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**A Comprehensive Mixed Logit Analysis of Crash Type Conditional on a
Crash Event**

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Crash Event**

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Thesis

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Dedication

To Eddie, for teaching me to believe in myself.

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Abstract

A Comprehensive Mixed Logit Analysis of Crash Type Conditional on a Crash Event

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This thesis presents a comprehensive mixed logit model of crash types, where the crash type outcomes are defined by a combination of the nature of collision and the types of vehicles involved in the crash. While prior research in the highway safety field has largely studied and modeled crashes along specific dimensions and categories, this study attempts to model the influence of various explanatory factors on crash type probabilities in a comprehensive and holistic way. The model considers 20 different crash types (alternatives) simultaneously. Using the 2011-2013 General Estimates System (GES) crash database in the United States, this research effort presents a mixed logit model that characterizes the effects of weather and seasonal variables, temporal attributes, roadway characteristics, and driver factors on the probability of observing various crash types. The model reveals the competing influences of various factors on different crash outcomes and the presence of significant unobserved heterogeneity in the manner in which variables affect crash type probabilities. The model offers a framework for

developing safety measures and devices that do not result in unintended consequences where a reduction in one crash type probability is met with an increase in another crash type probability.

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Chapter 1: Introduction

Impressive improvements have been made in the United States over the past several years when it comes to transportation safety statistics. A comparison of crash statistics between 2000 and 2010 in the U.S. shows fatalities per 100 million vehicle miles traveled reducing from 1.5 to 1.09, fatalities per 100,000 population reducing from 15.23 to 10.35, injured persons per 100 million vehicle miles traveled reducing from 116 to 77, and injured persons per 100,000 population reducing from 1,161 to 732 (National Highway Traffic Safety Administration or NHTSA, 2015). Despite these improvements, the total number of crashes continues to register an increase; there were 5.338 million crashes in 2011 and this number crept up to 5.687 million crashes in 2013 – thus continuing to render the goal of “towards zero deaths” elusive (NHTSA, 2015).

In an effort to enhance safety, transportation agencies and auto manufacturers continuously strive to implement safety improvements and effective counter-measures that would reduce the risk of crashes or reduce the degree of severity of the crash. Passive safety measures such as roadway improvements, barriers, signage, and striping are often utilized by roadway agencies to alert drivers to safety hazards and enhance safety. Seatbelts and airbags are examples of passive safety devices that auto manufacturers have introduced in vehicles to reduce crash severity. More recently, auto manufacturers have been introducing active safety systems that utilize sensor based technologies (such as radar, video, laser, and global positioning systems) to incorporate collision-avoidance applications such as adaptive cruise control, forward collision warning, lane departure warning, blind spot detection, and parking assist. Active safety systems may be considered as the initial steps on the path to full-fledged connectivity and automation that the auto and technology industry hopes to achieve over the next several decades.

The design and deployment of effective safety countermeasures (whether passive or active) requires a knowledge of, and the ability to model and quantify the effects of various roadway, environmental, vehicular, and driver factors that contribute to crashes of various types. In this context, it is desirable to understand and model how various factors influence crash occurrence while explicitly considering the type of crash and the type(s) of vehicle(s) involved. While there is a plethora of research examining the effects of variables on specific crash types (by type of collision, or by types of vehicles involved, or by type of location), to my knowledge, there is virtually no study that takes a comprehensive approach to modeling crash occurrence by type of collision and types of vehicles involved. This thesis aims to fill this gap in the literature by presenting a comprehensive model of crash types that considers these two key dimensions that characterize crashes.

In this study, crash records for 2011-2013 from the National Automotive Sampling System-General Estimates System (GES) crash database are used to estimate a mixed random parameter multinomial logit model of crash probability by collision and vehicle type. The model accounts for roadway attributes, weather and temporal attributes, and driver behavior. The mixed logit modeling approach is adopted to test for unobserved heterogeneity in the impacts of roadway characteristic variables on crash occurrence by type. The model system offers a holistic approach to identifying how various factors influence crash occurrence by collision and vehicle type, thus offering a mechanism to identify how counter-measures may simultaneously affect multiple crash types.

The remainder of this thesis is organized as follows. The next chapter offers a brief overview of crash modeling. The third chapter gives a description of the data used in this research effort while the fourth chapter presents the modeling methodology. The fifth chapter

offers a discussion of model estimation results. Concluding remarks are presented in the sixth and final chapter of the thesis.

Chapter 2: Modeling Crash Occurrence

Crashes are of many different types and involve a multitude of vehicle types. According to the NHTSA, the most common types of collisions in the U.S. are: rear-end collision with a motor vehicle in transport; angle collision with a motor vehicle in transport; collision with a fixed object (e.g., pole, tree); and collision with a non-fixed object (e.g., parked vehicle, pedestrian, bicyclist) (NHTSA, 2015). In the years 2011 through 2013, crash statistics in the U.S. show that about 68 percent of all crashes are collisions with motor vehicle in transport, 15 percent are collisions with a fixed object, and 14 percent are crashes with a non-fixed object. A little over two percent are non-collision events such as rollovers. As the severity of injury in a crash is often associated with the size and weight of vehicles involved, consideration of vehicle type is important in safety research. The NHTSA (NHTSA, 2015) defines six major vehicle type categories including passenger cars, light trucks, large trucks, motorcycles, buses, and other vehicles. Passenger cars and light trucks are involved in 95 percent of all crashes in the U.S., which is not surprising given their prevalence on the nation's roadways – both in sheer volume and in vehicle miles traveled.

Transportation safety is a broad subject with many different aspects involved. The key aspect of the prior research that this paper attempts to address is the fact that the literature has generally dealt with modeling and explaining the influence of various factors on crashes of a specific type, involving specific classes of vehicles, or occurring at specific locations. Neyens and Boyle (2007) examined the effects of distractions on crash occurrence among teenage drivers; they considered crash types (angular, rear-end, and collision with fixed object), but did not consider the types of vehicles involved in the crash. A study by Ghazizadeh and Boyle (2009) is another example of such a study examining the effects of distracted driving with

consideration of crash type, but with no consideration of vehicle type. Bham et al. (2011) estimated a multinomial logit model of collision type, and included consideration of the number of vehicles involved in the collision (single-vehicle versus multi-vehicle collisions), but did not consider vehicle size/body/weight in their characterization of crashes. There are other studies that have explicitly considered vehicle type in crash analysis. Abdel-aty and Abdelwahab (2004) modeled rear-end collisions involving light trucks using a nested logit structure; thus their analysis was focused on a very specific collision and vehicle type. Yan et al. (2005) used a logistic regression modeling approach to identify factors influencing rear-end collisions at signalized intersections, and included consideration of vehicle types (passenger car, passenger van, pickup/light truck, and large size vehicle) in their analysis. However, their analysis was limited to rear-end collisions at signalized intersections. Pai et al. (2009) used the mixed logit modeling methodology to examine factors contributing to motorcycle accidents at priority T-junctions, while Haque and Chin (2010) focused their analysis on motorcycle accidents at signalized intersections. Schneider et al. (2012) examined factors contributing to collisions involving an automobile and a motorcycle using crash record database for the State of Ohio. Crashes involving heavy vehicles have been studied quite extensively, given the concerns associated with injury severity when such vehicles are involved. Romo et al. (2014) and Stevenson et al. (2013) are examples of studies that focused on heavy vehicle crashes under specific circumstances. A study by Mitchell et al. (2015) compared factors contributing to crashes involving novice and mature drivers in New South Wales, Australia; once again, while the study considered different collision types, crashes are not distinguished by vehicle type.

A common aspect that is pervasive in the safety literature is that crashes of specific types or involving certain vehicle types or occurring at specific locations are generally analyzed and

modeled in isolation. This methodology has proven effective at identifying factors and countermeasures that influence specific crash types. However, this approach does not provide a holistic view of how factors and associated countermeasures can simultaneously and differentially affect crashes of diverse types and diverse vehicle types involved. This thesis aims to build on the accumulated knowledge in the literature about factors that affect crashes of different types to provide a more holistic model of crash probability with explicit consideration of collision and vehicle types in the definition of the crash types considered. Moreover, the thesis considers crashes that occur at any and all locations and times of the day, and does not focus on a specific subpopulation of transport system users. The comprehensive model system presented in this thesis considers eight different collision types and three different vehicle types as follows:

- Collision Types
 - Collision with a stationary object
 - Collision with a parked vehicle
 - Collision with a pedestrian
 - Collision with a bicyclist
 - Head-on collision (includes both front-to-front and opposite direction sideswipe collisions)
 - Angle collision (vehicles that are not traveling in the same direction collide at an angle to one another)
 - Rear-end collision (includes both front-to-rear and same direction sideswipe collisions)
 - Rear-to-side collision (rear of one vehicle collides with the side of another vehicle)

- Vehicle Types
 - Light vehicles (automobiles, utility vehicles, and light trucks $\leq 4,536$ kg Gross Vehicle Weight Rating)
 - Heavy vehicles (medium/heavy trucks $> 4,536$ kg Gross Vehicle Weight Rating)
 - Motorcycles, including motorcycles, mopeds, three wheeled motorcycle or mopeds, minibikes, and motor scooters

Prior research has shown that light vehicles, heavy vehicles, and motorcycles are each more prone to different types of crashes; by modeling all crashes comprehensively while explicitly accounting for collision and vehicle type, it will be possible to identify how explanatory factors affect different types of crashes within a unified holistic framework. For example, suppose there is a roadway characteristic that contributes to fewer angle collisions but increased rear-end collisions; the comprehensive model system presented in this thesis will be able to identify this competing influence, and thus help identify countermeasures that may help reduce crashes without resulting in unintended consequences. This thesis is intended to offer a comprehensive model of crash occurrence so that such a holistic perspective can be obtained when assessing the potential effectiveness of safety measures.

Chapter 3: Data Description

This study utilizes crash records from the 2011-2013 GES crash database. The crash records system is maintained by the NHTSA in the U.S. The GES database contains a nationally representative sample of crashes reported to and recorded by the police. The crashes involve at least one motor vehicle traveling on a roadway resulting in death, injury, or property damage. The accident reports included in the sample are chosen from 60 areas that reflect the geography, roadway mileage, population, and traffic conditions of the U.S. GES data collectors make weekly visits to approximately 400 police jurisdictions in the 60 areas across the U.S., where they randomly sample about 50,000 police accident reports each year (NHTSA, 2015). It should be noted that, because GES data are estimates, differences across years may be attributed at least partly to the sampling process (and may not be reflective of an actual trend).

The database compiled for this research effort included 151,557 motor vehicle crashes reported over the three year period. As indicated earlier, this study focuses on the four most common types of collisions that involve motor vehicles in transport (MVIT): head-on, angle, rear-end, and rear-to-side. The study also focuses on four non-MVIT collision types: collision with a stationary object, collision with a parked vehicle, collision with a pedestrian, and collision with a bicyclist. The three distinct vehicle body types are light vehicles, heavy vehicles, and motorcycles. Crashes that did not fall within any of these categories were excluded from the analysis. Crashes with incomplete or missing data on variables of interest were also excluded. Buses and vehicles in other category (farm equipment, golf carts, and construction equipment) were excluded from consideration as well. The final data set for use in this study includes 71,481 crashes.

