# Identifying Precrash Factors for Cars and Trucks on Interstate Highways: Mixed Logit Model Approach

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**Abstract:** This research investigates the factors that lead to three manners of collision (namely, rear-end, angle, and sideswipe) that occurred in the same direction of multilane interstate highways. Mixed logit (MXL) models were developed to estimate the probability of rear-end, angle, and sideswipe collisions as functions of vehicle-following attributes and other driving maneuvers immediately before collisions. The National Automotive Sampling System-General Estimates System crash data set, collected from 2005 to 2008, was used to estimate the model. This research analyzes collisions among passenger cars and trucks, with an emphasis on their vehicular characteristics. Results show that driving behavior is different when vehicular characteristics are different and when roles of the striking and struck vehicles are grouped according to cars and trucks. This research contributes to a better understanding of the differences in unsafe driving acts between cars and trucks, and implications on future policies on car and truck drivers. **DOI:** 10.1061/(ASCE)TE.1943-5436.0000621. © *2013 American Society of Civil Engineers.*

**Author keywords:** Random-parameters logit model; Vehicle characteristics; Crash role.



## Introduction

In the United States, the annual number of collisions in highways averaged 6.1 million from 2000 to 2009 (RITA 2010). Because the task of driving on highways is complex due to its interactivity and heterogeneity of traffic, and the prevalence of high-speed impacts, it is necessary to extend transportation safety analysis to identify factors that lead to the different manners of collision on interstate highways.

An increasing concern in highway safety is the presence and increase in volume of trucks in the traffic stream. Registered large trucks in the United States have increased from approximately 8.5 million in 2005 to almost 11 million in 2009 (FMCSA 2011b). Because of the different dynamical characteristics of trucks and passenger cars, drivers may misjudge others' maneuvers when following or traveling alongside a vehicle. It is not surprising that collisions that involve large commercial vehicles usually result in more severe injuries or fatalities compared to collisions that involve only passenger cars (Islam and Hernandez 2012). As reported in Knipling (2013), about 80% of truck-related fatalities occur in car-truck crashes in the United States. In 2009, 75 percent of fatal crashes involving trucks had "collisions with vehicle in transport" as the most harmful event (FMCSA 2011a). In addition, collisions involving trucks usually result in significant financial costs. The estimated total cost to society of crashes involving large single-unit trucks was \$14.7 billion, and for combination trucks, it was \$26.5 billion (FMCSA 2011a). It is necessary, then, to intensify efforts to study the close, yet relatively risky, interaction of different types of vehicles that share the road and identify inadequate or inappropriate actions that lead to these collisions.

In the analysis of crashes, crash type is an important descriptor, as is number of crashes, crash rate, and crash severity. Zaloshnja et al. (2004) looked into costs resulting from a particular type of collision at urban intersections. The purpose of the study was to evaluate traffic safety intervention effectiveness since the latter varies according to crash type. The comprehensive cost per crash, including medical-related costs, emergency services, property damage, lost productivity, and monetized value of pain, was estimated to examine crash effects by type. According to the results, the cost to society in 2001 dollars in no-intersection roads with a speed limit of 50 mph or higher is \$25.6 billion per year for rear-end collisions and \$25.1 billion per year for sideswipe collisions.

The manner of collision or crash types as an outcome of a crash that is related to driver, vehicle, and roadway factors has not been studied extensively, especially for highways. Typically, disaggregate models in crash analysis focus on injury severity levels as the outcome. Although studies have developed different statistical or econometric models to predict the manner of collision at intersections [see, for example, Abdel-Aty and Nawathe (2006), Keller et al. (2006), Kim et al. (2007) and Ye et al. (2009)], far less attention has been paid to analyzing factors that lead to the different types of collisions on interstate highways.

Investigating crash type is crucial when identifying potential safety improvements for a roadway. Crash type analysis is implemented in the Highway Safety Improvement Program (HSIP) Manual (Herbel et al. 2010) to quantify the actual or expected safety of a roadway. The HSIP Manual uses crash type to identify high-risk facilities for potential safety improvement.

This study is one of the first to construct statistical models that predict the type of same-direction collisions (which, according to police reports, may be rear-end, angle, or sideswipe) based on the roles and precrash actions of the passenger cars and/or trucks involved in a highway crash. The explanatory variables were segregated to account for precrash actions and attributes for each role in the crash (i.e., striking or struck vehicle). Four different models were developed for different types of vehicles (cars or trucks)

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involved in a two-vehicle collision. In this way, it is possible to study the factors that contribute to different types of collisions and identify causes that are specific to a particular type of vehicle.

A mixed logit (MXL) estimation procedure (Washington et al. 2011) was used to identify significant precrash factors describing vehicle characteristics and "follow-the-leader" behavior between the striking and struck vehicles. These possible factors are used to predict the possible manner of collision.

Unreported or inaccurate information in the crash data can be accommodated by using the MXL modeling approach. Factors not captured in the crash database concerning vehicle dynamics, such as weight, range of vision, and stability when driving, may have an effect on the model; and therefore, their influence must be considered. Factors attributed to the driver, such as driving experience, driving style (aggressive/defensive driving), unreported fatigue, and attentiveness, also may have an impact on the model. As a way to address possible reservations in the information provided from the data, the MXL model is proposed.

The main objective of this research is to develop four MXL models to predict the likelihood of the resulting manner of collision if there is a crash that involves two vehicles traveling in the same direction in a multilane interstate highway under no adverse weather conditions. A MXL model is developed for a specific role (strike or struck vehicle) played by a car or a truck involved in a two-vehicle collision. In each model, the response variable is the probability of a crash having a discrete manner of collision (rear-end, angle, or sideswipe). The independent variables or attributes considered are mainly driving behavior prior to the crash, especially vehicle following and lane changing. The second objective of this research is to use the MXL models to examine the roles of the vehicles in a crash (striking and struck) and observe the actions performed by each driver prior to the collision. The ultimate objective is to use the developed MXL models to deduce the differences in driving behavior with trucks and passenger cars when paired in a crash with same and different types of vehicle. Identifying similarities and differences in driver behavior of the same or different types of vehicle can contribute to a better understanding of events that caused the crash.

