column choice]

SPDNG	SINJ	INJ	NINJ
INJ	-.0224	.0226	-.0003

Derivative wrt change of X in row choice on Prob[column choice]

SOBER	SINJ	INJ	NINJ
INJ	.0195	-.0198	.0002

Derivative wrt change of X in row choice on Prob[column choice]

RURAL	SINJ	INJ	NINJ
NINJ	-.0060	-.0016	.0075

Derivative wrt change of X in row choice on Prob[column choice]

AGE4	SINJ	INJ	NINJ
NINJ	-.0026	-.0007	.0033

Derivative wrt change of X in row choice on Prob[column choice]

HIGH	SINJ	INJ	NINJ
NINJ	-.0045	-.0012	.0057

Derivative wrt change of X in row choice on Prob[column choice]

WKND	SINJ	INJ	NINJ
NINJ	-.0014	-.0004	.0018

8.5 Nlogit Code and Output for Sideswipe Collisions Model for Trucks Travelling in Different Directions

```
nlogit;lhs=x88
           ;choices=sinj,inj,ninj
           ;model:
           u(sinj) = sev     +bhigh*high +bNAB*NAB + bWet*Wet     /
    u(inj) =          bPNW*PNW + bInsct*Insct /
    u(ninj) = noinj +  bFall*Fall

;effects:high(*)/NAB(*)/Wet(*)/PNW(*)/Insct(*)/Fall(*);crosstab;full
$
Normal exit:   6 iterations. Status=0, F=    263.6318

--------------------------------------------------------------------
--------
Discrete choice (multinomial logit) model
Dependent variable                  Choice
Log likelihood function      -263.63178
Estimation based on N =    351, K =   8
Inf.Cr.AIC  =    543.3 AIC/N =    1.548
Model estimated: Nov 10, 2015, 13:44:25
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only   -288.7780  .0871 .0766
Chi-squared[ 6]          =     50.29247
Prob [ chi squared > value ] =   .00000
Response data are given as ind. choices
Number of obs.=   351, skipped    0 obs
--------+-----------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
     X88|  Coefficient       Error       z    |z|>Z*         Interval
--------+-----------------------------------------------------------
--------
     SEV|    1.76818***      .28937     6.11  .0000     1.20103
2.33532
   BHIGH|   -1.11450***      .23801    -4.68  .0000    -1.58099   -
.64801
    BNAB|    -.50710**       .23358    -2.17  .0299     -.96490   -
.04930
    BWET|    -.57486*        .30221    -1.90  .0571    -1.16718
.01746
    BPNW|     .74364***      .26985     2.76  .0059      .21475
1.27253
  BINSCT|   -1.88821*       1.06761    -1.77  .0770    -3.98070
.20428
   NOINJ|   -1.90480***      .39759    -4.79  .0000    -2.68406  -
1.12554
   BFALL|     .88371*        .52336     1.69  .0913     -.14206
1.90947
--------+-----------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
--------------------------------------------------------------------
--------

+-------------------------------------------------------+
| Cross tabulation of actual choice vs. predicted P(j)  |
| Row indicator is actual, column is predicted.         |
| Predicted total is F(k,j,i)=Sum(i=1,...,N) P(k,j,i).  |
| Column totals may be subject to rounding error.       |
+-------------------------------------------------------+
```

```
--------+-------------------------------------------------------------
NLOGIT Cross Tabulation for 3 outcome Multinomial Choice Model
XTab_Prb|          SINJ           INJ          NINJ         Total
--------+-------------------------------------------------------------
    SINJ|       130.000       66.0000       9.00000       205.000
     INJ|       67.0000       57.0000       6.00000       130.000
    NINJ|       8.00000       7.00000       1.00000       16.0000
   Total|       205.000       130.000       16.0000       351.000

+---------------------------------------------------------+
| Cross tabulation of actual y(ij) vs. predicted y(ij)    |
| Row indicator is actual, column is predicted.           |
| Predicted total is N(k,j,i)=Sum(i=1,...,N) Y(k,j,i).    |
| Predicted y(ij)=1 is the j with largest probability.    |
+---------------------------------------------------------+

--------+-------------------------------------------------------------
NLOGIT Cross Tabulation for 3 outcome Multinomial Choice Model
XTab_Frq|          SINJ           INJ          NINJ         Total
--------+-------------------------------------------------------------
    SINJ|       165.000       40.0000       .000000       205.000
     INJ|       69.0000       61.0000       .000000       130.000
    NINJ|       8.00000       8.00000       .000000       16.0000
   Total|       242.000       109.000       .000000       351.000

+-----------------------------------------------------+
| Elasticity             averaged over observations.|
| Effects on probabilities of all choices in model: |
| * = Direct Elasticity effect of the attribute.    |
+-----------------------------------------------------+
```

```
----------------------------------------------------------------------
--------
