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# Analysis Of Various Car-truck Crash Types Based On Ges And Fars Crash Databases Using Mutlinomial And Binary Logit Model

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# ANALYSIS OF VARIOUS CAR-TRUCK CRASH TYPES BASED ON GES AND FARS CRASH DATABASES USING MUTLINOMIAL AND BINARY LOGIT MODEL

by

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# ABSTRACT

Each year about 400,000 trucks are involved in motor vehicle crashes. Crashes involving a car and truck have always been a major concern due to the heavy fatality rates. These types of crashes result in about 60 percent of all fatal truck crashes and two-thirds of all police-reportable truck crashes. Car-truck crashes need to be analyzed further to study the trends for a car-truck crash and develop some countermeasures to lower these crashes. Various types of car-truck crashes are analyzed in this study and the effects of various roadway/environment factors and variables related to driver characteristics in these car-truck crashes are investigated. To examine the crash characteristics and to investigate the significant factors related to a car-truck crash, this study analyzed five years of data (2000-2004) of the General estimates system of National Sampling System (GES) and the Fatality Analysis Reporting system database (FARS). All two vehicle crashes including either a car or truck (truck-truck cases excluded because of their low percentage composition) were obtained from these databases. Based on the five year data (GES/FARS) the percentage of car-truck angle collisions constituted the highest percent of frequency of all types of car-truck collisions. Furthermore, based on the 2004 GES data there is a clear trend that the frequency of angle collision increases with the increase in driver injury severity. When analyzing the GES data it was observed that the percentage of angle collisions was the highest followed by the rear end and sideswipe (same direction) collisions respectively. When the fatalities were considered (FARS database used), the percentage of angle collisions was the highest followed by head-on and rear-end collisions. The nominal multinomial logit model and logistic regression models were utilized for this analysis.

Divided section, alcohol involvement, adverse weather conditions, dark lighting condition and old age of drivers had a significant effect on the car-truck crashes and were likely to increase the likelihood of a car-truck crash. Whereas dark but light conditions, young aged drivers showed a less likelihood of involving in a car-truck crash.

This research is significant in providing an insight into various car-truck crash types and provides with results, which have impacted the car-truck crashes. A better understanding of the factors impacting these crashes will help in providing better countermeasures, which would result in reducing the car-truck crashes.

This work is dedicated to my parents, Sri Thirupalappa Mannila and Sri Thirupathi devi, who encouraged me to march towards achieving my goal.

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# 1. INTRODUCTION

## 1.1 Background

Each year about 400,000 trucks are involved in motor vehicle crashes. Crashes involving a car and truck have always been a major concern due to the heavy fatality rates. High priority to car/truck proximity research-study of multi-vehicle collisions in which a truck collides with a passenger vehicle (car, pickup truck, sport utility vehicle, or van) has been given by FMCSA (Federal Motor Carrier Safety Administration). These types of crashes result in about 60 percent of all fatal truck crashes and two-thirds of all police-reportable truck crashes. Although trucks are involved in fewer crashes per million kilometers driven than private vehicle drivers they are, however, involved in a disproportionately large percentage of fatal crashes.

In 2000, 5,211 persons were killed and about 140,000 were injured in crashes involving trucks with a gross vehicle weight of more than 10,000 pounds (NHTSA 2001). Large trucks constitute a large proportion of the freeway and highway traffic. Due to their physical and operational characteristics, they can significantly impact traffic system performance, safety, and the travel experience of non-truck drivers. Many crashes between cars and large trucks occur because a maneuver performed by one of the vehicles is unanticipated by the other, leaving insufficient time to avoid the crash.

Angle collisions are one of the frequently occurring types of collisions, accounting for almost 40% of all reported car truck collisions in the US as reported by the General estimates system of National Sampling System (GES) for years 2000-2004. Angle collisions are more common in a car-truck collision due to the diversity in the maneuverability of a car and truck.

Based on the 2004 General Estimates System of National Sampling System (GES), it was found the 93,196 angle collisions that constitute the highest percent of frequency of all types of car-truck collisions (see Figure 1). Furthermore, there is a clear trend that the frequency of angle collision increases as the driver injury severity increases. Order of injury severity considered is shown below.

0- No injury

1- Possible injury

2- Non-incapacitating

3- Incapacitating

4- Fatal

5- Unknown injury severity

The frequency of angle crashes increased from no-injury to fatal injury.