## Literature Review

Statistical analysis of motor-vehicle crash data has been used to relate highway collision outcomes to a variety of factors, as reviewed in Savolainen et al. (2011). Most crash analysis primarily focused on the aftermath, described in terms of injury severity or property damage. Less attention has been paid to diverse failed interactions before the crash and that are explicitly found in the various manners of collision. This includes actions taken as a response to the impending danger, path of vehicle prior to crash, state of the driver, etc., which can give an insight of driving behavior that lead to a collision. In addition, econometric models that study the manner of collision are only found for crashes at intersections (Abdel-Aty and Nawathe 2006; Kim et al. 2007).

To address severe and costly crashes on highways, several safety studies have targeted collisions involving trucks to capture possible factors influencing these collisions (Council et al. 2003; Duncan et al. 1998). However, factors describing precrash actions in highways between trucks and passenger cars were not included in these investigations. Yan et al. (2009) constructed a multinomial logit (MNL) model to analyze vehicle type (car or truck) in terms of their roles (as a striking or struck vehicle) in rear-end crashes for car-truck and truck-car collisions. Although this approach for studying rear-end collisions among different vehicle types is new in the field, it has some limitations. This study did not consider critical events experienced by drivers before colliding (e.g., distraction, speed, and braking behavior) among the explanatory variables. A more comprehensive study should consider other possible manners outcomes of collision instead of exclusively analyzing rear-end crashes.

Abdel-Aty and Abdelwahab (2003) focused on the analysis of rear-end collisions. It specifically targeted two different types of vehicle: light trucks and cars. The analysis was performed using three models: MNL, heteroscedastic extreme value (HEV), and bivariate probit (BVP). These models were compared to account for possible limitations when restricting the study to one specific model specification: (1) the BVP model was used to account for two possible (binary) roles (striker and struck); (2) the MNL model was used to estimate four types of rear-end collisions based on vehicle type (i.e., car-car, car–light truck, light truck–light truck, and light truck–car); and (3) the HEV model was used to account for any independence of irrelevant alternative (IIA) issue in the MNL model.

In the modeling of different manners of collisions based on how trucks and passenger vehicles are paired, it is more reasonable to assume that the coefficients of some of the attributes are random. This is because some unobserved attributes could be accounting for rear-end, angle, and sideswipe collisions conditionally.

Recent literature in highway crash analysis using MXL can be found in Chen and Chen (2011), Milton et al. (2008), and Morgan and Mannering (2011). Although this study is mostly dedicated to addressing accident or injury severity, it finds that MXL is the best modeling approach to justify unobserved effects and heterogeneity among observations. For example, in the case of Milton et al. (2008) and its analysis of highway severities, road characteristics, environment, and driving behavior are the major players. These factors are expected to vary across roadway segments and thus are treated as random across the samples. In addition, inclusion of unobserved characteristics of roads and the environment are addressed by using MXL. Similarly, the proposed MXL model considers the variability of precrash actions, driving behavior, and communication between the vehicle driven and the vehicle interacting with in the analysis.

## Empirical Setting

The National Automotive Sampling System General Estimates System (NASS GES) database is a source for national safety statistics by the U.S. Department of Transportation, National Highway Traffic Safety Administration (NHTSA 2005) and serves as an instructive tool for motor vehicle manufacturers, insurance companies, government agencies, and researchers to enhance road safety.

The NASS GES crash data is collected from 400 police agencies across the United States. Police crash reports are processed by the National Center for Statistics and Analysis, a branch of the Policy and Operations in the NHTSA. GES is a probability-based representative sample for all motor crashes that resulted in fatalities, injuries and property damage. The GES database is a sample of the 6 million crashes occurring nationwide every year, containing information for about 50,000 collisions.

The GES database is managed via the Statistical Analysis System (SAS) software (SAS 2004) in which further data manipulation is possible. Data sets may be queried or created based on user-specified conditions with respect to subsets of data: accident, vehicle, maneuver, distraction, etc.

In this research, the NASS GES database was selected because it captures situational, environmental, vehicular, and human factors present during the collision. It also provides records of collisions involving all vehicles that traveled on U.S. highway systems. As mentioned previously, this study considered two types of vehicle: passenger cars and trucks. Trucks include tractor-trailers, single-unit trucks, or cargo vans having gross vehicle weight ratings (GVWRs) greater than 10,000 pounds as defined by the Insurance Institute for Highway Safety (IIHS 2009).

All the crash records from 2005 to 2008 were combined to form a single data set using SAS (SAS 2004). The combined data set was preprocessed to extract cases that meet the desired characteristics: collisions involving only two vehicles in the same roadway in the same direction on interstate highways under no adverse weather conditions. The constraint in traffic direction resulted in three common manners of collision: rear-end, angle, and sideswipe. To avoid the same crash being counted twice, information on the striking and struck vehicles involved in a collision were paired by the same case number. Further processing consisted of creating four separate data sets describing (1) Car striking car (C-C); (2) car striking truck (C-T); (3) truck striking car (T-C); and (4) truck striking truck (T-T), respectively. By having different data sets, it is possible to analyze differences on the three manners of collisions. In this way, it is possible to examine precrash scenarios describing vehicle-following and lane-changing behavior, as well as attributes of driver, road, and other factors that are exclusive to each vehicle pair. Additional information concerning the total crashes in each data set and total crashes corresponding to each manner is provided in Table 1.

### Defining Manner of Collision

In this research, the probability of each manner of collision is modeled as a function of the driver-vehicle-road interaction that took place before a crash. The dependent variable is the probability of the manner of collision that resulted from a failed driving maneuver between the two vehicles.

The manner of collision consists of three possible crash outcomes: rear-end, angle, and sideswipe. A detailed graphical representation and comprehensive description of manner of collision can be found in the Fatality Analysis Reporting System (FARS) manual (NHTSA 2010). NASS GES and FARS utilized by the NHTSA used similar sets of data but different coding and software. Fig. 1 portrays (a) rear-end, (b) angle, and (c) sideswipe collisions used in this study, which are depicted in the FARS Manual as Front-to-Rear (01), Front-to-Side, Same Direction (03), and Sideswipe–Same Direction (07) respectively.

