UNIVERSITY OF MARYLAND

National Transportation Center

Project ID: NTC2015-MU-R-9

Safety and Travel Time Reliability: Analyzing Large-Scale Truck Involved Crashes

FINAL REPORT

Lead University: North Carolina State University

P.I. (Lead Univ.) George List & Asad Khattak

Collaborative University: University of Maryland
P.I. (Collaborative Univ.) Lei Zhang

Submitted to:

National Transportation Center at Maryland (NTC@Maryland)
1124 Glenn Martin Hall
University of Maryland
College Park, MD 20742

October, 2017

ACKNOWLEDGEMENTS

This project was funded by the National Transportation Center @ Maryland (NTC@Maryland), one of the five National Centers that were selected in a nationwide competition, by the Office of the Assistant Secretary for Research and Technology (OST-R), U.S. Department of Transportation (US DOT).

DISCLAIMER

The contents of this report reflect the views of the authors, who are solely responsible for the facts and the accuracy of the material and information presented herein. This document is disseminated under the sponsorship of the U.S. Department of Transportation University Transportation Centers Program in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof. The contents do not necessarily reflect the official views of the U.S. Government. This report does not constitute a standard, specification, or regulation.

Work done in this project motivated dissemination of the following papers:

- Wali B., A. Khattak, & J. Xu, Contributory Fault and Level of Personal Injury to Drivers Involved in Head-on Collisions: Application of copula-based bivariate ordinal models. Forthcoming in Accident Analysis & Prevention, 2017.
- Xu J., Wali B. & A. Khattak, Injury Severity Analysis of Passenger Vehicle-Truck Collisions and Contributory Unsafe Pre-Crash Behaviors. Paper presented at the Transportation Research Board, National Academies, Washington, D.C., 2017.

TABLE OF CONTENTS

PROJECT REPORT

1 EXECUTIVE SUMMARY

Reducing truck involved crashes is a key goal of Federal Motor Carrier Safety Administration (FMCSA) and Federal Highway Administration (FHWA). Large trucks (Gross Vehicle Weight > 10,000 pounds) often account for 7% of the total vehicle miles traveled (VMT), but large trucks are involved in about 11% of all traffic crash fatalities (*1*). An important aspect of truck involved collisions is that they can be very disruptive and in some cases, fatalities and injuries are sustained by the occupants of the passenger vehicles rather than truck occupants (*2*). Large-scale events involving heavy trucks can be very costly, e.g., due to injuries and loss of life, goods movement disruptions, and travel time unreliability and traffic congestion. Such crashes have been lightly researched in the literature. Specifically, behavioral factors involved in such-like collisions such as unsafe driving acts, fault, and specific pre-crash driving maneuvers as well as roadways where such crashes are likely to occur need to be investigated. While truck involved crashes can involve many vehicles (involving more than two vehicles), two-vehicle passenger vehicle-truck collisions often constitute the majority of total truck involved fatal crashes (*3*).

This project is split into two phases. Phase 1 of this project focuses on investigating the associations between injury severity and unsafe pre-crash driving behaviors (both intentional and unintentional) of passenger vehicle and truck drivers. Due to complex interactions of factors associated with injury outcomes in passenger vehicle-truck collisions, fixed- and random-parameter ordered probit models are estimated using a comprehensive 2013 crash database in Virginia. The models account for unobserved heterogeneity that may arise due to unobserved factors and the models control for several factors that include collision type, roadway type, and temporal factors, while investigating driver behaviors. Compared to truck occupants, passenger vehicle occupants are six times more likely to sustain minor/possible and ten times more likely to receive serious/fatal injuries in collisions. Importantly, improper actions of passenger vehicle drivers (whether intentional or unintentional) are statistically significantly associated with higher likelihood of more severe injuries. Also, passenger vehicle-truck collisions during nighttime and early morning (1 AM to 8 AM) are associated with more severe occupant injuries. Model estimations suggest that the associations between key factors and level of injury severity are not consistent, and vary significantly across different passenger vehicle-truck collisions. Practical implications of the findings are discussed in detail in this report.

From the manner of collision stand-point, head-on collisions accounted for 26% of all motor-vehicle involved fatal crashes (*4*). Head-on collisions refer to a collision where the front-end of one vehicle collides with the front-end of another vehicle while the two vehicles are traveling in opposite directions. These types of collisions are the most severe crashes in terms of injury severity outcomes. Fatality and injury rate per 1,000 crashes in 2014, was recorded to be highest at 25 fatalities and 810 injuries respectively (*4*). On top of that, involvement of trucks in such-like collisions can further lead to more disastrous safety outcomes. This clearly demonstrates the urgency for careful investigation of the factors associated with head-on collisions and its implications on injury severities of drivers involved in head-on collisions. Furthermore, an important consideration in such analysis is to consider the fault status (as assigned by police officers) to one of the involved drivers and its implications on overall injury severity outcomes of head-on collisions.

Given the importance of head-one collisions, Phase 2 of this project focuses on investigating the degree of injury severity sustained by drivers involved in head-on collisions. Specifically, we are interested in how at-fault driver behavior and characteristics relate to injury outcomes of not-at-fault drivers. Due to unobserved factors, a methodological concern is the presence of potential correlations between injury outcomes of drivers involved in specific head-on collision. To address this concern, we present seemingly unrelated bivariate ordered response models by analyzing the joint injury severity probability distribution of at-fault and not-at-fault drivers. Moreover, the assumption of bivariate normality of residuals and the linear form of stochastic dependence implied by such models may be unduly restrictive. To test this, Archimedean copula structures and normal mixture marginals are integrated in the modeling framework. These can characterize complex forms of non-linear stochastic dependencies and non-normality of residuals in joint estimation framework. The models are calibrated using 2013 police reported two-vehicle head-on collision data from Virginia (N = 1,445), where at least one driver is at-fault. The results suggest that irrespective of fault status drivers involved in a crash are almost equally likely to receive the same levels of injuries-implying that there are a substantial number of fatal and severe injuries to not-at-fault drivers. Importantly, at-fault vehicle type (pick-up truck/van/SUV) is associated with smaller injury outcomes of at-fault driver, however, it is statistically significantly associated with higher injury outcomes of not-at-fault drivers. If the at-fault driver is fatigued, apparently asleep, or has been drinking the not-at-fault driver is more likely to sustain severe or fatal injury, given a crash. This is unsettling because the behavior of at-fault drivers can potentially result in severe injuries or loss of life of not-at-fault drivers. Implications of findings for safety countermeasure development are discussed.

2 INTRODUCTION

In this section, we briefly synthesize the research motivation pertaining to truck-passenger car collisions and two-vehicle head-on collisions. For ease of discussion, this chapter is divided into two sub sections.

2.1. PASSENGER VEHICLE-TRUCK COLLISIONS

The economic impacts and safety hazards resulting from truck involved crashes bring out freight transportation safety as a contemplative societal concern (*5; 6*). Large trucks (Gross Vehicle Weight > 10,000 pounds) account for around 7% of the total vehicle miles traveled (VMT), but large trucks are involved in about 11% of all traffic crash fatalities (*1*). In addition, truck involved collisions are often more disruptive (e.g. the damage of vehicle, roadway, and other traffic facilities) and costly (e.g. resulting in loss of life, use of emergency medical service (EMS), property damage, and traffic congestion)(*7*). From an injury severity perspective, in 2014, a total of 3600 people died in large truck involved crashes, out of which 16% were truck occupants and 68% were occupants of other vehicles (*2*).

While truck involved crashes can involve many vehicles (involving more than two vehicles), two-vehicle passenger vehicle-truck collisions often constitute the majority of total fatal crashes, and therefore are the focus in Phase 1. For instance, in 2014, two-thirds of all police-reported truck crashes involved a truck and another vehicle (*3*), and 63% of fatal large truck crashes involved two vehicles (*3*). Alarmingly, 97% of vehicle occupants killed in two-vehicle passenger vehicle-truck crashes were occupants of passenger vehicles (*2*). Another reason for focusing on two-vehicle passenger vehicle-truck crashes is the clarity in identifying the driver who acted unsafely. Despite the significant progress achieved in decreasing the national toll of truck involved fatalities, these statistics clearly demonstrate the urgency for careful investigation of the factors that are associated with injury severity outcomes in two-vehicle passenger vehicle-truck collisions.

Several studies have successfully disentangled the complex associations between key factors (such as driver age, gender, alcohol intake, and over-speeding) and most severe injury outcome in similar collisions, for example See (*8-11*). However, the under-researched issue is which unsafe driver behaviors (intentional vs unintentional improper actions of truck and passenger vehicle drivers) result in most severe injuries, given a crash? Relevant in this regard are the unsafe driving actions, which can substantially contribute to severe injury outcomes (*12-14*). In addition, due to several crash-, vehicle-, and driver-related unobserved factors, injury severity models often do not typically show high levels of goodness-of-fit to begin with; not accounting for unobserved heterogeneity can worsen the fit and adversely affect the policy implications of risk factors or countermeasures. Thus, the present study addresses the methodological concern of unobserved heterogeneity by capturing the complexities embedded in passenger vehicle-truck collision data. This is achieved by estimating fixed- and random-parameter ordered probit models.

2.2. TWO VEHILCE HEAD-ON COLLISIONS

From vehicle occupants' perspective, in 2014 out of the 32,675 transportation fatalities, 68% were incurred by drivers in the single and/or multivehicle crashes (*4*). From the manner of collision stand-point, head-on collisions accounted for 26% of all motor-vehicle involved fatal crashes (*4*). Head-on collisions refer to a collision where the front-end of one vehicle collides with the front-end of another vehicle while the two vehicles are traveling in opposite directions. These types of collisions are the most severe crashes in terms of injury severity outcomes. Fatality and injury rate per 1,000 crashes in 2014, recorded to be highest at 25 fatalities and 810 injuries respectively (*4*). On top of that, involvement of trucks in such-like collisions can further lead to more disastrous safety outcomes. This clearly demonstrates the need for careful investigation of the factors associated with head-on collisions and its implications on injury severities of drivers involved in head-on collisions. Furthermore, an important consideration in such analysis is to consider the fault status (as assigned by police officers) to one of the involved drivers and its implications on overall injury severity outcomes of head-on collisions. By using advanced statistical techniques, this project phase explicitly addresses this need by identifying broad range of factors contributing to injury severity of drivers involved in same head-on collision, an issue that has not been well-addressed in the literature researched. We present seemingly unrelated bivariate ordered response models by analyzing the joint injury severity probability distribution of at-fault and not-at-fault drivers. Moreover, the assumption of bivariate normality of residuals and the linear form of stochastic dependence implied by such models may be unduly restrictive. To test this, Archimedean copula structures and normal mixture marginals are integrated in the modeling framework. These can characterize complex forms of non-linear stochastic dependencies and non-normality of residuals in joint estimation framework.

3 LITERATURE REVIEW AND OBJECTIVE

3.1 LITERATURE REVIEW

Given the considerable costs truck involved collisions and severe head on collisions impose on the society, several researchers have investigated such collisions and the key factors that may be associated with injury outcomes. Thus, we first synthesize the previous studies with specific focus on methodological approaches that are used for establishing associations between different crash characteristics, unsafe pre-crash behaviors, and injury outcomes in passenger vehicle-truck collisions. Then, we synthesize the related research about driver's fault status and its impact on drivers' injury severity outcomes, as well as the methodology of jointly modeling injury severity of drivers involved in head-on collisions.

A broad spectrum of studies investigated the associations between several factors such as collision types, roadway types, vehicle types, and injury outcomes in passenger vehicle-truck collisions (*7; 15-19*). For instance, hit-objects, broadside collisions, rear-end collisions, and right/left turn crash types were found associated with higher injury severity outcomes (*7; 15; 16*). From the perspective of striking and struck vehicle, Duncan et al (*7*) concluded higher likelihood of severe injuries to passenger car occupants if struck by a truck (*7*). From roadway types, studies by Lemp et al. (*18*) and Khattak et al. (*17*) concluded higher likelihood of severe injury outcomes on curved sections and roadway sags (*17; 18*). Regarding vehicle and driver related factors, Chang and Mannering (*16*) and Christoforou et al. (*19*) found that greater number of occupants in a vehicle (or weighted vehicles) are associated with higher injury outcomes (*16; 19*). Likewise, females, older people, and non-use of seat belts were found associated with higher injury outcomes (*7; 18; 20*). Driver condition related factors such as fatigue or falling asleep, driving under influence, and physical or mental impairment are also documented to be associated with higher possibility of injury severity (*21-23*).

The role of driver actions in truck-involved crashes has also received considerable attention (*7; 16; 17; 20; 24*). Council et al. (*25*) investigated motor vehicle driver's unsafe driving acts (UDAs) that resulted (or contributed to) in passenger vehicle-truck crashes. The study concluded that most frequent unsafe behaviors were driving inattentively, improper merge, fail to stop or slow, and following too close (*25*). Likewise, several studies concluded speeding as the riskiest driving behavior in truck involved collisions (*7; 16; 17; 20*).

The afore-mentioned studies did not focus primarily on investigating a broad range of unsafe pre-crash driving behaviors, intentional and unintentional improper actions of either truck driver or passenger vehicle driver, and the implications on most severe injury outcomes of passenger vehicle-truck collisions. An explicit investigation of driver's unsafe pre-crash actions can help in developing actionable safety improvement strategies for passenger vehicle-truck collisions. Furthermore, due to the complex crash data structure and different unobserved crash, vehicle, and driver related factors, the associations between key driving behaviors and injury outcomes may vary significantly across different crashes. Ignoring the possibility of varying associations between key explanatory factors and injury outcomes can mask important information embedded in passenger vehicle-truck crash data (*26*). Note that while the study by Islam and Salvador (*20*) addresses unobserved heterogeneity in passenger vehicle-truck collisions by using a unique national level database, the study did not focus explicitly on investigating intentional and unintentional pre-crash behaviors and its associations with most severe injury outcomes in such collisions, which are studied in Phase 1 of this project.