Table 1 summarizes the distribution of crashes by crash type or alternative. Each record in the database corresponds to one reported motor vehicle crash, irrespective of the number of vehicles involved. A total of 20 crash alternatives were considered because some crash types that had very few observations had to be aggregated into a single alternative. For example, all collisions involving two heavy vehicles were combined into a single alternative. Also, collisions between a heavy vehicle and a motorcycle were excluded from the final data set due to a paucity of observations (even across the three years of observation).

Table 1: Distribution of Crash Types in Study Data Set

Crash Type	Frequency	Percentage
Collision between a light vehicle and a stationary object	21,109	29.5
Collision between a light vehicle and a parked vehicle	2,638	3.7
Collision between a light vehicle and a pedestrian	1,772	2.5
Collision between a light vehicle and a bicyclist	1,194	1.7
Collision between a heavy vehicle and a stationary object	1,540	2.2
Collision between a heavy vehicle and a parked vehicle	143	0.2
Collision between a heavy vehicle and pedestrian/bicyclist	94	0.1
Collision between a motorcycle and a stationary object, parked vehicle, pedestrian, bicyclist, or another motorcycle	3,013	4.2
Head-on collision between two light vehicles	2,905	4.1
Angle collision between two light vehicles	9,459	13.2
Rear-end collision between two light vehicles	17,471	24.4
Rear-to-side collision between two light vehicles	189	0.3
Collision between two heavy vehicles	369	0.5
Head-on collision between a light and a heavy vehicle	361	0.5
Angle collision between a light vehicle and a heavy vehicle	1,498	2.1
Rear-end or rear-to-side collision between a light vehicle and a heavy vehicle	4,536	6.3
Head-on or angle collision between a light vehicle and a motorcycle	782	1.1
Rear-end or rear-to-side collision between a light vehicle and a motorcycle	816	1.1
Head-on or angle collision between multiple vehicles	615	0.9
Rear-end or rear-to-side collision between multiple vehicles	977	1.4
Total	71,481	100.0

The dataset includes a host of explanatory variables that may be used in model specifications. Factors related to weather, time of day, roadway characteristics, and driver behavior are available in the dataset. Weather and temporal attributes include season, day of week, time of day, and weather conditions at time of crash. Roadway characteristics include intersection type, roadway alignment, traffic control devices, and trafficway description. Driver behavior variables include the violation type(s) charged to the driver. A very limited set of demographic variables such as age and gender are available, but were not included in the model specification of this study as safety countermeasures are frequently designed to address all drivers regardless of age and gender. While it is certainly plausible that some interventions are targeted towards certain demographics (such as the elderly or teenage drivers), this study focuses on the influence of non-personal factors on occurrence of crashes by type.

The study involved an extensive exploratory and descriptive analysis of the data to understand how crash occurrence may be associated with the variables available in the dataset. An illustrative example of the descriptive statistics is presented in Table 2. This table shows the distribution of collisions of light vehicles with a non-MVIT by explanatory factor. Table 4 in the Appendix contains the descriptive statistics for all collision types to see how the distributions varied by explanatory factor. These distributions and statistics helped perform the model specifications tested and adopted in this thesis.

Table 2: Descriptive Statistics of Light Vehicle Collisions with a Non-Motor Vehicle in Transport

	Light Vehicle Collision with Non-Motor Vehicle in Transport			
	Stationary Object	Parked Vehicle	Pedestrian	Bicyclist
	21109	2638	1772	1194
Weather/Temporal Attributes				
Season				
Autumn (base)	25.8%	25.3%	27.7%	28.0%
Winter	28.7%	25.9%	28.6%	17.2%
Spring	22.9%	23.8%	24.9%	24.0%
Summer	22.6%	25.1%	18.7%	30.8%
Weather				
Clear (base)	62.2%	74.1%	72.6%	78.6%
Cloudy	16.9%	14.9%	14.5%	15.5%
Rain or Drizzle	14.4%	7.6%	11.7%	5.4%
Snow	5.1%	2.7%	0.8%	0.1%
Fog or Smog	0.8%	0.3%	0.3%	0.2%
Severe Wind/Sand/Other	0.5%	0.3%	0.1%	0.3%
Day of Week				
Weekday (base)	66.7%	64.1%	75.3%	74.5%
Weekend	33.3%	35.9%	24.7%	25.5%
Time of Day				
12am-7am	29.1%	28.1%	14.6%	8.1%
7am-10am	16.0%	13.4%	14.3%	20.9%
10am-4pm (base)	23.3%	25.7%	24.5%	34.0%
4pm-8pm	18.2%	17.9%	31.8%	27.8%
8pm-12am	13.4%	14.9%	14.7%	9.1%
Roadway Characteristics				
Intersection Type				
Non-intersection (base)	93.1%	94.8%	55.0%	39.9%
Four-way Intersection	3.3%	2.3%	34.4%	42.9%
T-Intersection	3.1%	2.7%	9.7%	15.8%
Y-Intersection	0.3%	0.1%	0.4%	0.3%
Traffic circle, Roundabout or L-Intersection	0.2%	0.2%	0.6%	1.1%
Roadway Alignment				
Straight (base)	73.2%	91.2%	96.4%	97.4%
Curved	26.8%	8.8%	3.6%	2.6%
Traffic Control Device				
No Controls (base)	97.4%	98.8%	69.2%	62.1%
Traffic Signal	2.5%	1.1%	30.5%	37.4%
Flashing Signal	0.1%	0.0%	0.2%	0.5%
Other	0.0%	0.1%	0.1%	0.1%

Table 2 (continued)

Trafficway Description	Light Vehicle Collision with Non-Motor Vehicle in Transport			
	Stationary Object	Parked Vehicle	Pedestrian	Bicyclist
	21109	2638	1772	1194
Two-way, Not Divided (base)	54.0%	75.2%	55.0%	57.2%
Two-way, Divided, Unprotected Median	11.5%	7.8%	16.1%	15.7%
Two-way, Divided, Positive Median	25.9%	8.0%	13.8%	14.8%
One-way Traffic	2.2%	6.3%	6.8%	4.4%
Two-way, Undivided, Left-Turn Lane	2.0%	2.0%	7.6%	7.4%
Entrance/Exit Ramp	4.5%	0.7%	0.6%	0.6%
Driver Behavior				
Violation Charged to Driver in Vehicles				
None	65.9%	55.4%	77.8%	72.3%
Reckless Offense	4.0%	6.2%	3.0%	5.6%
Impairment Offense	4.3%	7.2%	0.6%	0.3%
Speed-related Offense	4.5%	3.0%	0.6%	0.2%
Rules of the Road	2.5%	2.7%	8.4%	12.1%
License, Registration, Equipment Violations	8.5%	9.9%	4.7%	4.7%
Multiple Violations Charged to Driver	10.4%	15.5%	5.0%	4.9%

Table 2 provides an initial glimpse into how collisions between a light vehicle and a non-MVIT may be associated with various explanatory factors. A majority of such collisions occur on weekdays; this is consistent with the fact that weekdays account for a larger portion of light vehicle travel compared to weekends. However, what is interesting to note is that the proportion of such crashes is even higher for collisions involving pedestrians and bicyclists on weekdays. This is confirmed by trends seen in 2009 National Household Travel Surveys (Santos et al., 2011), which showed greater prevalence of such non-motorized mode users on weekdays. Pedestrian- and bicyclist-involved collisions appear to occur more in the 4:00-8:00 PM hours. Sullivan and Flannagan's (2002) research study on the influence of light level on fatal pedestrian

and vehicle crashes has shown that the risk of nighttime incidents involving pedestrians can increase up to seven times compared to daytime. A research study by Shinar and Compton (2004) examining aggressive driving behaviors revealed that the likelihood of aggressive driving is higher when the value of time is high (i.e., rush hour), compared to travel periods where the value of time is low (i.e., non-rush weekday and weekend hours). The combination of these additional risk factors contributes to the increased number of collisions during this time period. The weather-related statistics indicate that a large proportion of crashes occur on clear days, although collisions with a stationary object show a higher percent (relative to other collision types) during rain and snow – an observation that is consistent with expectations.

Within the intersection-related crashes, bicyclists and pedestrians are quite vulnerable at four-way intersections and T-intersections, caused by the multiple conflict points and road rule violations prevalent at such intersections (Cinnamon et al., 2011). Curved roads and curved intersection approaches are associated with light vehicle crashes involving a stationary object (26.8 percent is considerably higher than other percentages in that row). A rather large percent of pedestrian- and bicyclist-involved crashes occur when a traffic signal is present (note that traffic signals can occur at non-intersection locations too, such as a crosswalk at a mid-block of a roadway); again, the presence of multiple conflict points and non-adherence to traffic signal indications contributes to these high percentages (30.5 percent for pedestrians and 37.4 percent for cyclists). Two-way divided roadways (that are likely to be wider to cross and operate at higher speeds) are associated with a higher prevalence of pedestrian and bicyclist involved crashes. In most crashes, drivers have not been charged or cited. In the case of collisions involving a stationary object or a parked vehicle, however, drivers are cited more than in collisions involving pedestrians and bicyclists.

The dataset was analyzed and descriptive statistics such as those in Table 2 were studied carefully to help identify trends in the data that could help perform the model specifications adopted in this thesis.

Chapter 4: Methodology

In this study, a mixed random parameter multinomial logit (MMNL) approach is adopted for modeling crash types, which are categorized by both the manner of collision and the vehicle type(s) involved. Each case in the dataset represents a reported motor vehicle crash that occurred between the years of 2011 to 2013 in the U.S. Therefore, the crash type involving the driver(s) of the motor vehicle(s) can be observed to be one among 20 distinct crash types (i.e., 20 alternatives). Each alternative represents one combination of crash type (e.g., rear-end or with a stationary object) and vehicle type (i.e., light vehicle, heavy vehicle, or motorcycle).

The likelihood of crash type $j(j = 1, 2, \dots, J)$ for driver $q(q = 1, 2, \dots, Q)$ can be specified as:

$$\begin{aligned} U_{qj} &= \boldsymbol{\beta}'_q \mathbf{x}_{qj} + \varepsilon_j \\ &= (\mathbf{b} + \tilde{\boldsymbol{\beta}})' \mathbf{x}_{qj} + \varepsilon_j \end{aligned} \quad (1)$$

where \mathbf{x}_{qj} is a column vector of explanatory variables that is related to weather/temporal attributes, roadway characteristics, and driver behavior factors. \mathbf{b} is a column vector of coefficients representing the mean effect of explanatory variables. $\tilde{\boldsymbol{\beta}}$ is a column vector of coefficients representing the random effect. Further, $\tilde{\boldsymbol{\beta}}$ is assumed to be distributed normal and uncorrelated across parameters, i.e., $\tilde{\boldsymbol{\beta}} \sim \text{MVN}(\mathbf{0}, \mathbf{v})$. Finally, ε_j is the random error term which is distributed independently and identically and has an extreme value distribution.