Following the exact definition in NHTSA (2010), rear-end and same-direction traffic collisions are literally outlined as follows:

1. Front-to-Rear (includes Rear-End): "A rear-end collision is one in which the front end of one vehicle collides with the back of another vehicle, while the two vehicles are traveling in the same direction. Use Front-to-Rear (includes Rear-Ends) for all 'rear-end' crashes and all crashes in which the front of one vehicle comes in contact with the rear of another in the First Harmful Event, regardless of the original direction of travel."
2. Front-to-Side, Same Direction "is used for angle crashes where the front of one vehicle makes contact with any point along the side of another in the First Harmful Event and the orientation of the vehicles at impact is in the same direction. This does not include right angles or broadside crashes (See Front-to-Side, Right Angle)."
3. Sideswipe, Same Direction "occurs if the following conditions apply to both vehicles:
   - The initial engagement does not overlap the corner of either vehicle by more than four inches, so that there is no significant involvement of the front or rear surface areas.
   - There is no pocketing of the impact in the suspension areas. The impact then swipes along the surface of the vehicle parallel to the direction of travel.
   - There is low retardation of the force along the surface of the vehicle."

**Table 1.** Number of Crashes

| Crash combination | Rear-end | Angle | Sideswipe | Total |
|---|---|---|---|---|
| C-C | 2,804 | 225 | 734 | 3,763 |
| C-T | 1,049 | 337 | 1,033 | 2,419 |
| T-C | 780 | 236 | 782 | 1,798 |
| T-T | 370 | 13 | 60 | 443 |
| Total | 5,003 | 811 | 2,609 | 8,423 |

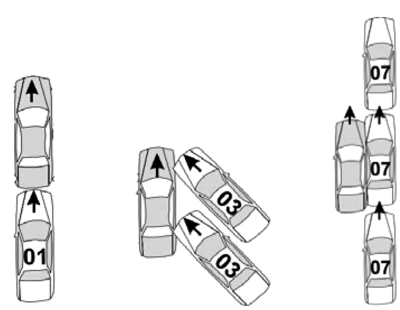
### Independent Variables

The independent variables, as found in the NASS GES database, include mainly vehicle activities prior to impact. In the NASS GES data set, precrash variables describe what the vehicle was doing just prior to the crash; what made the vehicle's situation critical; corrective action made, if any, to this critical situation; and location of the vehicle just prior to crash.

During the analysis, variables such as road geometry characteristics (e.g., relation to interchange, un/divided roadway, etc.), traffic conditions at peak and off-peak hours (e.g., congestion) and driver characteristics (e.g., young, old, female, male) also were considered. However, these factors did not make statistical significant contributions to the model and therefore were excluded.

Additional variables describe any distraction reported, road surface condition at the time of the crash, and the geographical location where the crash occurred. Driver distraction is considered as a state of the driver and thus describes any inattention by the driver. Condition of surface can be dry, wet, snow or slush, ice, sand, dirt, or oil. Geographical location is classified by the regions in the United States; each consists of several states.

A detailed description of variables used in this study can be found in Table 2. Table 3 lists the binary variables that are significant and common in the four estimated MXL models for C-C, C-T, T-C, and T-T, respectively. The mean of every variable and its standard deviation in parenthesis are presented in Table 3. The descriptive statistics shows how these characteristics vary among the different data sets.




(a) (b) (c)

**Fig. 1.** Possible manners of collision defined in the *FARS Manual* (NHTSA 2010); (a) rear-end; (b) angle; (c) sideswipe

**Table 2.** Variable Dictionary

| Variable | Variable description |
|---|---|
| DAYLGT | General light conditions at the time of the crash (1 if daylight, 0 otherwise) |
| DRY | Condition of road surface at the time of the crash (1 if dry, 0 otherwise) |
| FAGVSI | Striker driving at higher speed than struck vehicle (1 if yes, 0 otherwise) |
| FBRK | Action taken by striker in response to the impending danger (1 if braking, 0 otherwise) |
| FCHNGL | Vehicle precrash situation for striker (1 if changing lanes to the right or left, 0 otherwise) |
| FDISTR | Distraction reported by striker (1 if yes, 0 otherwise) |
| FENCRC | Critical event initiated by striker (1 if striker encroaching into struck vehicle's lane, 0 otherwise) |
| FGOING | Activity of striker prior to realization of critical event or prior to impact (1 if going straight, 0 otherwise) |
| FMANVR | Striker maneuvered to avoid something in the road (1 if maneuvered, 0 otherwise) |
| FNOTRL | Striking vehicle pulling no trailing unit (1 if no trailing unit, 0 otherwise) |
| FOVRDG | Critical event initiated by striker (1 if striker is traveling over the lane line or off the edge of the road, 0 otherwise) |
| FRDLEL | Path for striker prior to its first involvement in the crash (1 if vehicle stayed on roadway but left travel lane, 0 otherwise) |
| FSPEDR | Speed as a contributing factor to the cause of the crash according to striking vehicle (1 if yes, 0 otherwise) |
| FSTAYL | Path for striker prior to its first involvement in the crash (1 if vehicle stayed in travel lane, 0 otherwise) |
| FSTGHT | Precrash situation for striking vehicle (1 if travelling straight ahead on left or right lane, 0 otherwise) |
| INTERC | Relation to junction (1 if interchange area, 0 otherwise) |
| LDECST | Activity for struck vehicle prior to realization of critical event or prior to impact (1 if decelerating or stopped in traffic lane, 0 otherwise) |
| LGOING | Activity for struck vehicle prior to realization of critical event or prior to impact (1 if going straight, 0 otherwise) |
| LNOAVM | Action taken by the struck vehicle in response to the impending danger (1 if no avoidance maneuvered, 0 otherwise) |
| LNOTRL | Struck vehicle pulling no trailer units (1 if no trailing unit, 0 otherwise) |
| LOTHSP | Critical event initiated by struck vehicle (1 if traveling in same direction with lower speed, 0 otherwise) |
| LSTGHT | Precrash situation for struck vehicle (1 if straight ahead on left or right lane, 0 otherwise) |
| ONEAN | Alternative specific angle constant |
| ONERE | Alternative specific rear end constant |
| SOUTH | Region (1 if south, 0 otherwise) |
| SUMMER | Season (1 if summer, 0 otherwise) |
| WEST | Region (1 if west, 0 otherwise) |
| WINTER | Season (1 if winter, 0 otherwise) |



## Model Development

Discrete choice analysis was used to identify the effect that vehicle, driver, and road factors have on each possible manner of collision. It is possible to identify from the MXL model a particular combination of observed variables that describes the probability of an outcome—in this case, the manner of collision. A MXL model relaxes the assumptions related to IIA, independent and identically distributed (IID) errors present in a MNL model and allows observed and unobserved heterogeneity (Greene 2007).