In terms of driver's fault and its influence on injury severity outcomes, traffic safety literature includes some studies that explicitly assessed fault status and its impact on injury severity, albeit concluding mixed results (*27-30*). For instance, at-fault drivers at signalized intersection (irrespective of manner of collision) related crashes were observed to experience less severe injuries (*27*), as opposed to another study that concluded at-fault drivers are more likely to sustain severe injuries in similar situations (*28*). However, the study by Abdel-Aty (*27*) noted that the driver at fault may typically be the driver of the striking vehicle and that the driver of the struck vehicle can experience higher level of injuries. On the other hand, Savolainen and Mannering (*29*) concluded that at-fault motorcyclists are more likely to incur fatal injuries. Interestingly, young at-fault drivers were less likely to experience injuries in collisions (*30*) as opposed to older at-fault drivers who were more likely to be injured via own at-fault collisions (*31*). Zhang et al (*32*) conceptualized human, vehicle, road, and country-specific risk factors associated with pedestrian-motor vehicle accidents and concluded severe-injury odd-ratio of 1.565 for at-fault pedestrians in such crashes (*32*). While all of these studies provided valuable insights into understanding the associated factors, the results of afore-mentioned studies cannot be generalized to head on collisions and specifically to injury severities sustained by drivers with respect to fault designation involved in the same head on crash.

On the other end, few studies have considered simultaneous modeling of injury severities that are incurred by occupants involved in the same crash (*33*-*36*). For instance, Eluru et al. (*33*) simultaneously modeled injury severities sustained by multiple occupants of vehicles involved in the same crash. Likewise, by considering collision type as an explanatory factor in addition to other factors, Rana et al. (*34*) jointly modeled injury severity of two drivers involved in two-vehicle crashes through formulation of rigorous copula-based framework. Both of the studies advocated the case for jointly modeling injury severity levels associated with a specific crash. Furthermore, the studies highlighted implications of bivariate normality assumption, underlying the joint estimation of injury severities. However, the afore-mentioned studies did not explicitly investigate head on collisions or the associations of covariates on resulting injury severities with respect to fault status.

Rather than treating collision types as explanatory factors, few studies explicitly considered joint estimation of injury severities with respect to specific collision type. For instance, Yamamoto and Shankar (*35*) simultaneously analyzed driver's injury and most severely injured passenger's severities in collisions with fixed objects. The study reported significant positive correlations between error terms of driver and most severely injured passenger injury severities (*35*). In special relevance to our work, Russo et al. (*36*) devised a rigorous methodology for investigating factors affecting the degree of injury sustained by drivers involved in angle collisions at intersections. They concluded that, within a crash, not-at-fault drivers are generally more likely to be severely injured than at-fault counterparts (*36*). In agreement to the finding by Yamamoto and Shankar(*35*), Russo et al. (*36*) concluded that injury severity outcomes are correlated for drivers involved in the same crash, and that impacts of explanatory variables may be under- or over-estimated if such correlation is not considered explicitly (*36*). However, both of the above studies (*35*) and (*36*) assumed bivariate normal distribution of injury severity residuals terms. While studies in the literature (*36*) provide valuable insights into understanding of factors associated with drivers' injury severities involved in angle collisions, these results cannot be generalized to head on collisions.

Based upon literature synthesis, the need to examine the factors associated with driver injury severities in head on collisions in phase 2 by utilizing a simultaneous framework is evident. While this is done, consideration of contributing fault status provides deeper insights into better understanding the factors that are associated with injury outcomes. Furthermore, investigation of potential differences in injury outcomes of involved drivers in head on collision clearly warrants examination, given the highest fatality rates (*4*).

3.2 RESEARCH OBJECTIVE AND CONTRIBUTION

This report documents research activities focusing on five key objectives:

1. To quantify the associations of unsafe driving behaviors (specifically intentional and unintentional actions of truck and passenger vehicle drivers) with injury severity outcomes in passenger vehicle-truck collisions. (Phase 1)
2. To explore unobserved heterogeneity in associations of injury severity with unsafe pre-crash behaviors, while controlling for driver, vehicle, and roadway factors. (Phase 1)
3. Simultaneously investigate the degree of injury severities sustained by individual drivers involved in head on collisions. (Phase 2)
4. Distinguish the differential associations of correlates on resulting injury severities of two drivers with respect to fault status designation in head on collisions. (Phase 2)
5. Disentangle the anticipated non-normality of joint error distributions and unveil the complex forms of stochastic dependencies between the residuals. (Phase 2)

An explicit investigation of drivers' unsafe pre-crash actions in Phase 1 is likely to allow us developing actionable safety improvement strategies. In order to achieve the objectives, sophisticated fixed- and random-parameter ordered probit models are estimated by using real-world police reported crashes that allow unearthing embedded important relationships in crash data. The content is original and timely given the enormous costs sustained by society in consequence to passenger vehicle-truck collisions, and the implications of such collisions on occupants of passenger vehicles.

Phase 2 will allow us to understand the associations of driving behavior and fault status with injury severities sustained by drivers in head-on collisions. Given that such collisions are highly injurious; it is important to unmask important relationships embedded in the data when analyzing injury severity of drivers involved in same collision. The application of new copula-based modeling techniques in this phase is also both timely and original. In addition to the contribution in terms of new findings, the study methodologically contributes by integrating normal mixture marginals and copula structures in a standard bivariate ordered response-modeling framework. To the best of our knowledge, such methods have not been used extensively in the context of transportation safety, e.g., analysis of head on collisions.

4 PHASE1-INJURY SEVERITY ANALYSIS OF PASSENGER VEHICLE-TRUCK COLLISIONS AND CONTRIBUTORY UNSAFE PRE-CRASH BEHAVIORS

4.1 METHODOLOGY

4.1.1 Data Source

This phase used data from 2013 Virginia Police Crash Reports obtained for Virginia Department of Transportation. The database is comprehensive and well-organized containing records of crashes occurring across Virginia. For this study, three files are extracted from the database and are linked together in order to obtain several crash, vehicle, and person level information involved in passenger vehicle-truck collisions. Specifically, the crash file contains information on variables describing the crash, crash time, roadway characteristics, and collision type; the vehicle file contains information on vehicles such as vehicle body type, and the person file contains information on occupants (including driver) such as age and gender, level of injury sustained, and other driver related factors. All three files are linked together through a unique crash identification number. Figure 4.1 presents the data structure and conceptual framework. Note that passenger vehicles in this study include passenger car, pick-up truck, van, and sports utility vehicles (SUV).

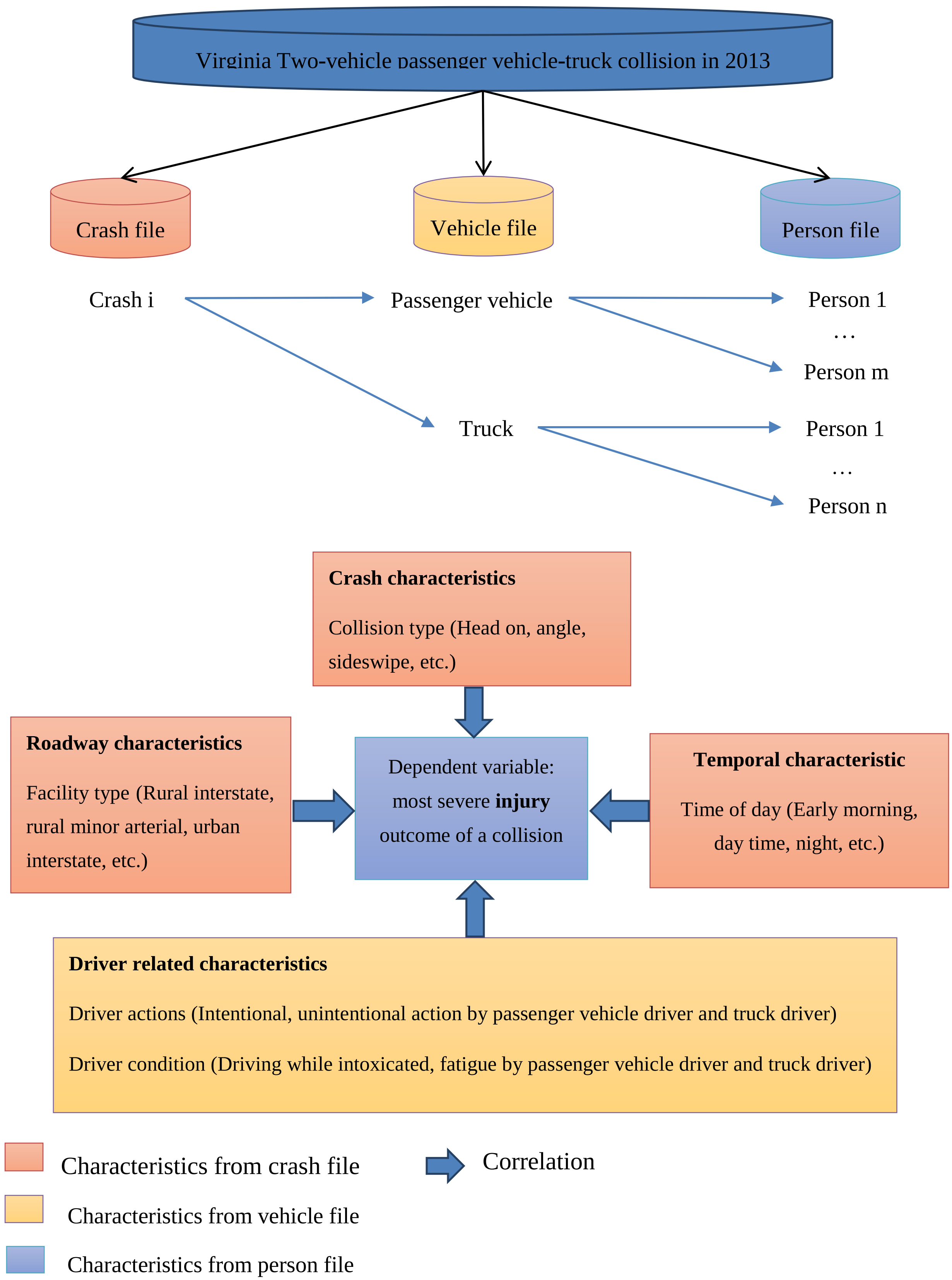

FIGURE 4.1 Data structure and conceptual framework

Specifically, among 121,601 crashes documented in the database, 7,501 are truck-involved crashes, and 4,926 crashes are two-vehicle passenger vehicle-truck crashes. Given the focus of this study (as explained earlier), two-vehicle passenger vehicle-truck collisions are extracted (i.e., 4926), which accounts for significant 66% of the total truck involved collisions. Given the national average of 63%, the sample size at hand is reasonably representative.

To better analyze the associations of drivers' actions with most severe injury outcome, the cases in which only one driver (either passenger vehicle or truck) undertook an improper action are selected. From collision type perspective, as the present study focuses on two-vehicle passenger vehicle-truck collisions, collision types such as non-collision, fixed object, collisions with train, motorcyclist, and animals are ignored. Finally, after data processing and cleaning, the resulting sample size contains 3,924 passenger vehicle-truck collisions such as rear end, angle, head on, and sideswipe same and opposite directions.

In terms of injury severity, this study regarded the most severe injury among all the occupants in both vehicles in a collision as the injury severity level of the crash. As reported in police crash report forms, four levels of injury severity are observed: killed, serious injury, minor injury, and non-injury (property damage only). But due to the limited number of crashes with fatalities, the injury severity scale is categorized into fatal/serious injury, minor injury, and no injury. Several studies in past have re-categorized injury severity scales due to limited cases with fatalities, see (*36*). Figure 4.2 summarizes the distribution of most severe injury severity outcome in sampled collisions while Table 4-2 presents the descriptive statistics of key variables analyzed.

Finally, to analyze the associations between unintentional and intentional driver actions (either truck driver or passenger vehicle driver), the driver actions (42 types of driver actions see Table 4-1) reported in VDOT police crash report forms are classified into four categories as:

1. Action 1: Passenger vehicle driver undertook no improper action while truck driver undertook an intentional improper action.
2. Action 2: Passenger vehicle driver undertook no improper action while truck driver undertook unintentional improper action.
3. Action 3: Passenger vehicle driver undertook intentional improper action while truck driver undertook no improper action.
4. Action 4: Passenger vehicle driver undertook unintentional improper action while truck driver undertook no improper action.

TABLE 4-1 Categories of Driver Action

Driver action	Description	
Intentional action	Speeding	Exceeded speed limit Exceeded safe speed
	Wrong place, no right-of-	Wrong side of road- not overtaking

	way	Did not have right-of-way Drive through work zone
	Following too close	Following too close
	Improper turn, lane change and passing	Improper turn- wide right turn Improper turn- cut corner on left turn Improper turn from wrong lane Other improper turn Improper passing Improper or unsafe lane change
	Disregarding officers, signals, and signs	Disregarded officer or flagger Disregarded traffic signal Disregarded stop or yield sign
Unintentional action	Avoiding objects	Avoiding pedestrian Avoiding other vehicle Avoiding animal Avoiding object in roadway
	Failing to maintain proper control	Fail to maintain proper control
	Other improper action	Driver distraction Overtaking on hill Overtaking on curve Overtaking at intersection Improper passing of school bus Cutting in Other improper passing Fail to signal or improper signal Improper backing Improper start from parked position Fail to stop at through high way- no sign Fail to set out flares or flags Fail to dim headlights Driving without lights Improper parking location Crowded off highway Hit and run Car ran away- no driver Blinded by headlights Other Eluding police Over correction

Note that the classification scheme adopted in this study is consistent with the Liu et al. (*37*), who investigated pre-crash driver actions in work zones. For convenience, the four categories of unsafe pre-crash driver actions will be referred to Actions 1 to 4 hereafter.