Average elasticity      of prob(alt) wrt HIGH     in SINJ
--------+-------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
--------+-------------------------------------------------------------
--------
    SINJ|    -.26354***       .01740   -15.15  .0000      -.29764   -
.22944
     INJ|     .19686***       .01336    14.74  .0000       .17068
.22304
    NINJ|     .19686***       .01336    14.74  .0000       .17068
.22304
--------+-------------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------
```

```
----------------------------------------------------------------------
--------
Average elasticity      of prob(alt) wrt NAB      in SINJ
--------+-------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error       z    |z|>Z*          Interval
```

```
--------+-------------------------------------------------------------
--------
    SINJ|    -.11847***      .00749   -15.82  .0000     -.13314    -
.10379
     INJ|     .11269***      .00718    15.70  .0000      .09862
.12676
    NINJ|     .11269***      .00718    15.70  .0000      .09862
.12676
--------+-------------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------



----------------------------------------------------------------------
--------
Average elasticity      of choice probabilities with respect to PNW
--------+-------------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
  Choice|  Coefficient      Error       z     |z|>Z*          Interval
--------+-------------------------------------------------------------
--------
    SINJ|    -.39609         .01675   -23.64  .0000     -.42893    -
.36325
     INJ|     .52798         .02071    25.49  .0000      .48739
.56858
    NINJ|     .00680         .00949      .72  .4734     -.01179
.02539
--------+-------------------------------------------------------------
--------
----------------------------------------------------------------------
--------

----------------------------------------------------------------------
--------
Average elasticity      of prob(alt) wrt INSCT    in INJ
--------+-------------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
  Choice|  Coefficient      Error       z     |z|>Z*          Interval
--------+-------------------------------------------------------------
--------
    SINJ|     .00538***      .00174     3.09  .0020      .00196
.00880
     INJ|    -.06455***      .01759    -3.67  .0002     -.09904    -
.03007
    NINJ|     .00538***      .00174     3.09  .0020      .00196
.00880
--------+-------------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
----------------------------------------------------------------------
--------



----------------------------------------------------------------------
--------
Average elasticity      of prob(alt) wrt FALL     in NINJ
```

```
--------+---------------------------------------------------------------
--------
        |                  Standard            Prob.      95%
Confidence
  Choice|  Coefficient       Error        z    |z|>Z*          Interval
--------+---------------------------------------------------------------
--------
    SINJ|    -.01762***      .00183    -9.65  .0000     -.02120   -
.01404
     INJ|    -.01762***      .00183    -9.65  .0000     -.02120   -
.01404
    NINJ|     .19638***      .01856    10.58  .0000      .16001
.23275
--------+---------------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
------------------------------------------------------------------------
--------
```

```
Elasticity wrt change of X in row choice on Prob[column choice]
--------+--------------------------
HIGH    |     SINJ      INJ     NINJ
--------+--------------------------
    SINJ|  -.2635    .1969    .1969
```

```
Elasticity wrt change of X in row choice on Prob[column choice]
--------+--------------------------
NAB     |     SINJ      INJ     NINJ
--------+--------------------------
    SINJ|  -.1185    .1127    .1127
```

```
Elasticity wrt change of X in row choice on Prob[column choice]
--------+--------------------------
NAB     |     SINJ      INJ     NINJ
--------+--------------------------
    SINJ|  -.1185    .1127    .1127
```

```
Elasticity of Choice Probabilities with Respect to PNW
--------+--------------------------
        |     SINJ      INJ     NINJ
--------+--------------------------
     PNW|  -.3961    .5280    .0068
```

```
Elasticity wrt change of X in row choice on Prob[column choice]
--------+--------------------------
INSCT   |     SINJ      INJ     NINJ
--------+--------------------------
     INJ|   .0054   -.0646    .0054
```

```
Elasticity wrt change of X in row choice on Prob[column choice]
--------+--------------------------
FALL    |     SINJ      INJ     NINJ
--------+--------------------------
    NINJ|  -.0176   -.0176    .1964
```