A better estimate can be obtained if the coefficients of some of the attributes are treated as random because some unobserved attributes could be accounting for rear-end, angle, and sideswipe collisions conditionally. Unobserved attributes also are assumed to exist due to the subjectivity of the data obtained from police crash reports. These variables can be hidden in the variability of perception when measuring driving actions and their consequences by the police officer or the parties involved in an accident investigation.

A MXL model should be an alternative approach to improve the performance of the model. For instance, some attributes with random coefficients could include movement prior to crash (traveling straight, stopped, changing lanes, etc.), as well as region and road surface conditions. We define $I$ as the set of outcomes, $I = \{$rear-end collision, angle collision, sideswipe collision$\}$. The MXL probability of an observation or collision $n$ that results in manner of collision $i$ ($i \in I$) may be expressed as (Washington et al. 2011)

$$P_{in} = \int_x \frac{\exp(V_{in})}{\sum_{\forall\ j \in I} \exp(V_{jn})} f(\beta|\varphi) d\beta \qquad (1)$$

where $P_{in}$ is the probability of a two-vehicle crash $n$ resulting in manner of collision $i$, given that a two-vehicle collision has occurred; $V_{in}$ is the deterministic component of the utility value of manner of collision $i$ associated with collision $n$; $f(\boldsymbol{\beta}|\varphi)$ is the density function that determines the weighted average of the probability; and $\phi$ is the parameter vector describing the mean and standard deviation.

The deterministic component of the utility value of manner of collision $i$ associated with collision $n$ is a linear function

$$V_{in} = \boldsymbol{\beta}_i \mathbf{X}_{in} \qquad (2)$$

where $\boldsymbol{\beta}_i$ is the row vector of parameters associated with the attributes of manner of collision $i$; and $\mathbf{X}_{in}$ is the column vector of observed attribute values of manner of collision $i$ for collision $n$.

Marginal effects were calculated to see how the probability of a manner of collision is influenced when changing a binary variable associated with attribute $k$ from 0 to 1. The marginal effect formula used is described as follows (Washington et al. 2011) (the subscript $n$ is dropped for simplicity):

$$\frac{\partial P_i}{\partial x_{ki}} = (1 - P_i) P_i \beta_k \qquad (3)$$

In addition, to test the practical use of random coefficients (i.e., MXL model) versus fixed coefficients (i.e., MNL model), a likelihood ratio test was performed (Jones and Hensher 2007) as follows:

$$\chi^2 = -2[LL_{\text{MNL}}(\beta^{\text{MNL}}) - LL_{\text{MXL}}(\beta^{\text{MXL}})] \qquad (4)$$

where $LL_{\text{MNL}}(\beta^{\text{MNL}})$ is the log-likelihood at convergence of the MNL model; and $LL_{\text{MXL}}(\beta^{\text{MXL}})$ is the log-likelihood at convergence of the MXL model.

**Table 3.** Descriptive Statistics for Independent Variables

| | C-C | | | | | | C-T | | | | | | T-C | | | | | | T-T | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Rear-end | | Angle | | Sideswipe | | Rear-end | | Angle | | Sideswipe | | Rear-end | | Angle | | Sideswipe | | Rear-end | | Angle | | Sideswipe | |
| Variable | Mean | Std deviation | Mean | Std deviation | Mean | Std deviation | Mean | Std deviation | Mean | Std deviation | Mean | Std deviation | Mean | Std deviation | Mean | Std deviation | Mean | Std deviation | Mean | Std deviation | Mean | Std deviation | Mean | Std deviation |
| DAYLGT | — | — | — | — | — | — | 0.6 | 0.5 | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| DRY | — | — | 0.9 | 0.2 | — | — | 0.9 | 0.3 | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| FAGVSI | — | — | — | — | — | — | 0.2 | 0.4 | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| FBRK | 0.1 | 0.3 | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | 0.2 | 0.4 | — | — | — | — |
| FCHNGL | — | — | — | — | — | — | — | — | 0.3 | 0.4 | — | — | — | — | — | — | 0.4 | 0.5 | — | — | — | — | — | — |
| FDISTR | — | — | — | — | 0.2 | 0.4 | — | — | 0.2 | 0.4 | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| FENCRC | — | — | — | — | — | — | — | — | — | — | 0.6 | 0.5 | — | — | — | — | — | — | — | — | — | — | — | — |
| FGOING | 0.7 | 0.5 | — | — | — | — | 0.6 | 0.5 | — | — | — | — | — | — | 0.5 | 0.5 | — | — | — | — | — | — | 0.8 | 0.4 |
| FMANVR | — | — | 0.2 | 0.4 | 0.2 | 0.4 | 0.2 | 0.4 | — | — | — | — | — | — | — | — | — | — | — | — | 0.3 | 0.5 | — | — |
| FNOTRL | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | 0.2 | 0.4 | — | — | — | — |
| FOVRDG | — | — | — | — | 0.2 | 0.4 | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| FRDLEL | — | — | — | — | — | — | — | — | — | — | 0.2 | 0.4 | 0.1 | 0.4 | — | — | 0.1 | 0.3 | — | — | — | — | — | — |
| FSPEDR | — | — | — | — | — | — | 0.3 | 0.4 | — | — | — | — | — | — | — | — | — | — | 0.3 | 0.4 | — | — | — | — |
| FSTAYL | 0.9 | 0.3 | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | 0.9 | 0.3 | — | — | — | — |
| FSTGHT | — | — | — | — | — | — | — | — | — | — | — | — | — | — | 0.1 | 0.3 | — | — | — | — | — | — | — | — |
| INTERC | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | 0.1 | 0.3 | — | — | — | — | — | — |
| LDECST | — | — | — | — | — | — | 0.2 | 0.4 | — | — | — | — | — | — | 0.2 | 0.4 | 0.2 | 0.4 | 0.5 | 0.5 | — | — | 0.5 | 0.5 |
| LGOING | — | — | — | — | — | — | — | — | — | — | — | — | 0.6 | 0.5 | — | — | — | — | — | — | — | — | — | — |
| LNOAVM | — | — | — | — | — | — | — | — | — | — | — | — | 0.2 | 0.4 | — | — | — | — | — | — | — | — | — | — |
| LNOTRL | — | — | — | — | — | — | — | — | 0.2 | 0.4 | — | — | — | — | — | — | — | — | 0.2 | 0.4 | — | — | — | — |
| LOTHSP | 0.7 | 0.4 | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| LSTGHT | — | — | — | — | — | — | — | — | — | — | 0.4 | 0.5 | — | — | — | — | — | — | — | — | — | — | — | — |
| SOUTH | — | — | — | — | 0.5 | 0.5 | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| SUMMER | — | — | — | — | — | — | — | — | — | — | — | — | — | — | 0.3 | 0.4 | — | — | — | — | — | — | — | — |
| WEST | — | — | — | — | — | — | 0.2 | 0.4 | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — | — |
| WINTER | — | — | 0.5 | 0.5 | — | — | — | — | — | — | 0.5 | 0.5 | — | — | — | — | — | — | — | — | — | — | — | — |

