MODELING CRASH RISK DUE TO TRAFFIC RULE VIOLATIONS FOR EDUCATION, ENFORCEMENT AND ENGINEERING COUNTERMEASURES

by

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ABSTRACT

PRAVEENA PENMETSA Modeling crash risk due to traffic rule violations for education, enforcement, and engineering countermeasures (UNDER THE DIRECTION OF DR. SRINIVAS S. PULUGURTHA)

With 1.3 million deaths, motor vehicle crashes contributed to 2.2% of the total deaths in the world during 2012. Traffic rule violations are the major reason for the occurrence of crashes and fatalities world-wide. Education, enforcement and engineering countermeasures are adopted to reduce traffic rule violations around the world. However, only a few studies primarily investigated traffic rule violations. Therefore, this study focuses on modeling crashes due to traffic rule violations by crash severity or injury severity to serve as a basis for practitioners when identifying and proposing different types of countermeasures. The study objectives are: (a) to model driver injury severity in crashes due to traffic rule violations to provide basis for education countermeasures, (b) to rank traffic rule violations for enforcement or prioritization purposes, and, (c) to model driver injury severity of at-fault and not at-fault drivers separately to identify if any engineering countermeasures can be implemented.

Crash data was gathered from the Highway Safety Information System (HSIS) for the state of North Carolina from 2009 to 2013. Separate data processing techniques were adopted for each objective of this study. The dependent variable in this study is driver injury severity. The five levels of severity (fatal, incapacitating injury, non-incapacitating injury, possible injury, and property damage only (PDO)) were redefined into three categories - severe injury (grouping fatal and incapacitating injury), moderate injury (grouping non-incapacitating injury and possible injury levels) and no injury (PDO).

The results from modeling driver injury severity as a function of only traffic rule violations indicates that most of the traffic rule violations have higher probabilities of resulting in severe driver injury compared to injury when disregarding traffic signals. Exceeding the speed limit is more likely to result in severe injury to the driver compared to driver injury due to disregarding traffic signals. The risk drivers violating traffic rules pose to themselves is higher than the risk they pose to other drivers. The findings from this modeling serve as evidence to educate and generate awareness among drivers of the risk of violating traffic rules for themselves as well as for other drivers.

Traffic rule violations were ranked to serve as a basis for enforcement and prioritization purposes. Relatively higher variations in ranks was observed when individual methods such as frequency (expressed as a function of the number of drivers violating traffic rules), crash severity, total crash cost per year and cost severity index were considered, whereas the variations in ranks was minimal when composite ranks were considered. The composite rank obtained by combining frequency and crash severity is recommended for prioritization of traffic rule violations, and hence, allocation of funding.

Crashes during extreme weather conditions, bad lighting conditions, on roads with speed limits greater than 45 mph, rural roads, road sections that are not straight level, and roads with access control are more likely to result in severe injury to the driver not at-fault in case of two-vehicle crashes. The findings assist transportation professionals to understand the driver injury severity of not at-fault drivers and at-fault drivers in two-vehicle crashes.

DEDICATION

to my

Family

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CHAPTER 1: INTRODUCTION

Motor vehicle crashes was ranked ninth among the leading causes of deaths in the world in 2012 (WHO, 2014). With 1.3 million deaths, motor vehicle crashes contributed to 2.2% of the total deaths in the world during 2012, compared to 1 million deaths in 2000. A relatively fewer number of fatalities occur in the developed countries when compared to developing countries. As an example, in 2014, around 6 million road crashes occurred resulting in 32,675 deaths in the United States. More than 2 million people were injured in these crashes (NHTSA, 2016). Still, it is a major concern because of the social and economic costs associated with these crashes. In addition, traffic crashes cause significant losses to society such as life and property losses, medical cost and traffic congestion, etc. In 2010, the estimated cost of road crashes in the United States, both reported and unreported, is equal to $242 billion (Blincoe et al., 2015). This cost excludes quality-of-life valuation. Overall, the cost of societal harm from road crashes in 2010 is estimated equal to $836 billion.

1.1 Background

More than 253 million vehicles were driven on United States roads in 2013 (Hirsch, 2014). With an increase in population and need for more travel, the number of vehicles on roads is increasing every year. To ensure safety of people with increasing number of vehicles on roads, transportation agencies focus on reducing crash frequency and crash severity (given a crash occurs). To implement countermeasures, to reduce both crash frequency and crash severity, a thorough understanding of factors that contribute to crashes and severity of crashes is necessary.

Over the last two decades, researchers have used several methods to analyze and understand causes of crashes, where they occurred and what needs to be done to improve road safety. Undoubtedly, the results from efforts by previous researchers have provided valuable insights to implement engineering countermeasures or education or enforcement to improve safety on roads. However, the “zero deaths on roads” vision still seem to be very far away.

Infrastructure, environment, vehicle, and human factors that are associated with crashes as well as severe crashes were evaluated in the past. However, human factors play a predominant role compared to other factors in crashes (Blanco, 2013). Sabey & Taylor (1980) reported that aberrant driving behavior is a vital human factor that contributes to road crashes. The aberrant driving behavior can be either unforced errors or intended deviations from practices that are to be followed to ensure safe movement on roads (Reason et al., 1990). These safe practices are put forward as traffic rules by transportation system managers. For example, road users must come to a complete stop at a red light. Similarly, road users should be travelling at posted speed limits under stated conditions. Such traffic rules ensure a safe and smooth flow of traffic on roads. However, drivers deviate from these safe practices and get involved in crashes.

Traffic rule violations are a type of aberrant driving behavior, and are the major reason for the occurrence of crashes and fatalities. For example, speeding and driving under the influence of alcohol together accounted for 58% of the total fatalities in the United

States (NHTSA, 2016). Speeding increases the crash risk (Delhomme et al., 2009, Parker et al., 1995 and West et al., 1992). During 1999 and 2000, around 1,990 and 1,294 people were killed at intersections for not obeying traffic signals and failing to yield the right-of-way, respectively in the United States (Campbell et al., 2004).

In general, two kinds of people are associated with road safety; road users (drivers, pedestrians, bicyclists, etc.) and transportation professionals (designers, practitioners, policy makers, etc.). Both must do their own part to ensure safety on roads. For example, drivers should comply with traffic rules, while transportation professionals should design vehicles and roads with adequate features, adopt enforcement policies, ensure safe practices, etc. to improve safety.

Drivers violate traffic rules intentionally or unintentionally. Transportation professionals should aim to reduce intentional and unintentional traffic rule violations to ensure safety of traffic rule violators as well as other road users. Intentional traffic rule violations could be reduced by enforcement policies. For example, drivers are charged with penalty points and fines; in North Carolina, a driver convicted of failing to yield the right-of-way to a pedestrian is charged with 4 penalty points on his/her driver's license. Besides enforcement, transportation professionals adopt education to increase the compliance of the drivers who intentionally violate traffic rules. In addition to enforcement and education, engineering countermeasures are also widely adopted across the globe to counteract with traffic rule violations. Engineering countermeasures are suitable to reduce unintentional traffic rule violations. However, only a few studies primarily investigated traffic rule violations. There is a need for crash injury severity models to understand the role of causal factors, identify suitable countermeasures and reduce traffic rule violations. Therefore, this study focuses on modeling crashes due to traffic rule violations based on crash severity or injury severity to serve as a basis for practitioners in proposing different types of countermeasures.

1.2 Objectives of This Dissertation

The goal of this study is to research and model crash injury severity due to traffic rule violations to enhance our understanding of the associated factors to suggest countermeasures and improve safety on roads. The objectives are:

a) to model driver injury severity in crashes due to traffic rule violations to serve as a basis for education countermeasures,

b) to rank traffic rule violations for enforcement or prioritization purposes, and,

c) to model driver injury severity of at-fault and not at-fault drivers separately to identify if any engineering countermeasures can be implemented.

1.2.1 Modeling Driver Injury Severity for Providing Education Countermeasures

Driver injury severity has been well-researched over the past two decades. However, only a few studies on driver injury severity in crashes due to traffic rule violations are available. Hence, the first objective of this study is to research the risk a) drivers pose to themselves by violating traffic rules, and, b) traffic rule violators pose to other road users as a function of traffic rule violation. The results should serve as a basis for transportation professionals to educate drivers about the risk associated with violating traffic rules.

1.2.2 Ranking Traffic Rule Violations for Prioritization/Enforcement

North Carolina crash reports identify around 30 traffic rule violations. Due to limited resources and funds, not all traffic rule violations can be addressed immediately. Thus, if transportation agencies must choose selected violations for implementing countermeasures, there is no study that provides critical traffic rule violations that need to be addressed to improve safety on roads through optimal use of resources. Hence, the second objective of this study is to rank traffic rule violations by severity, frequency, and cost. As mentioned earlier, penalty points are assigned if drivers are convicted of violating traffic rules in the United States and other countries. The ranks assigned can be used for a new penalty point system which increases the effectiveness of enforcement.

1.2.3 Modeling Driver Injury Severity of At-Fault and Not At-Fault Drivers

To reduce both crash frequency and crash severity, a thorough understanding of factors that contribute to crashes and severity of crashes is necessary. The current study extends the line of crash injury severity research by developing separate models for at-fault drivers and not at-fault drivers and examine a whole range of hidden elements that are associated with severe injury of drivers in crashes. The findings help in planning for engineering countermeasures and improve safety on roads.

1.3 Research Methodologies

Highway Safety Information Systems (HSIS) is a multistate crash database that gathers already collected crash data from seven different state agencies. The major objective of HSIS is to provide quality crash information necessary for highway safety studies. Hence, crash data was gathered from HSIS for the state of North Carolina from 2009 to 2013.

Injury severity in crashes has been a well-researched topic in traffic safety. Savolainen et al. (2011) provided an extensive literature review on several methods that were adopted to study injury severity in crashes. Broadly, the methods were classified into four groups; binary outcome models, ordered discrete outcome models, unordered discrete outcome models, and other.

The data and its limitations play a major role in determining the best methodology to be adopted. The outcome of a crash severity can be clearly identified as ordered; property damage only (PDO) to possible injury to capacitating injury to incapacitating injury to fatality. Among the ordered discrete outcome models, ordered probit model was primarily used by researchers in the past. Therefore, ordered probit model was chosen as an optimal method for achieving the objectives of this study. In case if the data fails to fit an ordered probit model, a generalized ordered logit model or partial proportion odds model is used.

1.4 Organization of the Dissertation

The rest of the dissertation is organized into six chapters. Chapter 2 provides a review of literature on topics that are relevant to the objectives of this study. Chapter 3 presents an overview on discrete choice modeling. Chapter 4 details the data processing techniques adopted to achieve the objectives of this study. Chapter 5 presents the results of this study, which would help in reducing the traffic rule violations. Finally, Chapter 6 presents the conclusions and recommendation for future research.

CHAPTER 2: LITERATURE REVIEW

This chapter presents a detailed overview of past studies that were carried out on modeling crashes; especially on crashes due to traffic rule violations. It also provides an in-depth discussion on the studies that used discrete choice models in traffic safety.

2.1 Modeling Driver Injury Severity for Providing Education Countermeasures

Ayuso et al. (2010) developed a multinomial logistic regression model to predict the severity of the crash when a traffic rule violation was the reason for the occurrence of the crash. Their study examined the combined effect of traffic rule violations as well. Different traffic violations were compared, with no traffic rule violation, to compute probabilities and estimate cost. The cost estimates can be biased as the probabilities used were computed comparing with no traffic rule violation.

Several other researchers included one or two variables related to traffic rule violation and examined their effect on injury severity of driver or injury severity of the crash. For example, Al-Ghamdi (2002) examined the effect of crash cause on severity of the crash. The crash causes evaluated in their study are speeding, running red light, following too closely, going wrong way, failure to yield, amongst others. Other related example studies include the effect of driving under the influence of alcohol (Tay et al., 2011; Rifaat et al., 2012), speeding (Abdel-Aty, 2003; Rifaat & Tay,2009; Yasmin et al., 2014), red light violation (Al-Ghamdi, 2002), etc. on crashes or injury severity.

Even though Ayuso et al. (2010) examined crashes due to traffic rule violations, their study cannot be used for educating drivers because it evaluated the severity of the crash rather than injury severity of the traffic violator. As normal people care or weigh themselves more than others, educating and creating awareness about potential crash risk they pose to themselves due to violating traffic rules may lead to a reduction in the number of crashes and contribute towards reaching the “zero traffic deaths” vision. Unarguably, traffic violators not only pose risk to themselves but also to other road users. These other road users may include drivers of other vehicles that did not violate any traffic rules, passengers in the vehicles involved in the crash, pedestrians or bicyclists. The risk traffic violators pose to other road users can be used to educate safe drivers and provide them a caution, to look thoroughly the surroundings and be careful when driving around aggressive or reckless drivers. Overall, this study aims at quantifying (1) the risk drivers pose to themselves (in terms of driver injury severity) by violating traffic rules, and, (2) the risk drivers (traffic violators) pose to other drivers who did not violate any traffic rules.

2.2 Ranking Traffic Rule Violations for Prioritization/Enforcement

As stated previously, Ayuso et al. (2010) examined crash severity in crashes due to traffic rule violations. Considering only severity for ranking traffic rule violations would lead to allocation of funds to traffic rule violations that result in more fatal or severe injury crashes (example, exceeding authorized speed limit on low traffic volume roads). Traffic rule violations with typical higher number of minor injury, possible injury or PDO crashes would be ignored in this case.

Tay (2001) compared fatality versus social cost to prioritize road safety initiatives. The study states that over-emphasis on fatal crashes may not result in optimal allocation of resources or funds. The optimal decision pertaining to allocation of resources should be based on marginal cost or related marginal effects (Tay, 2003; Tay, 2006).

In addition to crash severity, frequency and cost associated with violations can also considered to rank traffic rule violations. However, using crash frequency alone would lead to allocation of funds to traffic rule violations with more minor injury and PDO crashes (possibly, in high traffic volume and congested locations). The total crash cost and cost severity index may be correlated to either severity, crash frequency, or number of drivers violating a traffic rule and involved in crashes.

Pulugurtha et al. (2007) researched and summarized different methods through which high crash locations can be identified and ranked. In addition to individual methods, their study proposed the use of crash score method and compared it with the sum of the ranks method to combine the individual methods. A similar methodology is adopted in this study to rank traffic rule violations.

Using an appropriate or optimal combination of severity, frequency, total crash cost and / or cost severity index would maximize the merits and potentially lead to more efficient utilization of limited funds. Therefore, this study focuses on evaluating the ranking of traffic rule violations based on 1) severity, 2) frequency, 3) total crash cost, and, 4) cost severity index as well as their combinations for prioritization purposes. Discrete choice models are developed to rank traffic rule violations by severity.

2.3 Modeling Driver Injury Severity of At-Fault and Not At-Fault Drivers

Researchers have identified the need for examining single-vehicle crashes and two-vehicle or multi-vehicle crashes separately because of the difference in its impact (Wang and Kockelman 2005, Savolainen et al. 2007, Chen and Chen 2011). Lee and Li (2014) identified several factors that would influence the injury severity of drivers involved in single- and two-vehicle crashes using heteroscedastic ordered logit model. Based on the type of vehicles involved in two-vehicle crashes, nine different datasets were prepared.