4.1.2 Modeling Framework

An ordered probit modeling framework is used in this study due to the ordinal nature of response outcome (*17*). The model can be defined in terms of ordinal dependent variable Y^* as:

$$Y^* = \beta X + \delta \tag{4.1}$$

Where, Y is a dependent variable (in our case most severe injury outcome of a collision); β is a vector of estimated parameters; X is a vector of explanatory variable (driver action, collision type, collision time, and etc.); δ is error term, assuming it is normal distributed. Based on ordered probit model with normal residual distribution and from equation (4.1), the dependent variable Y^* can be formulated as below:

$$y = n \text{ if } \quad \gamma_{n-1} \le y^* < \gamma_n \tag{4.2}$$

Where, γ_n is estimated parameters that define the observed ordinal data y ; y is related to the latent variable y^*, through the estimated parameter γ_n, The probability of ordered probit model as follows:

$$P(y = n) = \emptyset(\gamma_n - \beta X) - \emptyset(\gamma_{n-1} - \beta X) \tag{4.3}$$

Where, $\emptyset(.)$ is a function of normal cumulative distribution.

Note that the above framework implies an unduly restrictive assumption of constant parameter effects across sampled observations. For instance, one coefficient is estimated for each explanatory factor at times when the associations between explanatory factors and injury severity may vary across sampled observations due to presence of several observed and unobserved factors (*36*). In the presence of such observed and unobserved factors (which are likely to be present in crash data), constraining the model coefficients to be fixed across observations can result in biased parameter estimates, as shown in various studies (*26; 38*). Therefore, random parameters can be incorporated in the estimation procedures through simulated maximum likelihood estimation techniques as:

$$\beta_i = \beta + \vartheta_i \tag{4.4}$$

Where, β' is the impact of changes in X. $\emptyset(.)$ is a function of standard normal distribution (*36; 39*). In this study, the random-parameter ordered probit model is estimated by simulated maximum likelihood estimation, and by using 200 Halton draws as recommended by other studies (*38*). For random parameters, we tested different distributions such as lognormal, triangular, Weibull, and normal distributions (discussed later).

Finally, after model estimation, the signs of parameter estimates are of importance, a positive sign shows an increase in probability of the most severe outcome and decrease in probability of least severe outcome, and vice versa for negative parameter estimates (*26*). However, the coefficients can be used to interpret the effects of explanatory factors on intermediate categories (*17*). As such marginal effects for sample means are estimated both for fixed and random-parameter ordered probit models as:

$$\frac{\partial P(y=n)}{\partial X} = -[\emptyset(\gamma_n - \beta X) - \emptyset(\gamma_{n-1} - \beta X)]\beta' \tag{4.5}$$

Where, β' is the impact of changes in X. $\emptyset(.)$ is a function of standard normal distribution.

4.2 RESULTS

4.2.1 Descriptive Statistics

The present study analyzes 3,924 passenger vehicle-truck crashes, which involve 7,848 vehicles and 8,181 individuals. Figure 4.2 shows the distributions of most severe injury outcomes of the overall collision (green bars), most severe injury outcomes of passenger vehicle (red bars), and most severe injury outcomes of truck (orange bars). The distributions provide important information embedded in the data. For instance, from an overall collision perspective, 5.9%, 15%, and 80% of the most severe injuries were serious/fatal, minor/possible, and no apparent/no injury, respectively. Importantly, the stratification of most severe injury outcomes on basis of passenger vehicle and truck reveals that, compared to truck occupants, passenger vehicle occupants are six times more likely to sustain minor/possible (14% vs 2.3%) and 10 times more likely to receive serious/fatal injuries (5.5% vs 0.5%). These findings are in agreement with several past studies, and confirm the reasonableness of the data (*7; 23; 40; 41*).

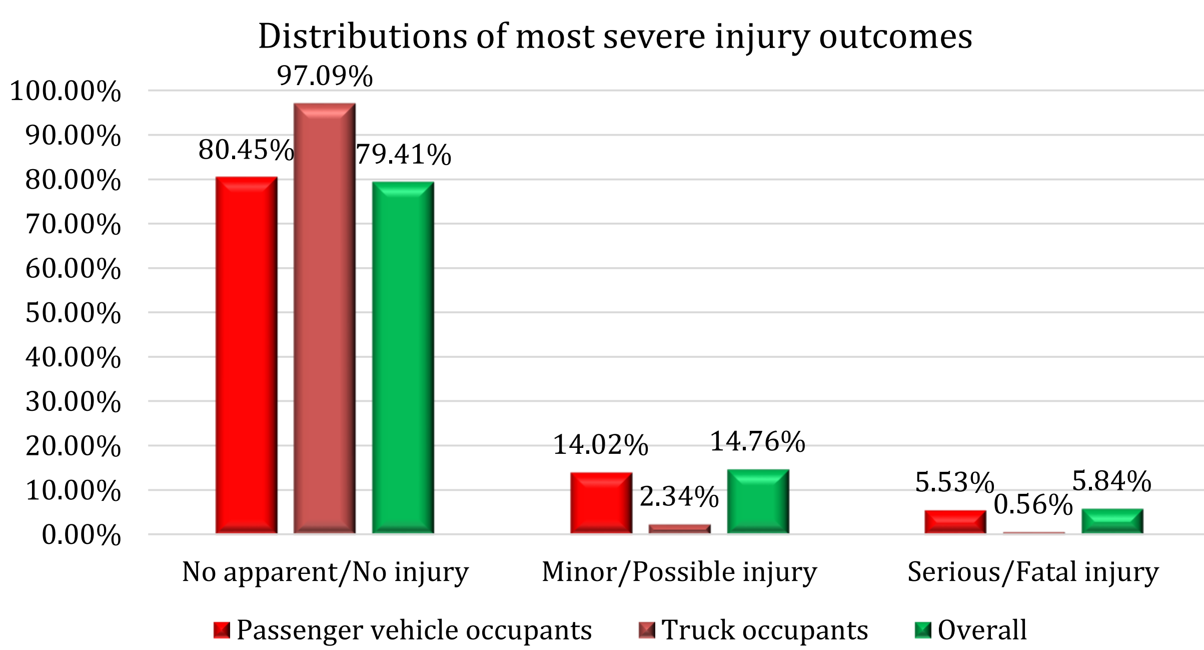

FIGURE 4.2 Most severe injury severity distributions in passenger vehicle-truck involved collisions

Regarding the key explanatory variables, Table 4-2 presents descriptive statistics of variables included in the fixed- and random-parameter ordered probit model. Table 4-2 displays the mean, standard deviation (SD), and the variance inflation factors (VIFs) value for each indicator variable. Due to several identified and unidentified interactions among key factors in crash data, multi-collinearity can arise and can affect model results significantly if not addressed carefully. Existence of multicollinearity among independent variables was checked by VIFs. As shown in Table 4-2, the VIF value of each variable is much smaller than 10, which indicates absence of significant multi-collinearity (*42*).

TABLE 4-2 Descriptive Statistics of Key Variables

Variable	Description	Mean	SD	VIF
Driver actions				
Action 1 indicator	1 if passenger vehicle driver undertook no improper action while truck driver undertook intentional improper action, 0 otherwise	0.355	0.478	1.316
Action 2 indicator	1 if passenger vehicle driver undertook no improper action while truck driver undertook unintentional improper action, 0 otherwise	0.106	0.308	1.129
Action 3 indicator	1 if passenger vehicle driver undertook intentional improper action while truck driver undertook no improper action, 0 otherwise	0.382	0.485	1.353
Action 4 indicator	1 if passenger vehicle driver undertook unintentional improper action while truck driver undertook no improper action, 0 otherwise	0.155	0.362	1.381
Collision type				
Head on indicator	1 if collision type is head on, 0 otherwise	0.017	0.13	1.042
Angle indicator	1 If collision type is angle, 0 otherwise	0.295	0.453	1.086
Injury Count	Total number of injuries in a collision	0.383	0.71	1.036
Roadway Type				
Rural interstate	1 if roadway type is rural interstate, 0 otherwise	0.147	0.354	1.184
Rural principal arterial	1 if roadway type is rural principal arterial, 0 otherwise	0.075	0.264	1.095
Rural minor arterial	1 if roadway type is rural minor arterial, 0 otherwise	0.049	0.216	1.065
Urban interstate	1 if roadway type is urban interstate, 0 otherwise	0.285	0.451	1.259
Driver condition				
Drink driving indicator	1 if passenger vehicle driver is drunk, 0 otherwise	0.021	0.146	1.029
Fatigue indicator	1 if passenger vehicle driver is fatigued or asleep, 0 otherwise	0.019	0.138	1.06
Demographics				
Age indicator	1 if passenger vehicle driver is 20-29 years old, 0 otherwise	0.24	0.427	1.018
Gender indicator	1 if passenger vehicle driver is female, 0 otherwise	0.086	0.281	1.027
Time of Day				

Night/morning indicator	1 if crash happened between 1 am and 8 am, 0 otherwise	0.213	0.41	1.007

Notes: Intentional actions refer to actions including speeding, wrong places, no right-of-way, following too close, improper turn, lane change and passing, and disregarding officers, signals, and signs. Unintentional actions refer to actions including avoiding objects, failing to maintain proper control, and other improper actions.

Based upon the descriptive statistics, the data seem to be of reasonable quality. In 36% of the collisions, passenger vehicle driver undertook no improper action while truck driver undertook intentional improper action (action 1), as opposed to 38% of collisions in which passenger vehicle driver undertook intentional improper action and truck driver undertook no improper action (action 2). Almost 30% of passenger vehicle-truck collisions were angle collisions, whereas the average total number of injuries involved in all collisions is 0.383 (Table 4-2). Approximately, 21% of passenger vehicle-truck collisions occurred between 1 AM – 8 AM.

4.2.2 Modeling Results

Explanatory variables are identified by developing simple correlation matrices of key factors with injury severity of the most severely injured person in passenger vehicle-truck collisions. This helped in identifying potential factors related to driver actions, collision types, roadway types, driver conditions, demographics, and temporal characteristics, which should be controlled for. Next, a series of fixed-parameter ordered probit models are estimated for the most severely injured person in collision, and all variables that were either statistically significant at 95% confidence level or theoretically important were retained for subsequent analyses. The results of the final fixed-parameter ordered probit model are presented in Table 4-3. Theoretically, fixed-parameter models constrain the parameter estimates (for explanatory variables) to be fixed across the entire sample (*26*), in our case passenger vehicle-truck collisions. Given the fact that several observed and unobserved factors can contribute to injury severity outcomes in such collisions, random-parameters are incorporated in conventional (fixed-parameter) ordered probit framework. Conceptually, random-parameter models provide the flexibility to allow the parameter estimates to vary across a sample observations with some pre-specified distribution (*38*). The results of random-parameter ordered probit model are presented in Table 4-3. The final random-parameter model includes 15 correlates of which 4 parameters exhibited statistically significant variability (as indicated by the standard deviation of parameter estimates) across the sampled collisions (Table 4-3). However, none of the 4 are related to unsafe driving behavior variables. Note that the variability exhibited by random parameters tends to be larger, indicating significant heterogeneity in the associations of these variables on injury outcomes. Moreover, Table 4-3 provides additional details for random-parameter model by giving percentage of passenger vehicle-truck collisions who exhibited parameter estimates above or below zero. These results suggest that the associations between some explanatory factors and injury outcomes may vary across sampled collisions, with positive parameter estimates for some collisions and negative for other collisions (see Table 4-3).

Note that random-effects ordered probit models were also estimated but did not result in significant improvement in model fit compared to random- parameter models.

TABLE 4-3 Modeling Results for Fixed and Random Parameter Ordered Probit Models

	Fixed Parameters		Random Parameters		Percent Observations	
Variable	□	t-stats	□	t-stats	Above 0	Below 0
Driver actions						
Action 1 indicator (Base)						
Action 2 indicator	-0.127	-1.134	-0.135	-1.612	---	---
Action 3 indicator	0.207	1.812	0.226	2.957	---	---
Action 4 indicator	0.28	1.212	0.329	3.496	---	---
Collision type						
Headon indicator	0.786	4.265	0.76	3.819	91.34%	8.66%
standard deviation	---	---	0.588	2.99		
Angle indicator	0.186	2.825	0.184	2.675	---	---
Injury Count	1.35	35.365	1.508	40.36	---	---
Roadway Type						
Rural interstate	0.353	3.948	0.375	3.977	---	---
Rural principal arterial	0.431	0.951	0.191	1.951	57.31%	42.69%
standard deviation	---	---	1.036	10.817		
Rural minor arterial	0.572	4.733	0.302	2.177	59.89%	40.11%
standard deviation	---	---	1.206	9.833		
Urban interstate	0.308	4.04	0.344	4.1	---	---
Driver condition						
Drinking & driving indicator	0.581	3.624	0.657	3.99	---	---
Fatigue indicator (pass. veh driver)	0.298	1.327	0.342	1.74	---	---
Demographics						
Age indicator	-0.149	-2.119	-0.255	-3.4	28.80%	71.12%
standard deviation	---	---	0.458	7.084		
Gender passenger vehicle driver indicator	0.273	2.736	0.273	2.489	---	---
Time of Day						
Early indicator	0.168	2.451	0.192	2.649	---	---
□ $\mu_{(1)}$	-2.065	-25.146	-2.192	-22.18		
□ $\mu_{(2)}$	1.354	25.283	1.503	28.177		
Number of observations	3274		3274			
Log-likelihood with constant only	-2104.44		-2104.44			
Log-likelihood at convergence	-1272.55		-1255.76			
Likelihood Ration Test	Chi-square = 33.58; p-value < 0.005					

Notes: □$_{(1)}$ and □$_{(2)}$ represent estimable threshold parameters that define the most severe injury outcomes of passenger vehicle-truck collisions.