In field it was observed that a car ran into a truck that was maneuvering a turn in spite of observing it at a safe distance. This scenario observed in the field raised many questions regarding car-truck crashes. A further investigation into car-truck crashes is required to understand this scenario.

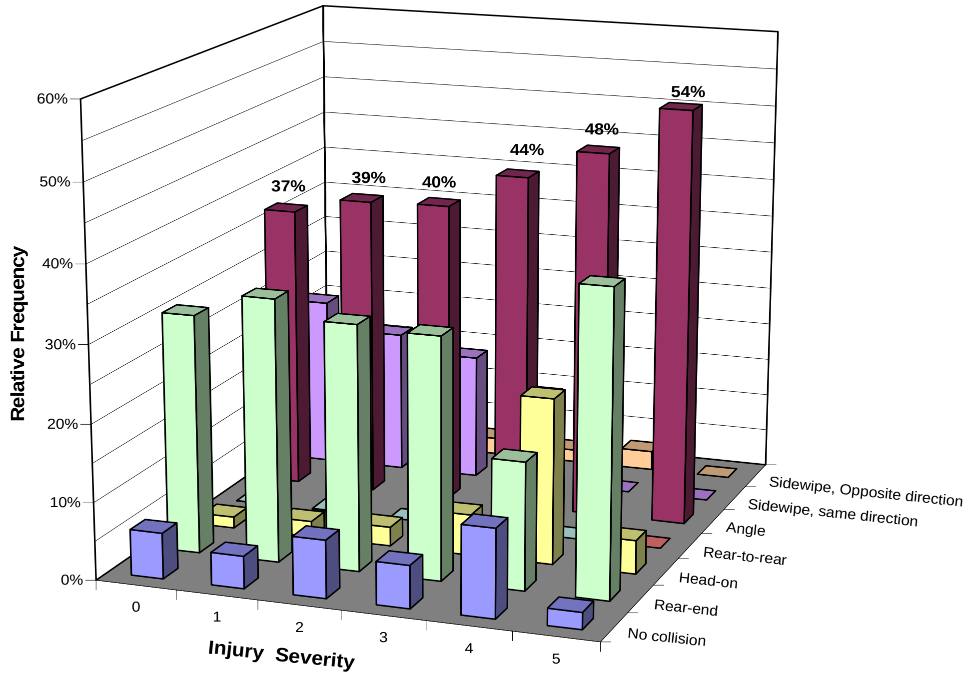


Figure 1: Relative frequency of all type of car-truck collisions (2004, GES)

When GES database was used it was found that the percentage of angle collisions were followed by rear-end and sideswipe collisions. When fatal car-truck collisions obtained from Fatality Analysis Reporting system database (FARS) database was analyzed it was found that percentage of angle collisions were followed by head-on and rear-end collisions. An attempt was made to analyze these types of collisions and interpret the effect of various road environment factors, and factors related to driver on these crashes. Moreover the effects of alcohol and roadway features on these collisions were also studied.

Typically, driver, vehicle and roadway/environment characteristics influence crash occurrence and injury severity. An angle collision between a car and truck is related to driving behavior and performance of vehicle at fault, and the crash risk is possibly associated with the fault vehicle. In case of rear-end and sideswipe (same direction) it was found that striking vehicle was more likely to be the cause of the collision and hence these collisions were categorized based on the vehicle role in this study. For head-on collisions the vehicle configuration was considered as car-car and car-truck. In all these cases car-car cases were considered to be the base case. The configurations car striking a truck and truck striking a car were compared to the base case.

The data over the years 2000 to 2004 from GES and FARS was used for the current research. National Automotive Sampling System (NASS) General Estimates System (GES) is directed by the National center for statistics and analysis, which is a component of research and development in NHTSA. The police collisions reports (PARS) from which GES data are coded are probability samples of police reported crashes that occurred in the United States. The database includes several files related to the crash, vehicle and person. Crash file contains information on characteristics and environmental conditions at the time of crash. Vehicle file contains information describing the vehicle and drivers involved in the crash are given in the vehicle file.  Person file contains information describing all persons involved in the crash. Each of these files can be interlinked to obtain necessary information.

Fatality Analysis Reporting System (FARS) is a collection of files documenting all qualifying, fatal crashes since 1975 that occurred within the 50 states, the District of Columbia, and Puerto Rico. This database includes several files related to the crash, vehicle and person. Each of these files can be interlinked and the necessary details can be obtained from these datasets.