Weiss et al. (2014) studied young drivers (<24 years) injury severity in crashes and compared factors that are more likely to result in severe injuries in single- and two-vehicle crashes. Their study reported that young drivers driving large vehicles are more likely to be severely injured in single-vehicle crashes compared to their injury in small vehicles in two-vehicle crashes. They have considered several variables of the other driver who was involved in crash along with young driver.

Shaheed et al. (2013) analyzed crash severity in two-vehicle crashes involving motorcycle. In addition to regularly used variables, their study also considered the driver and vehicle attributes of the non-motorcycle driver as well. Pai and Saleh (2008a, b) also analyzed motorcyclist injury severity at T-intersections.

Kockelman and Kweon (2002), using ordered probit models, examined factors that are likely to result in severe injuries in all crashes, single-vehicle crashes and two-vehicle crashes. Their study considered only the characteristics of both vehicle types but ignored characteristics of the both vehicle drivers. Yasmin et al. (2014) examined two-vehicle crashes using a coupla based approach. Their study jointly modeled collision type and driver injury severity in both vehicles. Abay et al. (2013) jointly studied injury severity of drivers involved in two-vehicle crashes considering the endogeneity of seat-belt use. Rana et al. (2010) developed a coupla based model accounting for endogeneity in injury severity models.

Chiou et al. (2013) used a bivariate ordered probit model to simultaneously examine the crash severity of both the vehicles involved in two-vehicle crashes considering information of both parties. Their study concluded that a bivariate generalized ordered probit model out performs a bivariate ordered probit model. Their study evaluated only intersection related crashes.

Duncan et al. (1998) explored truck-passenger car rear-end collisions to examine injury severity of passenger car occupants in crashes using ordered probit model. Zhu and Srinivasan (2011) evaluated factors that contribute to injury severity in crashes involving large trucks. Driver and vehicle characteristics of both the vehicles were considered in the analysis. Distracted truck drivers, car drivers driving under the influence of alcohol, and emotional factors play a significant role on severe injury in crashes. Zhu and Srinivasan (2011) used a heteroskedastic ordered probit model to evaluate the injury severity of every person involved in crashes. Qin et al. (2013) analyzed injury severity between car–truck and truck–truck crashes, yet could not find a critical distinction regardless of differential effects of impacts. Further, their study compared multinomial logit model, partial proportional odds model, and mixed logit model and concluded that partial proportional odds model performs better compared to the other two models.

Jiang et al. (2013) examined two-vehicle crashes by collision type using traditional ordered probit model and Bayesian ordered probit model. In addition to the traditional variables, their study evaluated the effect of pavement management factors on injury severity in rear-end, sideswipe, and angle collisions. However, the pavement management factors played a similar role irrespective of the collision type. Torrão et al. (2014) reported that the motor size of the accomplice vehicle influences the damage and severity of the other vehicle involved in crash. However, their study just considered attributes of two vehicles (e.g., age, weight, and speed), but not attributes of inhabitants in the vehicles. Wang and Kockelman (2005) developed a heteroscedastic ordered logit model and found an inverse impact of a few variables, for example, control weight, lighting condition, and grade on driver injury severity in single- and two-vehicle crashes.

Researchers have analyzed injury severity in two-vehicle crashes using univariate and bivariate regression models. In univariate regression models, crash severity or severe injury or driver injury of the interested vehicle was modeled considering traditional independent variables such as roadway, environmental, vehicle, and driver characteristics. Researchers identified the need for separating the dataset by collision type (head on, rear-end, sideswipe, etc.) to examine driver injury severity (Yasmin et al. 2014). A few other researchers modeled crashes separately based on the type of vehicles involved in crashes such as, truck-truck, truck-car, car-car, etc. (Lee and Li, 2014).

Studies have shown that there exists a difference in injury severity for at-fault drivers and not at-fault drivers (Chiou et al., 2013). However, there is no research that examined the factors contributing to injury severity of not at-fault drivers. This Dissertation extends the line of research by developing regression models for injury severity of fault and not at-fault drivers separately, conditional on the fact that a crash has occurred. Overall, a whole range of hidden elements (factors) that are associated with severe injury for fault and not at-fault drivers is investigated.

2.4 Regression Models

Table 1 shows different methodological approaches that were adopted by researchers to study injury severity in crashes. Regression models are the most common amongst them.

2.5 Limitations of Past Research

Driver injury severity is a well-researched topic. However, except Ayuso et al. (2010), no other study modeled injury severity solely as a function of traffic rule violations. Further, their study considered no traffic rule violation driver injury as the base for different traffic rule violations. Doing so would lead to erroneous odds estimation because the driver injury severity of a non-traffic rule violator is a function of the traffic rule violation committed by the violator. In addition, many common traffic rule violations were not considered and evaluated in their study.

There does not exist any study in the literature that modeled crash injury severity as a function of traffic rule violations. Moreover, ranking traffic rule violations to identify critical traffic rule violations and for several other purposes has not been done in the past.

Furthermore, past researchers have not differentiated and explored the role of at-fault and not at-fault drivers separately in modelling the injury severity. Additionally, the effect of at-fault drivers' vehicle/physical characteristics compared to not at-fault driver injury severity (or vice versa) has not been explored.

TABLE 1: Past Studies and their Methodological Approaches

Methodological Approach	**Past Studies**
Artificial neural networks	Delen et al. (2006), Chimba and Sando (2009a)
Bayesian hierarchical binomial logit	Huang et al. (2008)
Bayesian ordered probit	Xie et al. (2009)
Binary logit and binary probit	Shibata and Fukuda (1994), Farmer et al. (1997), Khattak et al. (1998), Krull et al. (2000), Zhang et al. (2000), Al-Ghamdi (2002), Bedard et al. (2002), Toy and Hammitt (2003), Ballasteros et al. (2004), Chang and Yeh (2006), Sze and Wong (2007), Lee and Abdel-Aty (2008), Pai and Salehi (2008a), Rifaat and Tay (2009), Haleem and Abdel-Aty (2010), Peek-Asa et al. (2010), Kononen et al. (2011), Moudon et al. (2011)
Bivariate binary probit	Lee and Abdel-Aty (2008)
Bivariate ordered probit	Yamamoto and Shankar (2004), de Lapparent (2008)
Bivariate generalized ordered probit	Chiou et al. (2013)
Classification and regression tree	Chang and Wang (2006)
Generalized ordered logit	Michalaki et al. (2015)
Heteroskedastic ordered logit/probit	O'Donnell and Connor (1996), Wang and Kockelman (2005), Lemp et al. (2011), Lee and Li (2014)
Log-linear model	Chen and Jovanis (2000)
Markov switching multinomial logit	Malyshkina and Mannering (2009)
Mixed logit	Milton et al. (2008), Weiss et al. (2014), Shaheed et al. (2013),
Mixed generalized ordered logit	Eluru et al. (2008)
Mixed joint binary logit-ordered logit	Eluru and Bhat (2007)
Multinomial logit	Shankar and Mannering (1996), Carson and Mannering (2001), Abdel-Aty and Abdelwahab (2004), Ulfarsson and Mannering (2004), Khorashadi et al. (2005), Islam and Mannering (2006), Kim et al. (2007), Malyshkina and Mannering (2008), Savolainen and Ghosh (2008), Schneider et al. (2009), Malyshkina and Mannering (2010), Rifaat et al. (2011), Schneider and Savolainen (2011), Ye and Lord (2011)
Multivariate probit	Winston et al. (2006)

TABLE 1: (continued)

Methodological Approach	**Past Studies**
Nested logit	Shankar et al. (1996), Chang and Mannering (1998), Chang and Mannering (1999), Lee and Mannering (2002), Abdel-Aty and Abdelwahab (2004), Holdridge et al. (2005), Savolainen and Mannering (2007), Haleem and Abdel-Aty (2010), Hu and Donnell (2010)
Ordered logit and ordered probit	Khattak et al. (1998), Klop and Khattak (1999), Renski et al. (1999), Khattak (2001), Khattak et al. (2002), Kockelman and Kweon (2002), Quddus et al. (2002), Abdel-Aty (2003), Austin and Faigin (2003), Kweon and Kockelman (2003), Zajac and Ivan (2003), Khattak and Rocha (2003), Donnell and Mason (2004), Khattak and Targa (2004), Abdel-Aty and Keller (2005), Lee and Abdel-Aty (2005), Shimamura et al. (2005), Garder (2006), Lu et al. (2006), Oh (2006), Siddiqui et al. (2006), Pai and Saleh (2007), Das et al. (2008),Gray et al. (2008), Pai and Saleh (2008b) Wang and Abdel-Aty (2008), Yamamoto et al. (2008), Chimba and Sando (2009b), Wang et al. (2009), Pai (2009), Haleem and Abdel-Aty (2010), Jung et al. (2010), Ye and Lord (2011), Zhu and Srinivasan (2011)
Partial proportional odds model	Wang and Abdel-Aty (2008), Wang et al. (2009), Rifaat et al. (2012), Qin et al. (2013), Sasidharan and Menendez (2014),
Random parameters (mixed) logit	Milton et al. (2008), Kim et al. (2008), Kim et al. (2010), Malyshkina and Mannering (2010), Altwaijri et al. (2011), Anastasopoulos and Mannering (2011), Moore et al. (2011), Ye and Lord (forthcoming, 2011), Morgan and Mannering (forthcoming)
Random parameters (mixed) ordered logit	Srinivasan (2002)
Random parameters ordered probit	Zoi et al. (2010), Paleti et al. (2010)
Sequential binary logit	Saccomanno et al. (1996), Dissanayake and Lu (2002 a,b)
Sequential binary probit	Yamamoto et al. (2008)
Sequential logit	Jung et al. (2010)
Simultaneous binary logit	Ouyang et al. (2002)

CHAPTER 3: DISCRETE CHOICE MODELS

This research focuses on exploring the limitations presented in Chapter 2 through the use of discrete choice modeling.

In statistics, regression models are used for estimating the relationship between dependent variable and independent variables. Basically, it evaluates how the dependent variable vary with change in the independent variables. In linear regression, the dependent variable is continuous in nature. The linear regression models are based on the following assumptions.

1. $y_i = \alpha + \beta x_i + \varepsilon_i$
2. $E(\varepsilon_i) = 0$
3. $var(\varepsilon_i) = \sigma^2$
4. $cov(\varepsilon_i, \varepsilon_j) = 0$
5. ε_i ~ Normal distribution

where,

y_i = response variable,

α = intercept,

β = slope,

x_i = independent or predictor variable, and,

ε_i = error term.

It is possible that the dependent or response variable is discrete or dichotomous in nature rather than continuous. If the dependent variable is discrete, the assumptions 1, 2, and 4 hold good but 3 and 5 are not applicable. Considering assumption 5 and assuming y_i takes only 0, 1, 2, 3 and so on, then the error term (ε_i) can yield only discrete values. In this case, it is not possible to have an error term that is normally distributed.

When the dependent variable is discrete in nature, discrete choice models are used to examine the relationship between the dependent variable and independent variables. Discrete choice models, theoretically or empirically, predicts choices made by people among a finite set of alternatives. Examples applications include the choice of which car to buy, where to go to college, and which mode of transport (car, bus, rail, etc.) to take to work.

A discrete choice model determines the likelihood that a person picks a specific option, with the likelihood expressed as a function of variables that identify with the options and the individual. In its general frame, the likelihood that the individual picks option “i” is presented as follows.

$$P_{ni} = \text{Prob(Person n choose option i)} = G(x_{ni}, x_{nj,j\neq i}, s_n, \beta)$$

where,

x_{ni} is a vector of attributes of option “i” faced by individual “n”,

$x_{nj,j\neq 1}$ is a vector of attributes of the other option (other than “i”) faced by individual “n”,

s_n is a vector of characteristics of person “n”, and

β is a set of parameters indicating the effects of variables on likelihood/probabilities, that can be estimated statistically.

Unlike linear regression models, discrete choice models predict the probability of occurrence of a dependent variable using a set of given independent variables. If the dependent variable is dichotomous in nature, a binary logit or probit model can be used. In logit model, the error terms are assumed to have gumbell distribution, whereas for probit model it is normal distribution. Most of the times, both models result in similar outputs.

If the dependent variable has more than two outcomes, and there does not exist any ordinal nature, then multinomial logit or probit (MNL) models can be used. MNL models are very widely used even though it has certain drawbacks. If the dependent variable has more than two outcomes (example, good or bad, true or false, etc.), then ordered logit or probit model are used.

The outcome of a crash severity can be clearly identified as ordered; PDO to possible injury to capacitating injury to incapacitating injury to fatality. Among the ordered discrete choice models, ordered probit model was primarily used in the past. The underlying relationship for the ordered probit model is as follows.

$$y^* = x^T\beta+\epsilon$$

where y^* is a latent variable (unobservable), x is the vector of independent variables, and, β is the vector of regression coefficients that can be estimated. The relation between y^* and y is (where y is supposed to be observed categories of response variable):

$$y = \begin{cases} 0\ if\ y^* \leq 0, \\ 1\ if\ 0 < \ y^* \leq \mu_1, \\ 2\ if\ \mu_1 < \ y^* \leq \mu_2, \\ . \\ . \\ . \\ N\ if\ \mu_{N-1} < y^* \end{cases}$$

The ordered probit method uses the observation of y, that are a form of censored data on y^*, and estimate the coefficients β using maximum likelihood estimates. This model assumes the effect of the independent variables to be identical across the categories of the dependent variable (proportional odds or parallel lines assumption).

The Brant test (Brant, 1990) can be utilized to test this supposition. If the test fails, a generalized ordered logit model can be preferred. The generalized ordered logit model lets the parallel lines assumption to relax and estimates different β (parameters) across the alternatives. The probability of choosing i is summed as,

$$P(y > i) = \frac{EXP(\beta_i X_n - \mu_i)}{1 + EXP(\beta_i X_n - \mu_i)}$$

where,

Xn is a vector of independent variables,

β_i is a vector of estimable parameters,

μ_i and μ_{i-1} are the upper and lower levels of the category i.

The distinction between this model and the standard ordered logit model is that βi is allowed to vary across the levels of the categorical dependent variable. For example, for one variable the parallel assumption may fail (β_1) and for another variable it might hold good (β_2). In this case, the equation will be as follows.

$$P(y > i) = \frac{EXP(\beta_1 X_1 + \beta_2 X_2 - \mu_i)}{1 + EXP(\beta_1 X_1 + \beta_2 X_2 - \mu_i)}$$

where, β_1 is free to vary across different levels of the dependent variable and β_2 is assumed constant across each level of the dependent variable.

CHAPTER 4: DATA PROCESSING & METHODOLOGY

The crash details are typically collected and reported by the law enforcement officers in the field. The reports are then entered into a crash database by the responsible state or local transportation agency staff. Any validation or reconstruction of crash is performed by law enforcement, state or local agencies.

Highway Safety Information Systems (HSIS) is a multistate crash database that gathers already collected crash data from seven different state agencies. The major objective of HSIS is to provide quality crash information necessary for highway safety studies. Hence, crash data was gathered from HSIS for the state of North Carolina from 2009 to 2013. HSIS provides all the necessary information pertaining to the crashes in four different files; accident, roadway, vehicle, and occupant. However, the information in the occupant file is not necessary for carrying out this research and, hence, it is not further used in this study. A unique identification number provided in both accident and vehicle files is used to join them. This joined file is combined with roadway file using the milepost and route number. The data provided by the HSIS contains (but not limited to) the following details.