Table 4-3 shows that incorporation of random-parameters resulted in overall improvement of fit compared to the fixed-parameter model. Moreover, following (*43*), a chi-square likelihood ratio test is conducted to investigate the statistical superiority of random-parameter ordered probit model against its fixed counterpart. The likelihood ratio test statistic is LR= $-2[LL(\beta_a) - LL(\beta_b)]$ where $LL(\beta_a)$ is the log-likelihood at convergence of fixed-parameter (restricted ordered probit) model, while $LL(\beta_b)$ is the log-likelihood at convergence of random-parameter (unrestricted ordered probit) model. The test statistic is χ^2 distributed with certain degrees of freedom i.e. difference in numbers of parameters between fixed-and random-parameter model. With 4 degree of freedom (i.e. four random parameters), the resulting χ^2 value is 33.58 (Table 4-3), which is greater than critical $\chi^2_{0.005,4}$ (99.5% level of confidence) of 14.860. Resultantly, at a 99.5% level of confidence, it can be concluded that random-parameter ordered probit model provides statistically superior results against the fixed-parameter ordered probit counterpart (*43*). Regarding functional form of random-parameters, normal, lognormal, and uniform distributions are tested (results not presented). However, all normally distributed random parameters provided better fit once they were assumed to be normally distributed. This finding is in agreement with traffic safety literature, see (*36; 38*).

Finally, as discussed in Khattak and Rocha (*44*) and Abdel-Aty (*27*), in order to interpret the associations between explanatory factors and intermediate response category (minor injury), marginal effects are provided for fixed- and random-parameter models in Table 4-4.

4.2.3 Discussion

In order to facilitate discussion of estimated models, the explanatory factors (Table 4-2) are categorized as: driver actions, collision types, roadway types, driver-related factors, and time of day.

Driver Actions

Regarding driver actions (Table 4-3), action 2 indicator, action 3 indicator, and action 4 indicator reveals important associations between driver actions (both truck and passenger vehicle driver) and injury outcomes. Action 1 indicator (if passenger vehicle driver undertook no improper action while truck driver undertook intentional improper action) is used as the base category. All unsafe driver actions were statistically insignificant (at 95% level of confidence) in the fixed- parameter model. From the random-parameter model, it can be seen that intentional improper action of passenger vehicle driver (action 3 indicator) as well as unintentional improper action of passenger vehicle driver (action 4 indicator) are both associated with higher injury outcomes. From a behavioral perspective, this finding is important in the sense that it highlights the higher propensity of receiving severe injuries, given a crash, irrespective of passenger vehicle driver undertaking intentional or unintentional improper actions. Similar insights were observed in (*20*), however, that study focused on maneuvers and not explicitly on intentional and unintentional actions (*20*). The action 2 indicator (passenger vehicle driver with no improper action and truck driver with unintentional improper action) is not statistically significant. Despite the fact that all unsafe driver actions are found to be fixed-parameters, the incorporation of random-parameters in ordered probit framework significantly enhanced the statistical significance of estimated parameters.

Driver Related Factors and Time of Day

Interestingly, if the passenger vehicle driver is fatigued or asleep in a collision, the injury severity is higher. While the parameter estimates for this variable are found to be fixed, the marginal effects obtained from fixed- and random-parameter models reveal differences. The average marginal effects for fatigue (Table 4-4) shows if the passenger vehicle driver is fatigued, then there is a 0.0786 decrease in the probability of having no apparent/no injury, a 0.073 increase in the probability of having minor injury, and a 0.0054 increase in probability of having serious/fatal injury, all for the most severely injured occupant in a passenger vehicle-truck collision. Notably, truck driver fatigue did not have a statistically significant association with injury severity. This result is interesting when coupled with the result that passenger vehicle-truck collisions at night and early morning hours (between 1 AM and 8 AM) are more injurious, perhaps capturing drivers' drowsiness. The marginal effects in Table 4-4 show that compared to other times of day, a collision that occurs during these times has a 3.7% higher chance of minor injury to occupants, and 0.2% increase in chance of receiving serious/fatal injuries. Note that drinking and driving is associated with more severe injury outcomes.

In terms of driver demographics, passenger vehicle drivers aged 20-29 years are negatively associated with injury outcomes. This finding is in agreement with Khattak and Rocha (*44*) and Kockelman and Kweon (*45*). However, we found that the age indicator is a normally distributed random-parameter with mean of -0.255 and standard deviation of 0.458, suggesting that for 28.8% of the collisions, passenger vehicle drivers aged 20-29 years are in fact positively associated with severe injuries. Contrarily, if the passenger vehicle driver is female (gender indicator), it is more likely that the most severe injured person may sustain high level of injuries. This finding is in agreement with (*7*), and potentially due to physiological differences, women may be more likely to sustain more injuries than men, especially if the passenger vehicle has only female drivers and no occupants. Note that, driver conditions and demographics of truck drivers were also tested but none of the variables were found to be statistically significant, and the results are not presented.

Roadway Types

Rural interstates, rural principal arterials, rural minor arterials, and urban interstates are all expected to be positively associated with more severe injury outcomes. Rural interstates seem to be associated with more severe crashes, compared with other roadway types.

Notably, rural principal arterials and rural minor arterials both resulted in random-parameters. With a mean of 0.191 and standard deviation of 1.036 (Table 4-3), rural principal arterials resulted in a normally distributed random-parameter, suggesting that the association between most severe injury outcomes and rural principal arterials is positive for 57.3% and negative for 42.7% of the collisions. Likewise, significant heterogeneity is observed in associations between rural minor arterial and most severe injury outcomes (Table 4-3). Moreover, the marginal effects obtained from the fixed- and random-parameter models have significant differences, especially for the extreme injury outcomes (Table 4-4). For collisions on rural interstate, the chances of serious/fatal injury increase by 0.9% (in the fixed parameter model) as opposed to 0.5% increase in the random parameter model.

Collision Types

Out of all collision-type related factors, head on and angle collisions (head on indicator and angle indicator) are found to be statistically associated with most severe injury outcomes in passenger vehicle-truck collisions. Numerous studies have found positive associations between collision types (head on and angle) and injury outcomes, for summary of different studies see Mannering and Bhat (*26*). However, from the passenger vehicle-truck collision perspective, the injury outcomes may be more severe potentially due to larger physical momentum of colliding trucks (*7*). As such, our results suggest that both head on and angle collisions are associated with larger propensity of severe injury outcomes. Both of these findings are in agreement with Khattak and Targa (*40*) who investigated injury severity and total harm in truck-involved work zone crashes (*40*). However, the present study suggests that head on indicator is found to be normally distributed random-parameter, suggesting positive association for 91.3% of the collisions and negative association for 8.66% of the collisions (Table 4-4). This heterogeneity may be due to several unobserved factors that are not known to the analyst from the data at hand. Likewise, larger numbers of injuries are also associated with higher propensity of most severe injury outcomes.

TABLE 4-4 Marginal Effects (Fixed and Random Parameter Ordered Probit Models)

	Fixed Parameter Model			**Random Parameter Model**		
Variables	No apparent/No injury	Minor injury	Serious/Fatal injury	No apparent/No injury	Minor injury	Serious/Fatal injury
Driver actions						
Action 2 indicator	0.0254	-0.023	-0.0021	0.0242	-0.023	-0.001
Action 3 indicator	-0.045	0.041	0.0041	-0.0446	0.042	0.0024
Action 4 indicator	-0.066	0.059	0.0066	-0.0717	0.067	0.0045
Collision type						
Head on indicator	-0.2348	0.197	0.0375	-0.21	0.189	0.0211
Angle indicator	-0.0412	0.037	0.0038	-0.0368	0.035	0.002
Injury Count	-0.2857	0.261	0.0248	-0.2873	0.272	0.0149

Roadway Type						
Rural interstate	-0.0854	0.076	0.009	-0.0834	0.078	0.0054
Rural principal arterial	-0.1101	0.097	0.0127	-0.0401	0.038	0.0024
Rural minor arterial	-0.1562	0.136	0.0204	-0.0674	0.063	0.0044
Urban interstate	-0.0701	0.063	0.0068	-0.0716	0.067	0.0043
Driver condition						
Drinking & driving indicator	-0.1613	0.14	0.0216	-0.1742	0.158	0.0158
Fatigue indicator	-0.0734	0.066	0.0079	-0.0786	0.073	0.0054
Demographics						
Age indicator	0.0302	-0.028	-0.0025	0.0448	-0.043	-0.0021
Gender passenger vehicle driver indicator	-0.0654	0.059	0.0067	-0.0594	0.056	0.0037
Time of Day						
Early indicator	-0.0377	0.034	0.0035	-0.0392	0.037	0.0022

5 PHASE 2- CONTRIBUTORY FAULT AND LEVEL OF PERSONAL INJURY TO DRIVERS

5.1 METHODOLOGY

5.1.1 Conceptual Framework

Figure 5.1 conceptualizes the key relationships in this study. By utilizing the police designated fault status assigned to one of the involved drivers, the current study characterizes injury severities of two drivers involved in the same head on collision with respect to fault status. This distinction is undertaken so that the associated correlates of injury severities are distinguished with respect to at-fault and not-at-fault status. Shown in Figure 5.1 are several important factors are considered and their associations with injury severities quantified. Furthermore, we posit that the injury outcomes of drivers involved in the same head on crash may be correlated due to the presence of several observed and/or unobserved factors. However, one of the typical approaches in such analysis is the typical assumption of bivariate standard normal error distributions. Nonetheless, joint normality as of bivariate standard normal error distribution may not always exist (*34; 46*). Also, the linear form of stochastic dependence which may be implied by bivariate normality may be restrictive (*47; 48*); as it is likely that the nature and degree of stochastic dependence (linear vs. non-linear) may vary across different head on collisions. Thus, we utilize a generalized bivariate ordered response modeling framework in seemingly unrelated specification by estimating the joint probability distribution of two ordered categorical variables i.e. injury severity of both drivers. Towards this end, in addition to estimating standard bivariate ordered probit models, we utilize rigorous statistical techniques to specify more flexible specification of bivariate ordinal model by using mixtures to allow for non-normality of joint error distribution (*49*) and several parametric copula structures (*48*) to unveil complex forms of stochastic dependencies (explained later in detail).

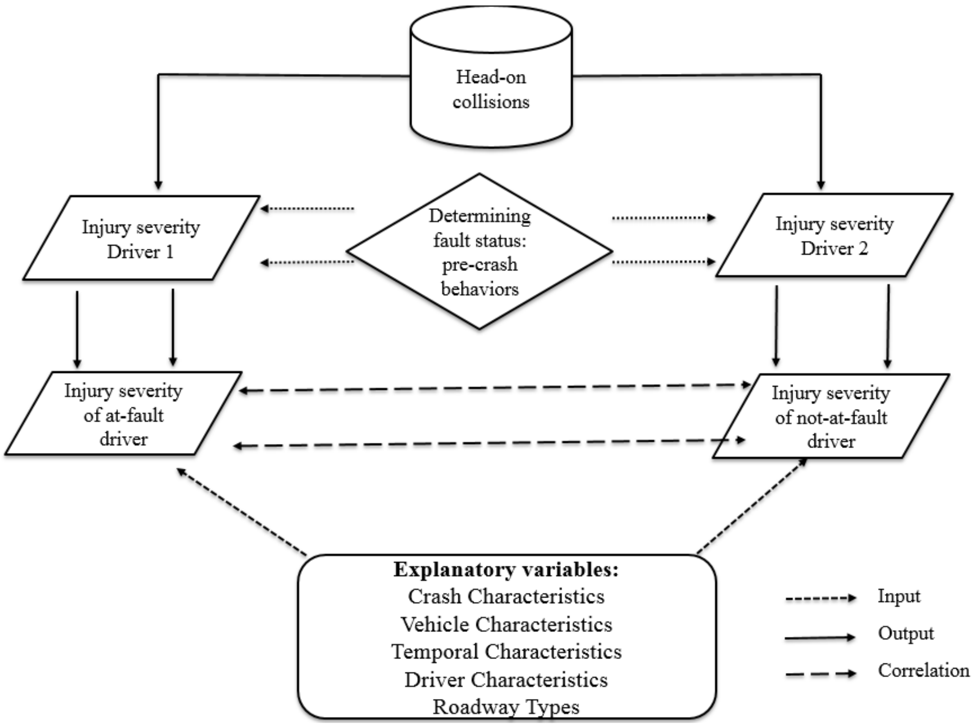

FIGURE 5.1 Study framework

5.1.2 Generalized Bivariate Ordered Probit Models (Copula Functions and Normal Mixture Marginals)

The general estimation framework for seemingly unrelated bivariate ordinal regression is presented, followed by a discussion of normal mixture marginals concept and copula methodology utilized in this study

Estimation Framework

For derivation of the likelihood function for bivariate ordered probit model with copula specification, let q_d be an index to represent two drivers ($d = 1\, for\, a\square - fault\, driver, 2\, for\, not - at - fault\, driver$) involved in head on collision and let l_d represent injury severity of the two drivers. For a four scale ordinal injury severity level, l_d can take the value of no-injury/no-apparent ($l_d = 1$), minor/possible injury ($l_d = 2$), serious injury ($l_d = 3$), and fatal injury ($l_d = 4$) respectively. Furthermore, let y_d represent observed injury severity sustained by at-fault and not-at-fault drivers in head on collision and $y_d{}^*$ represent the unobserved injury severity propensity of at-fault and not-at-fault drivers, and finally, φ_{l_d} be the threshold utilized to map observed injury severity with latent injury severity propensities. Then, we can have a bivariate ordered probit framework with seemingly unrelated specification to model injury severities of at-fault and not-at-fault driver as:

$$y_1 = l_1 \text{ if } \left(\varphi_{l_1-1} - \beta' x_{q_1}\right) < \tau_{q_{1j}} < \left(\varphi_{l_1} - \beta' x_{q_1}\right) \tag{5.1}$$

$$y_2 = l_2 \text{ if } \left(\varphi_{l_2-1} - \beta' x_{q_2}\right) < \tau_{q_{2j}} < \left(\varphi_{l_2} - \beta' x_{q_2}\right) \tag{5.2}$$