Thus the probability of observing a crash of type j for driver q can be written as (Revelt and Train, 1998):

$$P_{qj} = \int_{\tilde{\boldsymbol{\beta}}} \frac{\exp[(\mathbf{b} + \tilde{\boldsymbol{\beta}})' \mathbf{x}_{qj}]}{\sum_{\forall j} \exp[(\mathbf{b} + \tilde{\boldsymbol{\beta}})' \mathbf{x}_{qj}]} f(\tilde{\boldsymbol{\beta}} | \mathbf{0}, \mathbf{v}) d\tilde{\boldsymbol{\beta}} \quad (2)$$

As the integral in equation (2) does not have a closed form solution, a maximum simulated likelihood approach is used to obtain the probability of a crash. In the simulated likelihood approach, equation (2) may be written as:

$$P_{qj} = \frac{1}{R} \sum_{r=1}^R \frac{\exp[(\mathbf{b} + \mathbf{v}\mathbf{w}_r)' \mathbf{x}_{qj}]}{\sum_{\forall j} \exp[(\mathbf{b} + \mathbf{v}\mathbf{w}_r)' \mathbf{x}_{qj}]} \quad (3)$$

where \mathbf{w}_r is a column vector of Halton draws. In this study, 250 Halton draws are used in the maximum simulated likelihood estimation approach. Details about the maximum simulated likelihood estimation approach, and the use of Halton draws to compute choice probabilities, may be obtained in Bhat (2001).

Chapter 5: Model Estimation Results

A mixed multinomial logit model (MMNL) was estimated on the data set of 71,481 crash records considering 20 distinct crash alternatives. The mixed logit model was adopted to account for potential heterogeneity in the effects of certain variables on crash types by nature of collision and vehicle involvement. The methodology was coded in the GAUSS programming language and model estimation was accomplished using the simulated maximum likelihood approach. For convenience, the base category for model estimation was set as the collision between a light vehicle and a stationary object. It should be noted that the model indicates the probability of involvement in one of the crash types, given that a crash has occurred. The model does not purport to explain the propensity of crash occurrence, crash frequency, or crash/injury severity. The sole purpose of the model is to determine the influence of various factors on the likelihood of different crash types (conditional on a crash event) under various conditions.

This section presents a summary of key findings based on the model estimation results. For illustrative purposes, the model estimation results are furnished in their entirety for two specific alternatives in Table 3. The complete estimation results are presented in Table 5 in the Appendix. The descriptive write-up highlights results seen in Table 5. The write-up is organized with respect to the various sets of attributes considered in the model specification. The base alternative in the mixed logit model estimation results corresponds to light vehicle collisions with a stationary object.

The constants in the model reflect that the probability of virtually all crash types is lower than that of the base alternative – namely, the collision of a light vehicle with a stationary object. The one exception, where a positive constant is noted, is the rear-end collision between two light vehicles. It appears that collisions are likely to be more of the rear-end type (involving two light

vehicles) than other types of collisions (note that the constants have a meaningful interpretation because all exogenous variables are categorical).

Roadway characteristics (intersection type, roadway alignment, traffic control devices, and trafficway description) were tested in particular for random effects. Variables that have a statistically significant random effect parameter indicate that this particular crash alternative is being influenced by other unmeasured factors that were not accounted for in this study. One potential explanation for the variations in all variables with random effects may be caused by traffic volume (Wier et al., 2009; Brugge et al., 2002), a variable that is not available in this dataset. In addition, crash alternatives involving two moving agents will likely exhibit more variability compared to the base alternative (the collision of a light vehicle with a stationary object). Variations in these variables may be further explained through the unmeasured pre-crash maneuver of each agent involved.

Table 3. Illustrative Mixed Logit Model Estimation Results for Two Crash Type Alternatives

	Light Vehicle Collision with Non-MVIT			Collision Between Two Light Vehicles			
	Parked Vehicle	Pedestrian	Bicyclist	Head-on	Angle	Rear-End	Rear-Side
Constant	-1.4210	-2.7800	-3.2800	-1.8180	-1.2340	0.1010	-4.6920
Weather/Temporal Attributes							
Season (Base: Autumn)							
Winter	--	--	--	--	0.0490	--	--
Spring	--	--	--	--	0.0790	0.0790	--
Summer	--	--	--	--	--	--	--
Weather (Base: Clear, Fog or Smog ¹ , Severe Crosswind or Blowing Sand or Other Weather ¹)							
Cloudy	-0.2240	-0.2240	-0.2240	-0.1660	-0.2240	-0.2240	--
Rain/Drizzle	-0.5790	--	--	-0.1660	--	-0.2880	--
Snow	-0.5790	-0.9240	-0.9240	-0.1660	-0.9240	-0.9240	--
Day of Week (Base: Weekday)							
Weekend	0.1770	-0.4130	--	-0.4130	-0.4130	-0.4130	--
Time of Day (Base: 10am-4pm)							
12am-7am	--	-0.9150	-1.9350	-0.9150	-1.9350	-1.9350	-1.9350
7am-10am	--	--	--	-0.3280	-0.3280	-0.3280	--
4pm-8pm	--	0.4060	0.4060	--	-0.1430	-0.1430	--
8pm-12am	--	--	-0.8640	-0.8640	-0.8640	-1.4200	--
Roadway Characteristics							
Intersection Type (Base: Non-Intersection)							
4-way Intersection							
Mean	--	2.2810	2.2810	1.0270	2.2810	1.0270	1.0270
Std Dev	--	--	--	0.2340	--	0.2340	0.2340
T-Intersection							
Mean	--	0.7580	1.2190	--	1.2190	--	--
Std Dev	--	--	0.8690	--	0.8690	--	--
Y-Intersection							
Mean	--	0.7580	--	--	--	--	--
Std Dev	--	--	--	--	--	--	--
Traffic Circle							
Mean	0.2470	0.7580	0.2470	0.2470	--	--	0.2470
Std Dev	--	--	--	--	--	--	--
Roadway Alignment (Base: Straight)							
Curved							
Mean	-1.6780	-1.6780	-1.6780	--	-1.6780	-1.6780	--
Std Dev	--	--	--	--	--	--	--
Traffic Control Device (Base: No Controls, Other ¹)							
Traffic Signal							
Mean	-1.5500	1.5910	1.5910	1.5910	1.5910	1.5910	1.5910
Std Dev	--	--	--	--	--	--	--
Flashing Signal							
Mean	--	--	--	0.6990	0.6990	0.6990	0.6990
Std Dev	--	--	--	--	--	--	--

¹Estimated coefficients statistically insignificant at 95 percent confidence level

Table 3 (continued)

	Light Vehicle Collision with Non-MVIT			Collision Between Two Light Vehicles			
	Parked Vehicle	Pedestrian	Bicyclist	Head-on	Angle	Rear-End	Rear-Side
Constant	-1.4210	-2.7800	-3.2800	-1.8180	-1.2340	0.1010	-4.6920
Trafficway Description (Base: Two-way, Not Divided)							
Two-way, Divided, Unprotected Median							
Mean	-0.6710	0.0850	0.0850	-0.6710	0.0850	0.0850	--
Std Dev	--	0.9810	0.9810	--	0.9810	0.9810	--
Two-way, Divided, Positive Median Barrier							
Mean	-1.5180	-0.4830	--	-1.5180	-0.4830	0.0700	-0.4830
Std Dev	--	--	--	--	--	1.4670	--
One-way Traffic							
Mean	0.7420	0.7420	0.7420	-0.9380	--	0.7420	0.7420
Std Dev	0.3080	0.3080	0.3080	--	--	0.3080	0.3080
Two-way, Undivided, Left-Turn Lane							
Mean	--	0.8520	0.8520	0.8520	0.8520	0.8520	0.0490
Std Dev	--	0.6340	0.6340	0.6340	0.6340	0.6340	--
Entrance/Exit Ramp							
Mean	-1.5110	-1.5110	-1.5110	-1.5110	-1.5110	0.6280	--
Std Dev	--	--	--	--	--	0.3110	--
Driver Behavior							
Violation Charged to Driver in Vehicles (Base: None)							
Reckless	--	--	--	0.5870	0.5870	0.5870	--
Impairment	--	--	--	0.5480	-0.1830	-0.1830	--
Speed-related	--	--	--	-0.6520	-0.6520	1.2400	--
Rules of Road	--	--	--	1.5920	1.5920	--	--
Lic/Regn/Equip	--	--	--	0.4920	0.4920	0.4920	--
Multiple Violations	--	--	--	0.4540	0.4540	0.4540	--

¹Estimated coefficients statistically insignificant at 95 percent confidence level

5.1 SEASON AND WEATHER

Estimation results (shown in Table 5) suggest that crashes involving motorcycles are less likely to occur in the winter compared to other seasons of the year. Branas and Knudson (2001) stated that motorcycle fatalities are a function of the length of the riding season, which is shortened by factors such as lower temperatures and more precipitation; therefore, fewer motorcycles on the roads during winter months will naturally lead to fewer crashes involving motorcycles. Likewise, it was found that the probability of crashes involving motorcycles is higher in the spring and summer months. The likelihood of two light vehicles getting into an angle collision was found to be higher in the winter, compared to fall and summer (see Table 3). Wet and icy pavement conditions are known to cause drivers to lose breaking power and steering control, which contributes to a higher likelihood of angle crashes. Some coefficients are statistically significant, but not necessarily easily explained. For example, the higher propensity for angle and rear-end collisions in the spring (as signified by the positive coefficient of 0.0790) warrants further research.

An interesting finding is that all crash types are less likely to occur under adverse weather conditions (such as rain/drizzle, cloudy, and snow) in comparison to the collision involving a vehicle striking a stationary object. During inclement weather, roads are slippery and visibility is diminished; given a crash occurs under such conditions, the most likely crash type is where a driver skids off the road and strikes an object. Previous research (Kilpeläinen and Summala, 2007) has found that drivers are more cautious when

driving under adverse weather conditions; this is another reason why negative coefficients are associated with weather conditions in Table 3.

5.2 TEMPORAL ATTRIBUTES

The weekend days are associated with a lower likelihood of collisions between two light vehicles and collisions between a light vehicle and pedestrians. On weekends, travelers are likely to be more relaxed, traffic congestion is likely to be less severe, and travelers are likely pursuing more leisure-type activities. For these reasons, the lower propensity for such crash types is quite reasonable. The propensity for a crash type where a light vehicle strikes a parked vehicle is higher, however, on weekends. Travel trends from the National Household Travel Survey (Pucher et al., 2011) showed that a higher percentage of non-work trips are made on weekends compared to weekdays. The larger number of social recreational and shopping trips on weekends can contribute to travelers undertaking parking maneuvers to a larger degree than on weekdays. This finding is also consistent with that reported by Bham et al. (2011) who found that the risk of single-vehicle collisions is higher on weekends, whereas the risk of multi-vehicle collisions is higher on weekdays. They attributed this to lower traffic volumes on weekends. The lower prevalence of trucks and heavy vehicles on the roadways during weekends contributes to a lower propensity for crash types involving heavy vehicles on weekend days (seen in Table 5). Crashes involving motorcycles were found to be more likely on weekends, a finding that is consistent with the higher level of recreational motorcycle riding on weekends.