## Results and Discussion

The econometric software NLOGIT 4.0 (Greene 2007) was used to develop the MXL models. With this software, it was possible to separate the different categories of responses (manners of collision) and create new explanatory variables to better capture the effect that the variable of interest has on the outcome.

Tables 4 and 5 give the estimated results for the MXL models corresponding to C-C, C-T, T-C, and T-T collisions, respectively. In this section, the positive and negative influence of the independent variables used in each model, as dictated by their positive or negative coefficient, is discussed.

The alternative specific constant accounts for the systematic bias of all unobserved attributes that contribute to rear-end, angle, and sideswipe utility values. A negative alternative specific constant means that attributes not accounted for or found to have insignificant influence collectively reduces the probability of this outcome and therefore are less likely to contribute to the relevant manner of collision. For this study, the base case scenario is sideswipe collision since no alternative specific constant was specified in the utility function. The opposite is true for a positive alternative specific constant. The alternative specific constants across the different models are discussed further at the end of this paper.

The developed MXL model considers all unobserved attributes that are assumed to exist due to the subjectivity of the data obtained from police crash reports. These variables can be hidden in the variability of perception when measuring driving actions and their consequences by the police officer and/or the parties involved in an accident investigation. Random parameters were considered to vary across observations according to a normal distribution since it resulted in a good statistical fit. Other distributions, such as normal, lognormal, triangular, and uniform were tested but were not found to be statistically significant. The random parameters are obtained from repeated simulated draws. In this study, 1,000 random draws were employed using standard Halton sequence (SHS) intelligent draws as recommended by Bhat (2001).

The statistical significance of random parameters is also shown in Table 4 for each model. Further exploration of the unobserved factors taking part in the modeling can be found at the end of the discussion of the model when estimated random parameters are considered.

A log-likelihood ratio test between MNL and MXL was performed for each model. As can be seen in Table 5, the confidence level obtained indicates that MXL is more appropriate. According to the results, the null hypothesis that the MXL model is not statistically superior to the MNL model is rejected. This means that the MXL model provides a better approach to model the manner of collision.

### C-C (Model 1): Rear-End Collisions

For the rear-end-collision crash type, the results indicate that the striking vehicle is traveling straight and the vehicle in front is traveling at a lower speed. Although the striker's response is to brake and to stay in the same travel lane, the crash was not avoided. All these precrash variables influence the occurrence of a rear-end collision, so they have a positive sign. According to the marginal effects, if the struck car maintains a different speed (in this case a lower speed than the striker), the probability of rear-end collision increases by 8.4%. If the striker stays in the same lane prior to the crash, the probability of rear-ending the car in front increases by almost 4%. A braking performed by the striker to avoid collision also increases the chances of being involved in a rear-end collision, but at a smaller magnitude of 0.7%.

The random parameters estimated for the C-C model are related to the actions of the striking vehicle and struck vehicle. Interestingly, these variables describe the actions that both parties contribute to a rear-end collision and may be blamed for. The first random parameter describes possible speeding for the striker, and the second one describes the struck vehicle decelerating or stopping in the travel lane. It could be that unobserved variability exists in these factors because speeding and stopping in the lane may be interpreted as accepting responsibility for the crash. Therefore, these reported actions are not fixed across observations. The first random parameter has a mean of 1.097 and a standard deviation of (1.837). This indicates that for about 72% of car crashes, speeding increases the likelihood of a rear-end collision. The second random parameter has a mean of 1.907 and a standard deviation of (1.649). This suggests that in 88% of car crashes, a slower lead vehicle increases the likelihood of a rear-end collision.

### C-C (Model 1): Angle Collisions

The only contributing factor in the model for an angle collision between two cars is an avoiding maneuver before the crash. This maneuver was a reaction to avoid an object on the road. The probability of an angle collision between cars increases by 8.4% if the striking car maneuvered to avoid something on the road. However, angle collision is less likely among cars that crashed on a dry surface. This road condition decreases the probability of this outcome by 12.5%. This conversely implies that slippery road conditions also may increase the risk of an angled impact if a car steered to avoid hitting an object in its travel lane.

### C-C (Model 1): Sideswipe Collisions

According to the results in Table 4, sideswipe collisions among cars are influenced by the maneuvers performed before the crash, as well as any distraction present. If the striker maneuvered to avoid hitting an object and drove over the lane marker, the accident is more likely to be a sideswipe collision. If a car is driving over the lanes, or if it maneuvered to avoid something in the road, the probability to hit the vehicle on the side increases by almost 20% and 5.1%, respectively. If the crash occurred in the South region (Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, West Virginia, and Washington DC), the crash is less likely to be a sideswipe. Sideswipe collisions decreases by 1.1% if the striker reported a distraction. If a crash between cars occurred in the South region, the probability of having a sideswipe is decreased by 3%.

### C-T (Model 2): Rear-End Collisions

When analyzing a crash where the front of a car collided with the rear of a truck, the following variables were observed as significant in the MXL model. The expected straight travel, speeding factors, and sudden decelerations or stoppings are present the same way as observed with C-C collisions. A negative coefficient is found for daylight, meaning that C-T crashes during daylight are less likely to be rear-end collisions. This could lead to the assumption that the occurrence of a car colliding with a truck is due to a wrong perception of spacing between vehicles when there is no daylight. Daylight decreases the probability of a car rear-ending a truck by 3.6%. Another negative coefficient decreasing the likelihood of a rear-end collision is if the car maneuvered to avoid something on the road. The probability of rear-end collisions between a car and a truck decreases by 1.3% if the car maneuvered to avoid something on the road.