From the above seemingly unrelated ordered equation system, the joint probability that at-fault driver sustains injuries of severity level l_1 and not-at-fault driver sustains injuries of severity of level l_1 can be formulated as:

$$\begin{aligned} &P\left(y_{q_1} = l_1, y_{q_2} = l_2\right) \\ &= P\left(\left[\left(\varphi_{l_1-1} - \beta' x_{q_1}\right) < \tau_{q_1} < \left(\varphi_{l_1} - \beta' x_{q_1}\right)\right], \left(\varphi_{l_2-1} - \beta' x_{q_2}\right) < \tau_{q_2} \right. \\ &\qquad\qquad \left. < \left(\varphi_{l_2} - \beta' x_{q_2}\right)\right) \end{aligned} \tag{5.3}$$

$$\begin{aligned} &= P\left[\tau_{q_{1j}} < \left(\varphi_{l_1} - \beta' x_{q_1}\right), \tau_{q_2} < \left(\varphi_{l_2} - \beta' x_{q_2}\right)\right] - P\left[\tau_{q_1} < \left(\varphi_{l_1} - \right.\right. \\ &\left.\left.\beta' x_{q_1}\right), \tau_{q_{2j}} < \left(\varphi_{l_2-1} - \beta' x_{q_2}\right)\right] - P\left[\tau_{q_1} < \left(\varphi_{l_1-1} - \beta' x_{q_1}\right), \tau_{q_2} < \left(\varphi_{l_2} - \right.\right. \\ &\left.\left.\beta' x_{q_2}\right)\right] + P\left[\tau_{q_1} < \left(\varphi_{l_1-1} - \beta' x_{q_1}\right), \tau_{q_{2j}} < \left(\varphi_{l_2-1} - \beta' x_{q_2}\right)\right] \end{aligned}$$

The above joint probability functional form is dependent on the specifying the dependency structure between τ_{q_1}(residuals of at-fault equation) and τ_{q_2}(residuals of not-at-fault equation). Next, we introduce copula representations to re-write the joint probability function as:

$$\begin{aligned} &P\left(y_{q_1} = l_1, y_{q_2} = l_2\right) \\ &\qquad = C_\theta\left(v_{qI1}, v_{qI2}\right) - C_\theta\left(v_{qI1}, v_{qI2-1}\right) - C_\theta\left(v_{qI1-1}, v_{qI2}\right) \\ &\qquad + C_\theta\left(v_{qI1-1}, v_{qI2-1}\right) \end{aligned} \tag{5.4}$$

Where C_θ is the specific copula representations (comprehensive or non-comprehensive copulas) that can be used to characterize the stochastic dependency between τ_{q_1} and τ_{q_2}; v can be formulated as function of thresholds φ_{l_d} and β such that:

$$v_{qI1} = F_{\tau_1}\left(\varphi_{l_1} - \beta_j' x_{q_1}\right), v_{qI1-1} = F_{\tau_1}\left(\varphi_{l_1-1} - \beta_j' x_{q_1}\right) \quad (5.5)$$

$$v_{qI2} = F_{\tau_2}\left(\varphi_{l_2} - \beta_j' x_{q_2}\right), v_{qI2-1} = F_{\tau_2}\left(\varphi_{l_2-1} - \beta_j' x_{q_2}\right) \quad (5.6)$$

Finally, the summation of individual likelihood for each head on collision can provide the final likelihood function as:

$$R = \prod_{q=1}^{Q}\left\{\prod_{l_1,l_2=1}^{L}\left[P\left(y_{q_1} = l_1, y_{q_2} = l_2\right)\right]^{\gamma_{ql_1}\gamma_{ql_2}}\right\}^{w_q} \quad (5.7)$$

where $\gamma_{ql_{1j}}$ and $\gamma_{ql_{2j}}$ are dummy variables taking the value 1 if Driver 1 and Driver 2 involved in accident q of type j sustain injuries of levels l_{1j} and l_{2j}, respectively, and 0 otherwise. w_q is the weight for accident q used to represent an unbiased sample of head on collisions.

Copula Approach

For statistical models with dependency such as bivariate ordered probit with dependency in error terms, copula approaches are utilized for modeling joint distributions in order to estimate resulting model in closed-form with direct maximum likelihood algorithms (*48*). Copulas can be conceptualized as mathematical constructs, such as multivariate distribution function, used to generate stochastic dependence between random variables with pre-specified marginal distributions (*46; 48*). In our case random errors τ_{q_1} and τ_{q_2} with marginal distributions $F_{\tau_{q_1}}(.)$ and $F_{\tau_{q_2}}(.)$ respectively. In particular, copula approach differentiates between marginal distributions and stochastic dependence structures, so that the stochastic dependence between error terms is determined by the copula itself (*46*). Following (*48; 50*), if $U_1, U_2, U_3, \dots\dots, U_K$ are K uniformly distributed random variables, then the K-dimensional joint distribution or copula can be formulated as:

$$C_\theta(u_1, u_2, \dots, u_K) = \Pr(U_1 < u_1, U_2 < u_2, \dots, U_K < u_K) \quad (5.8)$$

Where: θ is copula parameter vector commonly defined as dependence parameter that conceptualizes dependence between two random variables. If we consider K random variables $\aleph_1, \aleph_2, \aleph_3, \dots \dots, \aleph_K$, each with a pre-specified univariate continuous marginal distribution such that $F(e_k) = \Pr(\aleph_k < e_k)$. Following (*34; 46*) (*51*), a joint K dimensional vector of random variables with pre-specified marginal distribution functions $F(e_k)$ can be formulated as:

$$\begin{aligned} (e_1, e_2, e_3, \dots \dots, e_k) &= \Pr(\aleph_1 < e_1, \aleph_2 < e_2, \dots \dots, \aleph_K < e_k) \\ &= \Pr[U_1 < F(e_1), U_2 < F(e_2), \dots \dots, U_K < F(e_k) \\ &= C_\theta[u_1 = F(e_1), u_2 = F(e_2), \dots \dots, u_K < F(e_k)] \end{aligned} \tag{5.9}$$

Keeping in view the above mathematical construct, we use a diverse suite of Archimedean class of copulas that have the capability of conceptualizing a broad range of stochastic dependency structures between τ_{q_1} and τ_{q_2} with pre-specified unit-parametric functional forms (*52*). For details, see (*47*). Specifically, Gaussian and Frank copulas are referred to as “comprehensive copulas” in terms of their ability to parameterize the full range of stochastic dependency by allowing positive and negative dependence with symmetry in both tails. Nonetheless, as compared to Gaussian copula, the Frank copula is characterized by stronger dependence in the middle of distribution and weaker dependence in distribution tails. The “non- comprehensive copulas” (i.e. Clayton, Gumbel and Joe) capture positive stochastic dependence only with asymmetry in distribution tails (*47*). Among the non-comprehensive copulas, Clayton characterizes strong dependence in left tail and weak dependence in right tail of the distribution. Contrarily, Gumbel and Joe copulas exhibit opposite patterns with weak dependence in left tail and strong dependence in right tail of specific distribution. However, the right tail dependence is stronger in Joe copula than in Gumbel copula. This said, Clayton copula can better represent a joint distribution of two random variables, i.e. error terms of at-fault and not-at-fault drivers, if the residuals are strongly correlated at low values and weakly correlated at high values, and vice versa for Joe and Gumbel copulas (*48*). In this study, we have tested all set of Archimedean copulas that will later be explained in detail.

Marginal distributions/Marginals

Let τ_{q_1} and τ_{q_2} be residuals/error-terms and let $F_{\tau_{q_1}}(.)$ and $F_{\tau_{q_2}}(.)$ be marginal distributions of two error terms respectively. For the error term τ_{q_1}, we specify marginal distributions $F_{\tau_{q_1}}(.)$ as the mixture of two normal components with the following parameterization:

$$F_{\tau_{q_1}}(\tau_{q_1}) = \pi_{\tau_{q_1}} \varphi\left(\frac{\tau_{q_1} - \mu_{\tau_{q_1}}}{\sigma_{\tau_{q_1}}}\right) + \left(1 - \pi_{\tau_{q_1}}\right) \varphi\left(\frac{\tau_{q_1} - \mu'_{\tau_{q_1}}}{\sigma'_{\tau_{q_1}}}\right) \tag{5.10}$$

Where: $\pi_{\tau_{q_1}}$ is the mixing probability, and $(\mu_{\tau_{q_1}}, \mu'_{\tau_{q_1}})$ and $(\sigma_{\tau_{q_1}}, \sigma_{\prime\tau_{q_1}})$ are location and dispersion parameters constrained to satisfy the mean and variance normalizations such as (*49*):

$$\pi_{\tau_{q_1}}\mu_{\tau_{q_1}} + (1 - \pi_{\tau_{q_1}})\mu'_{\tau_{q_1}} \equiv 0 \tag{5.11}$$

$$\pi_{\tau_{q_1}}\left(\sigma^2_{\tau_{q_1}} + \mu^2_{\tau_{q_1}}\right) + (1 - \pi_r)\left(\sigma'^2_{\tau_{q_1}} + \mu'^2_{\tau_{q_1}}\right)$$

The marginal distribution $F_{\tau_{q_2}}(.)$ for the error term τ_{q_2} can be obtained with a similar parameterization. With afore-mentioned two part normal mixtures for error terms, the following mixture types/marginal distributions can be empirically tested for both error terms or residuals (For a detailed discussion on mixture types, see (*47*)):

Normally distributed marginal distributions: *N* (0,1) distribution for error terms R and S

Mixture 1: R has two-part normal mixture and S has *N* (0,1) distribution

Mixture 2: R has *N* (0,1) distribution and S has two-part normal mixture

Mixture 3: Both error terms have different normal mixture distribution

Mixture 4: Both error terms have the same normal mixture distribution

The utilization of afore-mentioned normal mixtures can capture several distributional shapes, especially those that may involve bimodality and/or skewness (*53*).

5.2 DATA AND DESCRIPTIVE STATISTICS

The crash data file for model estimation is obtained from Virginia State crash records database and supplied by the Virginia Department of Transportation. The database contains detailed information about all types of police-reported crashes occurring on Virginia roads. For this study, data for all two-vehicle head on collisions (N = 1,445) involving 2,890 vehicles and drivers occurring in the state of Virginia for year 2013 are obtained. Altogether, the data at hand exhibits useful information on broad range of factors including alignment, roadway types, weather, road surface conditions, crash characteristics, vehicle, and driver characteristics. Also, the records contain detailed geographic and temporal information, pre-crash maneuvers and driver actions, information on driver safety equipment, and traffic control devices. Injury severities of two drivers involved in the same head on collision are assessed on four-point ordinal scale that classifies each driver's injury severity into one of the following categories:

- No injury/no apparent injury
- Minor injury/possible injury
- Serious injury
- Fatal injury

Due to a key focus of this study i.e. analyzing effects of fault status designation on injury outcomes, crashes in which no driver is found to be at-fault are not analyzed. This results in a sample size of 1445 (71 truck-involved and 1374 non-truck-involved) head on collisions (where at least one driver is at-fault), out of the total 1730 head on collisions occurred in 2013. Table 5-1 presents the joint frequency distribution of injury severity levels of the two dependent variables i.e. injury severity of at-fault and not-at-fault driver in truck involved and non-truck-involved head on collisions respectively.

TABLE 5-1 Joint Injury Severity Distribution and Descriptive Statistics of Key Variables in truck-involved and non-truck-involved head on collisions

Truck-involved head on collision					
Injury Severity of not-at-fault other vehicle driver	**Injury severity of at-fault truck driver**				
	No injury/No apparent	Minor injury/Possible	Serious injury	Fatal injury	**Total**
No injury/No apparent	10 (58.82%)	3 (17.65%)	0 (0%)	0 (0%)	13 (76.47%)
Minor injury/Possible	0 (0%)	0 (0%)	1(5.88%)	0 (0%)	1 (5.88%)
Serious injury	1(5.88%)	0 (0%)	1(5.88%)	1(5.88%)	3 (17.65%)
Fatal injury	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Total	11 (64.71%)	3 (17.65%)	2 (11.77%)	1 (5.88 %)	17 (100%)
Injury Severity of not-at-fault truck driver	**Injury severity of at-fault other vehicle driver**				
	No injury/No apparent	Minor injury/Possible	Serious injury	Fatal injury	**Total**
No injury/No apparent	28 (51.85%)	0 (0%)	1 (1.85%)	0 (0%)	29 (53.70%)
Minor injury/Possible	4 (7.41%)	2 (3.70%)	0 (0%)	0 (0%)	6 (11.11%)
Serious injury	10 (18.52%)	2 (3.70%)	1 (1.85%)	0 (0%)	13 (24.07%)
Fatal injury	5 (9.26%)	1 (1.85%)	0 (0%)	0 (0%)	6 (11.11%)
Total	47 (87.04%)	5 (9.26%)	2 (3.70%)	0 (0%)	54 (100%)
Non truck-involved head on collision					
Injury Severity of not-at-fault driver	**Injury severity of at-fault driver**				
	No injury/No apparent	Minor injury/Possible	Serious injury	Fatal injury	**Total**
No injury/No apparent	779 (56.70%)	136 (9.90%)	45 (3.28%)	2 (0.15%)	962 (70.01%)
Minor injury/Possible	89 (6.48%)	110(8.01%)	38 (2.77%)	6 (0.44%)	243 (17.69%)

Serious injury	54(3.93%)	30 (2.18%)	55 (4.00%)	9 (0.66%)	148 (10.77%)
Fatal injury	3 (0.22%)	4(0.29%)	11 (0.80%)	3 (0.22%)	21 (1.53%)
Total	925 (67.32%)	280 (20.38%)	149 (10.84%)	20(1.46%)	1374 (100%)

Table 5-1 helps spotting important patterns embedded in data related to associations of fault status with drivers' injury severity outcomes for truck-involved head-on collisions and non-truck-involved head on collisions.