- Driver characteristics: age, gender, driver is a resident of North Carolina or not, physical condition of the driver, driver injury, type of vehicle driving, and type of restraint used by the driver.

- Crash characteristics: type of crash, point of contact, impact speed, contributing factor of crash, and vehicle maneuver.
- Vehicle characteristics: type of the vehicle and number of axles.
- Road characteristics: name of the road, nearest milepost, area, number of lanes, annual average daily traffic, speed limit, type of pavement surface, left shoulder and right shoulder width, left shoulder and right shoulder type, median type and width, terrain, lane width, noticeable infrastructure nearby, presence of work zone area, work zone activity, and the county in which the crash occurred.
- Environmental characteristics: type of surface, weather condition, and light condition.

The dependent variable in this study is driver injury severity. The crash injury severity defines the maximum injury severity that occurred in the crash; it may be of the occupants, the drivers or the other road users (pedestrians or bicyclists) who are involved in that crash. HSIS defines 5 levels of injury severity; fatal, incapacitating injury, non-incapacitating injury, possible injury, and PDO. Incapacitating injury means the person was impaired or disabled because of the crash. Non-incapacitating injury is any injury, other than a fatal injury or an incapacitating injury, which is evident to observers at the scene of the crash. Possible injury requires very minimal medical assistance, while no injury is observed in case of PDO crash. In this study, the severity of driver injury was redefined into 3 categories. The fatal and incapacitating injury levels were combined and considered as severe injury category, while non-incapacitating injury and possible injury levels were combined and considered as moderate injury category. PDO is considered as the no injury category.

Each objective of this study needs different kind of data setting and data processing. The following sections detail the steps involved in data processing adopted for each objective of this study.

4.1 Modeling Driver Injury Severity for Providing Education Countermeasures

4.1.1 Risk Drivers Pose to Themselves

There are a total of 778,558 crash records in the received data from 2009 to 2013. The data was processed so that each row represents a vehicle involved in the crash. Data obtained showed that 1,302,581 vehicles were involved in these crashes. Crashes in which pedestrians or bicyclists are involved were not considered in the analysis (their contribution is not even 0.6% of the total crashes). The reason is that while examining risk traffic rule violators pose to themselves, a pedestrian or bicyclist risk will be different than that of a traffic rule violator in a vehicle.

The vehicle file provides the contributing factor for each vehicle involved in the crash. Consider an example in which a left turning vehicle at an intersection did not yield to the through traffic and ended up in a collision (crash) with a through vehicle. In this case, the left turning vehicle's contributing factor is recorded as “failing to yield the right-of-way” and the other vehicle's contributing factor is recorded as “no contributing factor.” In this case, the driver in the left turning vehicle violated the traffic rule and put himself/herself as well as the other driver and passengers at risk. In case the through vehicle exceeding the authorized speed limit, then the other vehicle's contributing factor is recorded as “exceeding authorized speed limit” while the violation of the left turning vehicle is still the same. The risk to the drivers and passengers of both the vehicles in the later case might be affected due to the additional violation of the through vehicle. Such multiple violations in a crash are not considered in the analysis to accurately assess the risk of a traffic violation to the driver himself/herself and other drivers. For the five-year database, around 39,000 crashes occurred in which more than one driver involved in the crash has committed some type of traffic violation. They were removed from the database and ignored for further analysis.

A driver may have violated multiple traffic rules (example, exceeding speed limit and disregarding road signs) that may have led to a crash. If all such combinations are considered, there would be more than (23*22)/2 combinations. Therefore, only the primary contributing factor by the driver that led to a crash was considered for analysis. This would minimize any ambiguity that could arise due to the effect of different driver contributing factors in a crash.

Not all traffic rule violations are of interest for this study. Hence, crashes that occurred due to traffic rule violations other than that of interest were removed from the data. Overall, records of the drivers who violated traffic rules listed in Table 2 were only extracted and considered for analysis. This final dataset to assess risk drivers pose to themselves due to violation of a traffic rule consisted of 457,599 records, implying that information pertaining to 457,599 drivers who violated traffic rules was used for analysis and modeling.

TABLE 2: Traffic Rule Violations Analyzed in this Study

S. No.	Traffic Rule Violations
0	No Contributing Factors
1	Disregarding Yield Sign
2	Disregarding Stop Sign
3	Disregarding Other Traffic Signs
4	Disregarding Traffic Signals
5	Disregarding Road Markings
6	Exceeding Authorized Speed Limit
7	Exceeding Safe Speed for Conditions
8	Failure to Reduce Speed
9	Improper Turn
10	Right Turn on Red
11	Crossed Center Line/Going Wrong Way
12	Improper Lane Change
13	Use of Improper Lane
14	Passed Stopped School Bus
15	Passed on Hill
16	Passed on Curve
17	Other Improper Passing
18	Failure to Yield Right-of-Way
19	Improper Backing
20	Improper Parking
21	Improper or No Signal
22	Followed Too Closely
23	Operated Vehicle in Erratic, Reckless, Careless, Negligent or Aggressive Manner
24	Operated Defective Equipment
25	Alcohol Use
26	Drug Use

4.1.2 Risk Drivers Pose to Other Drivers

As the focus is also to examine risk traffic violators pose to other drivers, a different data processing technique is adopted to achieve this objective. This can best be analyzed and modeled using only two-vehicle crashes. Therefore, single-vehicle crash records and multi-vehicle crash records (more than two vehicles involved in crash) were removed from the database. It is noteworthy to mention that pedestrian and bicycle crashes were also not considered.

Between 2009 and 2013, a total of 425,482 two-vehicle crashes occurred, which is approximately 54% of the total crashes. Crashes in which only one driver was found at-fault were considered for analysis. Out of 425,482 two-vehicle crashes, 387,090 crashes had only one driver at-fault. Of the 38,392 (425,482-387,090) deleted crash records, there exist ~12,000 crashes in which both drivers were not at-fault of the crash. For these ~12,000 crashes, the information for type of primary traffic rule violation committed and number of violations committed will not be available as no one committed any traffic rule violation. Hence, while developing the model, these crashes cannot be considered. That is the reason why “only one driver at fault” crashes were analyzed in this case.

At least 387,090 drivers were involved in crashes without their mistake. These drivers are posed to some type of injury or risk due to drivers violating traffic rules. Of the 387,090 crashes (records of drivers violating a traffic rule in two-vehicle crashes), records pertaining to traffic violations not listed in Table 2 were removed from the dataset. The final dataset to assess risk to other drivers due to violation of a traffic rule consisted of 326,147 records.

Figure 1 summarizes the data processing and development of final database for the analysis pertaining to the first research objective.

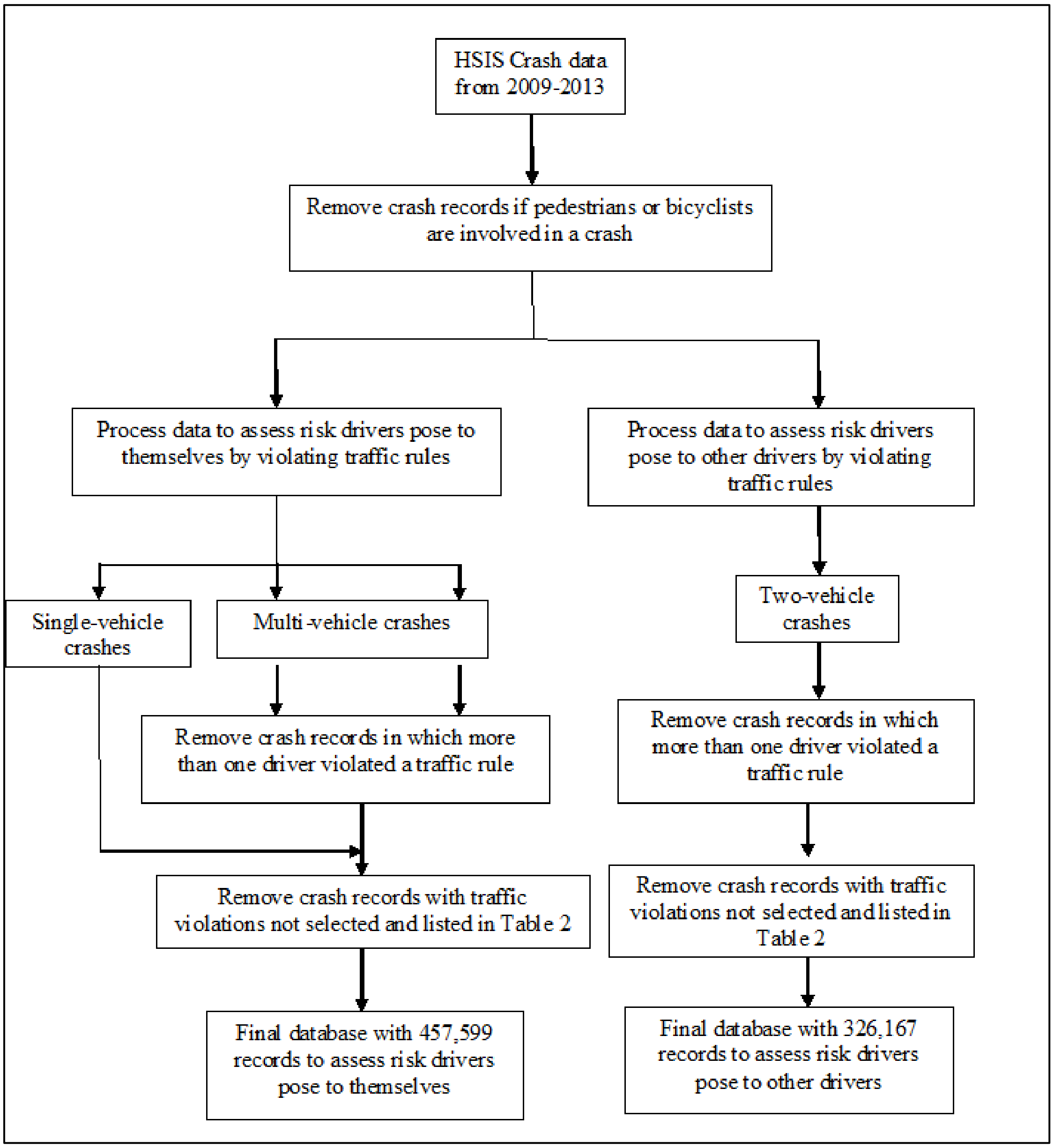

FIGURE 1: Data Processing Adopted for Preparing Database Necessary for Achieving Research Objective 1

4.2 Ranking Traffic Rule Violations for Prioritization/Enforcement

The raw crash data obtained from HSIS was modified such a way that each row represents a crash with all required details. This database was processed and used to rank traffic rule violations by crash injury severity, frequency, total crash cost and cost severity index.

A crash may have happened due to multiple traffic rule violations by a driver; as an example, a speeding drunk driver involved in a crash. As the specific role of each such contributing factor in the crash is not clear from the database, only the reported primary contributing factor was considered for analysis. Figure 2 explains the data cleaning process adopted for preparing the database for ranking traffic rule violations (second research objective).

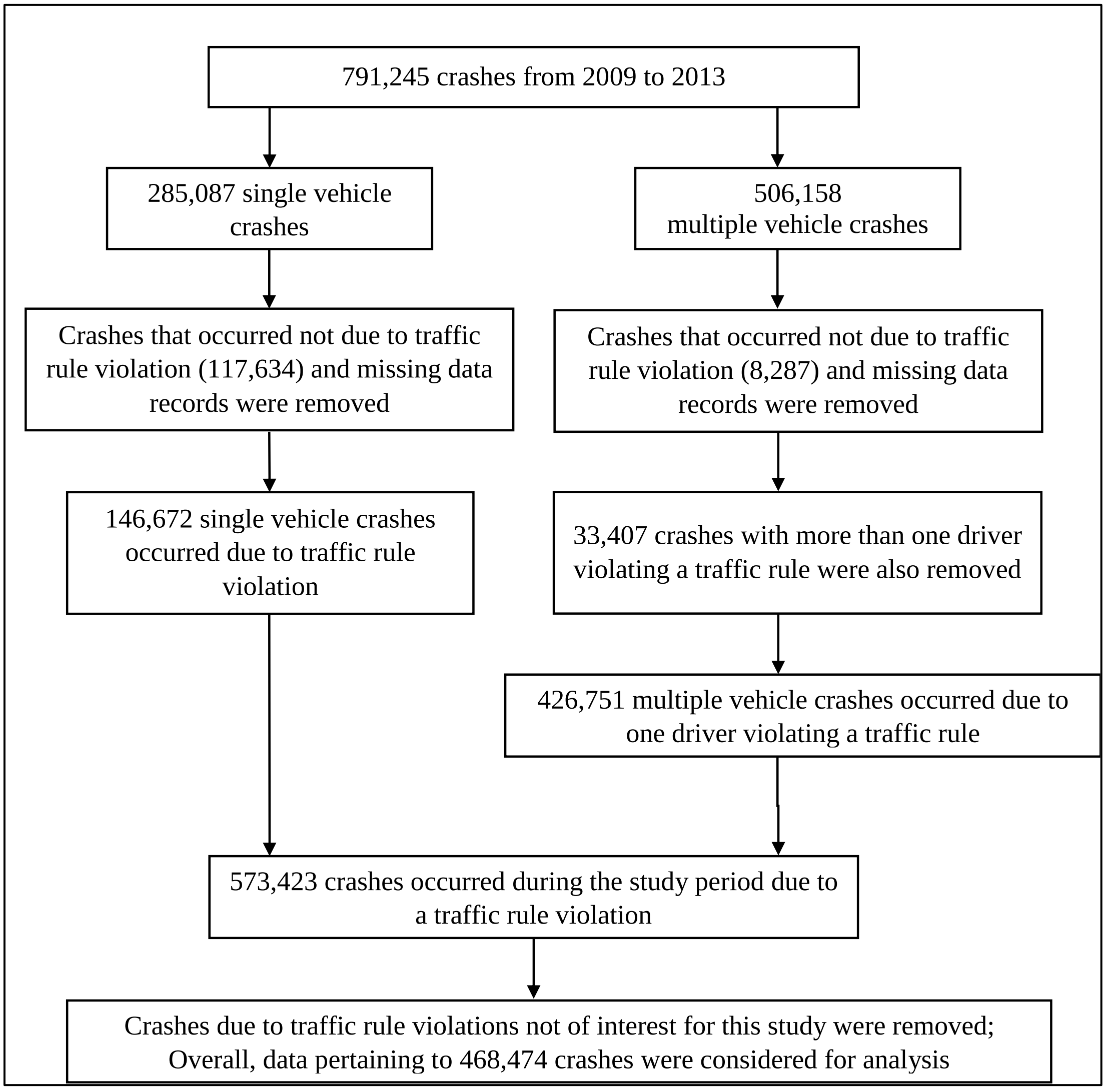

FIGURE 2: Data Processing Adopted for Preparing Database to Rank Traffic Violations by Severity

To rank traffic rule violations by crash injury severity, first the probabilities/likelihoods of different traffic rule violations should be computed.