**Table 4.** MXL Results; Coefficients, *t*-Statistics, and Marginal Effects

| | C-C | | | C-T | | | T-C | | | T-T | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Coefficient | *t*-statistics | Marginal effects | Coefficient | *t*-statistics | Marginal effects | Coefficient | *t*-statistics | Marginal effects | Coefficient | *t*-statistics | Marginal effects |
| Rear-end | | | | | | | | | | | | |
| ONERE | −2.128 | −7.583 | — | 0.879 | 2.507 | — | 0.477 | 3.174 | — | −2.546 | −4.474 | — |
| DAYLGT | — | — | — | −0.602 | −4.011 | −0.036 | — | — | — | — | — | — |
| DRY | — | — | — | 1.060 | 4.293 | 0.102 | — | — | — | — | — | — |
| FAGVSI | — | — | — | 0.558 | 3.144 | 0.013 | — | — | — | — | — | — |
| FBRK | 1.523 | 4.629 | 0.007 | — | — | — | — | — | — | 2.004 | 2.379 | 0.011 |
| FGOING | 0.546 | 2.966 | 0.012 | 1.109 | 7.145 | 0.090 | — | — | — | — | — | — |
| FMANVR | — | — | — | −0.675 | −3.737 | −0.013 | — | — | — | — | — | — |
| FNOTRL | — | — | — | — | — | — | — | — | — | −1.001 | −1.972 | −0.009 |
| FSPEDR | 1.097 **(1.837)** | 4.279 **(6.393)** | 0.003 | 0.674 | 4.068 | 0.022 | 2.226 | 7.778 | 0.034 | — | — | — |
| FSTAYL | 1.566 | 6.958 | 0.039 | — | — | — | — | — | — | 2.099 | 4.156 | 0.106 |
| LDECST | 1.907 **(1.649)** | 5.504 **(5.112)** | 0.002 | 2.717 | 10.772 | 0.044 | — | — | — | — | — | — |
| LGOING | — | — | — | — | — | — | −0.237 | −1.342 | −0.012 | — | — | — |
| LNOAVM | — | — | — | — | — | — | 0.600 | 2.864 | 0.016 | — | — | — |
| LNOTRL | — | — | — | — | — | — | — | — | — | 1.648 | 2.452 | 0.009 |
| LOTHSP | 4.232 | 16.227 | 0.084 | — | — | — | — | — | — | — | — | — |
| WEST | — | — | — | 0.469 | 2.661 | 0.011 | — | — | — | — | — | — |
| Angle | | | | | | | | | | | | |
| ONEAN | 0.522 | 1.974 | — | 2.122 | 9.312 | — | 0.779 | 3.895 | — | −4.374 | −8.414 | — |
| DRY | −0.975 | −3.787 | −0.125 | — | — | — | — | — | — | — | — | — |
| FCHNGL | — | — | — | 1.537 | 6.133 | 0.030 | — | — | — | — | — | — |
| FDISTR | — | — | — | −0.705 | −3.800 | −0.013 | — | — | — | — | — | — |
| FGOING | — | — | — | — | — | — | −1.451 **(1.849)** | −2.807 **(2.146)** | −0.050 | — | — | — |
| FMANVR | 2.029 | 6.853 | 0.084 | — | — | — | — | — | — | 1.365 | 2.105 | 0.105 |
| FSTGHT | — | — | — | — | — | — | 0.567 | 2.118 | 0.027 | — | — | — |
| LDECST | — | — | — | — | — | — | −3.038 | −5.233 | −0.005 | — | — | — |
| LNOTRL | — | — | — | −1.209 | −5.670 | −0.015 | — | — | — | — | — | — |
| SUMMER | — | — | — | — | — | — | −1.696 **(2.226)** | −2.263 **(2.842)** | −0.004 | — | — | — |
| Sideswipe | | | | | | | | | | | | |
| FDISTR | −0.469 | −2.361 | −0.011 | — | — | — | — | — | — | — | — | — |
| FCHNGL | — | — | — | — | — | — | 3.878 | 18.986 | 0.219 | — | — | — |
| FENCRC | — | — | — | 1.645 **(2.621)** | 5.647 **(6.371)** | 0.012 | — | — | — | — | — | — |
| FGOING | — | — | — | — | — | — | — | — | — | −4.282 **(2.745)** | −2.612 **(2.034)** | −0.034 |
| FMANVR | 2.276 | 7.949 | 0.051 | — | — | — | — | — | — | — | — | — |
| FOVRDG | 2.116 | 12.528 | 0.199 | — | — | — | — | — | — | — | — | — |
| FRDLEL | — | — | — | −1.37 | −4.838 | −0.030 | −0.634 | −2.481 | −0.010 | — | — | — |
| INTERC | — | — | — | — | — | — | −0.299 | −1.331 | −0.003 | — | — | — |
| LDECST | — | — | — | — | — | — | −1.841 | −6.851 | −0.006 | −2.945 | −4.560 | −0.039 |
| LSTGHT | — | — | — | 5.498 | 9.736 | 0.300 | — | — | — | — | — | — |
| SOUTH | −0.387 | −2.737 | −0.029 | — | — | — | — | — | — | — | — | — |
| WINTER | — | — | — | 0.633 | 2.957 | 0.020 | — | — | — | — | — | — |

Note: Bold font represents the standard deviation of that variable under the MXL estimation.

**Table 5.** MXL Model Results; Model Statistics

| Model statistics | C-C | C-T | T-C | T-T |
|---|---|---|---|---|
| Number of parameters | 16 | 18 | 15 | 10 |
| Log-likelihood at convergence | −1,118.004 | −1,246.184 | −1,048.044 | −151.023 |
| Log-likelihood at zero | −4,134.078 | −2,657.543 | −1,975.305 | −486.685 |
| Chi-squared | 6,032.149 | 2,822.718 | 1,854.523 | 671.323 |
| Number of observations | 3,763 | 2,419 | 1,798 | 443 |
| Fixed parameter log-likelihood at convergence | −1,134.079 | −1,261.569 | −1,051.057 | −151.9251 |
| Likelihood ratio (chi-squared) | 32.15 | 30.77 | 6.026 | 1.804 |
| Confidence level (%) | 99.99 | 99.98 | 95.09 | 99.82 |



Additional variables increasing the outcome of a car-truck crash to be rear-end are dry road conditions at the time of crash; and geographical location in the West region in the United States (Montana, Idaho, Washington, Oregon, California, Nevada, New Mexico, Arizona, Utah, Colorado, Wyoming, Alaska, and Hawaii). Some possible reasons for this variables being significant can be attributed to driving behaviors (e.g., aggressive following) in this region under ordinary weather conditions. As also described in Knipling (2013), occurrence of car-truck crashes is higher (80.8%) when pavement is dry and under no adverse weather conditions. According to the marginal effects, the most influential variables are the road is dry, when the truck decelerates or stopped in the lane and when the car keeps its direction. These variables increase the probability of rear-end collisions by 10.2%, 4.4%, and 9% respectively.