## 1.2 Research objectives

The main objective of this study was to investigate the crash propensity of different types of car-truck crashes through crash comparisons among different crash configurations. The crash configurations were classified into two groups; fault roles and hitting roles. Driver charged with the violations were termed as fault drivers. The fault role of the drivers involved in the crash was used to categorize the crash data to be analyzed for crashes. Fault roles were used to categorize the data fro angle crashes. While hitting role was assigned to the driver of the striking vehicle in the crash. Striking role was considered to analyze rear-end and sideswipe (same direction). Incase of the head-on collisions, the crash configuration was used to categories the data. The category was either a car-car (both the involving vehicles are cars) or a car-truck (one vehicle is a car and the other vehicle involved is a truck).The effect of series of potential risk factors classified by driver characteristics, road environments on the car-truck crashes were investigated. The research tried to identify the causes, which result in various car-truck crashes and the contribution of various significant factors that trigger a car-truck interaction into a collision.

Multinomial logistic regression models and binary logit models were used for hypothesis testing to identify the significant factors that contribute to these car-truck collisions. The driver of the vehicle who is charged with a driving violation was termed as faulty vehicle and the vehicle which was striking the other vehicle in the crash was termed as the striking vehicle. The modeling compared between the car-truck crashes to the base car-car crashes. The faulty vehicle in a car-truck angle collision and striking vehicle (rear-end & sideswipe (same direction) car-truck collision) is compared to the fault vehicle in a car-car angle and striking vehicle in car-car collisions (rear-end and sideswipe collision) respectively. The car-car cases were the base cases in the study.

# 2. LITERATURE REVIEW

## 2.1 General safety concerns about truck operations

FMCSA has given high priority to car/truck proximity research – study of multi-vehicle collisions in which a truck collides with a passenger vehicle (car, pickup truck, sport utility vehicle, or van). These types of crashes result in about 60 percent of all fatal truck crashes and two-thirds of all police-reportable truck crashes (Peeta S., et al., 2005). Identifying the behaviors of either driver that lead to collisions is a first step towards developing countermeasures (Harkey, D., et al. 2002).

Driver behavior has been extensively studied in the past. Peeta, S., et al., (2005) focused on modeling of the behavior of non-truck drivers in the vicinity of trucks and capture those interactions. The type of collision and the in-depth analysis of the crash trend have not been studied. Other studies (Peeta, S., et al., 2000) suggest that truck drivers and non-truck drivers can react differently to the routing information provided through an advanced information system. A new parameter called driver discomfort level to incorporate the various factors that affect individual driver actions/interactions was created. Furthermore, they characterized the effects of these interactions at a system level to address real-world problems. They tried to provide a measurable definition of car–truck interactions, identify the causal factors, develop a methodological framework to model the interactions, and enable the evaluation of alternative strategies to mitigate them.

Past studies (Stuster, J., 1999; Kostyniuk, L.P., et al., 2002) suggest that the presence of trucks can significantly impact the driving actions of non truck drivers, and that these impacts are key causal factors for car–truck crashes. Recent research has stressed on the effect of aberrant driver behaviors on the crashes, which was done using the driver behavior questionnaires (Sullman, M.J.M., et. al 2002).

Although trucks are involved in fewer crashes per million kilometer driven than private vehicle drivers (Walton, D., 1999), they are, however, involved in a disproportionately large percentage of fatal crashes. Hanowski, R.J., et al., (2005) carried out research on involvement of driver distractions of the truck drivers in crashes. In that study, it was observed that three main causes for a crash to occur were judgment error, other vehicle, and driver distraction. For a critical incident to be assessed with a ‘‘driver distraction’’ contributing factor, the driver had to be engaged in a tertiary task immediately before the incident occurred. Tertiary tasks included using a cell phone, tuning the radio, eating, looking away from the forward roadway, and similar tasks that did not directly involve the driver’s primary task of safely operating the vehicle. Distraction types were identified and important insight was also gained into the relative safety impacts of different distracting agents and behaviors.