- For non-truck-involved head-on collisions, irrespective of fault-status, drivers are almost equally likely to sustain at least serious or fatal injury i.e. 12.3% of not-at-fault drivers' vs 12.35% of at-fault drivers. This finding is unsettling because the behavior of at-fault drivers can potentially cause equal harm to not-at-fault drivers resulting in severe injuries or loss of life of not-at-fault drivers.
- For truck-involved head on collisions, if truck drivers are at-fault drivers, the result is similar to non-truck-involved head on collisions. Irrespective of fault-status, drivers are equally to sustain at least serious or fatal injury i.e. 17.65% for both at-fault truck drivers and not-at-fault other vehicle drivers. However, for truck drivers are not-at-fault drivers, the influence of fault-status on injury severity outcomes of not-at-fault driver is more pronounced. Alarmingly, compared to only 3.70% of at-fault drivers, 35.18% of not-at-fault drivers received at least serious or fatal injuries, which is nearly ten times the likelihood of at-fault drivers receiving at least serious injuries.

The above findings point out to the exigency of explicit analysis of truck involved head-on collisions, and to understand the influence of fault designation on injury severity outcomes. However, due to limited sample of truck-involved collisions (only 71 collisions), a separate analysis cannot be conducted. Nonetheless, the rigorous statistical analysis in later sections helps understanding the influence of truck involvement (as an explanatory factor) on overall injury outcomes of involved drivers.

Next, Table 5-2 presents the contingency table for joint frequency distributions of different injury severity levels of at-fault and not-at-fault drivers, for all head-on collisions.

As there can be different number of drivers in each category, total percentages (each frequency is presented as percentage of total N = 1,445) are given in brackets that help to spot patterns in the data. It is observed that there are statistically significant associations between injury severities of at-fault and not-at-fault drivers (Pearson Chi-Square of 390.65 with p-value≈ 0.000) and thus null hypothesis of no association between injury severity of at-fault and not-at-fault drivers can be rejected at a 99% confidence level. Furthermore, examination of the summary statistics reveals that irrespective of fault status, drivers are almost equally likely to receive at least minor or possible injury. It shows that compared to 32% of not-at-fault drivers, 30.5% of at-fault drivers received at least minor/possible injury respectively. In the case of head on collisions, the implications of striking and struck vehicle may not apply due to dissipation of energy in opposite directions and thus equal likelihood of at-fault and not-at-fault drivers to sustain injuries. Looking at the data another way, there are a substantial number of fatal and severe injuries to not-at-fault drivers, given head-on crashes.

The bottom panel in Table 5-2 presents the description and descriptive statistics of key crash, vehicle, and driver related variables that were found to significantly affect injury severities of at-fault and not-at-fault drivers.

Specifically, 34% of the at-fault drivers were driving pickup truck, Van, or SUV, 3% of at-fault drivers were either fatigued or apparently slept while driving, and 44% of at-fault driver maneuvered the vehicle while going straight ahead. Note that at-fault driver vehicle type (truck, van, SUV) is specifically included to investigate the influence of truck involvement on overall injury severity outcomes, specifically to not-at-fault drivers. Based on their distributions, key summary statistics, and extraction from a well-organized and integrated state database, the underlying data is of reasonable quality.

TABLE 5-2 Contingency Table for Joint Injury Severity Distribution and Descriptive Statistics of Key Variables

	Injury severity of at-fault driver				
Injury Severity of not-at-fault driver	No injury/No apparent	Minor injury/Possible	Serious injury	Fatal injury	**Total**
No injury/No apparent	817 (56.5%)	93 (6.4%)	65 (4.5%)	8 (0.6%)	983 (68.0%)
Minor injury/Possible	139 (9.6%)	112 (7.8%)	32 (2.2%)	5 (0.3%)	288 (19.9%)
Serious injury	46 (3.2%)	39 (2.7%)	57 (3.9%)	11 (0.8%)	153 (10.6%)
Fatal injury	2 (0.1%)	6 (0.4%)	10 (0.7%)	3 (0.2%)	21 (1.5%)
Total	1004 (69.4%)	250 (17.3%)	164 (11.3%)	27 (1.9%)	1445 (100%)

Pearson Chi-Square = 390.65; p-value $\approx$ 0.000

Kendall's tau rank coefficient = 0.4236; Asymptotic Standard Errors= 0.024

Variable	**Description**	**Mean/SD/Min/Max**
Crash characteristics		
Fatal injury count	Number of fatal injury counts involved in the crash	0.04/0.24/0/5
Darkness indicator	1 if crash occurred in darkness/road not lighted, 0 otherwise	0.13/0.33/0/1
Stop sign indicator	1 if stop sign was present, 0 otherwise	0.12/0.320/1
Rural indicator	1 if incident occurred on rural minor arterial, 0 otherwise	0.07/0.25/0/1
Weather indicator	1 if adverse weather conditions were present, 0 otherwise	0.20/0.40/0/1
At-fault driver related factors		
At-fault vehicle indicator	1 if at-fault vehicle type is pick-up truck, van or SUV truck,	0.34/0.47/0/1

	0 otherwise	
Restraint indicator	1 if no driver safety restraint system was used, 0 otherwise	0.07/0.26/0/1
Airbag indicator	1 if airbag was deployed in combination, 0 otherwise	0.03/0.18/0/1
Vehicle speed (mph)	Vehicle speed in miles per hour	27.50/16.22/1/120
Driver age indicator	1 if at-fault driver is 60 years old or more, 0 otherwise	0.15/0.35/0/1
Driver eject indicator	1 if driver is partially or totally ejected, 0 otherwise	0.02/0.16/0/1
At-fault driver condition indicator*	1 if at-fault driver was fatigued or apparently slept, 0 otherwise	0.03/0.17/0/1
At-fault drunk driver indicator*	1 if at-fault driver was obviously drunk, 0 otherwise	0.04/0.20
At-fault driver maneuver indicator*	1 if at-fault driver was going straight ahead, 0 otherwise	0.44/0.49/0/1
Not-at-fault driver related factors		
Restraint indicator	1 if no driver safety restraint system was used, 0 otherwise	0.03/0.16/0/1
Airbag indicator	1 if airbag was deployed in combination, 0 otherwise	0.05/0.21/0/1
Vehicle speed (mph)	Vehicle speed in miles per hour	29.69/14.23
Driver age indicator	1 if at-fault driver is 60 years old or more, 0 otherwise	0.14/0.35/0/1
Driver eject indicator	1 if driver is partially or totally ejected, 0 otherwise	0.02/0.13/0/1

Note: * indicates variables that are also included in not-at-fault driver injury severity model

5.3 MODELING RESULTS

5.3.1 Model Selection and Performance Comparison

The univariate (independent) ordered probit models and bivariate ordered probit models (with different copula specifications) were derived from a systematic process to include most important variables (available in the data set) on basis of statistical significance, specification parsimony, and intuition. Initially, a series of univariate ordered probit models were developed to conceptualize correlates of injury severity of at-fault and not-at-fault drivers. Next, a series of bivariate ordinal regression models were developed with five different copula constructs (Gaussian, Clayton, Frank, Gumbel, and Joe) to examine the stochastic dependency between error terms of both drivers. For brevity, we only present the final summary statistics (goodness-of-fit measures) of estimated models with different copula specifications in Table 5-3. Table 5-3 also presents the summary statistics of independent models (i.e. two univariate ordered probit models for at-fault and not-at-fault drivers). Following (*47*) and (*54*), Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), and Log-likelihood at convergence can be used to evaluate competing models. As can be seen in Table 5-3, among all copula models, the results suggest that bivariate ordered probit regression with Gumbel copula provided the best fit with log-likelihood at convergence of -1678.12 and BIC of 3587.90 respectively. Note that in all of copula models, however, the dependency parameters "C_θ" are highly statistically significant.

TABLE 5-3 Summary Goodness-of-Fit Measures for Copula Based Two-Part Mixture Models

Bivariate ordinal regressions with different copulas						
Model	N	LL(□)	DOF***	AIC	BIC	θ
Independent*	1,119	-1736.94	32	3537.873	3698.519	N/A
Gaussian**	1,119	-1688.82	33	3443.637	3609.304	0.4389(0.0397)
Frank	1,119	-1687.15	33	3440.307	3605.974	2.9223(0.3206)
Clayton	1,119	-1700.02	33	3466.029	3631.695	1.0167(0.1675)
Gumbel	1,119	-1678.12	33	3422.243	3587.909	1.3725(0.0505)
Joe	1,119	-1678.09	33	3422.18	3587.847	1.5403(0.0741)
Best Copula Model with Marginal Mixtures						
Gumbel	1,119	-1678.12	33	3422.243	3587.909	1.3725(0.0505)
Gumbel with two-part normal mixture & *N* (0,1)	1,119	-1671.74	36	3415.472	3596.199	1.3763(0.0510)

Notes:

* "Independent" are two univariate ordered probit models for at-fault and not-at-fault drivers.

**Gaussian copula with no mixture is analogous to standard bivariate ordered probit model and thus "θ" for Gaussian model is numerically equal to the Polychoric correlation coefficient.

*** DOF = Degrees of Freedom.

Using the preferred Gumbel copula, we allow for non-normal distributions in bivariate residuals by investigating different mixture types as explained in the methodology section. In summary, on basis of log-likelihood at convergence and BIC values (Table 5-3), we observed Gumbel with mixture 1 type (i.e. two-part normal mixture for residuals of at-fault equation and *N* (0,1) for residuals of not-at-fault equation) resulting in best fit among all competing mixture types (as discussed in the methodology section). The characterization of one and/or both marginal distributions of error terms as two-part normal mixtures can conceptualize the non-normality exhibited by residual distributions (*47*). Table 5-4 summarizes the results from the following three models:

- Category 1: Independent univariate ordered probit models for injury severity of at-fault and not-at-fault drivers
- Category 2: Gumbel copula based bivariate ordered model
- Category 3: Gumbel copula based two-part normal mixture model

Finally, Chi-square goodness-of-fit tests are conducted for comparing category 1 and category 2 models, and comparing category 2 and category 3 models. For the former comparison, the likelihood ratio statistic between the two models is $-2 * (-1678.12 + 1736.94) = -117.64$, which is far greater than critical Chi-square value for 1 degree of freedom (one additional parameter in copula-based bivariate model) at 99.5% level of confidence (*47*), thus suggesting superior statistical performance of category 2 model as compared to category 1.

For the later comparison, the likelihood ratio statistic between the two models is $-2 * (-1671.74 + 1678.12) = -12.76$, which is greater than the critical Chi-square value for 3 degree of freedom (three additional mixture parameters in copula-based mixture model) at 99% level of confidence (*47*), thus concluding superior statistical performance of category 3 model as compared to the category 2 model.

5.3.2 Key Findings

In this section, we present the results of best copula models (on basis of goodness-of-fit statistics) i.e. category 2 and 3 models are compared with independent models (category 1) that does not consider the residual correlations between at-fault and not-at-fault drivers. In order to facilitate discussion, we will refer to the three competing models as category 1, category 2, and category 3 models respectively. Specifically, Table 5-4 presents the model parameter estimates where a positive sign indicates an increase in probability of most severe injury outcomes (fatal injury) and decrease in probability of least severe injury outcomes (no injury/no apparent injury) respectively and vice versa. However, in order to interpret the associations on intermediate categories of injury severity (minor and serious injury), average "marginal effects" are provided (Table 5-5) for category 1 and 3 models for comparison purposes. The copula dependency parameters "C_θ" is highly significant both for category 2 and 3 models. For instance, the C_θ estimate (1.41) translates to Kendall's τ correlation of 0.29, suggesting a relatively strong positive correlation between injury severity outcomes of at-fault and not-at-fault drivers. This strong positive correlation may be due to unobserved factors (unknown to analyst) and that such factors are jointly associated with increase or decrease of the injury severity level of each driver involved in head on collisions.

Regarding marginal distribution of at-fault error component, as presented in Table 5-5, we found two-part normal mixture resulting in best fit. The results from category 3 model, referring to Eq. 9, resulted in marginal distribution of residual τ_{q_1} as a mixture of less dominant component ($\pi_{\tau_{q_1}} = 0.42$) centered left to zero ($\mu_{\tau_{q_1}} = -0.79$), with a dominant secondary mixing parameter ($1 - \pi_{\tau_{q_1}} = 0.57$) intuitively centered above zero ($\mu'_{\tau_{q_1}} = 0.59$). Regarding dispersion, less dominant component ($\pi_{\tau_{q_1}} = 0.42$) is largely dispersed with $\sigma_{\tau_{q_1}} = 0.92$, as opposed to $\sigma_{\prime\tau_{q_1}} = 0.22$. Thus, the two-part mixture marginal distribution represented in Eq. 9 is fully specified. It is important to note that all of these parameters for two-part mixture marginals are statistically significant at 99.5% level of confidence and thus validating the mixture marginal distribution of residuals of at-fault driver injury severity. Note that, as per results of the best model (category 3), the marginal distribution for not-at-fault residual τ_{q_2} is observed to be normal N (0, 1) with mean zero and variance one. For more details regarding mixtures, interested readers are referred to (*49*).

While the parameter estimates for all three categories of models are similar in direction, it can be seen that the parameter estimates and standard errors (different z-scores) widely differ in magnitude between the three competing models. Moreover, the marginal effects obtained from category 1 and 3 models are significantly different in magnitude and in some cases with different directions, especially for intermediate categories of response variables. All of these findings confirm the importance of addressing stochastic and complex form of dependence in injury severity propensity (through copula representation) and non-normality between residuals (through marginal mixtures) between drivers (with respect to at-fault and not-at-fault status) involved in the same (head on) collision.