### C-T (Model 2): Angle Collisions

In the case of a car traveling alongside a heavy vehicle, the model indicates that an intended maneuver was attempted by the car but failed. This can be inferred from the precrash situation influencing the likelihood of an angle collision due to lane changing. If a car changes lanes, the probability of hitting the truck traveling to the side increases by 3%. It seems that cars misjudge the gap from the adjacent lane and the speed and position of the truck traveling on the side.

A negative effect is obtained from the variable describing a distraction by the striker. The probability of an angle crashes decreases by 1.3% if the car driver did not experience a distraction. This reinforces the idea that performing a risky maneuver, rather than distraction, influences the likelihood of this type of crash.

An additional variable with a negative influence in this crash outcome is a truck with no trailing unit. The collision between a car and a truck at an angle deceases by 1.5% if the truck has no trailing unit. It could be that vehicle dimensions play a role in angle collisions. The behavior to drive a truck with no unit may differ than when it is carrying cargo, and this may be misleading for a car attempting to change lanes.

### C-T (Model 2): Sideswipe Collisions

Having a different combination of vehicles but keeping the same striker vehicle type as car gives an interesting perspective on sideswipe collisions. A sideswipe crash in a car-truck collision is more likely to occur if a truck is traveling straight ahead on the left or right lane of the car, or if the crash occurs in winter. According to the marginal effects, the probability of a car crashing into a truck in a sideswipe manner increases by 30% if the truck is going straight. If a crash occurs during winter, the probability of a sideswipe collision increases by 2%. It is less likely to occur if the striker left the lane prior to the crash. Sideswipe collisions slightly decreases by 3% if the car lefts the travel lane.

The likelihood of a sideswipe collision is increased if the car encroaches the next lane where the truck is traveling. However, this variable behaves differently across observations since some unobserved factors not captured in the data set also may be influencing this variable. For instance, for a crash in winter, the car could have skidded involuntarily to the other lane. The parameter has a mean value of 1.645 and standard deviation of (2.621). This indicates that 73% of car-truck collisions are more likely to be sideswipe if the striking vehicle encroaches the next lane.

### T-C (Model 3): Rear-End Collisions

When a crash involves a truck striking a car, it is more likely to be a rear-end type if the truck was speeding and the car in front took no action to avoid the collision. Again, speed is considered a contributing factor to the cause of a rear-end collision. For this combination of vehicles, it is interesting to see that the struck car did not respond to the impeding danger. The marginal effect indicates that rear-end collisions between a truck and a car, where the truck is blamed for the accident, increases by 3.4%; and it increases by 1.6% when there is a speed-related collision and the car does not make an evasive maneuver when realizing the imminent impact. A crash is less likely to be a rear-end type if the car is going straight before the truck runs into it. The event of a car going straight decreases by 1.2% for this type of collision. Although this might seem unexpected, a possible explanation could be that the car suddenly merged into the truck's lane, and going straight was not the car's path prior to the impact.

### T-C (Model 3): Angle Collisions

If the truck is traveling straight ahead in the adjacent lane of the vehicle before crashing, it will influence the likelihood of an angle collision. The chances for a truck to collide at an angle with a car increases by 2.7% if the truck travels straight ahead on the left or right lane. However, if a car decelerates or stops in a traffic lane, an angle crash outcome is less likely to occur. Car decelerating or stopping decreases the outcome by 0.5%.

Both random estimates have a negative influence in the outcome of angle collisions when a crash has occurred, meaning that it is less likely to be an angle crash. The first random estimate describes the truck to be going straight prior to colliding with the car. This random parameter has a mean of −1.451 and a standard deviation of (1.849). This suggests that in 78% of crashes where a truck hit a car, the outcome is less likely to be an angle collision if the truck was going straight. Other unobserved behavior such as merging before the crash may cause random effects on the model. The second random parameter relates to the season in which the crash occurred. In this study, the summer season is defined as the months of June, July, and August. Its variability across observations is assumed to exist because other months may be reported as summer. The statistical values of −1.696 for mean and (2.2226) for standard deviation indicate that 78% of these crashes involving a truck and a car are less likely to be angle collisions.

### T-C (Model 3): Sideswipe Collisions

One of the actions prior to impact that can result in a sideswipe collision between a truck and a car is changing lanes. The precrash variables with negative coefficients that affect having a crash that is not a sideswipe are the truck leaving travel lane and the car decelerating or stopping in the travel lane. Further, a crash on an interchange contributes to collision types other than sideswipe.

The variable with the highest marginal effect among the attributes in this utility function is the truck changing lanes. This event increases the probability of this outcome by 21.9%. Other variables have less influence on the outcome. The truck staying on the roadway but leaving the travel lane decreases the probability of a sideswipe collision by 1%. If the car decelerates or stops, this diminishes the outcome probability by 0.6%. Interestingly, if the crash occurs at an interchange, sideswipe collisions decrease by 0.3%.

### T-T (Model 4): Rear-End Collisions

In T-T rear-end collisions, the precrash actions performed by the striker that affects the outcome of a rear-end collision between two trucks is braking and staying in the travel lane. If the truck stays in the same lane, the probability of crashing into the truck in front increases by 10.6%. If the truck brakes as a response to the impending danger, the probability of striking the leading truck increases by 1.1%. Also, if the struck truck was not pulling any trailing unit, it also affects the likelihood of this particular manner of collision. When the truck in front does not carry a trailing unit, the probability of a rear-end collision among trucks increases by 0.9%. Interestingly, if the striker also has no cargo unit, it is less likely for the outcome to be a rear-end collision. If the truck striking another truck that has no trailing unit, the chances of collision decrease by almost 1%. This could mean that a truck misjudges the trajectory of the truck in front because of its smaller dimensions. It could motivate the trailing truck to behave more aggressively and tailgate the truck in front. Another reason for this type of impact could be attributed to the differences in braking capabilities of larger and smaller trucks.