Studies were carried out to determine the relative contribution of truck drivers and passenger car drivers to the crash problem. Harkeya, D., et al, (USDOT FHWA) conducted a study which (1) examined “fault” in total car/truck crashes for comparison with “fault” in previous studies of fatal crashes, (2) used crash data to attempt to verify “Unsafe Driving Acts (UDAs)” identified by expert panels in past studies, and (3) identified “critical combinations” of roadway facility type, roadway location, and crash type based on “total harm” – a measure combining both the frequency and severity of the crash. Few recent studies were directly related to the car/truck proximity issue. Blower, D., (1998) used data from two different sources – the

Trucks involved in fatal collisions (TIFA) files for fatal crashes, and NHTSA's National automotive sampling system General estimates system (NASS GES) for non-fatal crashes.

Some studies related to the economics of car-truck crashes have also been done. Zaloshnja, E., Miller, T.R., (2004) tried to estimate the cost of highway crashes involving large trucks by type of truck involved. These costs represent the present value of all costs over the victims' expected life span that resulted from a crash. They include medically related costs, emergency service costs, property damage costs, lost productivity, and the monetized value of the pain, suffering, and lost quality of life that a family experiences because of death or injury.

Studies related to the crashworthiness were done earlier. Mock, C.N., et al., (2004) studied the relationship between body weight and risk of death and serious injury in motor vehicle and it was observed that increased occupant body weight is associated with increased mortality in automobile crashes. This is probably due in part to increased co-morbid factors in the weight occupants. However, it is possibly also due to an increased severity of injury in these occupants. These findings may have implications for vehicle safety design, as well as for transport safety policy. The Motor carrier safety improvement act of 1999 (MCSIA, LTCC 2006) mandated a study to determine the causes of, and contributing factors to, crashes involving commercial motor vehicles. MCSIA also directed the Secretary to transmit to Congress the results of the study. The U.S. Department of transportation's (DOT) Federal motor carrier safety administration (FMCSA) and National highway traffic safety administration (NHTSA) conducted a multiyear, nationwide study of factors that contribute to truck crashes.

The Large Truck Crash Causation Study (LTCCS) identifies areas that need to be addressed by effective crash countermeasures. The LTCCS contains the same type of descriptive data as the primary national traffic safety databases described above, but also focuses on precrash factors such as driver fatigue and distraction, vehicle condition, weather, and roadway problems.

## 2.2 Crash database applications in traffic safety

Previous studies (Blower, D., 1998) used data from two different sources – the Trucks Involved in Fatal Collisions (TIFA) files for fatal crashes, and NHTSA' s National Automotive Sampling System General Estimates System (NASS GES) for non-fatal crashes. GES and Fatality Analysis reporting system (FARS) have been widely accepted crash databases for crash analysis. Abdelwahab, H., and Abdel-Aty, M., (2004), have used FARS for analysis of rear-end fatal collisions. Abdel-Aty, M., and Abdelwahab, H., (2004) used GES crash database to study the effect of the geometric incompatibility of light truck vehicles (LTV)—light-duty trucks, vans, and sport utility vehicles—on drivers' visibility of other passenger cars involved in rear-end collisions. These crash databases were used in the current study to analyze the car-truck crashes.

### 2.2.1 GES crash database

The GES obtains its data from a nationally representative probability sample selected from the estimated 6.3 million police-reported crashes, which occur annually. NASS GES analytical user's manual 1998-2003 provides with information on the GES database and its variables. The crashes in GES include those that result in a fatality or injury and those involving major property damage. Although various sources suggest that there are many more crashes that are not reported to the police, the majority of these unreported crashes involve only minor property damage and no significant personal injury. By restricting attention to police-reported crashes, the GES concentrates on those crashes of greatest concern to the highway safety community and the general public. The GES is directed by the National Center for Statistics and Analysis, which is a component of Research and Development in NHTSA. The data obtained by GES data collectors in 60 geographic sites across the United States. These data collectors make weekly, biweekly, or monthly visits to approximately 400 police agencies within the 60 sites. During the visit, the data collectors compile a list all police traffic crash reports (PARs) not previously listed and then select a sample of the listed PARs. The police collisions reports (PARs) from which GES data are coded as a probability sample of police-reported crashes that occurred in the United States. Since each crash that occurred in the survey year had a chance of being selected, the design makes it possible to compute not only national estimates but also probable errors associated with the estimates.