8.6 Nlogit Code and Output for Sideswipe Collisions Model for Trucks Travelling in the Same Directions

```
 nlogit;lhs=x58
           ;choices=sinj,inj,ninj
           ;model:
           u(sinj) = sev    +  bDylght*Dylght + bNPNW*NPNW +
bWinter*Winter   /
    u(inj) =             bInsct*Insct + bNcntrl*Ncntrl  /
    u(ninj) = noinj    + bFall*Fall;
           effects:Insct(*);crosstab;full $
Normal exit:   6 iterations. Status=0, F=    2298.976

-----------------------------------------------------------------------
--------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -2298.97584
Estimation based on N =   5374, K =   8
Inf.Cr.AIC  =   4614.0 AIC/N =     .859
Model estimated: Nov 10, 2015, 13:45:13
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only  -2363.5470  .0273 .0266
Chi-squared[ 6]          =    129.14235
Prob [ chi squared > value ] =   .00000
Response data are given as ind. choices
Number of obs.=  5374, skipped    0 obs
--------+--------------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
     X58|  Coefficient       Error       z     |z|>Z*         Interval
--------+--------------------------------------------------------------
--------
     SEV|    2.16523***      .16524    13.10  .0000     1.84136
2.48910
 BDYLGHT|     .38060***      .08218     4.63  .0000      .21953
.54167
   BNPNW|    -.63024***      .10609    -5.94  .0000     -.83817   -
.42231
 BWINTER|     .16076*        .09099     1.77  .0773     -.01759
.33910
  BINSCT|    -.51504***      .13431    -3.83  .0001     -.77829   -
.25179
 BNCNTRL|     .37582**       .15080     2.49  .0127      .08025
.67139
   NOINJ|   -5.41796***      .72206    -7.50  .0000    -6.83318  -
4.00274
   BFALL|    1.64250*        .86703     1.89  .0582     -.05685
3.34185
--------+--------------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------
--------

+--------------------------------------------------------+
| Cross tabulation of actual choice vs. predicted P(j)   |
| Row indicator is actual, column is predicted.          |
| Predicted total is F(k,j,i)=Sum(i=1,...,N) P(k,j,i).   |
| Column totals may be subject to rounding error.        |
+--------------------------------------------------------+

--------+-----------------------------------------------------
```

```
NLOGIT Cross Tabulation for 3 outcome Multinomial Choice Model
XTab_Prb|          SINJ           INJ           NINJ          Total
--------+----------------------------------------------------------
    SINJ|       3843.00        687.000       5.00000        4535.00
     INJ|       687.000        145.000       1.00000        833.000
    NINJ|       5.00000        1.00000       .000000        6.00000
   Total|       4535.00        833.000       6.00000        5374.00

+--------------------------------------------------------+
| Cross tabulation of actual y(ij) vs. predicted y(ij)   |
| Row indicator is actual, column is predicted.          |
| Predicted total is N(k,j,i)=Sum(i=1,...,N) Y(k,j,i).   |
| Predicted y(ij)=1 is the j with largest probability.   |
+--------------------------------------------------------+

--------+----------------------------------------------------------
NLOGIT Cross Tabulation for 3 outcome Multinomial Choice Model
XTab_Frq|          SINJ           INJ           NINJ          Total
--------+----------------------------------------------------------
    SINJ|       4535.00        .000000       .000000        4535.00
     INJ|       833.000        .000000       .000000        833.000
    NINJ|       6.00000        .000000       .000000        6.00000
   Total|       5374.00        .000000       .000000        5374.00

+----------------------------------------------------+
| Elasticity             averaged over observations.|
| Effects on probabilities of all choices in model: |
| * = Direct Elasticity effect of the attribute.    |
+----------------------------------------------------+

--------------------------------------------------------------------
--------
Average elasticity      of prob(alt) wrt INSCT    in INJ
--------+-----------------------------------------------------------
--------
        |                 Standard            Prob.      95%
Confidence
  Choice|  Coefficient      Error       z    |z|>Z*         Interval
--------+-----------------------------------------------------------
--------
    SINJ|     .00671***      .00024    27.97  .0000       .00624
.00718
     INJ|    -.06968***      .00228   -30.56  .0000      -.07414    -
.06521
    NINJ|     .00671***      .00024    27.97  .0000       .00624
.00718
--------+-----------------------------------------------------------
--------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
--------------------------------------------------------------------
--------


Elasticity wrt change of X in row choice on Prob[column choice]
--------+--------------------------
INSCT    |    SINJ      INJ     NINJ
--------+--------------------------
     INJ|   .0067   -.0697    .0067
```