TABLE 5-4 Model Estimation Results

Variable	Category 1 Model		Category 2 Model		Category 3 Model	
At-Fault Driver	Parameter	z-score	Parameter	z-score	Parameter	z-score
Darkness indicator	0.02	0.23	0.08	0.76	0.08	1.05
Stop sign indicator	-0.27	-1.75	-0.32	-2.21	-0.17	-1.77
Fatal count	1.63	8.02	1.74	8.77	1.81	8.24
Rural indicator	0.66	5.1	0.66	5.16	0.37	3
Fault vehicle indicator	-0.16	-2.01	-0.15	-1.87	-0.08	-1.5
Restraint indicator	0.81	6.21	0.69	5.54	0.46	3.75
Airbag indicator	0.22	1.3	0.31	1.93	0.25	1.94
Vehicle speed (mph)	0.02	7.98	0.01	6.38	0.01	3.85
Driver age indicator	0.4	3.73	0.32	3.26	0.19	2.55
Driver eject indicator	0.96	4.09	1.16	5.36	0.94	3.85
Weather indicator	-0.2	-2.17	-0.18	-1.95	-0.13	-2.19

At-fault driver condition indicator	0.43	2.27	-0.45	2.42	0.27	1.89
μ_1	1.19	12.26	1.06	11.5	0.96	11.33
μ_2	2.01	18.89	1.91	18.3	1.49	8.3
μ_3	3.8	18.23	3.51	18.12	2.85	10.51
Not-at-Fault Driver						
Darkness indicator	0.21	1.86	0.21	1.91	0.22	2.03
Stop sign indicator	-0.37	-2.59	-0.38	-2.76	-0.37	-2.67
Fatal count	1.48	8.04	1.58	8.74	1.64	9.1
Rural indicator	0.39	3.01	0.48	3.82	0.45	3.56
Fault vehicle indicator	0.32	4.13	0.3	3.92	0.31	3.99
Restraint indicator	0.89	4.22	0.79	4.01	0.8	4.06
Airbag indicator	0.26	1.71	0.16	1.13	0.16	1.12
Vehicle speed (mph)	0.01	6.83	0.01	5.18	0.01	5.14
Driver age indicator	0.16	1.56	0.08	0.87	0.08	0.85
Driver eject indicator	1.18	4.69	1.29	5.55	1.3	5.6
At-fault drunk driver indicator	0.28	1.59	0.32	1.95	0.32	1.94
Weather indicator	-0.11	-1.26	-0.07	-0.81	-0.08	-0.92
At-fault driver maneuver indicator	0.22	2.88	0.19	2.73	0.2	2.8
At-fault driver condition indicator	0.53	2.82	0.53	2.86	0.51	2.75
α_1	1.37	11.69	1.18	10.65	1.19	10.63
α_2	2.25	17.67	2.07	16.79	2.07	16.78
α_3	3.89	18.92	3.56	18.66	3.59	18.68
C_θ (Dependency parameter)	----	---	1.37	27.14	1.41	26.95
Kendall's τ correlation	----		0.27		0.29	

Notes: μ1, μ2, μ3, α1, α2, α3 are the threshold cutting parameters of joint model defining the injury severities of two drivers.

Regarding driver-specific behaviors and attributes, the at-fault driver condition indicator, driver was fatigued or apparently asleep, is associated with higher propensity of severe or fatal injury, however the magnitude of association is significantly larger for not-at-fault drivers (see parameter estimate and marginal effects in Tables 5-3 and 5-5). This points to the importance of further investigating fatigue and night driving. We also investigated the association of alcohol usage of at-fault drivers (at-fault drunk driver indicator) on resulting injury severities of the at-fault and not-at-fault drivers. We did not find a statistically significant association of this indicator variable on at-fault driver injury severity, however, at-fault drivers under the influence of alcohol are statistically significantly associated with higher propensity of severe and/or fatal injuries of not-at-fault drivers. Note that this finding is not consistent with the finding in an earlier study (*36*) where at-fault drivers alcohol/drug use was associated with higher injury severity of at-fault driver involved in angled collisions, partly due to different collision mechanics of angled and head on collisions. Moreover, the significant marginal effect (0.0984) for severe injury of the not-at-fault driver indicates the importance of reducing drunk driving. Regarding the at-fault driver maneuver indicator (at-fault driver going straight ahead), the results suggest that this driving maneuver is associated with significantly higher propensity of severe or fatal injury for not-at-fault drivers (marginal effects of 0.0571 and 0.0075 respectively). Again, at-fault driver maneuver is not observed to be statistically significantly associated with injury severity of the at-fault driver. Note that we utilized the afore-mentioned important variables related to at-fault driver in both equations in order to quantify the impacts of at-fault driving errors and fault status on injury severity of not-at-fault drivers. Collectively, the afore-mentioned results suggest that driving errors of at-fault driver has substantial negative consequences for injury severity of not-at-fault drivers. This points to developing a taxonomy of errors that are frequently committed by at-fault drivers and to reducing deadly behaviors that may harm not-at-fault drivers.

Turning to other variable of interest with respect to vehicle type, our results suggest that if the at-fault driver's vehicle type is a pick-up truck, van or SUV truck (fault vehicle indicator), then at-fault driver has a lower propensity to receive severe or fatal injury, not statistically significant though (See Table 5-5). However, the same fault vehicle indicator (at-fault truck/SUV/van) is associated with, and statistically significant, significantly higher propensity of severe injury or fatal injury for not-at-fault drivers(marginal effects of 0.0937 and 0.0195 for severe and fatal injury respectively). This finding is important in sense that it captures the influence of at-fault driver truck (or heavy vehicle) involvement on injury outcomes of not-at-fault driver. This in turn points out to the need of assembling truck-involved head-on collisions database, and analyzing the behavioral factors (among others) associated with such disastrous safety outcomes.

TABLE 5-5 Marginal Effects for Category 1 and 3 Models

	Marginal Effects - Category 3 Model Injury levels				Marginal Effects - Category 1 Model Injury levels			
Variables	1	2	3	4	1	2	3	4
At-Fault Driver								
Darkness indicator	-0.0382	-0.0006	0.0385	0.0003	-0.0085	0.0039	0.0041	0.0005
Stop sign indicator	0.0852	-0.0062	-0.0785	-0.0005	0.0871	-0.0401	-0.0415	-0.0054
Fatal count	-0.4036	-0.1962	0.1321	0.4677	-0.4600	0.2120	0.2190	0.0284
Rural indicator	-0.1936	0.0461	0.1468	0.0007	-0.1811	0.0830	0.0860	0.0112
Fault vehicle indicator	0.0412	0.0004	-0.0413	-0.0003	0.0370	-0.0170	-0.0176	-0.0020
Restraint indicator	-0.1620	-0.0863	0.2399	0.0084	-0.2503	0.1154	0.1193	0.0155
Airbag indicator	-0.0995	-0.0354	0.1327	0.0022	-0.0592	0.0273	0.0282	0.0036
Vehicle speed (mph)	-0.0040	-0.0005	0.0052	0.0000	-0.0062	0.0028	0.0029	0.0030
Driver age indicator	-0.0785	-0.0233	0.1004	0.0014	-0.0930	0.0428	0.0443	0.0057
Driver eject indicator	-0.2619	-0.1641	0.3563	0.0697	-0.2656	0.1225	0.1266	0.0165
Weather indicator	0.0582	0.0140	-0.0713	-0.0009	0.0593	-0.0273	-0.0282	-0.0036
At-fault driver condition	-0.1068	-0.0403	0.1444	0.0026	-0.0979	0.0451	0.0466	0.0060

indicator								
Not-at-Fault Driver								
Darkness indicator	-0.0880	0.0166	0.0632	0.0082	-0.0559	0.0257	0.0266	0.0034
Stop sign indicator	0.1474	-0.0353	-0.1005	-0.0117	0.1093	-0.0504	-0.0520	-0.0068
Fatal count	-0.3496	-0.2251	0.2615	0.3133	-0.4602	0.2120	0.2190	0.0287
Rural indicator	-0.1782	0.0469	0.1182	0.0130	-0.1256	0.0579	0.0598	0.0070
Fault vehicle indicator	-0.1101	-0.0031	0.0937	0.0195	-0.0987	0.0455	0.0470	0.0061
Restraint indicator	-0.2444	-0.0649	0.2268	0.0824	-0.2643	0.1219	0.1259	0.0164
Airbag indicator	-0.0601	0.0022	0.0491	0.0089	-0.0818	0.0377	0.0389	0.0051
Vehicle speed (mph)	-0.0053	0.0005	0.0041	0.0007	-0.0064	0.0029	0.0030	0.0004
Driver age indicator	-0.0312	0.0042	0.0235	0.0034	-0.0467	0.2150	0.0222	0.0029
Driver eject indicator	-0.3226	-0.1630	0.2845	0.2010	-0.3695	0.1704	0.1760	0.0230
At-fault drunk driver indicator	-0.1153	-0.0041	0.0984	0.0209	-0.0881	0.0406	0.0419	0.0054
Weather indicator	0.0309	-0.0022	-0.0246	-0.0041	0.0376	-0.0182	-0.0188	-0.0024
At-fault driver maneuver indicator	-0.0788	0.0142	0.0571	0.0075	-0.0736	0.0339	0.0350	0.0045
At-fault driver condition indicator	-0.1733	-0.0216	0.1547	0.0402	-0.1782	0.0821	0.0848	0.0111

Note: No injury/no apparent (1), minor injury/possible injury (2), serious injury (3), and fatal injury (4).

Returning to crash-specific variables (Table 5-4), the results suggest that head on collisions in darkness (darkness indicator), number of fatalities (fatal count), and collisions on rural minor arterial roadways (rural indicator) are all associated with higher propensity of severe injuries irrespective of whether a driver is at-fault or not-at-fault. However, the magnitudes of correlation vary significantly with respect to at-fault and not-at-fault driver designation (see parameter estimates in Table 5-4). For instance, referring to marginal effects in Table 5-5, head on collisions in darkness increase the probability of severe injury by 0.0385 for at-fault driver as compared to almost double the magnitude for not-at-fault driver (marginal effect of 0.0632) respectively. Furthermore, the presence of a stop sign (stop sign indicator) and adverse weather (weather indicator) are associated with lower injury severity propensity both for at-fault and not-at-fault drivers. This finding is intuitive as drivers are likely to be more cautious in driving during adverse weather conditions. All of these findings are consistent with prior research (*33*) (*36*). Intuitively, restraint indicator (no driver safety restraint system) and airbag indicator (if both airbags in a vehicle are deployed in combination) are associated with higher propensity of injury severity for at-fault and not-at-fault driver. Note that the relationship is correlative as airbags may be deployed after a severe head on collision has already taken place.

At-fault and not-at-fault drivers traveling at higher speeds (indicative of aggressive or risky driving behavior) are more prone to receiving severe injuries. For instance, a one-unit increase in vehicle speed is associated with 0.0052 increase in probability to receive severe injury for at-fault driver and 0.0041 increase in probability to receive severe injury for not-at-fault driver respectively (Table 5-5). Furthermore, older drivers (driver age indicator) are also more likely to sustain severe injuries in head on collision, partly reflective of physiological differences between older and younger drivers. Notably, a statistically significant variation in injury outcomes for older drivers was observed, i.e., older age has more pronounced negative injury severity consequences for at-fault drivers than not-at-fault drivers (see marginal effects in Table 5-5). This requires further investigation and may be indicative of varying levels of driving skills among older drivers.

6 LIMITATIONS, CONCLUSION AND IMPLICATION

6.1 LIMITATIONS

The phase 1 focuses on two-vehicle passenger vehicle-truck collisions due to significant portion of such collisions among all truck-involved collisions. However, investigating unsafe pre-crash behaviors and injury outcomes in more than two vehicle truck involved collisions also deserves attention. The study uses real-world police reported crashes, which has many intrinsic limitations (*26; 40*). For example, the driver actions and injury severity reported in police crash reports are assumed to be accurate. However, it may be quite difficult for police officers to reconstruct what happened in a collision post-fact. Thus, the results of this study are dependent on the accuracy of information provided in police-reported crash forms. Furthermore, several other unobserved driver, vehicle, and crash related factors in that can be associated with injury outcomes of at-fault and not-at-fault drivers are not analyzed in phase 2. Note that due to intrinsic limitations associated with police-reported crash data, it is likely that characteristics of at-fault drivers may be under-reported. For instance, given the nature of police reported crashes, it may be difficult to determine (on part of police officer) whether a driver is fatigued or apparently asleep. In reality, the number of cases in which at-fault drivers are either fatigued or apparently asleep may be more than the reported ones.

6.2 CONCLUSION

To understand injury risk in transportation crashes, factors that contribute to the injury outcomes need investigation. Phase 1 contributes by quantifying associations of intentional and unintentional improper actions of truck and passenger vehicle drivers and driver condition with the most severe injury severity outcomes in passenger vehicle-truck collisions. Phase 1 study also explicitly accounts for unobserved heterogeneity and finds that some of the correlates have both positive and negative associations with injury severity. Rigorous fixed- and random-parameter ordered probit models are estimated using 2013 statewide data from the Commonwealth of Virginia.

Meanwhile developing a deeper understanding of individual level severity outcomes in the same crash has come to focus in recent years, as opposed to analysis of the most severe injury in a crash. While studies have simultaneously examined the injury severity outcomes of vehicle occupants involved in the same crash, practically no study, to the best of our knowledge, has simultaneously investigated the factors associated with driver injury severity outcomes while considering fault status. We posit that simultaneous modeling of individual drivers' injury severity in head on collisions in phase 2 can provide a deeper understanding of underlying correlates. Notably, the explicit consideration of the differential associations with respect to fault status can be of broader interest to the transportation safety profession. Moreover, such a multidimensional simultaneous analysis of driver injury severities in head on collision has methodological challenges associated with joint modeling framework and stochastically complex residual dependencies.

Significant efforts went into processing the raw data and linking different databases for collecting important information on crash, vehicle, and driver related factors for both phase 1 and phase 2. The model results of phase 1 showed that compared to fixed-parameter and random-effects ordered probit models, random- parameter model provide superior fit to data at hand together with providing fuller information regarding the relationships between key factors and most severe injury outcomes. Phase 2 was achieved by estimating generalized bivariate ordered response models with different copula structures to characterize the complex form of stochastic dependency between two error components and normal mixture marginals to allow for non-normality of joint error distribution. Specifically, generalized bivariate ordered response model with Gumbel copula and mixture marginals were observed to provide the best fit to the data at hand. Methodologically, the study provides significant evidence that copula based models with normal mixture marginals have significant potential in providing a better understanding of associated factors through explicit characterization of stochastic dependency and residual non-normality.