From 1988 to 1999 GES data items were organized into three SAS data sets: the Crash, Vehicle/Driver, and Person data sets. Starting in 2000 the Event data set is also available. These four data sets contain the following types of information:

- The Crash Data Set contains information on crash characteristics and environmental conditions at the time of the crash. There is one record per crash.
- The Vehicle/Driver Data Set contains information describing the vehicles and drivers involved in the crash. There is one record per vehicle.
- The Person Data Set contains general information describing all persons involved in the crash: drivers, passengers, pedestrians, pedal cyclists, and non-motorists. It includes information such as age, sex, and vehicle occupant restraint use, and injury severity. There is one record per person.

- The Event Data Set contains a brief description of each harmful event in a crash including the vehicles or objects involved and the general area of vehicle damage. The most harmful event number for each vehicle is recorded in the Vehicle file, enabling the identification of the vehicle or object involved in the vehicle's most harmful event. There is one record per event.

Each of these datasets can be inter-related by variables that are common in these datasets. Our study is an explanatory study and it would be fair enough to deal with the sample data rather than the projected data which is obtained by using the weights for each observation. This study deals with various environmental factors and incorporating the weight by simply replicating each observations by weight number of times wouldn't be a fair method to follow. Hence sample GES database has been used in our study. Abdel-Aty, M., and Abdelwahab, H., (2004b) in their study used the sample GES data base to analyze the rear-end crashes.

### 2.2.2 FARS crash database

The Fatality Analysis Reporting System (FARS) contains data on a census of fatal traffic crashes within the 50 States, the District of Columbia, and Puerto Rico (Tessmer, J.M., 2002). To be included in FARS, a crash must involve a motor vehicle traveling on a traffic way customarily open to the public and result in the death of a person (occupant of a vehicle or a non-occupant) within 30 days of the crash. FARS has been operational since 1975 and has collected information on over 989,451 motor vehicle fatalities and collects information on over 100 different coded data elements that characterize the crash, the vehicle, and the people involved.

FARS data are critical to understanding the characteristics of the environment, traffic way vehicles, and persons involved in the crash. Three of these sections address each of the three principle files, namely the crash, vehicle and person files. These files can be related with each other with some common variables. The crash file contains crash characteristics and environmental conditions at the time of the crash. The vehicle file contains information describing the vehicles and drivers involved in the crash. The person file contains information describing all persons involved in the crash: drivers, passengers, pedestrians, pedal cyclists, and non-motorists. It includes information such as age, sex, and vehicle occupant restraint use, and injury severity.

## 2.3 Crash types

Early efforts were made to study the different types of crashes. Some studies dealt with the crashes including the car and a light vehicle truck. The effect of age and alcohol involvement was also focused in earlier studies. Angle, rear-end, sideswipe (same direction) and head-on car-truck crashes were analyzed in this study. Few studies in the past dealt with these crash types in general no studies were found dealing with the car-truck angle, rear-end, sideswipe(same direction) and head-on collisions in particular.

### 2.3.1 Angle

Very few studies dealt with car and truck angle collisions in particular. Abdel-Aty, M., and Abdelwahab, H., (2004a) studied the effect of the increased percentage of light truck vehicle (LTV) registrations on fatal angle collisions trends in US. The analysis investigated the number of annual fatalities that result from angle collisions as well as collision configuration (car–car, car–LTV, LTV–car, and LTV–LTV).

The analysis into the configuration of the collision indicated the seriousness of angle collisions involving an LTV striking a common passenger car (LTV–car). It was found that light vehicle truck striking a car (LTV-car configuration) has a higher increasing rate.

### 2.3.2 Rear-end

Rear end collisions constitute a substantial portion of the crashes amongst the car-truck collisions. Past studies discussed the rear end collisions to a vast extent. Abdel-Aty, M., Abdelwahab, H., (2004c) have studied the effect of the increased percentage of light truck vehicles (LTV) in traffic on fatalities by manner of collision (rear-end), and also tried to address the impact of crash configuration (car–car, car–LTV, LTV–car, and LTV-LTV). They used time series models which incorporate the percentage of LTVs in traffic to analyze and forecast future trends of fatality that result from rear-end collisions.

Crash configuration was taken into account and four categories were formed: car-car, car-truck, truck-car and truck-truck. The first vehicle mentioned in this configuration was the following vehicle and the other was the leading vehicle. From their study models were developed to describe future trends of fatal rear-end collisions in the US. FARS database was used to develop a time series model. Also, the models do not account for other explanatory variables such as speed limits, congestion, or enforcement that may affect the fatal rear-end collisions.