To rank traffic rule violations based on the number of drivers violating the traffic rule (frequency), the same raw crash data with each row representing a crash was used for analysis. The total number of drivers committing a selected traffic rule violation from 2009 to 2013 is defined as the frequency in this study. The ranks are then assigned based on the frequency of the traffic rule violations.

The total loss due to motor vehicle crashes in the United States is estimated equal to $836 billion in 2010 (Blincoe et al., 2015). These costs include both societal harm and economic loss. For implementing any countermeasures, cost-benefit ratio plays a key role in the decision making process. HSIS provides the cost of PDO. For estimating the cost of different traffic rule violations, there is a need to consider other costs involved in the crash (besides PDO cost). Crash cost estimates were used due to lack of such detailed data.

The North Carolina Department of Transportation (NCDOT) periodically provides the cost estimates associated with crashes. As the crash data considered in this study is from 2009 to 2013, crash costs for different severities during this time period are gathered and summarized in Table 3.

TABLE 3: Crash Costs for Different Severities - 2009 to 2013 (NCDOT)

Crash Severity	**Year**				
	2009	**2010**	**2011**	**2012**	**2013**
Severe Injury	$1,900,000	$2,000,000	$1,900,000	$2,000,000	$4,451,000
Moderate Injury	$48,000	$49,000	$50,000	$50,000	$117,000
PDO	$5,000	$5,100	$5,300	$5,400	$6,700

There is a drastic increase in the crash cost in 2013 compared to the previous years. This is because, from 2013, NCDOT decided on using the Value of Statistical Life (VSL) for estimating the crash costs. As from here on NCDOT will adopt the VSL crash costs, 2013 crash costs were used in this study.

Depending on the crash severity, the cost of each reported crash is assessed using cost estimates shown in Table 3. The total crash cost of each traffic rule violation is then computed. For example, disregarding yield sign had 9 severe injury crashes, 265 moderate injury crashes, and 494 PDO crashes from 2009 to 2013. The total crash cost per year for disregarding yield sign in North Carolina = (4,451,000*9 + 117,000*265 + 6700*494) / 5 = $14,874,760. Similarly, the total crash cost per year for different traffic rule violations are computed.

In addition to the total crash cost per year, a cost severity index is also computed and considered for ranking traffic rule violations. The cost severity index in this study is equal to total cost of a traffic rule violation divided by the number of crashes occurred due to that violation. For the same example mentioned above, the cost severity index for disregarding yield sign = (4,451,000*9 + 117,000*265 + 6700*494) / (9 + 265 + 494) = $96,840. Conceptually, it is similar to the computation of equivalent PDO (EPDO) crash, while it could also be termed as the average crash cost of the selected traffic rule violation. Ranks are then assigned for traffic rule violations based on the total crash cost per year and the cost severity index.

4.3 Modeling Driver Injury Severity of At-Fault and Not At-Fault Drivers

The data processing adopted for examining risk traffic violators pose to other road users was used for this objective. Each row represents a crash, with information of roadway, environmental, vehicle and driver characteristics. Table 4 shows all the variables that were considered for injury severity analysis. Records with missing information for the variables mentioned in Table 4 were removed from the database.

TABLE 4: Variables Evaluated for Identifying Engineering Countermeasures

Variable	**Categories**	**Variable**	**Categories**
Driver Injury Severity	PDO	Light Condition	Daylight
	Moderate Injury		Dusk
	Severe Injury		Dawn
Location	Rural		Dark – Lighted Roadway (DLR)
	Urban		Dark – Roadway Not Lighted (DRL)
Road Surface Condition	Dry		Dark – Unknown Lighting (DUL)
	Wet		Other
	Water Standing/Moving (WSM)	Road Characteristics	Straight – Level
	Ice		Straight – Hillcrest (SH)
	Snow		Straight – Grade (SG)
	Slush		Straight – Bottom (SB)
	Sand, Mud, Dirt, Gravel (SMDG)		Curve – Level (CL)
	Fuel, Oil		Curve – Hillcrest (CH)
	Other		Curve – Grade (CG)
Weather Condition	Clear		Curve – Bottom (CB)
	Cloudy		Other
	Rain	Road Classification	Interstate (IN)
	Snow		US Route (USR)
	Fog, Smog, Smoke (FSS)		NC Route (NCR)
	Sleet, Hall, Freezing Rain/Drizzle (SHFR)		State Secondary Route (SSR)
	Severe Crosswinds (SC)		Local Street (LS)
	Blowing Sand, Dirt, Snow (BSDS)		Public Vehicular Area (PVA)
	Other		Private Road, Driveway (PRD)
Speed Limit	<=25 mph.		Other
	26-45 mph.	Drivers' Age	<=18 years
	46-55 mph.		19-25 years
	>55 mph.		26-40 years
Terrain	Flat		41-55 years
	Rolling		56-70 years
	Mountainous (MOUN)		

TABLE 4: (continued)

Variable	Categories	Variable	Categories
Road Configuration	One-Way, Not Divided	Drivers' Violation	Disregarding Traffic Signs/Signals/Markings (DTS)
	Two-Way, Not Divided (TWND)		Exceeding Speed Limit (ESL)
	Two-Way, Divided, Unprotected Median (TWDUM)		Exceeding Safe Speed Limit for Conditions (ESSL)
	Two-Way, Divided, Positive Median Barrier (TWDPM)		Followed Closely (FC)
	Unknown		Improper Maneuver (IM)
Access	No Access Control		Improper Passing (IP)
	Partial Control (PC)		Failure to Yield the Right-of-Way (FYRW)
	Full Control (FC)		Inattention/Distraction (ID)
Drivers' Physical Condition	Apparently Normal		Aggressive/Reckless Driving (ARD)
	Illness		Impaired Driving (IMPD)
	Fatigue		Crossed Centerline/ Wrong Way (WW)
	Fell Asleep, Fainted, Loss of Consciousness (FFLC)		Other
	Impairment Due to Med. Drugs, Alcohol (IMDA)	Median Type	Undivided Roadway
	Medical Condition (MC)		Rigid Pos. Barrier (RPB)
	Other Physical Impairment (OPI)		Cont. Turn Lane (CTL)
	Restriction Not Complied with (RNC)		Paved Mountable (PM)
	Other		Curb
Number of Violations Committed by At-Fault Driver	One		Grass
	Two		Positive Barrier (POB)
	Three		Parkland, Business (PB)
			Couplet
Drivers' Gender	Male		Flexible Pos. Barrier (FPB)
	Female		Striped
			Semi-Rigid Pos. Barrier (SRPB)

TABLE 4: (continued)

Variable	**Categories**
Vehicle Type	Passenger Car
	Pickup/Light Truck/Van (PLTV)
	Sports Utility Vehicle (SUV)
	Bus
	Truck/Tractor or Truck/Tractor Trailer (TT)
	Farm Vehicle (FV)
	Two-wheeler (TW)
	Other

CHAPTER 5: RESULTS

This chapter details all the results obtained after developing discrete choice models.

5.1 Modeling Driver Injury Severity for Providing Education Countermeasures

An ordered probit model was developed to examine the effect of different traffic rule violations (independent variable) on driver injury severity of the traffic rule violator (dependent variable). Unarguably, factors such as age and gender of the driver, lighting condition and other network characteristics have an effect on the number of crashes (possibly, injury severity). However, the intent is not to have such independent variables control the role of traffic violation on risk. Therefore, these variables were not considered as independent variables in this study.

Two different sets of ordered probit models were developed; 1) to examine risk drivers pose to themselves by violating traffic rules, and, 2) to examine risk drivers violating traffic rules pose to other drivers. The maximum likelihood estimate was used in estimating the coefficients of the variables. The coefficients of the model explain whether the independent variable increases or decreases the probability of happening of the dependent event. To explain the extent of the effect of the independent variables on occurrence of the dependent variable, the odds ratio concept was used. The odds ratios also indicate the probability value.

In logistic regression models, the reference variable should be defined so that the odds can be estimated. In all the models developed, the dependent reference variable is PDO. The two different cases for which models are developed are:

- Risk drivers pose to themselves by violating traffic rules when compared to risk drivers pose to themselves by disregarding traffic signals.
- Risk drivers violating traffic rules pose to other drivers when compared to risk non traffic rule violators pose to other drivers.

The rationale for selecting disregarding traffic signals as the reference variable is that, among many traffic rule violations, drivers perceived this violation to be more risky compared to others.

5.1.1 Risk Drivers Pose to Themselves

Initially, an ordered probit model was developed to examine the risk drivers pose to themselves in crashes by violating traffic rules. Brant test was carried out to check for parallel lines or proportional odds assumption. A p-value of less than 0.01 was obtained for this model, which indicates the null hypothesis should be rejected. As the simple ordered probit model failed to fit the data, a generalized ordered logit model was developed. Table 5 summarizes the results obtained. Since, the partial proportional model failed, rather than one single coefficient for all dependent variables, two coefficients will be present.

A positive sign for severe injury implies that the corresponding traffic rule violation is going to result in a severe injury compared to moderate injury and PDO for a traffic rule violator. Similarly, the negative coefficients indicate that it is less likely to be severe injury compared to moderate injury and PDO. A positive sign for moderate injury explains that it is more likely to result in severe and moderate injury compared to PDO. A negative sign for moderate injury explains that the corresponding traffic rule violation is less likely to result in severe or moderate injuries to traffic rule violators. For model presented in Table 5, all the traffic rule violations are compared with disregarding traffic signal.

A p-value less than 0.10 implies the corresponding traffic rule violation is not significant at a 90% confidence level. Coefficients of severe injury of Disregarding yield sign, right turn on red, passing a stopped school bus, passing on a hill, failing to yield the right-of-way, improper parking and improper or no signal are statistically not significant. Similarly, for moderate injury, disregarding traffic signs, disregarding other road markings, passing on a hill, and passing on a curve are not significant.

Traffic rule violations such as disregarding yield sign, failure to reduced speed, improper turn, right turn on red, improper lane change, passed on a hill, improper backing, passing a stopped school bus, and followed too closely are less likely to result in both severe and moderate injuries to traffic rule violators compared to driver injury due to disregarding traffic signals. Disregarding stop signs, disregarding road markings, exceeding authorized speed limit, exceeding safe speed for conditions, crossed center line/going wrong way, passed on curve, other improper passing, operated vehicle erratically, driving recklessly or aggressively, alcohol use, and drug use are more likely to result in both severe and moderate injuries compared to disregarding traffic signal. Traffic rule violation such as disregarding other traffic signs, failing to yield the right-of-way, use of improper lane, improper parking, improper or no signal, operated defective equipment are more likely to result in severe injury and less likely to result in moderate injury compared to disregarding traffic signals.

TABLE 5: Generalized Ordered Logit Model for Examining Risk Drivers Pose to Themselves

Traffic Rule Violations	**Severe Injury**			**Moderate Injury**		
	Estimate	**Standard Error**	**p-value**	**Estimate**	**Standard Error**	**p-value**
Intercept	-5.31	0.11	<.01	-1.00	0.02	<.01
Disregarding Yield Sign	-0.06	0.55	0.91	-0.51	0.10	<.01
Disregarding Stop Sign	1.67	0.14	<.01	0.44	0.03	<.01
Disregarding Other Traffic Signs	0.99	0.27	<.01	-0.10	0.07	0.13
Disregarding Road Markings	1.22	0.20	<.01	0.04	0.05	0.43
Exceeding Authorized Speed Limit	3.28	0.12	<.01	1.29	0.03	<.01
Exceeding Safe Speed for Conditions	1.20	0.11	<.01	0.14	0.02	<.01
Failure to Reduce Speed	-1.00	0.12	<.01	-1.11	0.02	<.01
Improper Turn	-0.61	0.20	<.01	-0.86	0.03	<.01
Right Turn on Red	-0.14	0.65	0.83	-1.63	0.17	<.01
Crossed Center Line/Going Wrong Way	2.51	0.12	<.01	0.67	0.02	<.01
Improper Lane Change	-0.55	0.17	<.01	-1.56	0.03	<.01
Use of Improper Lane	0.99	0.22	<.01	-0.29	0.06	<.01
Passed Stopped School Bus	-0.06	2.72	0.98	-1.14	0.60	0.05
Passed on Hill	-0.11	2.38	0.96	-0.73	0.45	0.11
Passed on Curve	1.50	0.64	0.02	0.01	0.21	0.94
Other Improper Passing	0.62	0.22	<.01	-0.87	0.05	<.01
Failure to Yield Right-of-Way	0.15	0.12	0.21	-0.43	0.02	<.01
Improper Backing	-2.06	0.50	<.01	-2.90	0.09	<.01

TABLE 5: (continued)

Traffic Rule Violations	Severe Injury			Moderate Injury		
	Estimate	Standard Error	p-value	Estimate	Standard Error	p-value
Improper Parking	0.11	0.63	0.86	-1.58	0.19	<.01
Improper or No Signal	0.19	1.3	0.89	-0.71	0.27	<.01
Followed Too Closely	-1.3	0.32	<.01	-1.38	0.04	<.01
Operated Vehicle in Erratic, Reckless, Careless, Negligent or Aggressive Manner	2.28	0.12	<.01	0.88	0.02	<.01
Operated Defective Equipment	0.69	0.17	<.01	-0.36	0.04	<.01
Alcohol Use	2.49	0.12	<.01	0.78	0.02	<.01
Drug Use	1.75	0.17	<.01	0.94	0.05	<.01

Table 6 provides the odds ratio values for "risk drivers pose to themselves" model. The odds ratios are not reported for insignificant variables.

If a driver disregarding a yield sign, he/she is equally likely to succumb to a severe injury as in disregarding traffic signals. Disregarding yield sign is 0.6 times less likely to result in moderate driver injury compared to driver injury in disregarding traffic signals. Disregarding stop sign is ~5 times more likely to result in severe driver injury and 1.5 times more likely to result in moderate driver injury. Disregarding road markings and exceeding safe speed for conditions are ~3 times more likely to result in severe injuries.