In general, all crash types are less likely to occur between 12 midnight and 7:00 AM when there is less traffic on the roadways. Between 4:00 PM and 8:00 PM, there is a higher likelihood of crashes involving a light vehicle colliding with a pedestrian or bicyclist. These positive coefficients (0.4060) reflect the higher propensity for pedestrian and bicycle crashes to occur in the afternoon and evening peak hours when individuals are pursuing a variety of activities, traffic volumes are high, and children are pursuing after school activities. Cinnamon et al. (2011) conducted research on several high-incident intersections in Vancouver, Canada and found that pedestrian and motor vehicle violations occurred to a higher degree in the afternoon peak period of 4:00 PM to 6:00 PM. Collisions involving two light vehicles are most likely to occur in the midday (10:00 AM to 4:00 PM) as evidenced by the negative coefficients on all other time of day variables.

5.3 ROADWAY CHARACTERISTICS

A variety of roadway characteristics were included in the model specification and tested for random effects to capture potential unobserved heterogeneity that may be present in the way in which a roadway characteristic affects crash type probabilities.

5.3.1 Intersection Type

In general, it is seen that crashes of various types are more likely to occur at intersections, including four-way intersections, T-intersections, Y-intersections, and roundabouts. The larger number of conflict points and approaches at intersections increases the propensity for crashes that involve pedestrians and bicyclists, and collisions

of various types that involve two vehicles. Niewoehner and Berg (2005) stated that the higher seat position of truck drivers leads to many more blind spots in front of, adjacent to and behind the truck, compared to a passenger car. This can explain the increase in the likelihood of heavy vehicle collisions with pedestrians and bicyclists, and head-on and angle collisions with light vehicles at four-way and T-intersections. The study conducted by Pai and Saleh (2008) regarding motorists' failure to yield violations in motorcycle accidents at T-junctions found that automobile drivers tend to use smaller safety gaps when pulling out in front of motorcycles, compared with cars. It is difficult for drivers to judge the necessary clearance distance of oncoming motorcycles traveling at high speeds, leading to a higher risk of a collision with a motorcycle. In addition, the absence of clear pedestrian crosswalks and the inability to adequately assess vehicular maneuvers at Y-intersections contributes to greater pedestrian-involved crashes at such intersections (California Department of Transportation, 2010).

Unobserved heterogeneity is significant at four-way intersections for head-on, rear-end, and rear-to-side collisions involving two light vehicles. This is a result of the presence of unobserved factors (not contained in the data set) that affect crash type propensity; for example, traffic volume, geometric configuration of approach and turning lanes, adjoining land uses, and turning movements affect crash type probabilities. All of these factors remain unmeasured and hence the effect of a four-way intersection on crash type probabilities exhibits a significant amount of heterogeneity. Findings in this paper corroborate results reported by Niewoehner and Berg (2005) and Pai and Saleh (2008), who noted that crashes of various types are more prevalent at intersections.

The statistically significant standard deviation term for light vehicle collisions with a bicyclist at T-intersections indicates the presence of unobserved heterogeneity. This could be attributed to the pre-crash maneuver of the bicyclist, which is not included in this research study. If bicyclists are at-fault for the collision, this could be a result of the bicyclist violating the right-of-way rules at the intersection (e.g. running red lights at signalized intersections, or going when they do not have right-of-way at unsignalized intersections). Johnson et al. (2013) attributed the main reasons that bicyclists infringe on red lights at signalized intersections to (1) turning left, (2) inductive detector loop did not detect the bicyclist, (3) no other road users were present, and (4) using a pedestrian crossing. At T-intersections, it is possible that more of these scenarios are mistakenly perceived by bicyclists to be safe, due to the fact that there are fewer vehicle approaches to be cognizant of. Unobserved heterogeneity is also significant at T-intersections for angle collisions between two light vehicles. The dataset does not capture the number of lanes going in each direction or whether the T-intersection has a continuous right-turn lane. Right-turning vehicles that fail to yield to oncoming traffic will result in a higher likelihood for angle collisions. On the other hand, T-intersections with only one lane going in each direction reduce the likelihood for sideswipe-same direction crashes (included in the angle crash category).

5.3.2 Roadway Alignment

An examination of roadway alignment effects suggests that crashes of various types are less likely to occur on curved roads and curved intersection approaches, in comparison to the base alternative of crashes that involve a vehicle striking a stationary object. Wang et al. (2013) noted that road curvature has unexpected safety benefits as drivers slow down when maneuvering around curves, tend to be more alert and careful when navigating curves, and are less likely to be bored and sleepy when their path involves curves. If a crash does occur, then it was found that it is more likely to be one where the driver runs off the road and strikes a stationary object (Bham et al., 2011). Motorcycle collisions, on the other hand, are more likely to occur on curved roads, a finding that is consistent with expectations (shown in Table 5).

5.3.3 Traffic Control Device

Traffic signals are likely to be present at intersections and locations where traffic volumes are high, the number of conflict points is high, and safety hazards exist. As such, it is not surprising that the presence of a traffic signal is associated with a higher crash probability for crashes of various types (e.g., crash types involving pedestrians, bicyclists or multiple vehicles), except for the crash type where a light vehicle collides with a parked vehicle. As parked vehicles are not likely to be in the vicinity of a signal (regulations to increase the visibility between pedestrians and approaching vehicles), this finding is consistent with expectations.

5.3.4 Trafficway Description

In general, two-way, divided roads with or without protected medians are able to reduce the likelihood of single-vehicle and multi-vehicle crash types, compared to undivided two-way roads. Several exceptions are seen in the statistically significant standard deviation terms, indicating the presence of unobserved heterogeneity.

Unobserved heterogeneity is significant for rear-end collisions between two light vehicles on two-way, divided streets with a positive median barrier. Adding traffic volume at the time of the incident into the dataset used for analysis may be able to shed light on the variation seen in this variable. Medians are typically installed for highways with heavy traffic volumes (Yan et al., 2005), a roadway environment known to increase the likelihood for rear-end collisions (caused by stop-and-go maneuvers).

Descriptors of the trafficway influence crash type probabilities significantly. Consider a two-way roadway with an unprotected median. The propensity for angle, rear-end, and pedestrian/bicyclist involved crashes is higher, as evidenced by the positive (mean) coefficient. The standard deviation is also statistically significant, indicating the presence of unobserved heterogeneity. Bicyclists and pedestrians have been known to cross trafficways mid-block when a crosswalk is not conveniently located within close proximity. In doing so, they are more likely to be involved in a crash as drivers are not expecting to encounter such road users outside of designated crosswalks or bike lanes. A previous study has shown that drivers are also less sensitive to jaywalkers and will not yield as often, or decelerate as much, compared to the way they would for pedestrians legally crossing at crosswalks (Zheng et al., 2015). This phenomenon can contribute to an

increase in crash propensity for bicyclists and pedestrians on two-way roadways with an unprotected median. On the other hand, a median can serve as a protective shelter for pedestrians and bicyclists, thus decreasing the crash propensity. Lane width or presence of a bike lane are additional roadway characteristic factors that are not included in the analysis. The width of the median may eliminate the extra road width required for a bike lane. The absence of bike lanes can increase the number of collisions with bicyclists, while the presence of bike lanes is associated with a lower risk of incidents involving bicyclists (Reynolds et al., 2009). In other words, there may be considerable variation in how this particular trafficway configuration affects crash propensity for bicyclists and pedestrians; the mixed logit model offers a way to capture the unobserved heterogeneity or variation in the impacts of this trafficway configuration variable.

Rear-end collisions between two light vehicles and collisions between two heavy vehicles show a greater propensity to occur on divided highways; this may appear counter-intuitive at first, but is consistent with results reported by Yan et al. (2005) who noted that such roadways can see higher rates of collisions because highways with higher traffic volumes tend to install divided medians as a safety measure. The study stated that heavy traffic volumes increase the opportunities for rear-end collisions because of the smaller gaps between vehicles. However, the significant unobserved heterogeneity term for these crash types indicates that the safety benefits of medians (separates oncoming traffic) can be effective for reducing collisions involving light or heavy vehicles.

As expected, head-on collisions involving two vehicles are less likely to occur on one-way streets. However, crashes involving a non-MVIT and rear-end crashes are more

likely to occur on one-way streets. As one-way streets are more likely to be encountered in dense central city areas, it is not surprising to see higher crash propensities involving a non-MVIT (parked vehicles on the side of the road, pedestrians, and bicyclists are likely to be present in larger numbers in such locations). The significant heterogeneity term suggests that factors such as the pre-crash maneuver of the vehicle, the configuration of the one-way street, the surrounding land use, and the provision of sidewalks, crosswalks, and bicycle lanes may contribute to variation in how one-way streets affect crash type probabilities. In a research study conducted by Gayah and Daganzo (2012) comparing the capacity for one-way and two-way signalized street networks, they first outlined the arguments made by supporters and opponents of one-way networks. Opponents cited increased driver inattention and faster travel speeds on one-way streets to be the cause of increased collisions involving a non-MVIT or rear-end collisions. On the other hand, proponents of one-way streets stated that they create fewer conflicting maneuvers at intersections (eliminates permissive left-turn maneuvers) and reduce congestion (offers higher vehicle flows), thus reducing common intersection collision types.

In general, when a continuous left-turn lane is present on a two-way, undivided roadway, there is a higher likelihood for all crash types. This is consistent with expectations, since the introduction of a conflict zone between the left-turning and oncoming vehicles will increase the likelihood for more types of collisions. Kim and Washington (2006) found high annual average daily traffic and high number of driveways on the major road to increase the number of angle crashes involving left-turning vehicles. Continuous left-turn lanes may be used for turning into a parking lot or

driveway, rather than onto another road. Parking lots and driveways are generally found near areas with high levels of foot traffic (e.g. shopping malls, business parks, residential areas). The extra foot traffic is likely to increase the possibility of collisions with pedestrians or bicyclists. Bicyclists can use the lane for left-turns as well, putting them directly in the line of traffic, which can also increase the likelihood of collision with vehicles. Unobserved heterogeneity is significant for light vehicle collisions with pedestrians or bicyclists and for head-on, angle, and rear-end collisions between two light vehicles. One explanation for increased safety on roads with continuous left-turn lanes is that the installation of left-turn lanes removes waiting vehicles from the through-traffic stream, which has the benefit of reducing the likelihood of rear-end crashes caused by vehicles going straight. This also reduces the pressure on the left-turning vehicle (by causing traffic to be backed up) and gives them more time to choose a gap that is safe for turning, thus reducing the possibility of head-on and angle collisions, or even collisions with pedestrians and bicyclists (Federal Highway Administration, 2014).