Moreover rear end collisions are frequently the predominant collision type at signalized intersections. Efforts were made to study rear-end collision probabilities at the signalized intersections. These rear-end collisions result from the combination lead-vehicle deceleration and the ineffective response of the following vehicle's driver to this deceleration. Wang, Y., et al., (2003) put efforts to estimate crash probabilities using information on traffic flow, traffic regulations, roadway geometrics, and human factors from four-legged signalized intersections in Tokyo, Japan. Data was collected over a period of four years from 1992-1995 for150 intersections in the Tokyo metropolitan area.

The occurrence of rear-end collision was studied based on the probability of encountering an obstacle vehicle and the probability of a driver failing to react quickly enough to avoid a collision with the obstacle vehicle. The probability of encountering an obstacle vehicle was assumed to be a function of the frequency of disturbances that cause the driver of a leading vehicle in a vehicle pair to decelerate.

Approaches with a median fence and four-phase signal control were found to lower the probability of encountering an obstacle vehicle. The existence of median fences can prevent pedestrians from crossing illegally thus reducing disturbances that may cause an obstacle vehicle.

Abdel-Aty, M., and Abdelwahab, H., (2004b) studied the effect of the geometric incompatibility of light truck vehicles (LTV)—light-duty trucks, vans, and sport utility vehicles—on drivers' visibility of other passenger cars involved in rear-end collisions. They considered the sample data of GES crash database (2000) in their analysis. The projected observations which were obtained using the weights given for each observation were used to find the distribution It was observed that angle crashes were followed by rear-end over for the year 2000. Effort was put in to explore the effect of the lead vehicle's size on the rear-end crash configuration. Nested logit models were calibrated to estimate the probabilities of the four rear-end crash configurations as a function of driver's age, gender, vehicle type, vehicle maneuver, light conditions, driver's visibility and speed. The two level nesting structures that groups the CarTrk in one group and the other categories (CarCar, TrkCar, TrkTrk) into another group was found to be the best-nested logit model.

Another study by Yan, X., et al., (2005) tried to investigate the crash propensity for different vehicle roles (striking or struck) that are involved in the rear-end collisions at signalized intersections and identify the significant risk factors related to the traffic environment, the driver characteristics, and the vehicle types. This study presented results of a thorough investigation into the relationship between the rear-end collisions and a series of potential risk factors classified by driver characteristics, road environments, and vehicle type.

The multivariate logistic regression analysis was used to identify the significant factors directly associated with the rear-end collisions occurring at the signalized intersection. It was observed that in most rear-end cases, the leading vehicles did not take a major responsibility for the collisions but they could have performed an unexpected stop; on the other hand, the main contributing causes to the crash for the striking vehicle were found to be careless driving and following too closely.

Some studies focused on the rear-end collision scenarios categorized by type of human error (Hiramatsu, M., and Obara, H., 2000). They tried to shed some light on the thematic concern of why people cause rear end collision; an analysis was made of the characteristics of human error in this type of crash. Vehicles were analyzed based on the striking (following) and preceding (struck) vehicle. Simulation based on Monte Carlo method was used to analyze the rear-end collisions.

Wang, X., and Abdel-Aty, M., (2006) attempted to develop equations based on negative binomial link function to model rear-end crash frequencies at signalized intersections. This study investigated the temporal and spatial correlation for longitudinal data and intersection clusters along corridors for the rear-end crashes at signalized intersections. The intersection level rear-end crash frequency model is capable of identifying the intersection related significant factors by modeling the relationship between the numbers of rear-end crashes and the intersection geometric design features, traffic control and operational features, and traffic characteristics. The significant variables, were divided into five types: traffic characteristics, geometric design features, traffic control and operational features, location type, and corridor level factors and some intersection related variables were identified as significantly influencing rear-end crash occurrences at signalized intersections

### 2.3.3 Head-on

Earlier studies focused on the effect of percentages of light truck vehicle on head-on fatal crashes. Abdelwahab, H., and Abdel-Aty, M., (2004d) developed time series models that incorporate the percentage of light truck vehicles (LTVs) in traffic and used them to analyze and forecast the future fatality trends that result from head-on collisions. It tried to address the impact of the three-crash configuration (car-car, car/LTV, and LTV-to-LTV). But this study was limited to crashes that involved only passenger cars. Moreover it was found that annual deaths of both truck-truck and car-truck crashes exhibited an increasing trend and car-truck had the highest annual death over the years 1995-2000. It was also observed that LTVs are severely harming occupants of other passenger cars with which they collide. This indicates that an LTV provides safety to its occupants and inversely affects occupants of other cars. Only the percentage of increase of LTVs was considered in this study to analyze the increase in fatality rates in the three vehicle configurations.