TABLE 6: Odds Ratios of Risk Drivers Pose to Themselves

Traffic Rule Violations	Severe Injury			Moderate Injury		
	Point Estimate	95% Wald Confidence Limits		Point Estimate	95% Wald Confidence Limits	
Disregarding Yield Sign	-			0.60	0.50	0.73
Disregarding Stop Sign	5.31	4.07	6.93	1.55	1.46	1.64
Disregarding Other Traffic Signs	2.70	1.60	4.56	-		
Disregarding Road Markings	3.39	2.29	5.03	-		
Exceeding Authorized Speed Limit	26.56	21.05	33.53	3.66	3.44	3.88
Exceeding Safe Speed for Conditions	3.33	2.65	4.19	1.15	1.11	1.20
Failure to Reduce Speed	0.37	0.29	0.47	0.33	0.32	0.34
Improper Turn	0.55	0.37	0.80	0.42	0.40	0.45
Right Turn on Red	-			0.20	0.14	0.27
Crossed Center Line/Going Wrong Way	12.29	9.77	15.46	1.94	1.86	2.04
Improper Lane Change	0.58	0.42	0.80	0.21	0.20	0.22
Use of Improper Lane	2.68	1.75	4.11	0.75	0.67	0.83
Passed Stopped School Bus	-			0.32	0.10	1.04
Passed on Hill	-			-		
Passed on Curve	4.49	1.29	15.61	-		
Other Improper Passing	1.87	1.22	2.84	0.42	0.38	0.47
Failure to Yield Right-of-Way	-			0.65	0.63	0.68
Improper Backing	0.13	0.05	0.34	0.06	0.05	0.07
Improper Parking	-			0.21	0.14	0.30

TABLE 6: (continued)

Traffic Rule Violations	Severe Injury			Moderate Injury		
	Point Estimate	95% Wald Confidence Limits		Point Estimate	95% Wald Confidence Limits	
Improper or No Signal	-			0.49	0.29	0.84
Followed Too Closely	0.27	0.15	0.51	0.25	0.23	0.27
Operated Vehicle in Erratic, Reckless, Careless, Negligent or Aggressive Manner	9.82	7.8	12.35	2.4	2.3	2.51
Operated Defective Equipment	2	1.44	2.79	0.7	0.65	0.75
Alcohol Use	12.1	9.61	15.22	2.19	2.09	2.29
Drug Use	5.75	4.05	8.16	2.55	2.32	2.81

Disregarding other traffic sign is ~2.7 times more likely to result in severe driver injury. Exceeding authorized speed limit is almost 27 times more likely to result in severe driver injury and ~4 times more likely to result in moderate driver injury when compared to disregarding traffic signals. Improper turn and improper lane change are ~0.5 times less likely while crossed center line and alcohol use are ~12 times more likely to result in severe injuries when compared to disregarding traffic signals. Improper backing and following too closely are the least likely to result in severe injuries. Overall, 13 out of 21 considered traffic rule violations are more likely to result in severe driver injury to traffic rule violators when compared to disregarding traffic signal, while 7 out of 21 considered traffic rule violations are more likely to result in moderate driver injury compared to disregarding traffic signal.

5.1.2 Risk Traffic Rule Violators Pose to Other Drivers

Traffic violators not only put themselves at risk but also put other drivers at risk. Therefore, this part of the study focused on risk drivers violating traffic rules pose to other drivers. Initially, an ordered probit model was developed and tested for parallel lines assumption. As the data failed to fit ordered probit model, a generalized ordered probit model was developed. Table 7 summarizes risk to other drivers due to a driver violating a traffic rule. Odds ratios as well as 95% Wald confidence limits for odds ratios are shown in Table 8. The reference variable for this part of study is “no traffic rule violation”.

Disregarding yield sign, disregarding road markings, right turn on red, followed too closely, improper backing, and passing on a curve had insignificant severe injury coefficients and significant moderate injury coefficients. Passing on hill, passing a stopped school bus, and improper or no signal have insignificant severe and moderate injury coefficients.

Traffic rule violations such as failure to reduce speed and improper lane change are statistically significant and less likely to result in severe injuries compared to no traffic rule violation. Improper backing, improper lane change, and right turn on red are less likely to result in moderate injury compared to no traffic rule violation. Table 8 provides the risk (in terms of probabilities) to other road users because of a driver violating a traffic rule.

TABLE 7: Generalized Ordered Logit Model for Examining Risk to Other Drivers

Traffic Rule Violations	Severe Injury			Moderate Injury		
	Estimate	Standard Error	p-value	Estimate	Standard Error	p-value
Intercept	-6.39	0.21	<0.01	-1.93	0.03	<0.01
Disregarding Yield Sign	0.97	0.63	0.12	0.72	0.10	<0.01
Disregarding Stop Sign	2.38	0.24	<0.01	1.72	0.04	<0.01
Disregarding Other Traffic Signs	1.34	0.46	0.00	1.09	0.07	<0.01
Disregarding Traffic Signals	1.34	0.24	<0.01	1.34	0.03	<0.01
Disregarding Road Markings	0.82	0.54	0.13	0.36	0.08	<0.01
Exceeding Authorized Speed Limit	3.11	0.27	<0.01	1.58	0.07	<0.01
Exceeding Safe Speed for Conditions	1.60	0.25	<0.01	0.83	0.04	<0.01
Failure to Reduce Speed	-0.81	0.23	0.00	0.58	0.03	<0.01
Improper Turn	0.52	0.27	0.06	0.54	0.03	<0.01
Right Turn on Red	0.53	0.84	0.53	-0.30	0.15	0.04
Crossed Center Line/Going Wrong Way	3.23	0.22	<0.01	1.44	0.03	<0.01
Improper Lane Change	-0.52	0.30	0.09	-0.33	0.04	<0.01
Use of Improper Lane	1.23	0.43	0.00	0.07	0.09	0.45
Passed Stopped School Bus	-0.04	9.32	1.00	0.12	1.09	0.91
Passed on Hill	-0.14	5.11	0.98	0.70	0.47	0.13
Passed on Curve	-0.29	3.68	0.94	0.76	0.30	0.01
Other Improper Passing	1.17	0.34	0.00	0.16	0.06	0.01
Failure to Yield Right-of-Way	1.37	0.22	<0.01	0.99	0.03	<0.01

TABLE 7: (continued)

Traffic Rule Violations	Severe Injury			Moderate Injury		
	Estimate	**Standard Error**	**p-value**	**Estimate**	**Standard Error**	**p-value**
Improper Backing	-0.01	0.4	0.99	-0.72	0.06	<0.01
Improper Parking	1.56	0.84	0.06	0.25	0.2	0.21
Improper or No Signal	-0.31	3.31	0.92	-0.19	0.37	0.61
Followed Too Closely	-0.6	0.44	0.18	0.46	0.04	<0.01
Operated Vehicle in Erratic, Reckless, Careless, Negligent or Aggressive Manner	2.58	0.24	<0.01	1.16	0.05	<0.01
Operated Defective Equipment	0.95	0.38	0.01	0.16	0.06	0.01
Alcohol Use	2.74	0.24	<0.01	1.48	0.05	<0.01
Drug Use	2.78	0.36	<0.01	1.61	0.1	<0.01

TABLE 8: Odds Ratio of Risk to Other Drivers

Traffic Rule Violations	Severe Injury			Moderate Injury		
	Point Estimate	**95% Wald Confidence Limits**		**Point Estimate**	**95% Wald Confidence Limits**	
Disregarding Yield Sign	-			2.05	1.70	2.48
Disregarding Stop Sign	10.79	6.71	17.35	5.60	5.18	6.07
Disregarding Other Traffic Signs	3.83	1.57	9.40	2.98	2.58	3.45
Disregarding Traffic Signals	3.83	2.41	6.09	3.81	3.58	4.05
Disregarding Road Markings	-			1.43	1.21	1.69
Exceeding Authorized Speed Limit	22.36	13.15	38.03	4.86	4.25	5.56

TABLE 8: (continued)

Traffic Rule Violations	Severe Injury			Moderate Injury		
	Point Estimate	95% Wald Confidence Limits		Point Estimate	95% Wald Confidence Limits	
Exceeding Safe Speed for Conditions	4.95	3.02	8.13	2.29	2.12	2.47
Failure to Reduce Speed	0.45	0.28	0.71	1.79	1.7	1.89
Improper Turn	1.69	0.99	2.88	1.72	1.6	1.84
Right Turn on Red	-			0.74	0.56	0.99
Crossed Center Line/Going Wrong Way	25.36	16.5	38.99	4.22	3.94	4.51
Improper Lane Change	0.6	0.33	1.08	0.72	0.67	0.77
Use of Improper Lane	3.41	1.46	7.98	-		
Passed Stopped School Bus	-			-		
Passed on Hill	-			-		
Passed on Curve	-			2.13	1.18	3.85
Other Improper Passing	3.22	1.66	6.24	1.17	1.04	1.32
Failure to Yield Right-of-Way	3.94	2.58	6.02	2.7	2.56	2.85
Improper Backing	-			0.49	0.43	0.55
Improper Parking	4.76	0.92	24.56	-		
Improper or No Signal	-			-		
Followed Too Closely				1.58	1.46	1.71
Operated Vehicle in Erratic, Reckless, Careless, Negligent or Aggressive Manner	13.21	8.21	21.27	3.19	2.92	3.49
Operated Defective Equipment	2.58	1.22	5.46	1.18	1.04	1.34
Alcohol Use	15.53	9.68	24.91	4.4	4.03	4.81
Drug Use	16.12	7.97	32.58	4.99	4.13	6.04

In a two-vehicle crash, if the driver exceeds authorized speed limit, he/she is going to put the other driver at risk. It is 22 times more likely to result in severe injury compared to another two-vehicle crash where there is no traffic rule violation. Alcohol and drugs are equally likely to put the other driver at risk. Going wrong way is 25 times more likely to put other drivers at risk, which is highest among all traffic violations. Disregarding other traffic signs, disregarding traffic signals, use of improper lane, other improper passing, and failing to yield the right-of-way are almost 3 times more likely to result in severe injuries to other drivers compared to no traffic rule violation.

5.2 Ranking Traffic Rule Violations for Prioritization/Enforcement

The results obtained from analysis using severity, frequency, total crash cost and cost severity index are presented in this section.

5.2.1 Ranking by Frequency

As mentioned earlier, a total of 1,315,059 vehicles were involved in crashes from 2009 to 2013. Of these, 636,119 vehicles (i.e., 48.86% of the total vehicles) were involved in crashes without violating any traffic rules. The frequency and the percent contribution of each traffic rule violation to total vehicles involved in crashes are computed and presented in Table 9. First rank was assigned for the traffic rule violation that had the highest frequency.

Failure to reduce speed is ranked 1st, followed by failure to yield the right-of-way. Exceeding safe speed limit for conditions outnumbered exceeding authorized speed limit and is ranked 3rd. Improper lane change is ranked 4th, followed by aggressive driving and crossing center-line/going wrong way. Disregarding traffic signals is as frequent as crossing center-line/going wrong way and is ranked 7th. Driving under the influence of drugs, operating defective equipment, following too closely, improper or no signal, improper backing, improper parking, passing a stopped school bus, passing on a hill, passing on a curve, other improper passing, use of improper lane, right turn on red, improper turn, right turn on red, exceeding authorized speed limit, disregarding other traffic signs, disregarding yield sign, disregarding road markings, and disregarding stop sign are less frequent than disregarding traffic signals.

TABLE 9: Frequency of Traffic Rule Violations

Traffic Rule Violation	**Frequency**	**% to Total Drivers Involved in Crashes**	**Rank**
Failure to Reduce Speed	176,945	35.74%	1
Failing to Yield the Right-of-way	91,898	18.56%	2
Exceeding Safe Speed for Conditions	56,266	11.36%	3
Improper Lane Change	25,067	5.06%	4
Operated Vehicle in Erratic, Reckless, Careless, Negligent or Aggressive Manner	21,288	4.30%	5
Crossed Center-line / Going wrong way	17,469	3.53%	6
Disregarding Traffic Signals	17,467	3.53%	7
Driving Under the Influence of Alcohol	16,742	3.38%	8
Improper Turn	15,953	3.22%	9
Following Too Closely	10,608	2.14%	10
Improper Backing	7,566	1.53%	11
Exceeding Authorized Speed Limit	7,421	1.50%	12
Disregarding Stop Sign	7,241	1.46%	13
Operated Defective Equipment	7,158	1.45%	14
Other Improper Passing	3,972	0.80%	15
Use of Improper Lane	2,977	0.60%	16
Disregarding Road Markings	2,553	0.52%	17
Driving Under the Influence of Drugs	1,987	0.40%	18
Disregarding Other Traffic Signs	1,539	0.31%	19
Disregarding Yield Sign	909	0.18%	20
Improper Parking	831	0.17%	21
Right Turn on Red	654	0.13%	22
Improper or No Signal	416	0.08%	23
Passing on a Curve	137	0.03%	24
Passing on a Hill	44	0.01%	25
Passing a Stopped School Bus	35	0.01%	26
Total Number of Vehicles	495,143	100.00%	

The top five traffic rule violations account for 75% of the total vehicles that violated traffic rules. Passing a stopped school bus followed by passing on a hill are the least frequently occurred traffic rule violations in North Carolina. The notable thing about improper lane change is that even though the number of crashes is almost 3.4 times exceeding speed limit, the number of fatalities due to improper lane change is very less. Passing on a hill and passing on a curve led to a relatively fewer numbers of crashes from 2009 to 2013.

5.2.2 Ranking by Severity

An ordered probit model was developed and tested for parallel lines assumption. The parallel lines test showed the necessity to have separate coefficients across the categories of the dependent variable (crash severity). Hence, a generalized ordered logit model was adopted to rank traffic rule violations by severity. Results obtained from the generalized ordered logit model are presented in Table 10. A p-value less than 0.10 indicates that the variable is significant at a 90% confidence level.

Traffic rule violations such as crossed center line/going wrong way, and passed on a curve coefficients are not statistically significant for moderate injury. This implies that the difference between the coefficients of these traffic rule violations and disregarding traffic signals is statistically same as zero (as coefficient is zero, the probability or odds ratio will be 1). Improper parking, improper or no signal, right turn on red, operated defective equipment, passed on hill, Disregarding yield sign, and Disregarding other traffic signs have insignificant coefficients for severe injury.

An odds ratio of 1 is assigned for disregarding traffic signals (as it is the reference variable), so as to assign a rank for this traffic rule violation. The odds ratio of insignificant variables is replaced by 1.0 (as explained above). Rank was assigned for severe injury and moderate injury separately based on the computed odds ratio.

TABLE 10: Generalized Ordered Logit Model for Crash Severity

Parameter	Severe Injury			Moderate Injury		
	Estimate	**Standard Error**	**p-value**	**Estimate**	**Standard Error**	**p-value**
Intercept	-4.23	0.07	<0.01	0.02	0.02	0.11
Disregarding Yield Sign	-0.21	0.34	0.54	-0.61	0.08	<0.01
Disregarding Stop Sign	1.08	0.09	<0.01	0.08	0.03	0.01
Disregarding Other Traffic Signs	0.32	0.21	0.12	-0.31	0.06	<0.01
Disregarding Road Markings	0.35	0.16	0.03	-0.61	0.05	<0.01
Exceeding Authorized Speed Limit	2.38	0.07	<0.01	0.52	0.03	<0.01
Exceeding Safe Speed for Conditions	0.33	0.07	<0.01	-0.65	0.02	<0.01
Failure to Reduce Speed	-1.33	0.08	<0.01	-0.77	0.02	<0.01
Improper Turn	-0.81	0.12	<0.01	-0.92	0.02	<0.01
Right Turn on Red	-0.41	0.43	0.34	-1.39	0.10	<0.01
Crossed Center Line/Going Wrong Way	1.70	0.07	<0.01	0.03	0.02	0.24
Improper Lane Change	-1.10	0.11	<0.01	-1.59	0.02	<0.01
Use of Improper Lane	0.43	0.16	0.01	-0.87	0.05	<0.01
Passed Stopped School Bus	2.29	0.52	<0.01	-0.77	0.40	0.05
Passed on Hill	-0.23	1.48	0.88	-0.86	0.35	0.01

TABLE 10: (continued)

Parameter	Severe Injury			Moderate Injury		
	Estimate	Standard Error	p-value	Estimate	Standard Error	p-value
Passed on Curve	1.55	0.38	<0.01	-0.29	0.18	0.12
Other Improper Passing	0.37	0.14	0.01	-0.94	0.04	<0.01
Failure to Yield Right-of-Way	0.02	0.07	0.8	-0.4	0.02	<0.01
Improper Backing	-1.68	0.24	<0.01	-2.38	0.05	<0.01
Improper Parking	-0.42	0.47	0.37	-1.73	0.13	<0.01
Improper or No Signal	-0.54	1.18	0.65	-0.96	0.23	<0.01
Followed Too Closely	-1.79	0.23	<0.01	-0.97	0.03	<0.01
Operated Vehicle in Erratic, Reckless, Careless, Negligent or Aggressive Manner	1.48	0.07	<0.01	0.08	0.02	<0.01
Operated Defective Equipment	0	0.12	1	-0.98	0.03	<0.01
Alcohol Use	1.68	0.07	<0.01	0.09	0.02	<0.01
Drug Use	1.28	0.12	<0.01	0.23	0.05	<0.01

Exceeding authorized speed limit had the highest odds in favor of resulting in a severe injury and moderate injury, and is ranked 1st in both categories. This traffic rule violation is ~10 times more likely to result in a severe injury when compared to disregarding traffic signals. Driving under the influence of alcohol is ~5 times more likely to result in a severe injury compared to disregarding traffic signals and is ranked 4th and 3rd in severe and moderate injury category. Crossing center line or going wrong way is 5.5 and 1.0 times more likely to result in severe and moderate injuries, respectively. Followed too closely has the least odds in favor of severe injury followed by improper backing. Passing a stopped school bus is almost 10 times more likely to result in severe injuries and less likely to result in moderate injuries.