### T-T (Model 4): Angle Collisions

The likelihood of an angle collision between trucks is influenced mainly by the maneuvering of the striker to avoid an object on the road. This is supported by the negative alternative specific constant, which includes additional variables not accounted for. If the striker performs a maneuver to avoid something on the road, the chance of hitting the adjacent truck at an angle increases by 10.5%.

### T-T (Model 4): Sideswipe Collisions

The T-T sideswipe manner of collision was challenging, as the only significant variables in the model have negative influences that decrease the likelihood of the collision. However, this variable may be useful since it can describe how a sideswipe collision does *not* occur. The only fixed parameter describes the struck vehicle as decelerating or stopping in the lane. If the struck truck decelerates or stops, the chances of this outcome decrease by almost 4%. A possible explanation of why any deceleration of two vehicles traveling side by side will not result in sideswiping can be that the decelerated vehicle would be left behind, and this action finally may result in a different manner of collision.

The other parameter, which is treated as random, describes a negative effect in the outcome because of its negative sign. This variable describes the striker as going straight before collision. For an impact along the side of both vehicles, it is expected that an activity that indicates a movement, such as steering, is more suitable. With regard to unobserved factors affecting this variable, strikers may use this definition as an excuse for not paying attention to the road. Assuming this, this action may be reported differently in the observations, so it can be considered as random. This parameter has a mean of −4.282 and a standard deviation of (2.745). The likelihood of getting involved in a sideswipe collision is 94% less likely when the striker was going straight.

## Comparing Different Driving Behavior

This section compares the different possible manners of collision that are more or less likely to occur according to the developed MXL models. The results for each vehicle crash combination point out the different manner of collisions when a vehicle strikes the same and different types of vehicle. The manner of collision will reflect unsafe driving behavior and vehicle dynamics when interacting with same or different types of vehicle. This analysis is based on the sign of the alternative specific constants for rear-end and angle collisions for each model, as shown in Table 4.

For instance, if a car hit a truck, according to the positive coefficients of 0.879 and 2.122 for rear-end and angle, respectively, and all attributes being equal, it is less likely to be a sideswipe collision. In the same way, in a crash where a truck ran into a car, the positive values of 0.477 and 0.779 for rear-end and angle constants indicate that it is more likely to be a rear-end or an angle collision rather than a sideswipe. However, in a collision that involves two trucks, the negative values of −2.546 and −4.374 in rear-end and angle collisions tell that it is more likely to be a sideswipe. For crashes involving two cars, the coefficients of −2.128 and 0.522 for rear-end and angle, respectively, demonstrates that the manner of collision is more likely to be angle.

Knowing the previous likelihood of the manner of collision, it can be interpreted that cars can better interact with the same vehicles in front and large vehicles on the side traveling parallel. However, cars are more likely to fail to follow a truck in a safe manner and change lanes when a truck or a car is in the adjacent lane. This is supported by the findings in Knipling (2013), which point to a greater frequency of aggressive driving in car drivers than truck drivers and errors attributed to car drivers. Accordingly, a failed interaction among trucks describes a possible failure of trucks interacting with cars traveling in front or positioned in the adjacent lane ahead or behind the truck. Longitudinal interaction errors could occur in part because of “trucks’ relative inability to evade an errant car,” as mentioned in Knipling (2013). For trucks failing to interact with cars in the adjacent lane, a possible hypothesis can be referred to the lack of visibility when trucks move from left to right, as suggested in Knipling (2013). Also, it indicates unsafe driving behavior when the truck matches the position of another truck traveling in the adjacent lane. This can be partly due to trucks’ lack of stability and the aerodynamics involved when two trucks are traveling side by side.

## Policy Implications

One of the aims of this research is to aid in the decisions made by public officials to reduce the likelihood of rear-end, angle, and sideswipe collisions. The following measures are suggested as an attempt to contribute to safety improvements on highways.

Roadway improvements should consider the sight distance, acceleration/deceleration capabilities, and vehicular dimensions of cars and trucks. Proper road access to arterials should look into removing slower-turning vehicles such as trucks from traffic lanes. Performing traffic forecast on conflicted sites may help foster the understanding of the trend of unsafe movements. Adjusting the U.S. transportation infrastructure based on the current types of vehicle in traffic is essential to increase throughput.

Revisions in lane width or lane delineations, for instance, may need to be made to allow different types of vehicles to interact safely on highways. Even vehicle configurations may have to change to make drivers more aware of vehicles changing lanes. New configurations of turning signals, electronic onboard devices, or both may warn drivers so they can avoid crashing into the car in the next lane. This may result in reducing angle and sideswipe collisions. Restricting traffic to left or right lanes that are labeled as acceleration or deceleration lanes can allow for driving maneuvers based on vehicle capabilities. This could be complemented by designated different speed limits to trucks and cars. In addition, a separation policy when following a different type of vehicle can help eliminate rear-end collisions.

Improvements in state-highway programs and law enforcement are crucial to minimizing the possible manners of collision on highways. Providing education to drivers on the different vehicles on the road and their capabilities can be the first step toward promoting safety awareness.

## Conclusions

This research has explored the use of the MXL model to quantify the contributions of vehicle characteristics, vehicle following, and precrash attributes, among other factors, on the probabilities of three manners of collision on interstate highways.

The activity of the striker prior to collision is of special interest since vehicle-following attributes are incorporated in the model to try to explain unsafe interactions between two vehicles prior to a rear-end crash. An angle collision between the same or different vehicle types can be commonly attributed to conscious yet aggressive lane changing or unpredicted maneuvers that changed the vehicle's path. In particular, this manner of collision between cars and trucks, regardless of their role, is expected to occur due to the difference in size and dynamics between two distinct types of vehicles, whether one changes lanes on purpose or not. On interstate highways, trucks are driven mostly in the right lane(s), so an inherent lane separation exists between cars and trucks. This behavior is expected to contribute to angle collisions in crashes between a car and a truck. It is expected that a collision in a sideswipe manner occurs when the same vehicles are traveling next to each other in adjacent lanes. It is suspected that an occurrence of this type of collision between cars and trucks will be attributed to the difference in longitudinal dimensions. Identifying and understanding driver behavior leads to responsible countermeasures for road and insurance policy design and exposes risk implications for truck companies.

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