The forecasts from the fitted ARIMA (2, 0, 0) time series model of head-on collisions showed that during the next ten years, annual deaths in head-on collisions will reach 5,325 by the year 2010, representing an 8% increase. Also, the model forecasts show that the annual deaths in passenger vehicles due to truck/truck head-on collisions will consistently increase over the next ten years. It reaches 1,000 deaths by the year 2010. Most of the earlier studies focused on injury severity of head-on car-car crashes and the factors effecting the injury severity.

Some efforts were put to study the influencing factors on the injury severity of restrained front seat occupants in car-car head-on collisions (E Miltner, E., and Salwender, H.J., 1995). The main factors that influenced occupant injury severity were: the energy equivalent speed (EES); the change of velocity (delta u); the maximum deformation depth; and the collision angle. As per the results of a multivariate analysis: EES influenced the injury severity at all body locations except the spinal cord; occupant position effected only head injury severity, with drivers being more severely injured; occupant age influenced the injury severity at the thorax, abdomen, and extremities and maximum abbreviated injury score (MAIS) as well. A multivariate logistic regression analysis was performed in which the collision variables were simultaneously tested against injury severity.

It was observed from the study that the injury severity increased with an increasing mass ratio (mass of oncoming car divided by mass of case car)-however, without statistical significance due to the large distribution. It was found that the risk of receiving a fatal injury is approximately three to four times higher with an EES over 60 km/h.

Few studies tried to develop mathematical models to study the relative collision safety in cars (Vadeby, A.M., 2004). The car-car head-on collision was used to determine how much of injury risk in a crash depends on the car-make. The damage severity for two head-on colliding vehicles depends on various factors such as the masses of the two cars involved, the change of speed of each vehicle and the design of the car, a factor connected to car model. Person's age and sex influence the injury risk in collisions that are otherwise similar.

Studies were carried out to enhance the traffic safety. Larsen, L., and Kines, P., (2002) carried out multidisciplinary in-depth investigations of head-on and left turn road collisions. Both head-on and left turn collisions were analyzed. The drivers, to whom the crash factors were primarily related in the head-on collisions, were characterized by their conscious risk-taking behavior. The main crash factors were excessive speed, drunk driving and driving under the influence of illegal drugs. A trial period of two year (1996-1998) was considered each limited to a geographical area of the country.

In 1996–1997, the focus was on head-on collisions between motor vehicles, as this was proved to be a crash type with very serious consequences. In the 10-year period prior to the study, head-on collisions accounted for 18% of all road fatalities and 38% of all fatalities in collisions between motor vehicles only. Furthermore, little was known of the factors leading to these kinds of collisions. The head on collisions were divided in to three categories

- Head on collision during overtaking
- Head on collision on opposite vehicle's lane
- Other Head on collision.

Almost all crash factors in that study were human factors, and they were solely related to the active driver i.e. the driver who drove over into the opposite lane. The main crash factors in the 17 observed head-on collisions were excessive speed, drunk driving and driving under the influence of illegal drugs. All the drivers in those categories were younger than the age of 40, and most of them had previous records for speeding or drug convictions. Excessive speed was judged to be a crash factor in eight collisions, and appeared in combination with other crash factors, in particular driving under the influence of alcohol, illegal drugs or in relation to lack of experience.

Another characteristic crash factor was driving under the influence of alcohol and/or illegal drugs. Three collisions involved attempts at overtaking, and all of them were carried out in a reckless manner. None of them occurred directly as frontal collisions in the course of overtaking. Rather, the problem was related to maneuvering the vehicle.

When crash factors related to the road and road environments were judged it was found that in only one crash road markings in relation to road repair were misleading, which contributed to a driver driving into the lane of the oncoming traffic. In three collisions it was found that the main crash factor was speeding, drivers coped with the right-hand soft shoulder in an erroneous way, which resulted in their vehicle skidding over into an oncoming vehicle.

Studies related to Segment characteristics and severity of head-on crashes on two-lane rural highways (Garder, P., 2006) was carried out. Head-on crashes accounted for less than 5% but constituted to half of all fatalities. Data analyzed in the study was provided by Maine Department of Transportation and covered all head-on crashes over the period 2000–2002 during which there were 3136 head-on crashes reported.