TABLE 11: Ranking Traffic Rule Violations by Crash Severity

Traffic Rule Violation	**Odds Ratio**		**Rank**		**Rank by Crash Severity**
	Severe Injury	**Moderate Injury**	**Severe Injury**	**Moderate Injury**	
Exceeding Authorized Speed Limit	10.82	1.68	1	1	1
Driving Under the Influence of Alcohol	5.35	1.09	4	3	2
Crossed Center Line/Going Wrong Way	5.46	1.00*	3	6	3
Driving Under the Influence of Drugs	3.58	1.26	7	2	3
Operated Vehicle in Erratic, Reckless, Careless, Negligent or Aggressive Manner	4.41	1.08	6	4	5
Passed on Curve	4.69	1.00*	5	6	6
Disregarding Stop Sign	2.95	1.08	8	5	7
Passed Stopped School Bus	9.85	0.46	2	14	8
Disregarding Traffic Signals	1.00	1.00	14	6	9
Disregarding Other Traffic Signs	1.00*	0.73	14	9	10
Disregarding Road Markings	1.42	0.54	11	12	10
Failure to Yield Right-of-Way	1.02	0.67	13	10	10
Exceeding Safe Speed for Conditions	1.39	0.52	12	13	13
Disregarding Yield Sign	1.00*	0.54	14	11	13
Use of Improper Lane	1.54	0.42	9	17	15

TABLE 11: (continued)

Traffic Rule Violation	**Odds Ratio**		**Rank**		**Rank by Crash Severity**
	Severe Injury	**Moderate Injury**	**Severe Injury**	**Moderate Injury**	
Other Improper Passing	1.45	0.39	10	19	16
Passed on Hill	1.00*	0.43	14	16	17
Improper or No Signal	1.00*	0.38	14	20	18
Operated Defective Equipment	1.00*	0.38	14	22	19
Right Turn on Red	1.00*	0.25	14	23	20
Failure to Reduce Speed	0.26	0.46	24	15	21
Improper Parking	1.00*	0.18	14	25	21
Improper Turn	0.44	0.4	22	18	23
Improper Lane Change	0.33	0.2	23	24	24
Followed Too Closely	0.17	0.38	26	21	24
Improper Backing	0.19	0.09	25	26	26

The sum of the ranks was computed by simply adding ranks of severe injury and moderate injury. The lowest sum was given the first rank. This is the overall rank assigned for traffic rule violations based on crash severity. Passing on a curve, passing a stopped school bus, disregarding stop sign, operating vehicle aggressively, crossing center line/going wrong way, driving under the influence of alcohol and drugs, and exceeding speed limit are ranked lower than disregarding traffic signals. This implies that, if severity of crash is considered as a basis to address traffic rule violations, disregarding traffic signals should be given least preference when compared to these traffic rule violations. Improper backing, improper lane change and followed too closely are the least ranked traffic rule violations based on crash severity.

5.2.3 Ranking by Cost

Table 4 summarizes the estimated total crash cost and cost severity index along with corresponding ranks for different traffic rule violations. The total cost of failing to yield the right-of-way crashes is approximately \$2 billion per year and is ranked 1^{st}. This traffic rule violation is followed by failure to reduce speed. Exceeding safe speed for conditions is ranked 3^{rd}, followed by operating vehicle erratically or aggressively. Passing on a hill is the least ranked. The contribution of crossing center-line/going wrong way and operating vehicle erratically or aggressively to the total crash cost is almost the same. Exceeding authorized speed limit is ranked 7^{th} and is immediately followed by disregarding traffic signals. However, the total crash cost per year for exceeding authorized speed limit is almost twice that of disregarding traffic signals. The total cost of passing on a hill related crashes is ~\$300,000 per year, and is ranked the least.

Based on the cost severity index, passing a stopped school bus is ranked 1^{st} with a value of ~\$1 million. Passing a stopped school bus is followed by exceeding authorized speed limit with a cost severity index value of ~\$600,000. Crossing center-line/going wrong way is ranked 3^{rd}, followed by driving under the influence of alcohol. Operating vehicle erratically or aggressively is ranked 5^{th} and passing on a curve is ranked 6^{th}. The least rank (26) is assigned for improper backing. Passing on a hill is ranked 25^{th}.

Comparing the ranks of traffic rule violations assigned based on the total crash cost and the cost severity index shows certain discrepancies. A few violations, even though ranked highest based on cost severity index are ranked least based on the total crash cost per year. One such example is passing a stopped school bus. This traffic rule violation is ranked 1st based on the cost severity index, whereas it is ranked 24th based on the total crash cost per year. This could be attributed due to fewer vehicles violating this traffic rule.

Similarly, failure to reduce speed is ranked 2nd based on the total crash cost per year, whereas it is ranked 21st based on the cost severity index. There are also traffic rule violations for which the ranks are relatively close in both the cases. A few such traffic rule violations are operating vehicle erratically/aggressively, other improper passing, passing on a hill, crossing center-line/going wrong way, right turn on red, disregarding stop sign, and disregarding yield sign.

TABLE 12: Ranking by Traffic Rule Violations by Cost

Traffic Rule Violations	**Total Cost Per Year**		**Cost Severity Index**	
	Total Cost per Year	**Rank**	**Cost Severity Index**	**Rank**
Failure to Yield Right-of-Way	$2,009,451,820	1	$114,591.40	15
Failure to Reduce Speed	$1,945,145,280	2	$58,648.42	21
Exceeding Safe Speed for Conditions	$1,417,439,300	3	$130,593.83	12
Operated Vehicle in Erratic, Reckless, Careless, Negligent or Aggressive Manner	$1,278,191,060	4	$325,206.36	5
Crossed Center Line/Going Wrong Way	$1,262,545,520	5	$381,341.52	3
Driving Under the Influence of Alcohol	$1,210,498,360	6	$376,890.95	4
Exceeding Authorized Speed Limit	$851,216,340	7	$664,701.19	2
Disregarding Traffic Signals	$414,998,900	8	$123,828.52	14
Disregarding Stop Sign	$339,181,280	9	$242,757.86	8
Improper Lane Change	$220,298,960	10	$46,659.67	23
Improper Turn	$193,796,640	11	$66,624.26	20
Operated Defective Equipment	$132,494,740	12	$100,603.45	16
Driving Under the Influence of Drugs	$107,132,360	13	$277,688.85	7

TABLE 12: Ranking by Traffic Rule Violations by Cost

Traffic Rule Violations	Total Cost Per Year		Cost Severity Index	
	Total Cost per Year	**Rank**	**Cost Severity Index**	**Rank**
Other Improper Passing	$84,840,420	14	$125,096.46	13
Followed Too Closely	$82,824,500	15	$48,249.16	22
Disregarding Road Markings	$60,050,820	16	$131,229.94	11
Use of Improper Lane	$59,671,060	17	$131,434.05	10
Disregarding Other Traffic Signs	$38,773,900	18	$144,570.84	9
Improper Backing	$38,071,720	19	$27,560.24	26
Disregarding Yield Sign	$14,922,900	20	$96,776.26	17
Right Turn on Red	$8,666,020	21	$72,946.30	18
Passed on Curve	$7,376,860	22	$304,828.93	6
Improper Parking	$6,654,480	23	$66,946.48	19
Passed Stopped School Bus	$5,527,780	24	$921,296.67	1
Improper or No Signal	$655,400	25	$34,861.70	25
Passed on Hill	$315,640	26	$41,531.58	24

5.2.3 Relationship between the Ranks and Computing the Composite Ranks

Four different individual methods (severity, frequency, total crash cost and cost severity index) were computed for each traffic rule violation. There are huge variations in ranks assigned for traffic rule violations using the aforementioned individual methods. For example, failure to reduce speed is ranked 21st by severity and is ranked 1st by frequency. This traffic rule violation is not a critical one based on severity.

Table 13 shows the Spearman's correlation coefficient between the ranks. A Spearman's correlation coefficient close to ± 1 implies perfect correlation between the two subject ranks, while a Spearman’s correlation coefficient close to 0 implies no correlation between the two subject ranks.

Frequency is strongly correlated with the total crash cost per year, while severity is strongly correlated with the cost severity index. Therefore, the following combinations were considered to estimate composite ranks; 1) severity and frequency, 2) total crash cost per year and cost severity index, 3) severity and the total crash cost per year, and, 4) frequency and the cost severity index.

TABLE 13: Spearman's Correlation Coefficients for Ranks

Spearman Correlation Coefficient	**Severity**	**Frequency**	**Total Cost per Year**	**Cost Severity Index**
Severity	1.00	-0.01	0.31	0.90
Frequency		1.00	0.92	-0.02
Total Cost per Year			1.00	0.28
Cost Severity Index				1.00

Different weights can be considered when summing individual ranks to compute the composite rank. These weights should be based on a well-defined logic. For simplicity, in this study, the composite ranks were estimated assuming equal weights for all the individual ranks. The sum of the ranks was first computed by simply adding ranks for the considered individual methods. The lowest sum was given the first rank. Table 6 displays the composite ranks obtained for different combinations adopted: 1) severity and frequency, 2) total crash cost per year and cost severity index, 3) severity and total crash cost per year, and 4) frequency and cost severity index.

Considering the composite rank obtained by combining severity and frequency, crossed center line/going wrong way is ranked 1st. Driving under the influence of alcohol and operating vehicle erratically/aggressively are ranked 2nd, followed by failing to yield the right-of-way. Disregarding traffic signals and exceeding safe speed for conditions are ranked 6th. Passing a stopped school bus is the ranked 20th.

Considering the composite rank obtained by combining frequency and cost severity index, crossing center-line/going wrong way is ranked 1st, followed by operating vehicle erratically or aggressively. Driving under the influence of alcohol is ranked 3rd, followed by exceeding authorized speed limit. Exceeding safe speed limit for conditions is ranked 5th, while failing to yield the right-of-way is ranked 6th. Disregarding traffic signals and disregarding stop sign are ranked 7th followed by failure to reduce speed. Passing on a hill is ranked the least.

TABLE 14: Composite Ranks for Traffic Rule Violations

Traffic Rule Violation	**Individual Ranks**				**Composite Ranks**			
	Total Crash Cost	**Cost Severity Index**	**Frequency**	**Crash Severity**	**Severity & Frequency**	**Total Crash Cost & Cost Severity Index**	**Severity & Total Crash Cost**	**Frequency & Cost Severity Index**
Crossed center line/Going wrong way	5	3	6	3	1	1	1	1
Driving under the influence of alcohol	6	4	8	2	2	4	1	3
Operated vehicle in erratic, reckless, careless, negligent or aggressive manner	4	5	5	5	2	2	4	2
Failing to yield the right-of-way	1	15	2	10	4	6	5	6
Exceeding authorized speed limit	7	2	12	1	5	2	1	4
Disregarding traffic signals	8	14	7	9	6	9	9	7
Exceeding safe speed for conditions	3	12	3	13	6	5	6	5

TABLE 14: (continued)

Traffic Rule Violation	Individual Ranks				Composite Ranks			
	Total Crash Cost	**Cost Severity Index**	**Frequency**	**Crash Severity**	**Severity & Frequency**	**Total Crash Cost & Cost Severity Index**	**Severity & Total Crash Cost**	**Frequency & Cost Severity Index**
Disregarding stop sign	9	8	13	7	8	7	6	7
Driving under the influence of drugs	13	7	18	3	9	8	6	10
Failure to reduce speed	2	21	1	21	10	10	10	9
Disregarding road markings	16	11	17	10	11	12	11	14
Improper lane change	10	23	4	24	12	19	19	12
Disregarding other traffic signs	18	9	19	10	13	12	12	14
Passing on a curve	22	6	24	6	14	16	12	18
Other improper passing	14	13	15	16	15	12	14	14
Use of improper lane	17	10	16	15	15	12	16	11
Improper turn	11	20	9	23	17	18	19	17
Disregarding yield sign	20	17	20	13	18	20	18	21
Operated defective equipment	12	16	14	19	18	16	15	18
Following too closely	15	22	10	24	20	20	21	20
Passing a stopped school bus	24	1	26	8	20	11	16	12
Improper backing	19	26	11	26	22	24	26	21
Improper or no signal	25	25	23	18	23	25	23	25
Improper parking	23	19	21	21	24	23	25	23
Passing on a hill	26	24	25	17	24	25	23	26
Right turn on red	21	18	22	20	24	22	22	23

The critical (top ranked) traffic rule violations are almost same irrespective of the combination adopted. To confirm the results from a statistical analysis perspective, the spearman's rank correlation test was carried out between the composite ranks that are obtained by combining several individual ranks. The correlation coefficient between composite ranks has a minimum value of 0.70, indicating that the top traffic rule violations are fairly consistent irrespective of the combination of individual methods to compute the composite rank.

Relatively higher variations in ranks was observed when individual methods such as severity, frequency (expressed as a function of number of drivers violating traffic rules), total crash cost per year and cost severity index were considered, whereas the variations are observed to be minimal when composite ranks are considered.

5.3 Modeling Driver Injury Severity of At-Fault and Not At-Fault Drivers

The frequency of the independent variables that are to be evaluated in this study are shown in Table 16. Of the 349,454 not at-fault drivers, 77.33% sustained PDO, 22.26% had moderate injury, and 0.41% had severe injuries whereas 86.87% of at-fault drivers sustained PDO only. Around 63% of not at-fault drivers were involved in crashes in urban areas. Road characteristics analyzed in this study include road classification, road configuration, access, terrain, speed limit and median type. The vehicle type of drivers who were at-fault and not at-fault is classified into eight categories. Passenger cars contributed to ~58% of the at-fault drivers' vehicle type, whereas their contribution to not at-fault drivers' vehicle type is 55%. The type of traffic rule violation committed by at-fault driver is classified into 12 categories. Among the at-fault drivers, 71% had committed only one traffic rule violation, 25% had committed two traffic rule violations and ~3% had committed three traffic rule violations. Around 40% of the crashes occurred due to following closely or failing to reduce speed.