Rear-end collisions have a higher propensity at entrance and exit ramps (compared to two-way undivided roads). A previous study (McCartt et al., 2004) characterized ramp-related collisions on urban interstate roadways in Northern Virginia and found rear-end collisions to be the most predominate crash type on entrance ramps. Following too closely due to traffic congestion was the main contributing factor in these crashes. The significant heterogeneity for this variable suggests that unobserved factors influence rear-end crash propensity. Liu et al. (2009) revealed a relationship between freeway lane arrangement types and crash rates. Lane consistency (avoiding lane

reduction) and lane balance (proportion of the number of lanes before and after the merge) can help reduce ramp-related collisions. Heavy vehicles were found to have an increased likelihood of getting into a collision at entrance/exit ramps with other light or heavy vehicles, as well as stationary objects. Heavy vehicles require more time to react, compared to other vehicle types, so sudden stop and go maneuvers or objects falling out of vehicles' cargo space will pose as a crash risk for heavy vehicles.

5.4 DRIVER BEHAVIOR

Compared to the base case involving a collision of a vehicle with a non-MVIT object, drivers are more likely to be charged in collisions that involve multiple vehicles (collisions between two light vehicles in Table 3). When a vehicle strikes a non-MVIT object, it can be difficult to identify the individual who is at fault, provided that pedestrians have the right-of-way at controlled intersections and in marked crosswalks, but are also known to violate road rules which can elicit collisions with vehicles. On the other hand, when two vehicles are involved in a collision, one or more of the drivers are usually at fault thus resulting in a citation. Reckless driver behavior, not following rules of the road, drivers with faulty equipment and expired license/registration, and drivers with multiple infractions are shown to contribute to all types of collisions involving two light vehicles (except for rear-to-side collisions). Speed related infractions contribute less to head-on and angle crashes, and more to rear-end collisions – a finding consistent with the notion that higher speeds require longer stopping distances and hence the higher likelihood of rear-end collisions. Impaired driving contributes positively to head-on

collisions (because drivers are not able to maintain their path), but negatively to angle and rear-end collisions – a finding that is somewhat counterintuitive and worthy of additional investigation. It may be that angle and rear-end collisions are associated more with other driver infractions than impaired driving.

5.5 GOODNESS OF FIT MEASURES

The mixed logit model offers a superior goodness of fit to the simpler multinomial logit model that does not account for unobserved heterogeneity. The log-likelihood value for the model with constants-only is -153472.9825 with 19 parameters. The multinomial logit model has a log-likelihood value of -99021.4303 with 90 parameters, while the mixed logit model has a log-likelihood value of -93364.7000 with 100 parameters. The improvement in the log-likelihood due to the inclusion of explanatory variables with heterogeneity terms results in the following:

$$\rho_C^{-2} = 1 - \frac{-93364.70 - 100}{-153472.98 - 19} = 0.34$$

In addition, the improved fit offered by the mixed logit over the multinomial logit may be assessed by computing the likelihood ratio χ^2 statistic as:

$$-2[-99021.4303 - (-93364.7000)] = 11313.50$$

This value is far greater than the critical χ^2 statistic of 28.30 at 12 degrees of freedom.

This implies that the additional parameters introduced in the mixed logit specification offer significant explanatory power and capture unobserved heterogeneity that is not adequately accounted for in the multinomial logit model.

Chapter 6: Summary and Conclusions

This thesis presents a comprehensive framework for modeling highway safety considering the full range of crash types defined by the nature of collision and vehicles involved. Previous research in the transportation safety arena has largely focused on analyzing and modeling crash occurrence, crash frequency, or injury severity for a subgroup of transport system users along specific dimensions. While such literature has offered rich insights into the factors that contribute to crashes and injury severity of different types, it does not provide a holistic view of the influence of various explanatory factors on a multitude of crash types simultaneously. How does a certain roadway attribute affect the probability of a rear-end collision involving two vehicles and the probability of a crash involving a light vehicle striking a pedestrian? The answer to such a question can be obtained by modeling all crash type outcomes in a single comprehensive model. More importantly, by examining how a factor affects multiple crash type outcomes simultaneously, it is possible to devise countermeasures, improvements to roadway geometry, and traffic control strategies while minimizing unintended consequences.

In this thesis, a comprehensive model of roadway crash type is presented. The model considers 20 different crash type alternatives, considering eight different collision types and three different vehicle types. A mixed logit model of crash type is estimated using the 2011-2013 GES crash database. Roadway characteristics, weather and seasonal attributes, temporal attributes are explanatory factors included in the model. In addition,

the mixed logit model specification accommodates for the presence of unobserved heterogeneity in the effects of various factors on crash type propensity. In general, it is found that several roadway attributes exhibit such unobserved heterogeneity; this is not surprising given that the data set does not include detailed information about traffic volumes and congestion levels, lane configurations, bicycle and pedestrian facilities, and adjoining land uses. The mixed logit model specification is able to account for variations in impacts due to such unobserved factors and is found to offer a statistically superior goodness-of-fit in comparison to the regular multinomial logit model.

The importance of modeling safety in a comprehensive framework is evident in the model estimation results. For example, the model estimation results show that the introduction of an unprotected median in a two-way roadway could reduce head-on collisions between two light vehicles. Similarly, converting a street to a one-way street will result in reduced likelihood of head-on collisions. However, these strategies alone contribute positively to the probability of other crash types, unless the strategies are implemented in a way that minimizes unintended consequences. Both of these variables exhibit considerable unobserved heterogeneity in the manner in which they impact crash type probabilities. Through careful consideration of such unobserved factors, it will be possible to design effective safety measures that produce the intended and desired outcomes without increasing a different type of crash risk. The introduction of a positive median barrier appears to decrease the probability of several crash types, thus suggesting it is an effective safety measure; however, it also increases the probability of specific crash types including a heavy vehicle striking a stationary object, rear-end collision

between two light vehicles, and collision between two heavy vehicles. It is important to understand how and why median barriers contribute positively to such crash types; the provision of median barriers can then be combined with other safety measures that reduce or eliminate the increase in probability of certain crash types. For example, restrictions on the passage of heavy vehicles during certain high traffic periods of the day may be a strategy that can be combined with the provision of median barriers.

This study offers insights into factors affecting the probability of crashes of various types by comprehensively considering all crash types simultaneously. The results should be of value in the design of automotive safety systems; for example, the results in this thesis suggest that pedestrian and bicyclist safety is compromised when a larger heavy vehicle approaches an intersection, attributed to the fact that heavy vehicle drivers are not able to see pedestrians and bicyclists easily and are distracted by the presence of other vehicles and conflicting movements at intersections. Heavy vehicles can be equipped with sensors alerting drivers to the presence of such non-motorized road users. Comprehensive models of safety will be of considerable value in the march towards vehicle connectivity and automation.

Appendix

Table 4: Descriptive Statistics of All Crash Types in Study Data Set

	Light Vehicle Collision with Non-MVIT				Heavy Vehicle Collision with Non-MVIT			Motorcycle Collision with Non-MVIT or Another Motorcycle
	Stationary Object	Parked Vehicle	Pedestrian	Bicyclist	Stationary Object	Parked Vehicle	Pedestrian/Bicyclist	
	21109	2638	1772	1194	1540	143	94	3013
Weather/Temporal Attributes								
Season								
Autumn (base)	25.8%	25.3%	27.7%	28.0%	26.4%	25.9%	25.5%	25.0%
Winter	28.7%	25.9%	28.6%	17.2%	24.5%	24.5%	23.4%	9.8%
Spring	22.9%	23.8%	24.9%	24.0%	24.1%	21.0%	24.5%	28.3%
Summer	22.6%	25.1%	18.7%	30.8%	25.0%	28.7%	26.6%	36.9%
Weather								
Clear (base)	62.2%	74.1%	72.6%	78.6%	61.4%	72.7%	72.3%	82.7%
Cloudy	16.9%	14.9%	14.5%	15.5%	15.4%	18.9%	17.0%	12.8%
Rain or Drizzle	14.4%	7.6%	11.7%	5.4%	17.4%	4.2%	10.6%	3.8%
Snow	5.1%	2.7%	0.8%	0.1%	4.5%	3.5%	0.0%	0.0%
Fog or Smog	0.8%	0.3%	0.3%	0.2%	0.4%	0.7%	0.0%	0.3%
Severe Wind/Sand/Other	0.5%	0.3%	0.1%	0.3%	0.9%	0.0%	0.0%	0.3%
Day of Week								
Weekday (base)	66.7%	64.1%	75.3%	74.5%	85.8%	88.1%	86.2%	60.8%
Weekend	33.3%	35.9%	24.7%	25.5%	14.2%	11.9%	13.8%	39.2%
Time of Day								
12am-7am	29.1%	28.1%	14.6%	8.1%	24.5%	16.1%	11.7%	11.6%
7am-10am	16.0%	13.4%	14.3%	20.9%	22.6%	28.0%	22.3%	11.5%
10am-4pm (base)	23.3%	25.7%	24.5%	34.0%	34.9%	39.2%	43.6%	38.8%
4pm-8pm	18.2%	17.9%	31.8%	27.8%	11.1%	11.2%	19.1%	26.4%
8pm-12am	13.4%	14.9%	14.7%	9.1%	6.9%	5.6%	3.2%	11.8%

Table 4 (continued)

	Light Vehicle Collision with Non-MVIT				Heavy Vehicle Collision with Non-MVIT			Motorcycle Collision with Non-MVIT or Another Motorcycle
	Stationary Object	Parked Vehicle	Pedestrian	Bicyclist	Stationary Object	Parked Vehicle	Pedestrian/Bicyclist	
	21109	2638	1772	1194	1540	143	94	3013
Roadway Characteristics								
Intersection Type								
Non-intersection (base)	93.1%	94.8%	55.0%	39.9%	91.2%	91.6%	50.0%	82.6%
Four-way Intersection	3.3%	2.3%	34.4%	42.9%	4.7%	4.2%	38.3%	9.8%
T-intersection	3.1%	2.7%	9.7%	15.8%	3.6%	3.5%	9.6%	6.7%
Y-intersection	0.3%	0.1%	0.4%	0.3%	0.3%	0.0%	0.0%	0.3%
Traffic circle, Roundabout or L-Intersection	0.2%	0.2%	0.6%	1.1%	0.1%	0.7%	2.1%	0.6%
Roadway Alignment								
Straight (base)	73.2%	91.2%	96.4%	97.4%	70.0%	89.5%	93.6%	64.5%
Curved	26.8%	8.8%	3.6%	2.6%	30.0%	10.5%	6.4%	35.5%
Traffic Control Device								
No Controls (base)	97.4%	98.8%	69.2%	62.1%	95.4%	98.6%	62.8%	92.8%
Traffic Signal	2.5%	1.1%	30.5%	37.4%	4.4%	1.4%	37.2%	7.0%
Flashing Signal	0.1%	0.0%	0.2%	0.5%	0.1%	0.0%	0.0%	0.2%
Other	0.0%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%
Trafficway Description								
Two-way, Not Divided (base)	54.0%	75.2%	55.0%	57.2%	32.2%	55.2%	50.0%	55.0%
Two-way, Divided, Unprotected Median	11.5%	7.8%	16.1%	15.7%	12.9%	14.0%	22.3%	12.6%
Two-way, Divided, Positive Median	25.9%	8.0%	13.8%	14.8%	37.8%	16.1%	17.0%	18.8%
One-way Traffic	2.2%	6.3%	6.8%	4.4%	2.6%	9.8%	9.6%	3.7%
Two-way, Undivided, Left-Turn Lane	2.0%	2.0%	7.6%	7.4%	0.8%	2.1%	1.1%	3.5%
Entrance/Exit Ramp	4.5%	0.7%	0.6%	0.6%	13.6%	2.8%	0.0%	6.5%