The findings of phase 1 showed that compared to truck occupants, passenger vehicle occupants are six times more likely to sustain minor/possible and ten times more likely to receive serious/fatal injuries. All else being equal, intentional improper actions of passenger vehicle drivers as well as unintentional improper action of passenger vehicle driver are both associated with higher injury severity in crashes. Passenger vehicle driver related factors, especially fatigue is associated with higher injury outcomes. Importantly, compared with other times of day, passenger vehicle-truck collisions during night and early morning (1 AM-8 AM) are associated with higher injury severity in such collisions.

The findings of phase 2 collectively provide new knowledge about complex interaction of several factors and its influence on injury severities sustained by drivers. For non-truck-involved head-on collisions, irrespective of fault-status, drivers are almost equally likely to sustain at least serious or fatal injury i.e. 12.3% of not-at-fault drivers' vs 12.35% of at-fault drivers. However, for truck-involved head-on collisions, the influence of fault-status on injury severity outcomes of not-at-fault driver is more pronounced. Alarmingly, compared to only 7% of at-fault drivers, 31% of not-at-fault drivers received at least serious or fatal injuries, which is more than three times the likelihood of at-fault drivers receiving at least serious injuries.

Moreover, fatigued or apparently asleep at-fault drivers and at-fault alcohol influenced drivers are significantly associated with higher propensity of fatal injury of the not-at-fault driver. Collectively with other results discussed in phase 2, the afore-mentioned results suggest that driving errors of the at-fault driver have more negative consequences on injury severity of the not-at-fault driver than its association with the at-fault driver's own injury severity.

6.3 IMPLICATIONS

From a behavioral perspective of phase 1, specific taxonomy of driver errors, whether intentional or unintentional, should be targeted given that passenger vehicle driver errors are significantly associated with higher injury outcomes. The safety literature shows numerous examples where intentional errors are associated with higher injury outcomes. However, in the case of passenger vehicle-truck collisions, unintentional errors are also of concern. Driver awareness and training programs such as educating passenger vehicle drivers about driving carefully in the vicinity of trucks, may also target driver errors that increase injury severity, given a crash. Regarding driver behavior and conditions, driving while fatigued, asleep, or collisions during night and early morning are high-risk factors associated with injury severity. Measures should be considered that minimize such risk factors. Finally, from methodological standpoint, the study results imply that addressing unobserved heterogeneity is important in injury analysis of such collisions. Ignoring unobserved heterogeneity can mask important information embedded in data which may affect the quantification of risk factors and hence the development of appropriate strategies. From a practical perspective of phase 2, several important findings emerge from the analysis. First, both at-fault and not-at-fault drivers involved in head on collisions are almost equally likely to receive at least minor/possible injury. This finding accentuates the necessity of policy measures to reduce the likelihood of such crashes altogether. The at-fault drivers that are fatigued or apparently fell asleep and alcohol-influenced are significantly associated with higher chance of not-at-fault driver getting fatal injury. This finding is unsettling because the behavior and characteristics of at-fault drivers can potentially result in the loss of a life or severe injury of not-at-fault driver. These findings point out to the exigency of relevant countermeasures such as alcohol campaigns, and reduction of driving when fatigued or night driving specially under alcohol influence. The afore-mentioned results that driving errors of the at-fault driver have more negative consequences on injury severity of the not-at-fault driver than its association with the at-fault driver's own injury severity clearly calls upon targeting the specific taxonomy of errors undertaken frequently by at-fault drivers and to reduce such deadly behavior that may cause severe impairments to not-at-fault drivers, in addition to the at-fault drivers.

References

[1] National Cooperative Highway Research Program. Heavy Tucks Type of Program Being Addressed.

[2] IIHS. *Insurance Institute for Highway Safety, Large Trucks* http://www.iihs.org/iihs/topics/t/large-trucks/fatalityfacts/large-trucks.
[3] FHWA. *Federal Motor Carrier Safety Administration. Large Truck and Bus Crash Facts. 2014*. https://www.fmcsa.dot.gov/safety/data-and-statistics/large-truck-and-bus-crash-facts-2014.
[4] NHTSA. *Traffic Safety Factrs 2014*, 2014.
[5] Friswell, R., and A. Williamson. Work characteristics associated with injury among light/short-haul transport drivers. *Accident Analysis & Prevention,* Vol. 42, No. 6, 2010, pp. 2068-2074.
[6] Newnam, S., and N. Goode. Do not blame the driver: a systems analysis of the causes of road freight crashes. *Accident Analysis & Prevention,* Vol. 76, 2015, pp. 141-151.
[7] Duncan, C., A. Khattak, and F. Council. Applying the ordered probit model to injury severity in truck-passenger car rear-end collisions. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1635, 1998, pp. 63-71.
[8] Hanrahan, R. B., P. M. Layde, S. Zhu, C. E. Guse, and S. W. Hargarten. The association of driver age with traffic injury severity in Wisconsin. *Traffic injury prevention,* Vol. 10, No. 4, 2009, pp. 361-367.
[9] Thompson, J., M. Baldock, J. Mathias, and L. Wundersitz. Older drivers in rural and urban areas: Comparisons of crash, serious injury, and fatality rates. 2010.
[10] Gonzalez, R. P., G. R. Cummings, H. A. Phelan, S. Harlin, M. Mulekar, and C. B. Rodning. Increased rural vehicular mortality rates: roadways with higher speed limits or excessive vehicular speed? *Journal of Trauma and Acute Care Surgery,* Vol. 63, No. 6, 2007, pp. 1360-1363.
[11] Clarke, D. D., P. Ward, C. Bartle, and W. Truman. Killer crashes: fatal road traffic accidents in the UK. *Accident Analysis & Prevention,* Vol. 42, No. 2, 2010, pp. 764-770.
[12] Tasca, L. *A review of the literature on aggressive driving research*. Citeseer, 2000.
[13] Goodwin, A. H., L. J. Thomas, W. L. Hall, and M. E. Tucker. Countermeasures that work: A highway safety countermeasure guide for state highway safety offices.In, 2010.
[14] Paleti, R., N. Eluru, and C. R. Bhat. Examining the influence of aggressive driving behavior on driver injury severity in traffic crashes. *Accident Analysis & Prevention,* Vol. 42, No. 6, 2010, pp. 1839-1854.
[15] Golob, T. F., and W. W. Recker. An analysis of truck-involved freeway accidents using log-linear modeling. *Journal of Safety Research,* Vol. 18, No. 3, 1987, pp. 121-136.
[16] Chang, L.-Y., and F. Mannering. Analysis of injury severity and vehicle occupancy in truck-and non-truck-involved accidents. *Accident Analysis & Prevention,* Vol. 31, No. 5, 1999, pp. 579-592.

[17] Khattak, A. J., R. J. Schneider, and F. Targa. Risk factors in large truck rollovers and injury severity: analysis of single-vehicle collisions. *Transportation Research Record*, 2003.
[18] Lemp, J. D., K. M. Kockelman, and A. Unnikrishnan. Analysis of large truck crash severity using heteroskedastic ordered probit models. *Accident Analysis & Prevention,* Vol. 43, No. 1, 2011, pp. 370-380.
[19] Christoforou, Z., S. Cohen, and M. G. Karlaftis. Vehicle occupant injury severity on highways: an empirical investigation. *Accident Analysis & Prevention,* Vol. 42, No. 6, 2010, pp. 1606-1620.
[20] Islam, M., and S. Hernandez. Large truck–involved crashes: exploratory injury severity analysis. *Journal of Transportation Engineering,* Vol. 139, No. 6, 2013, pp. 596-604.
[21] Kostyniuk, L. P., F. M. Streff, and J. Zakrajsek. *Identifying unsafe driver actions that lead to fatal car-truck crashes*. AAA Foundation for Traffic Safety, 2002.
[22] Khorashadi, A., D. Niemeier, V. Shankar, and F. Mannering. Differences in rural and urban driver-injury severities in accidents involving large-trucks: an exploratory analysis. *Accident Analysis & Prevention,* Vol. 37, No. 5, 2005, pp. 910-921.
[23] Zhu, X., and S. Srinivasan. A comprehensive analysis of factors influencing the injury severity of large-truck crashes. *Accident Analysis & Prevention,* Vol. 43, No. 1, 2011, pp. 49-57.
[24] Stuster, J. The unsafe driving acts of motorists in the vicinity of large trucks.In, Anacapa Sciences, 1999.
[25] Council, F., D. Harkey, D. Nabors, A. Khattak, and Y. Mohamedshah. Examination of fault, unsafe driving acts, and total harm in car-truck collisions. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1830, 2003, pp. 63-71.
[26] Mannering, F. L., and C. R. Bhat. Analytic methods in accident research: methodological frontier and future directions. *Analytic methods in accident research,* Vol. 1, 2014, pp. 1-22.
[27] Abdel-Aty, M. Analysis of driver injury severity levels at multiple locations using ordered probit models. *Journal of safety research,* Vol. 34, No. 5, 2003, pp. 597-603.
[28] Huang, H., H. C. Chin, and M. M. Haque. Severity of driver injury and vehicle damage in traffic crashes at intersections: a Bayesian hierarchical analysis. *Accident Analysis & Prevention,* Vol. 40, No. 1, 2008, pp. 45-54.
[29] Savolainen, P., and F. Mannering. Probabilistic models of motorcyclists' injury severities in single-and multi-vehicle crashes. *Accident Analysis & Prevention,* Vol. 39, No. 5, 2007, pp. 955-963.

[30] Haleem, K., and M. Abdel-Aty. Examining traffic crash injury severity at unsignalized intersections. *Journal of safety research,* Vol. 41, No. 4, 2010, pp. 347-357.
[31] Ichikawa, M., S. Nakahara, and A. Taniguchi. Older drivers' risks of at-fault motor vehicle collisions. *Accident Analysis & Prevention,* Vol. 81, 2015, pp. 120-123.
[32] Zhang, G., K. K. Yau, and X. Zhang. Analyzing fault and severity in pedestrian–motor vehicle accidents in China. *Accident Analysis & Prevention,* Vol. 73, 2014, pp. 141-150.
[33] Eluru, N., R. Paleti, R. Pendyala, and C. Bhat. Modeling injury severity of multiple occupants of vehicles: Copula-based multivariate approach. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2165, 2010, pp. 1-11.
[34] Rana, T., S. Sikder, and A. Pinjari. Copula-based method for addressing endogeneity in models of severity of traffic crash injuries: application to two-vehicle crashes. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2147, 2010, pp. 75-87.
[35] Yamamoto, T., and V. N. Shankar. Bivariate ordered-response probit model of driver's and passenger's injury severities in collisions with fixed objects. *Accident Analysis & Prevention,* Vol. 36, No. 5, 2004, pp. 869-876.
[36] Russo, B. J., P. T. Savolainen, W. H. Schneider, and P. C. Anastasopoulos. Comparison of factors affecting injury severity in angle collisions by fault status using a random parameters bivariate ordered probit model. *Analytic methods in accident research,* Vol. 2, 2014, pp. 21-29.
[37] Liu, J., A. Khattak, and M. Zhang. What role do precrash driver actions play in work zone crashes? Application of hierarchical models to crash data. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2555, 2016, pp. 1-11.
[38] Anastasopoulos, P. C., and F. L. Mannering. A note on modeling vehicle accident frequencies with random-parameters count models. *Accident Analysis & Prevention,* Vol. 41, No. 1, 2009, pp. 153-159.
[39] Greene, W. H. *Econometric analysis*. Pearson Education India, 2003.
[40] Khattak, A., and F. Targa. Injury severity and total harm in truck-involved work zone crashes. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1877, 2004, pp. 106-116.
[41] Khattak, A. Injury severity in multivehicle rear-end crashes. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1746, 2001, pp. 59-68.
[42] Khattak, A., J. Liu, B. Wali, X. Li, and M. Ng. Modeling Traffic Incident Duration Using Quantile Regression. *Transportation Research Record Journal of the Transportation Research Board*, 2016.
[43] Washington, S. P., M. G. Karlaftis, and F. Mannering. *Statistical and econometric methods for transportation data analysis*. CRC press, 2010.

[44] Khattak, A., and M. Rocha. Are SUVs" supremely unsafe vehicles"?: Analysis of rollovers and injuries with sport utility vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1840, 2003, pp. 167-177.
[45] Kockelman, K. M., and Y.-J. Kweon. Driver injury severity: an application of ordered probit models. *Accident Analysis & Prevention,* Vol. 34, No. 3, 2002, pp. 313-321.
[46] Bhat, C. R., and N. Eluru. A copula-based approach to accommodate residential self-selection effects in travel behavior modeling. *Transportation Research Part B: Methodological,* Vol. 43, No. 7, 2009, pp. 749-765.
[47] Hernandez-Alava, M., and S. Pudney. BICOP: a Stata command for fitting bivariate ordinal regressions with residual dependence characterised by a copula function and normal mixture marginals.In, Understanding Society at the Institute for Social and Economic Research, 2015.
[48] Trivedi, P. K., and D. M. Zimmer. *Copula modeling: an introduction for practitioners*. Now Publishers Inc, 2007.
[49] McLachlan, G., and D. Peel. *Finite mixture models*. John Wiley & Sons, 2004.
[50] Portoghese, A., E. Spissu, C. R. Bhat, N. Eluru, and I. Meloni. A copula-based joint model of commute mode choice and number of non-work stops during the commute. *Rivista Internazionale di Economia dei Trasporti,* Vol. 38, No. 3, 2011, p. 337.
[51] Sklar, A. Random variables, joint distribution functions, and copulas. *Kybernetika,* Vol. 9, No. 6, 1973, pp. (449)-460.
[52] Genest, C., and L.-P. Rivest. Statistical inference procedures for bivariate Archimedean copulas. *Journal of the American statistical Association,* Vol. 88, No. 423, 1993, pp. 1034-1043.
[53] Titterington, D. M., A. F. Smith, and U. E. Makov. *Statistical analysis of finite mixture distributions*. Wiley, 1985.
[54] Long, J. S., and J. Freese. *Regression models for categorical dependent variables using Stata*. Stata press, 2006.