TABLE 15: Frequency of the Variables Considered for this Study

Variable	**Categories**	**Not At-Fault (%)**	**At-Fault (%)**
Driver Injury Severity (Dependent Variable)	PDO	270,249 (77.33)	303,576 (86.87)
	Moderate Injury	77,781 (22.26)	44,286 (12.67)
	Severe Injury	1424 (0.41)	1592 (0.42)
Location	Rural	130,068 (37.22)	
	Urban	219,386 (62.78)	
Road Surface Condition	Dry	289,401 (82.82)	
	Wet	54,740 (15.66)	
	Water Standing/Moving (WSM)	1,560 (0.45)	
	Ice	1,601 (0.46)	
	Snow	1,565 (0.45)	
	Slush	452 (0.13)	
	Sand, Mud, Dirt, Gravel (SMDG)	68 (0.02)	
	Fuel, Oil	8 (<0.01)	
	Other	59 (0.02)	
Weather Condition	Clear	252,372 (71.82)	
	Cloudy	60,652 (17.36)	
	Rain	32,286 (9.64)	
	Snow	1,908 (0.55)	
	Fog, Smog, Smoke (FSS)	1,091 (0.31)	
	Sleet, Hall, Freezing Rain/Drizzle (SHFR)	890 (0.25)	
	Severe Crosswinds (SC)	30 (0.01)	
	Blowing Sand, Dirt, Snow (BSDS)	15 (<0.01)	
	Other	210 (0.06)	
Light Condition	Daylight	283,238 (81.05)	
	Dusk	8,060 (2.31)	
	Dawn	4,097 (1.17)	
	Dark – Lighted Roadway (DLR)	29,679 (8.49)	
	Dark – Roadway Not Lighted (DRL)	23,931 (6.85)	
	Dark – Unknown Lighting (DUL)	364 (0.10)	
	Other	85 (0.02)	
Drivers' Gender	Male	191,893 (54.91)	
	Female	157,561 (45.09)	
Terrain	Flat	67,114 (19.21)	
	Rolling	259,604 (74.29)	
	Mountainous (MOUN)	22,736 (6.51)	

TABLE 15: (continued)

Variable	Categories	Not At-Fault (%)	At-Fault (%)
Drivers' Age	<=18 years	15,568 (4.45)	35,308 (10.10)
	19-25 years	54,902 (15.71)	82,604 (23.64)
	26-40 years	108,858 (31.15)	93,577 (26.78)
	41-55 years	99,583 (28.50)	69,591 (19.91)
	56-70 years	55,744 (15.95)	44,503 (12.74)
	>70 years	14,799 (4.23)	23,871 (6.83)
Vehicle Type	Passenger Car	191,833 (54.90)	200,982 (57.51)
	Pickup/Light Truck/Van (PLTV)	73,967 (21.17)	73,730 (21.10)
	Sports Utility Vehicle (SUV)	67,842 (19.41)	60,040 (17.18)
	Bus	1,784 (0.51)	979 (0.28)
	Truck/Tractor or Truck/Tractor Trailer (TT)	9,848 (2.82)	10,785 (3.09)
	Farm Vehicle (FV)	0 (0.00)	4 (<0.01)
	Two-wheeler (TW)	3,016 (0.86)	2,071 (0.59)
	Other	1,164 (0.33)	863 (0.25)
Drivers' Violation	Disregarding Traffic Signs/Signals/Markings (DTS)	-	20,040 (5.73)
	Exceeding Speed Limit (ESL)	-	898 (0.26)
	Exceeding Safe Speed Limit for Conditions (ESSL)	-	6,067 (1.74)
	Followed Closely (FC)	-	135,581 (38.80)
	Improper Maneuver (IM)	-	39,054 (11.18)
	Improper Passing (IP)	-	2,598 (0.74)
	Failure to Yield the Right-of-Way (FYRW)	-	77,452 (22.16)
	Inattention/Distraction (ID)	-	45,134 (12.92)
	Aggressive/Reckless/Driving (ARD)	-	2,733 (0.78)
	Impaired Driving (IMPD)	-	3,319 (0.95)
	Crossed Centerline/Going Wrong Way (WW)	-	7,324 (2.10)
	Other	-	9,254 (2.65)
Speed Limit	<=25 mph.	5,279 (1.51)	
	26-45 mph.	205,700 (58.86)	
	46-55 mph.	109,097 (31.22)	
	>55 mph.	29,378 (8.41)	
Number of Violations Committed-Fault driver	One	-	249,555 (71.41)
	Two	-	88,239 (25.25)
	Three	-	11,660 (3.34)

TABLE 15: (continued)

Variable	Categories	Not At-Fault (%)	At-Fault (%)
Drivers' Physical Condition	Apparently Normal	348,929 (99.85)	337,901 (96.69)
	Illness	104 (0.03)	247 (0.07)
	Fatigue	31 (0.01)	773 (0.22)
	Fell Asleep, Fainted, Loss of Consciousness (FFLC)	20 (0.01)	1,397 (0.40)
	Impairment Due to Medications, Drugs, Alcohol (IMDA)	186 (0.05)	7,321 (2.09)
	Medical Condition (MC)	64 (0.02)	1,135 (0.32)
	Other Physical Impairment (OPI)	62 (0.02)	285 (0.08)
	Restriction Not Complied with (RNC)	17 (<0.01)	82 (0.02)
	Other	41 (0.01)	313 (0.09)
Median Type	Undivided Roadway	201,105 (57.55)	
	Rigid Pos Barrier (RPB)	6,549 (1.87)	
	Continuous Turn Lane (CTL)	40,143 (11.49)	
	Paved Mountable (PM)	12,482 (3.57)	
	Curb	11,142 (3.19)	
	Grass	49,627 (14.20)	
	Positive Barrier (POB)	20,628 (5.90)	
	Parkland, Business (PB)	144 (0.04)	
	Couplet	1,413 (0.40)	
	Flexible Pos Barrier (FPB)	2,617 (0.75)	
	Striped	401 (0.11)	
	Semi-Rigid Pos Barrier (SRPB)	3,203 (0.92)	
Road Characteristics	Straight – Level	268,266 (76.77)	
	Straight – Hillcrest (SH)	10,597 (3.03)	
	Straight – Grade (SG)	46,655 (13.35)	
	Straight – Bottom (SB)	2,485 (0.71)	
	Curve – Level (CL)	11,368 (3.25)	
	Curve – Hillcrest (CH)	1,560 (0.45)	
	Curve – Grade (CG)	8,060 (2.31)	
	Curve – Bottom (CB)	407 (0.12)	
	Other	56 (0.02)	
Access	No Access Control	246,193 (70.45)	
	Partial Control (PC)	62,615 (17.92)	
	Full Control (FC)	40,646 (11.63)	

TABLE 15: (continued)

Variable	Categories	Not At-Fault (%)	At-Fault (%)
Road Classification	Interstate (IN)	33,144 (9.48)	
	US Route (USR)	62,984 (18.02)	
	NC Route (NCR)	59,108 (16.91)	
	State Secondary Route (SSR)	57,854 (16.56)	
	Local Street (LS)	133,301 (38.15)	
	Public Vehicular Area (PVA)	2,588 (0.74)	
	Private Road, Driveway (PRD)	76 1(0.02)	
	Other	399 (0.11)	
Road Configuration	One-Way, Not Divided	14,490 (4.15)	
	Two-Way, Not Divided (TWND)	201,622 (57.70)	
	Two-Way, Divided, Unprotected Median (TWDUM)	81,499 (23.32)	
	Two-Way, Divided, Positive Median Barrier (TWDPM)	51,660 (14.78)	
	Unknown	183 (0.05)	

Note: Single values under not at-fault and at-fault columns indicate that breakdown is not applicable for these independent variables.

Failure to yield the right-of-way accounted for 22% of the crashes. Improper passing includes passing over a stopped school bus, passing on a hill, passing on curve, etc. Improper maneuver includes right turn on red, improper turn, improper lane change, improper lane use, overcorrected or oversteered, improper backing or parking or signaling, etc.

The age of drivers involved in crashes is classified into 6 categories; novice (<=18 years), young (19-25 years), 26-40 years, 41-55 years, 56-70 years, elderly (>=70 years). Around 10% of the total at-fault drivers and ~4% of the not at-fault drivers were novice drivers. Drivers less than 25 years contributed to ~33% of the at-fault drivers whereas their contribution is just ~19% of the total not at-fault drivers. Similarly, elderly drivers are more likely to be at-fault compared to not at-fault drivers (~7% versus ~4%, respectively). Out of the at-fault and not at-fault drivers, ~55% and 52% are males, respectively.

The physical condition of the drivers who were involved in crashes was classified into 9 categories. Approximately 99% of the not at-fault drivers and 97% of at-fault drivers are apparently normal. Of the at-fault drivers, 2% were driving under the influence of medication, drugs, or alcohol. Speed limit being a continuous variable is categorized into 4; less than 25 mph, 26 to 45 mph, 46 to 55 mph and greater than 55 mph. A majority of the two-vehicle crashes occurred on 26 to 45 mph roads, while only 8% occurred on greater than 55 mph roads. Most of the two-vehicle crashes occurred on undivided roads, rolling terrains, and no access control roads.

Odds proportionality tests was performed, and the tests gave a p-value less than 0.05 (95% confidence level). Therefore, separate parameters are needed across the categories for at least one or more independent variables (as ordered probit failed to comply with parallel lines assumption). A fully non-proportional odds model was developed to check which variables need the relaxation of proportional odds assumption. Table 16 shows the independent variables and results obtained from the proportional odds test.

Variables such as road surface condition, weather condition, road configuration, access, terrain, median type, at-fault drivers' physical condition and gender had p-value greater than 0.05 for not at-fault model. This indicates that the null hypothesis cannot be rejected for these variables. Hence, for these variables, there exist only one coefficient which explains the effect across the categories of the dependent variable.

TABLE 16: Proportional Odds Test for Individual Independent Variables

Variable	Not At-Fault		At-Fault	
	Wald Chi-Square	**p-value**	**Wald Chi-Square**	**p-value**
Location	7.72	0.01	21.61	<0.01
Road Surface Condition	4.62	0.80	9.18	0.33
Weather Condition	7.58	0.37	4.67	0.70
Light Condition	22.62	0.00	9.96	0.13
Road Characteristics	28.63	0.00	28.10	0.00
Road Classification	27.62	0.00	21.29	0.00
Road Configuration	4.49	0.34	7.15	0.13
Access	1.81	0.41	3.84	0.15
Terrain	0.72	0.70	1.84	0.40
Median Type	10.36	0.50	19.22	0.06
Speed Limit	25.61	<0.01	15.68	0.00
Fault Drivers' Physical Condition	10.40	0.24	25.96	0.00
Not At-Fault Drivers' Physical Condition	23.04	0.00	19.90	0.01
At-Fault Drivers' Gender	0.01	0.92	50.45	<0.01
Not At-Fault Drivers' Gender	4.00	0.05	<0.01	0.95
At-Fault Drivers' Age	17.16	<0.01	97.46	<0.01
Not At-Fault Drivers' Age	138.22	<0.01	8.06	0.15
At-Fault Drivers' Vehicle Type	81.58	<0.01	5.20	0.52
Not At-Fault Drivers' Vehicle Type	93.52	<0.01	106.34	<0.01
At-Fault Drivers' Violation	460.85	<0.01	297.38	<0.01
Number of Violations Committed by Fault Driver	38.98	<0.01	11.92	<0.01

Similarly, variables for at-fault model are also identified. The other variables in Table 16, reject the null hypothesis, which shows the need for these variables to have different coefficients across the categories.

The variables that failed proportional odds assumption were relaxed to have different coefficients for different driver injury severity levels. Using "proc logistic" in

SAS, a partial proportional odds model was developed for driver injury severity of not at-fault drivers and at-fault drivers separately. The results obtained are presented in Table 17.

TABLE 17: Odds Ratios for Injury Severity of Not At-Fault & At-Fault Drivers

Variable	Categories	Not at-fault Driver Injury Severity Model		At-fault Driver Injury Severity Model	
		Severe Injury	Moderate Injury	Severe Injury	Moderate Injury
Road Surface Condition ®-Dry	Wet	0.95		0.97*	
	Water Standing/Moving (WSM)	1.19		1.19	
	Ice	0.69		0.65	
	Snow	0.64		0.55	
	Slush	0.88*		0.64	
	Sand, Mud, Dirt, Gravel (SMDG)	0.71*		0.44*	
	Fuel, Oil	1.50*		2.7*	
	Other	1.76		2.15	
Weather Condition ®-Clear	Cloudy	1.04		1.02*	
	Rain	1.02*		0.98*	
	Snow	0.78		0.86*	
	Fog, Smog, Smoke (FSS)	1.10*		1.14*	
	Sleet, Hall, Freezing Rain/Drizzle (SHFR)	1.17*		0.96*	
	Severe Crosswinds (SC)	0.21*		0.34*	
	Blowing Sand, Dirt, Snow (BSDS)	1.40*		2.34*	
	Other	0.83*		0.92*	
Light Condition ®-Daylight	Dusk	1.5	1.05*	1.02*	
	Dawn	1.49*	1.11	1.09*	
	Dark – Lighted Roadway (DLR)	1.29	1.1	1.15	
	Dark – Roadway Not Lighted (DRL)	1.7	1.22	1.25	
	Dark – Unknown Lighting (DUL)	0.36*	1.01*	1.21*	
	Other	0.78*	0.99*	1.12*	
Terrain ®-Flat	Rolling	0.95		0.94	
	Mountainous (MOUN)	0.78		0.76	

TABLE 17: (continued)

Variable	**Categories**	**Not at-fault Driver Injury Severity Model**		**At-fault Driver Injury Severity Model**	
		Severe Injury	**Moderate Injury**	**Severe Injury**	**Moderate Injury**
Road Configuration ®-One Way Not Divided	Two-Way, Not Divided (TWND)	1.36		1.89	
	Two-Way, Divided, Unprotected Median (TWDUM)	1.31		1.81	
	Two-Way, Divided, Positive Median Barrier (TWDPM)	1.32		1.88	
	Unknown	1.24*		1.09*	
At-Fault Drivers' Physical Conditions ®-Apparently Normal	Illness	0.96*		2.41*	2.46
	Fatigue	1.36		1.04*	1.55
	Fell Asleep, Fainted, Loss of Consciousness (FFLC)	2.11		2.33	3.28
	Impairment Due to Medications, Drugs, Alcohol (IMDA)	1.58		2.61	1.96
	Medical Condition (MC)	1.53		3.54	4.99
	Other Physical Impairment (OPI)	1.38		3.16	1.48
	Restriction Not Complied with (RNC)	1.64		6.63	2.14
Not At-Fault Drivers' Vehicle Type ®-Passenger Car	Pickup/Light Truck/Van (PLTV)	0.79	0.8	1.76	1.29
	Sports Utility Vehicle (SUV)	0.61	0.74	1.55	1.19
	Bus	0.06	0.27	4.51	1.61
	Truck/Tractor or Truck/Tractor Trailer (TT)	0.18	0.29	6.3	2.61
	Two-wheeler (TW)	38.71	17.73	0.36	0.48
	Farm Vehicle (FV)	0.96*	0.77	1.68*	1.0*
At-Fault Drivers' Age ®-26-40 years	<=18 years	1.04*	1.01*	0.94*	0.92
	19-25 years	1.12*	1.01*	0.9*	1.0*
	41-55 years	0.94*	1.01*	1.16	1.01*
	56-70 years	0.74	0.99*	1.37	1.06
	>70 years	1.14*	1.03*	2.54	1.19