Table 4 (continued)

	Light Vehicle Collision with Non-MVIT				Heavy Vehicle Collision with Non-MVIT			Motorcycle Collision with Non-MVIT or Another Motorcycle
	Stationary Object	Parked Vehicle	Pedestrian	Bicyclist	Stationary Object	Parked Vehicle	Pedestrian/Bicyclist	
	21109	2638	1772	1194	1540	143	94	3013
Driver Behavior								
Violation Charged to Driver in Vehicles								
None	65.9%	55.4%	77.8%	72.3%	64.8%	67.8%	84.0%	75.2%
Reckless Offense	4.0%	6.2%	3.0%	5.6%	4.5%	4.9%	2.1%	3.0%
Impairment Offense	4.3%	7.2%	0.6%	0.3%	0.4%	0.0%	0.0%	2.1%
Speed-related Offense	4.5%	3.0%	0.6%	0.2%	8.5%	3.5%	1.1%	2.8%
Rules of the Road	2.5%	2.7%	8.4%	12.1%	3.8%	5.6%	8.5%	0.9%
License, Registration, Equipment Violations	8.5%	9.9%	4.7%	4.7%	13.8%	11.2%	1.1%	7.7%
Multiple Violations Charged to the Driver	10.4%	15.5%	5.0%	4.9%	4.3%	7.0%	3.2%	9.2%

Table 4 (continued)

	Collision between Two Light Vehicles				Collision between Two Heavy Vehicles	Collision between a Light Vehicle and a Heavy Vehicle		
	Head-On	Angle	Rear-End	Rear-to-Side		Head-On	Angle	Rear-End/Rear-to-Side
	2905	9459	17471	189	369	361	1498	4536
Weather/Temporal Attributes								
Season								
Autumn (base)	25.1%	25.8%	26.4%	20.6%	24.9%	23.8%	24.4%	27.6%
Winter	26.2%	25.1%	24.0%	28.6%	22.8%	25.2%	29.3%	23.7%
Spring	25.9%	25.2%	25.0%	25.4%	23.3%	24.9%	24.1%	24.0%
Summer	22.8%	23.9%	24.6%	25.4%	29.0%	26.0%	22.2%	24.7%
Weather								
Clear (base)	67.8%	72.4%	71.0%	69.3%	72.1%	64.8%	66.2%	71.0%
Cloudy	16.4%	15.5%	16.9%	16.9%	14.1%	15.5%	14.9%	16.1%
Rain or Drizzle	11.2%	9.8%	10.2%	10.1%	8.4%	12.5%	13.4%	10.0%
Snow	3.7%	1.9%	1.5%	3.7%	4.1%	6.6%	4.9%	2.2%
Fog or Smog	0.6%	0.3%	0.2%	0.0%	0.3%	0.6%	0.7%	0.3%
Severe Wind/Sand/Other	0.3%	0.2%	0.2%	0.0%	1.1%	0.0%	0.1%	0.3%
Day of Week								
Weekday (base)	73.8%	76.7%	79.5%	68.8%	92.4%	85.6%	87.1%	87.5%
Weekend	26.2%	23.3%	20.5%	31.2%	7.6%	14.4%	12.9%	12.5%
Time of Day								
12am-7am	12.6%	7.8%	6.1%	5.8%	14.6%	15.8%	15.3%	14.5%
7am-10am	18.1%	19.3%	19.6%	18.5%	22.5%	24.1%	28.2%	26.0%
10am-4pm (base)	35.5%	41.6%	43.2%	48.1%	45.0%	41.8%	38.1%	39.4%
4pm-8pm	23.6%	23.4%	25.4%	21.7%	13.3%	12.7%	12.6%	14.0%
8pm-12am	10.3%	7.9%	5.7%	5.8%	4.6%	5.5%	5.9%	6.1%

Table 4 (continued)

	Collision between Two Light Vehicles				Collision between Two Heavy Vehicles	Collision between a Light Vehicle and a Heavy Vehicle		
	Head-On	Angle	Rear-End	Rear-to-Side		Head-On	Angle	Rear-End/ Rear-to-Side
	2905	9459	17471	189	369	361	1498	4536
Roadway Characteristics								
Intersection Type								
Non-intersection (base)	59.5%	25.4%	62.4%	79.9%	84.8%	81.2%	46.9%	80.9%
Four-way Intersection	29.1%	57.6%	27.0%	10.6%	11.1%	14.7%	38.0%	13.1%
T-intersection	10.2%	15.9%	9.9%	8.5%	3.3%	3.9%	14.0%	5.3%
Y-intersection	0.6%	0.7%	0.4%	0.5%	0.5%	0.0%	0.4%	0.2%
Traffic circle, Roundabout or L- Intersection	0.6%	0.5%	0.3%	0.5%	0.3%	0.3%	0.7%	0.4%
Roadway Alignment								
Straight (base)	80.8%	96.6%	95.9%	95.2%	93.5%	74.0%	94.3%	93.0%
Curved	19.2%	3.4%	4.1%	4.8%	6.5%	26.0%	5.7%	7.0%
Traffic Control Device								
No Controls (base)	72.6%	49.2%	72.0%	89.9%	88.9%	86.1%	64.6%	85.9%
Traffic Signal	27.1%	49.5%	27.6%	9.5%	10.6%	13.6%	34.6%	13.9%
Flashing Signal	0.3%	1.3%	0.2%	0.5%	0.5%	0.3%	0.8%	0.1%
Other	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.1%
Trafficway Description								
Two-way, Not Divided (base)	72.0%	53.0%	39.1%	65.1%	20.3%	72.6%	41.5%	18.6%
Two-way, Divided, Unprotected Median	11.3%	20.3%	18.0%	11.6%	14.6%	7.8%	17.7%	15.3%
Two-way, Divided, Positive Median	8.6%	15.3%	28.9%	12.7%	55.6%	15.0%	30.5%	56.6%
One-way Traffic	0.7%	3.3%	4.0%	4.8%	3.5%	0.3%	5.5%	3.6%
Two-way, Undivided, Left-Turn Lane	7.1%	7.9%	7.1%	4.2%	2.2%	4.2%	3.5%	2.3%
Entrance/Exit Ramp	0.4%	0.3%	2.9%	1.6%	3.8%	0.3%	1.2%	3.5%

Table 4 (continued)

	Collision between Two Light Vehicles				Collision between Two Heavy Vehicles	Collision between a Light Vehicle and a Heavy Vehicle		
	Head-On	Angle	Rear-End	Rear-to-Side		Head-On	Angle	Rear-End/ Rear-to-Side
	2905	9459	17471	189	369	361	1498	4536
Driver Behavior								
Violation Charged to Driver in Vehicles								
None	95.1%	94.4%	96.9%	97.4%	97.8%	98.3%	97.5%	98.1%
Reckless Offense	4.8%	3.6%	8.6%	5.8%	4.3%	4.2%	3.3%	4.6%
Impairment Offense	3.9%	1.4%	1.2%	3.7%	0.0%	1.9%	1.3%	1.3%
Speed-related Offense	2.1%	1.2%	11.3%	4.8%	11.1%	3.3%	3.7%	7.3%
Rules of the Road	21.5%	35.1%	13.6%	4.8%	20.6%	20.2%	24.0%	17.0%
License, Registration, Equipment Violations	11.2%	11.8%	11.3%	22.2%	7.6%	8.0%	10.7%	10.1%
Multiple Violations Charged to Driver	14.0%	11.0%	9.4%	6.3%	1.9%	10.8%	10.5%	7.3%

Table 4 (continued)

	Collision between a Light Vehicle and a Motorcycle		Collision between Multiple Vehicles	
	Head-On/ Angle	Rear-End/ Rear-to-Side	Head-On/ Angle	Rear-End/ Rear-to-Side
	782	816	615	977
Weather/Temporal Attributes				
Season				
Autumn (base)	22.6%	24.9%	27.2%	25.9%
Winter	13.4%	13.0%	27.2%	23.1%
Spring	27.5%	26.7%	23.3%	24.4%
Summer	36.4%	35.4%	22.4%	26.6%
Weather				
Clear (base)	81.8%	82.8%	75.3%	74.3%
Cloudy	14.5%	13.7%	14.8%	16.6%
Rain or Drizzle	3.7%	3.3%	8.0%	8.3%
Snow	0.0%	0.0%	1.6%	0.6%
Fog or Smog	0.0%	0.0%	0.2%	0.2%
Severe Wind/Sand/Other	0.0%	0.1%	0.2%	0.0%
Day of Week				
Weekday (base)	72.1%	70.1%	75.8%	80.6%
Weekend	27.9%	29.9%	24.2%	19.4%
Time of Day				
12am-7am	6.8%	7.1%	7.8%	4.2%
7am-10am	11.8%	15.0%	21.8%	17.2%
10am-4pm (base)	43.0%	41.8%	40.8%	46.7%
4pm-8pm	28.1%	27.3%	22.0%	25.2%
8pm-12am	10.4%	8.8%	7.6%	6.8%

Table 4 (continued)

	Collision between a Light Vehicle and a Motorcycle		Collision between Multiple Vehicles	
	Head-On/ Angle	Rear-End/ Rear-to-Side	Head-On/ Angle	Rear-End/ Rear-to-Side
	782	816	615	977
Roadway Characteristics				
Intersection Type				
Non-intersection (base)	38.5%	68.4%	0.7%	4.7%
Four-way Intersection	39.6%	21.1%	89.3%	79.5%
T-intersection	20.3%	9.9%	8.5%	14.2%
Y-intersection	1.0%	0.5%	0.7%	0.6%
Traffic circle, Roundabout or L-Intersection	0.5%	0.1%	1.0%	0.9%
Roadway Alignment				
Straight (base)	92.5%	95.0%	98.0%	97.5%
Curved	7.5%	5.0%	2.0%	2.5%
Traffic Control Device				
No Controls (base)	67.8%	83.2%	0.0%	0.0%
Traffic Signal	31.3%	16.8%	99.2%	98.0%
Flashing Signal	0.9%	0.0%	0.8%	1.2%
Other	0.0%	0.0%	0.0%	0.8%
Trafficway Description				
Two-way, Not Divided (base)	62.7%	33.7%	44.2%	35.8%
Two-way, Divided, Unprotected Median	13.9%	16.7%	28.3%	26.1%
Two-way, Divided, Positive Median	13.6%	36.6%	19.2%	24.5%
One-way Traffic	1.7%	4.7%	2.9%	2.9%
Two-way, Undivided, Left-Turn Lane	8.1%	6.6%	5.2%	8.3%
Entrance/Exit Ramp	0.1%	1.7%	0.2%	2.5%