TABLE 17: (continued)

Variable	**Categories**	**Not at-fault Driver Injury Severity Model**		**At-fault Driver Injury Severity Model**	
		Severe Injury	**Moderate Injury**	**Severe Injury**	**Moderate Injury**
At-Fault Drivers' Vehicle Type ®-Passenger Car	Pickup/Light Truck/Van (PLTV)	1.47	1.14	0.71	
	Sports Utility Vehicle (SUV)	1.55	1.1	0.75	
	Bus	2.86	1.04*	0.21	
	Truck/Tractor or Truck/Tractor Trailer (TT)	3.6	1.33	0.25	
	Farm Vehicle (FV)	0.76*	2.42*	0.27*	
	Two-wheeler (TW)	0.31	0.24	25.72	
	Other	2.47	1.07*	1.08*	
Median Type ®-Undivided Road	Rigid Pos Barrier (RPB)	0.88		1.00*	
	Continuous Turn Lane (CTL)	0.96		0.93	
	Paved Mountable (PM)	1.02*		0.89	
	Curb	1.03*		0.96*	
	Grass	0.96		0.97	
	Positive Barrier (POB)	0.9		0.93	
	Parkland, Business (PB)	1.28*		0.99*	
	Couplet	1.15		1.47	
	Flexible Pos. Barrier (FPB)	0.86		0.88*	
	Striped	0.66		0.69	
	Semi-Rigid Pos. Barrier (SRPB)	0.89		0.91*	
Access ®-No Access Control	Partial Access Control	0.99		0.96	
	Full Access Control	0.98		0.96	
At-Fault Drivers' # Violations ®-One	Two	1.68	1.22	1.27	1.27
	Three	2.86	1.48	2.15	1.57
At-Fault Drivers' Gender®-Male	Female	0.98		1.13	1.65

TABLE 17: (continued)

Variable	Categories	Not at-fault Driver Injury Severity Model		At-fault Driver Injury Severity Model	
		Severe Injury	Moderate Injury	Severe Injury	Moderate Injury
At-Fault Drivers' Violation ®- Disregarding Traffic Signs/Signals/ Markings	Exceeding Speed Limit (ESL)	2.22	1.04*	3.53	1.28
	Exceeding Safe Speed Limit for Conditions (ESSL)	0.81*	0.69	1.04*	0.69
	Followed Closely (FC)	0.09	0.47	0.13	0.28
	Improper Maneuver (IM)	0.21	0.26	0.32	0.26
	Improper Passing (IP)	0.28	0.28	0.38	0.28
	Failure to Yield the Right-of-Way (FYRW)	0.5	0.66	0.52	0.64
	Inattention/Distraction (ID)	0.18	0.41	0.18	0.26
	Aggressive/Reckless Driving (ARD)	1.36	0.73	1.25*	0.8
	Impaired Driving (IMPD)	0.81*	0.64	0.73*	0.49
	Crossed Centerline/Going Wrong Way (WW)	2.27	0.9	0.43	0.35
	Other	0.29	0.28	2.34	0.98*
Road Characteristics ®- Straight Level	Straight – Hillcrest (SH)	1.26*	1.12	1.15*	1.18
	Straight – Grade (SG)	1.13*	1.15	1.36	1.15
	Straight – Bottom (SB)	2.2	1.35	1.28*	1.5
	Curve – Level (CL)	1.89	1.27	2.03	1.32
	Curve – Hillcrest (CH)	1.73	1.23	1.62	1.2
	Curve – Grade (CG)	1.48	1.22	1.37	1.32
	Curve – Bottom (CB)	0.57*	0.91*	1.21*	1.12*
	Other	4.09*	0.71*	0.77*	0.62*
Not At-Fault Drivers' Age ®- 26-40 years	<=18 years	0.55	0.67	0.96*	
	19-25 years	0.78	0.9	1.03	
	41-55 years	1.25	1.09	0.99*	
	56-70 years	1.45	1.09	1.0*	
	>70 years	2.77	0.95	0.97*	
Location ®-Rural	Urban	0.63	0.86	0.48	0.81

TABLE 17: (continued)

Variable	Categories	Not at-fault Driver Injury Severity Model		At-fault Driver Injury Severity Model	
		Severe Injury	**Moderate Injury**	**Severe Injury**	**Moderate Injury**
Speed Limit ®-46-55 mph	<=25 mph.	0.57*	0.56	0.24	0.48
	26-45 mph.	0.6	0.83	0.64	0.78
	>55 mph.	1.05*	0.84	0.97*	0.87
Road Classification ®-Interstate	US Route (USR)	2.04	1.17	2.05	1.21
	NC Route (NCR)	2.05	1.18	2.1	1.22
	State Secondary Route (SSR)	1.50*	1.07*	1.53	1.01*
	Local Street (LS)	1.28*	1.13	1.24*	1.14
	Public Vehicular Area (PVA)	0.11*	0.42	0.33	0.36
	Private Road, Driveway (PRD)	3.17*	0.62*	0.76*	0.34*
	Other	0.54*	0.87*	0.53*	0.69*
Not At-Fault Drivers' Physical Conditions ®-Apparently Normal	Illness	0.73*	0.94*	0.59*	0.87*
	Fatigue	3.54*	1.42*	7.59	1.81*
	Fell Asleep, Fainted, Loss of Consciousness (FFLC)	0.63*	1.53*	0.33*	0.93*
	Impairment Due to Medications, Drugs, Alcohol (IMDA)	4.81	1.84	6.81	2
	Medical Condition (MC)	5.88	2.9	1.23*	0.89*
	Other Physical Impairment (OPI)	10.61	3.85	5.17*	1.32*
	Restriction Not Complied with (RNC)	4.97*	1.26*	0.96*	1.69*
	Other	20.07	3.4	0.68*	1.9*
Not At-Fault Drivers' Gender ®-Male	Female	1.35	1.53	0.93	

When the road surface is covered by ice and snow, the odds of resulting in a severe injury compared to moderate and PDO is 0.69 and 0.61 times that of dry surface condition for not at-fault drivers. Except snow and cloudy weather condition, rest all are not significant in resulting in a severe injury for not at-fault driver. Weather conditions has no effect on at-fault driver injury severity. Dusk, dark - lighted road, and dark - road not lighted are 1.5, 1.29, and 1.7 times more likely to result in a severe injury for not at-fault drivers. Dark-lighted roadway is 1.29 times more likely to result in a severe injury for not at-fault driver whereas it is 1.15 times likely to result in a severe injury for at-fault driver. Light conditions effect not at-fault drivers compared to at-fault drivers.

Terrain has similar effect on both at-fault and not at-fault drivers. Two-way not divided roadways are 1.36 and 1.89 times likely to result in severe injury for not at-fault and at-fault drivers, respectively compared to one-way not divided road. Roads with any other speed limit are less likely to result in moderate injuries compared to roads with speed limit between 46-55 mph. However, higher speed limits are more likely to result in severe injuries. Speed limit has similar effect on both at-fault and not at-fault drivers.

Drivers' own physical condition is more likely to affect their own injury severity compared to the other drivers' physical conditions. At-fault drivers who fell asleep or fainted or lost consciousness are 2.1 times likely to result in severe injury to not at-fault driver compared to at-fault drivers' normal physical condition. At-fault drivers' restriction not complied with are 6.6 times more likely to result in severe injury to at-fault driver compared to normal physical condition. At-fault drivers' age least effects the not-at fault driver injury severity. Among different vehicle types, motorcyclists not at-fault are observed to have the highest risk. The odds of a two-vehicle crash resulting in severe injury to motorcyclist not at-fault is 38.71 times higher that of a not at-fault driver in a passenger car. When the at-fault driver is driving a bus, he/she is 2.86 times more likely to severely injure the not at-fault driver compared to a passenger car driver. Motorcyclists are 0.31 times likely to severely injure (compared to moderate and PDO) the not at-fault driver compared to a passenger car driver. At-fault drivers driving larger vehicles are less likely to succumb severe injuries and more likely to pose severe injuries to other drivers and vice-versa. Road classification and access control almost effects both at-fault and not-at fault driver similarly.

Among all the traffic rule violations by the at-fault driver observed in this study, following closely is least likely to result in severe injury to not at-fault driver. If the at-fault driver has two or three violations, the chances that not at-fault driver is severely injured is 1.68 and 2.86 times compared to at-fault driver with one traffic rule violation. The odds of severe injury and moderate injury for urban roads are 0.63 and 0.86 compared to rural roads. Partial access and full access control have almost equal odds in favor of severe injury compared to no access control.

Female not at-fault drivers are 1.35 and 1.53 times more likely to succumb severe and moderate injuries compared to male drivers, indicating that the risk to the female drivers is higher even though they are not at-fault compared to their male counterparts.

CHAPTER 6: CONCLUSIONS

Traffic rule violations are the major reason for the occurrence of crashes and fatalities on roads. By modeling driver injury severity as a function of only traffic rule violations, it was evident that most of the traffic rule violations have higher probabilities of resulting in severe driver injury compared to injury when disregarding traffic signals. Exceeding the speed limit is more likely to result in severe injury to the driver compared to driver injury due to disregarding traffic signals. However, going the wrong way is more likely to result in severe injury to other drivers compared to any other traffic violation. The associated risk varies by the type of traffic rule violation. The risk drivers violating traffic rules pose to themselves is higher than the risk they pose to other drivers. The findings from this modeling serve as evidence to educate and generate awareness among drivers of the risk of violating traffic rules for themselves as well as for other drivers. Educating drivers about the risk associated with various traffic rule violations could help them develop safe driving behaviors, which would eventually improve safety on roads and contribute toward reaching the "zero traffic deaths" vision.

Traffic rule violations are ranked to serve as a basis for enforcement and prioritization purposes. Relatively higher variations in ranks was observed when individual methods such as frequency (expressed as a function of the number of drivers violating traffic rules), crash severity, total crash cost per year and cost severity index were considered, whereas the variations are minimal when composite ranks are considered. This indicates that adopting combined methods for ranking has a smoothing effect in addition to capturing the merits of considered individual methods.

Considering the quality of data and the sound analytical approach (technical merit), the composite rank obtained by combining frequency and crash severity is recommended for prioritization of traffic rule violations, and hence, allocation of funding. Using this composite rank could also optimize the allocation of resources and account for possible marginal effects. If practitioners do not have access to tools to develop generalized ordered logit models (preferred over multinomial logit model considering the ordinal nature of the dependent variable for the subject analysis) to compute crash severity, this study recommends the use of composite rank obtained by combining frequency and cost severity index as an alternative. Based on the findings, the top five traffic rule violations that practitioners should give high priority in North Carolina are crossing center-line/going wrong way, operating vehicle aggressively, driving under the influence of alcohol, exceeding authorized speed limit, and failed to yield the right-of-way.

North Carolina Division of Motor Vehicle (DMV) issues 5 penalty points on driver's license when a driver is convicted of passing a stopped school bus. This traffic rule violation has the highest penalty points among different traffic rule violations in North Carolina. An average of 7 crashes per year occurred due to passing a stopped school bus in North Carolina from 2009 to 2013. This shows the effect of enforcement along with penalty points on the number of crashes due to this traffic rule violation. Such findings are well supported by another recent study which indicated a correlation between traffic tickets issued and a decrease in fatalities and severe injuries (Nazif-Munoz et al., 2015).

Overall, a decrease in the number of convictions and an improvement in safety may be observed if the critical top ranked traffic rule violations are given the highest penalty points. However, the current penalty point system adopted by North Carolina DMV does not seem to follow a similar rationale. For example, based on the composite rank obtained from frequency and crash severity, going wrong way is ranked 1st, while following too closely is ranked 20th. North Carolina DMV convict's drivers with 4 penalty points for following too closely and driving on the wrong side of the road. The numbers of penalty points are same even though a difference in ranks is observed between these two traffic rule violations. The findings from this research can be used by policy makers to revisit the penalty point system and update the penalty points as well as fines. This could eventually reduce crashes and fatalities on roads, and hence, societal costs.

The results obtained indicate that two-vehicle crashes occurred during extreme weather conditions, bad lighting conditions, on roads with speed limits greater than 45 mph, rural roads, road sections that are not straight level, and roads with access control are more likely to result in severe injury to the not at-fault driver. This might be because of lower sight distances on high speed roads. Adopting variable speed limits with decreased speeds on road segments with lower sight distances and higher grade changes along with appropriate warning signs will help reduce both the frequency and severity of such crashes. Older drivers (>70 years) and female drivers, at-fault in two-vehicle crashes, are less likely to severely injure drivers not at-fault. Also, the risk to female drivers was observed to be higher even though they are not at-fault compared to their male counterparts. Further, motorcyclists not at-fault are observed to have the highest risk. Most of the crashes involving motorcycles result in a severe injury to the motorcyclist. Better education to the drivers to adopt safe distances and to drive more cautiously when sharing a road with motorcyclists could help improve overall safety to the motorcyclist. As the number of traffic rule violations by an at-fault driver increases, the chances of not at-fault driver being severely injured increases. Exceeding speed limit, aggressive or reckless driving, and going wrong are more likely to result in severe injuries to drivers not at-fault compared to disregarding traffic signals/signs/markings. These results from this study assist transportation professionals understand the driver injury severity of not at-fault drivers and at-fault drivers in two-vehicle crashes.

6.1 Limitations and Scope for Further Research

In this study, only drivers involved in crashes were taken into consideration for analysis and modeling. Subject to availability of quality data, the study could be extended to examine the effect of violating a traffic rule on passengers, pedestrians, and bicyclists. Likewise, only the primary contributing factor or traffic rule violation was taken into consideration for analysis and modeling in this research. Certain combinations of multiple traffic rule violations may increase risk to drivers and other road users. The risk could vary by gender, age group, lighting condition, and network characteristics. The effect of combinations of traffic rule violations on risk to drivers and other road users by gender, age group, or other characteristics merits research and investigation in the future. Drivers often perceive that violating a traffic rule does not lead to a crash or severe crash. However, the reality may be far different than what drivers often perceive. There is also a need to compare risk due to violating traffic rules by age and gender with risk perceptions by age and gender to identify and educate target groups whose perceptions substantially differ from the reality.

While this study recommends revisiting the penalty points and fines for each traffic rule violation, it does not look at specific penalty points or fine amount for each traffic rule violation. Further, only the primary contributing of the driver was considered as the reason for the occurrence of a crash (in ranking by crash severity). Unarguably, the crash severity may be higher if multiple traffic rule violations are involved in a crash. The relationships between penalty points, fine and single or multiple traffic rule violations by a driver involved in a crash need to be considered and examined in the future.

Examining injury severity of drivers who were at-fault and comparing them with injury severity of drivers not at-fault to identify the factors that affect both drivers also merit an investigation.

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