Table 4 (continued)

	Collision between a Light Vehicle and a Motorcycle		Collision between Multiple Vehicles	
	Head-On/ Angle	Rear-End/ Rear-to-Side	Head-On/ Angle	Rear-End/ Rear-to-Side
	782	816	615	977
Driver Behavior				
Violation Charged to Driver in Vehicles				
None	94.4%	95.8%	99.3%	99.4%
Reckless Offense	6.0%	7.5%	6.2%	19.2%
Impairment Offense	1.3%	1.7%	2.0%	6.3%
Speed-related Offense	1.2%	5.9%	3.3%	17.0%
Rules of the Road	32.2%	15.1%	50.2%	14.9%
License, Registration, Equipment Violations	9.6%	11.5%	28.0%	23.5%
Multiple Violations Charged to Driver	15.5%	13.0%	0.0%	0.0%

Table 5: Mixed Logit Model Estimation Results for All Crash Types in Study Data Set

	Light Vehicle Collision with Non-MVIT			Heavy Vehicle Collision with Non-MVIT			Motorcycle Collision with Non-MVIT or Another Motorcycle
	Parked Vehicle	Pedestrian	Bicyclist	Stationary Object	Parked Vehicle	Pedestrian/Bicyclist	
Constant	-1.4210 (-5.38)	-2.7800 (-8.25)	-3.2800 (-9.06)	-2.6450 (-7.41)	-4.4440 (-5.19)	-5.5660 (-10.96)	-1.6760 (-4.90)
Weather/Temporal Attributes							
Season (Base: Autumn)							
Winter	--	--	--	--	--	--	-0.7160 (-5.01)
Spring	--	--	--	--	--	--	0.0790 (3.85)
Summer	--	--	--	--	--	--	0.4330 (12.81)
Weather (Base: Clear, Fog or Smog ¹ , Severe Crosswind or Blowing Sand or Other Weather ¹)							
Cloudy	-0.2240 (-8.11)	-0.2240 (-8.11)	-0.2240 (-8.11)	-0.2240 (-8.11)	-0.2240 (-8.11)	--	-0.3350 (-9.97)
Rain or Drizzle	-0.5790 (-8.65)	--	--	--	--	--	-1.5330 (-15.74)
Snow	-0.5790 (-8.65)	-0.9240 (-16.24)	-0.9240 (-16.24)	--	--	--	--
Day of Week (Base: Weekday)							
Weekend	0.1770 (6.01)	-0.4130 (-17.07)	--	-1.0820 (-3.04)	-1.0820 (-3.04)	-1.0820 (-3.04)	0.1770 (6.01)
Time of Day (Base: 10am-4pm)							
12am-7am	--	-0.9150 (-2.96)	-1.9350 (-5.78)	-0.9150 (-2.96)	-0.9150 (-2.96)	-0.9150 (-2.96)	-1.9350 (-5.78)
7am-10am	--	--	--	--	--	--	-0.7380 (-16.55)
4pm-8pm	--	0.4060 (9.23)	0.4060 (9.23)	-0.6830 (-18.93)	--	--	--
8pm-12am	--	--	-0.8640 (-2.35)	-0.8640 (-2.35)	--	--	-0.8640 (-2.35)

¹ Estimated coefficients statistically insignificant at 95 percent confidence level

Table 5 (continued)

	Light Vehicle Collision with Non-MVIT			Heavy Vehicle Collision with Non-MVIT			Motorcycle Collision with Non-MVIT or Another Motorcycle
	Parked Vehicle	Pedestrian	Bicyclist	Stationary Object	Parked Vehicle	Pedestrian/Bicyclist	
Roadway Characteristics							
Intersection Type (Base: Non-Intersection)							
4-way Intersection							
Mean	--	2.2810 (6.17)	2.2810 (6.17)	--	--	2.2810 (6.17)	1.0270 (6.23)
Std. Dev.	--	--	--	--	--	--	-0.2340 (-2.49)
T-Intersection							
Mean	--	0.7580 (9.47)	1.2190 (4.53)	--	--	1.2190 (4.53)	0.4380 (7.65)
Std. Dev.	--	--	0.8690 (4.75)	--	--	0.8690 (4.75)	--
Y-Intersection							
Mean	--	0.7580 (9.47)	--	--	--	--	--
Traffic circle, Roundabout or L-Intersection							
Mean	0.2470 (2.32)	0.7580 (9.47)	0.2470 (2.32)	--	--	--	--
Roadway Alignment (Base: Straight)							
Curved							
Mean	-1.6780 (-5.38)	-1.6780 (-5.38)	-1.6780 (-5.38)	--	--	--	0.5300 (7.89)
Std. Dev.	--	--	--	--	--	--	0.2510 (3.49)
Traffic Control Device (Base: No Controls, Other ¹)							
Traffic Signal							
Mean	-1.5500 (-8.34)	1.5910 (3.83)	1.5910 (3.83)	0.5280 (7.33)	-1.5500 (-8.34)	0.5280 (7.33)	0.5280 (7.33)
Std. Dev.	--	--	--	--	--	--	--
Flashing Signal							
Mean	--	--	--	--	--	--	--

¹ Estimated coefficients statistically insignificant at 95 percent confidence level

Table 5 (continued)

Trafficway Description (Base: Two-way, Not Divided)	Light Vehicle Collision with Non-MVIT			Heavy Vehicle Collision with Non-MVIT			Motorcycle Collision with Non-MVIT or Another Motorcycle
	Parked Vehicle	Pedestrian	Bicyclist	Stationary Object	Parked Vehicle	Pedestrian/Bicyclist	
Two-way, Divided, Unprotected Median							
Mean	-0.6710 (-15.15)	0.0850 (2.72)	0.0850 (2.72)	0.6020 (8.96)	0.6020 (8.96)	0.6020 (8.96)	0.0850 (2.72)
Std. Dev.	--	0.9810 (11.06)	0.9810 (11.06)	--	--	--	0.9810 (11.06)
Two-way, Divided, Positive Median							
Mean	-1.5180 (-7.03)	-0.4830 (-14.53)	--	1.2470 (5.15)	-0.4830 (-14.53)	--	--
Std. Dev.	--	--	--	0.3940 (2.34)	--	--	--
One-way Traffic							
Mean	0.7420 (14.06)	0.7420 (14.06)	0.7420 (14.06)	0.7420 (14.06)	0.7420 (14.06)	0.7420 (14.06)	0.7420 (14.06)
Std. Dev.	0.3080 (1.84)	0.3080 (1.84)	0.3080 (1.84)	0.3080 (1.84)	0.3080 (1.84)	0.3080 (1.84)	0.3080 (1.84)
Two-way, Undivided, Left-Turn Lane							
Mean	--	0.8520 (14.04)	0.8520 (14.04)	0.0490 (4.92)	--	--	--
Std. Dev.	--	0.6340 (2.92)	0.6340 (2.92)	--	--	--	--
Entrance/Exit Ramp							
Mean	-1.5110 (-12.35)	-1.5110 (-12.35)	-1.5110 (-12.35)	1.8360 (6.51)	--	--	0.6280 (10.65)
Std. Dev.	--	--	--	--	--	--	0.3110 (2.17)
Driver Behavior							
Violation Charged to Driver in Vehicles (Base: None)							
Reckless Offense	--	--	--	--	--	--	--
Impairment Offense	--	--	--	--	--	--	--
Speed-related Offense	--	--	--	--	--	--	--
Rules of the Road	--	--	--	--	--	--	--
License, Registration, Equipment Violations	--	--	--	--	--	--	--
Multiple Violations Charged to Driver	--	--	--	--	--	--	--

¹ Estimated coefficients statistically insignificant at 95 percent confidence level

Table 5 (continued)

	Collision between Two Light Vehicles				Collision between Two Heavy Vehicles	Collision between a Light Vehicle and a Heavy Vehicle		
	Head-On	Angle	Rear-End	Rear-to-Side		Head-On	Angle	Rear-End/Rear-to-Side
Constant	-1.8180 (-6.04)	-1.2340 (-4.21)	0.1010 (4.34)	-4.6920 (-6.36)	-3.9630 (-6.77)	-3.6110 (-6.51)	-2.3490 (-6.37)	-1.4310 (-4.77)
Weather/Temporal Attributes								
Season (Base: Autumn)								
Winter	--	0.0490 (2.46)	--	--	--	--	--	--
Spring	--	0.0790 (3.85)	0.0790 (3.85)	--	--	--	--	--
Summer	--	--	--	--	--	--	--	--
Weather (Base: Clear, Fog or Smog ¹ , Severe Crosswind or Blowing Sand or Other Weather ¹)								
Cloudy	-0.1660 (-3.85)	-0.2240 (-8.11)	-0.2240 (-8.11)	--	-0.3350 (-9.97)	-0.3350 (-9.97)	-0.3350 (-9.97)	-0.3350 (-9.97)
Rain or Drizzle	-0.1660 (-3.85)	--	-0.2880 (-8.63)	--	--	--	--	-0.6130 (-12.90)
Snow	-0.1660 (-3.85)	-0.9240 (-16.24)	-0.9240 (-16.24)	--	--	--	--	-0.9240 (-16.24)
Day of Week (Base: Weekday)								
Weekend	-0.4130 (-17.07)	-0.4130 (-17.07)	-0.4130 (-17.07)	--	-1.0820 (-3.04)	-1.0820 (-3.04)	-1.0820 (-3.04)	-1.0820 (-3.04)
Time of Day (Base: 10am-4pm)								
12am-7am	-0.9150 (-2.96)	-1.9350 (-5.78)	-1.9350 (-5.78)	-1.9350 (-5.78)	-0.9150 (-2.96)	-0.9150 (-2.96)	-0.9150 (-2.96)	-0.9150 (-2.96)
7am-10am	-0.3280 (-13.16)	-0.3280 (-13.16)	-0.3280 (-13.16)	--	--	--	--	--
4pm-8pm	--	-0.1430 (-5.75)	-0.1430 (-5.75)	--	-0.6830 (-18.93)	-0.6830 (-18.93)	-0.6830 (-18.93)	-0.6830 (-18.93)
8pm-12am	-0.8640 (-2.35)	-0.8640 (-2.35)	-1.4200 (-3.77)	--	-1.4200 (-3.77)	-1.4200 (-3.77)	-1.4200 (-3.77)	-1.4200 (-3.77)

¹ Estimated coefficients statistically insignificant at 95 percent confidence level

Table 5 (continued)

	Collision between Two Light Vehicles				Collision between Two Heavy Vehicles	Collision between a Light Vehicle and a Heavy Vehicle		
	Head-On	Angle	Rear-End	Rear-to-Side		Head-On	Angle	Rear-End/Rear-to-Side
Roadway Characteristics								
Intersection Type (Base: Non-Intersection)								
4-way Intersection								
Mean	1.0270 (6.23)	2.2810 (6.17)	1.0270 (6.23)	1.0270 (6.23)	--	1.0270 (6.23)	1.3640 (15.24)	--
Std. Dev.	-0.2340 (-2.49)	--	-0.2340 (-2.49)	-0.2340 (-2.49)	--	-0.2340 (-2.49)	0.4770 (2.34)	--
T-Intersection								
Mean	--	1.2190 (4.53)	--	--	--	--	0.4380 (7.65)	-0.4120 (-2.00)
Std. Dev.	--	0.8690 (4.75)	--	--	--	--	--	0.5430 (2.89)
Y-Intersection								
Traffic circle, Roundabout or L-Intersection	0.2470 (2.32)	--	--	0.2470 (2.32)	0.2470 (2.32)	0.2470 (2.32)	0.2470 (2.32)	0.2470 (2.32)
Roadway Alignment (Base: Straight)								
Curved								
Mean	--	-1.6780 (-5.38)	-1.6780 (-5.38)	--	-1.6780 (-5.38)	--	-1.6780 (-5.38)	-1.6780 (-5.38)
Std. Dev.	--	--	--	--	--	--	--	--
Traffic Control Device (Base: No Controls, Other ¹)								
Traffic Signal								
Mean	1.5910 (3.83)	1.5910 (3.83)	1.5910 (3.83)	1.5910 (3.83)	1.5910 (3.83)	1.5910 (3.83)	1.5910 (3.83)	1.5910 (3.83)
Std. Dev.	--	--	--	--	--	--	--	--
Flashing Signal	0.6990 (3.92)	0.6990 (3.92)	0.6990 (3.92)	0.6990 (3.92)	0.6990 (3.92)	0.6990 (3.92)	0.6990 (3.92)	0.6990 (3.92)

¹ Estimated coefficients statistically insignificant at 95 percent confidence level

Table 5 (continued)

Trafficway Description (Base: Two-way, Not Divided)	Collision between Two Light Vehicles				Collision between Two Heavy Vehicles	Collision between a Light Vehicle and a Heavy Vehicle		
	Head-On	Angle	Rear-End	Rear-to-Side		Head-On	Angle	Rear-End/Rear-to-Side
Two-way, Divided, Unprotected Median								
Mean	-0.6710 (-15.15)	0.0850 (2.72)	0.0850 (2.72)	--	0.6020 (8.96)	0.0850 (2.72)	0.0850 (2.72)	--
Std. Dev.	--	0.9810 (11.06)	0.9810 (11.06)	--	--	0.9810 (11.06)	0.9810 (11.06)	--
Two-way, Divided, Positive Median								
Mean	-1.5180 (-7.03)	-0.4830 (-14.53)	0.0700 (2.62)	-0.4830 (-14.53)	1.2470 (5.15)	-0.4830 (-14.53)	--	1.2470 (5.15)
Std. Dev.	--	--	1.4670 (13.53)	--	0.3940 (2.34)	--	--	0.3940 (2.34)
One-way Traffic								
Mean	-0.9380 (-6.61)	--	0.7420 (14.06)	0.7420 (14.06)	--	--	0.7420 (14.06)	0.7420 (14.06)
Std. Dev.	--	--	0.3080 (1.84)	0.3080 (1.84)	--	--	0.3080 (1.84)	0.3080 (1.84)
Two-way, Undivided, Left-Turn Lane								
Mean	0.8520 (14.04)	0.8520 (14.04)	0.8520 (14.04)	0.0490 (4.92)	--	--	--	0.0490 (4.92)
Std. Dev.	0.6340 (2.92)	0.6340 (2.92)	0.6340 (2.92)	--	--	--	--	--
Entrance/Exit Ramp								
Mean	-1.5110 (-12.35)	-1.5110 (-12.35)	0.6280 (10.65)	--	1.8360 (6.51)	--	--	0.6280 (10.65)
Std. Dev.	--	--	0.3110 (2.17)	--	--	--	--	0.3110 (2.17)
Driver Behavior								
Violation Charged to Driver in Vehicles (Base: None)								
Reckless Offense	0.5870 (14.10)	0.5870 (14.10)	0.5870 (14.10)	--	--	--	--	0.5870 (14.10)
Impairment Offense	0.5480 (5.63)	-0.1830 (-2.65)	-0.1830 (-2.65)	--	--	--	--	--
Speed-related Offense	-0.6520 (-7.85)	-0.6520 (-7.85)	1.2400 (28.77)	--	--	--	--	1.2400 (28.77)
Rules of the Road	1.5920 (52.90)	1.5920 (52.90)	--	--	1.1350 (32.80)	1.1350 (32.80)	1.1350 (32.80)	1.1350 (32.80)
License, Registration, Equipment Violations	0.4920 (16.28)	0.4920 (16.28)	0.4920 (16.28)	--	--	--	--	0.4920 (16.28)
Multiple Violations Charged to Driver	0.4540 (14.42)	0.4540 (14.42)	0.4540 (14.42)	--	--	0.4540 (14.42)	0.4540 (14.42)	0.4540 (14.42)

¹ Estimated coefficients statistically insignificant at 95 percent confidence level

Table 5 (continued)

	Collision between a Light Vehicle and a Motorcycle		Collision between Multiple Vehicles	
	Head-On/ Angle	Rear-End/ Rear-to-Side	Head-On/ Angle	Rear-End/ Rear-to-Side
Constant	-3.0550 (-6.43)	-2.9140 (-6.59)	-6.7680 (-11.57)	-5.1990 (-10.02)
Weather/Temporal Attributes				
Season (Base: Autumn)				
Winter	-0.7160 (-5.01)	-0.7160 (-5.01)	--	-0.7160 (-5.01)
Spring	--	--	--	--
Summer	0.4330 (12.81)	0.4330 (12.81)	--	--
Weather (Base: Clear, Fog or Smog ¹ , Severe Crosswind or Blowing Sand or Other Weather ¹)				
Cloudy	-0.3350 (-9.97)	-0.3350 (-9.97)	-0.3350 (-9.97)	-0.3350 (-9.97)
Rain or Drizzle	-0.6130 (-12.90)	-0.6130 (-12.90)	-0.6130 (-12.90)	-0.6130 (-12.90)
Snow	--	--	--	--
Day of Week (Base: Weekday)				
Weekend	0.1770 (6.01)	0.1770 (6.01)	-1.0820 (-3.04)	-1.0820 (-3.04)
Time of Day (Base: 10am-4pm)				
12am-7am	-1.9350 (-5.78)	-1.9350 (-5.78)	-2.1520 (-14.99)	-2.1520 (-14.99)
7am-10am	-0.7380 (-16.55)	-0.7380 (-16.55)	--	-0.7380 (-16.55)
4pm-8pm	--	--	--	-0.6830 (-18.93)
8pm-12am	-0.8640 (-2.35)	-1.4200 (-3.77)	-1.4200 (-3.77)	-1.4200 (-3.77)

¹ Estimated coefficients statistically insignificant at 95 percent confidence level

Table 5 (continued)

	Collision between a Light Vehicle and a Motorcycle		Collision between Multiple Vehicles	
	Head-On/ Angle	Rear-End/ Rear-to-Side	Head-On/ Angle	Rear-End/ Rear-to-Side
Roadway Characteristics				
Intersection Type (Base: Non-Intersection)				
4-way Intersection				
Mean	2.2810 (6.17)	1.3640 (15.24)	1.3640 (15.24)	--
Std. Dev.	--	0.4770 (2.34)	0.4770 (2.34)	--
T-Intersection				
Mean	1.2190 (4.53)	--	--	--
Std. Dev.	0.8690 (4.75)	--	--	--
Y-Intersection				
	--	--	--	--
Traffic circle, Roundabout or L-Intersection				
	0.2470 (2.32)	0.2470 (2.32)	0.2470 (2.32)	0.2470 (2.32)
Roadway Alignment (Base: Straight)				
Curved				
Mean	-1.6780 (-5.38)	-1.6780 (-5.38)	-1.6780 (-5.38)	-1.6780 (-5.38)
Std. Dev.	--	--	--	--
Traffic Control Device (Base: No Controls, Other ¹)				
Traffic Signal				
Mean	--	--	5.5280 (19.55)	5.5280 (19.55)
Std. Dev.	--	--	1.4060 (7.39)	--
Flashing Signal				
	-0.4240 (-3.81)	-0.4240 (-3.81)	--	--

¹ Estimated coefficients statistically insignificant at 95 percent confidence level

Table 5 (continued)

Trafficway Description (Base: Two-way, Not Divided)	Collision between a Light Vehicle and a Motorcycle		Collision between Multiple Vehicles	
	Head-On/ Angle	Rear-End/ Rear-to-Side	Head-On/ Angle	Rear-End/ Rear-to-Side
Two-way, Divided, Unprotected Median				
Mean	-0.6710 (-15.15)	--	-0.6710 (-15.15)	-0.6710 (-15.15)
Std. Dev.	--	--	--	--
Two-way, Divided, Positive Median				
Mean	-0.4830 (-14.53)	0.0700 (2.62)	-0.4830 (-14.53)	--
Std. Dev.	--	1.4670 (13.53)	--	--
One-way Traffic				
Mean	-0.9380 (-6.61)	0.7420 (14.06)	-0.9380 (-6.61)	-0.9380 (-6.61)
Std. Dev.	--	0.3080 (1.84)	--	--
Two-way, Undivided, Left-Turn Lane				
Mean	--	--	--	--
Std. Dev.	--	--	--	--
Entrance/Exit Ramp				
Mean	--	0.6280 (10.65)	--	-0.1890 (-2.97)
Std. Dev.	--	0.3110 (2.17)	--	--
Driver Behavior				
Violation Charged to Driver in Vehicles (Base: None)				
Reckless Offense	0.5870 (14.10)	0.5870 (14.10)	0.5870 (14.10)	2.3420 (19.29)
Impairment Offense	--	--	--	-0.1830 (-2.65)
Speed-related Offense	--	--	--	2.3860 (18.61)
Rules of the Road	1.1350 (32.80)	1.1350 (32.80)	1.5280 (18.34)	1.5280 (18.34)
License, Registration, Equipment Violations	0.4920 (16.28)	0.4920 (16.28)	1.8130 (18.31)	1.8130 (18.31)
Multiple Violations Charged to Driver	0.4540 (14.42)	0.4540 (14.42)	--	--

¹ Estimated coefficients statistically insignificant at 95 percent confidence level

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