Drivers making errors or misjudging situations cause a majority of head-on crashes on two-lane, rural roads in Maine. Roads with more than two lanes on average have a lower percentage of crashes producing serious injuries than two-lane roads do. Alcohol or drugs was a factor in one in 12 crashes and one in nine fatal head-on crashes. Only a small minority of head-on crashes occurred because someone was trying to pass another vehicle (one in 19 crashes and one in 14 fatal crashes). This study was limited only to two-lane highway and the vehicle type was not mentioned.

### 2.3.4 Sideswipe (same direction)

Very few studies in the past dealt with sideswipe collisions. Past studies by Farmer, C.M., et al., (1997) tried to investigate the relationship of vehicle and crash characteristics to injury severity. In that study injury type and severity among front outboard occupants of passenger vehicles struck in the side by another passenger vehicle and recorded in the United States National Crash Sampling System Crashworthiness Data System were examined in relation to the location of impact, the angle of impact, occupant gender and age, seat belt use, the weight and body style of the side-impacted vehicle, and the weight and body style of the striking vehicle. It was found that old aged drivers were three times as likely as younger occupants in similar crashes to be seriously injured.

Subjects that were considered were 4,226 front outboard occupants of model year 198l-93 passenger cars and light trucks struck (principal impact) on either side by the front of another car or light truck and included in the electronic files of the 1988-92 National Crash Sampling System Crashworthiness Data System (NASSCDS) .

Moreover a light truck was considered to be more aggressive than a passenger car as the striking vehicle in a side impact crash, partly because of its greater weight, but also because its front end is relatively stiffer and higher.

## 2.4 Statistical modeling in traffic safety analysis

Shankar, V., and Mannering, F., (1996) used multinomial logit model to analyze the single motor vehicle severity levels. Multinomial logit was considered to be a promising approach to evaluate the determinants when there are multiple levels for a target variable.

Al-Ghamdi, A.S., (2002) used a binary logit model to evaluate the influence of crash factors on crash severity. Crash severity was a dichotomous variable and to analyze a dichotomous variable with two categories binary logit model has been considered a suitable model to analyze.

Multiple logistic model was used by Yan, X., et al., (2005) to analyze the Characteristics of rear-end accidents at signalized.

Abdel-Aty, M., and Abdelwahab, H., (2004a, c, d,) used time series models to study the angle, head-on and rear end collisions.

Negative binomial models were used in the past studies to study crashes. Wang, X., and Abdel-Aty, M., (2006) generalized estimating equations with negative binomial link function to model rear-end crash frequencies at signalized intersections to account for the temporal or spatial correlation among the data.

Nested logistic regression model has been used to analyze rear-end collisions including the role of driver's visibility and light truck vehicles using a nested logit structure (Abdel-Aty, M., and Abdelwahab, H., 2004a). Nested logit models were calibrated to estimate the probabilities of the four rear-end crash configurations as a function of driver's age, gender, vehicle type, vehicle maneuver, light conditions, driver's visibility and speed.

Statistical models played an important role in analyzing the crashes and have resulted an efficient tool to investigate and understand the crashes. Significant characteristics and their impact on the crashes were investigated using these statistical models in the past.

In the current research, multinomial and logistic models have been used to investigate the car-truck crash types.

# 3. METHODOLOGY

The above stated research efforts have shown that there is a tremendous amount of work done in crashes involving trucks but very less has be done related to different car-truck crash types. In current study an effort has been put to find out the specific patterns that result in various car-truck collisions when compared to a car–car collision.

The crash databases National Automotive Sampling System General Estimates System (NASS GES) and Fatality Analysis Reporting System (FARS) over the years 2000-2004 is used in this study. The literature has shown that GES and FARS have been well-accepted databases for crash analysis due to its vast number of variables covering all the features that might be very representative of the crash for entire United States.

GES Data items are organized into several datasets: the Crash, Vehicle/Driver, and Person data sets. Files may be linked with a specific feature of a traffic crash. Files may be linked as needed to combine the information contained in each other. Three files used in the analysis presented here were the crash (containing information on crash characteristics and environmental conditions at the time of the crash), vehicle/driver (containing information describing the vehicles and drivers involved in the crash), and person file (describing all persons involved in the crash and information about their age, gender, sex etc.). GES database are coded from police crash reports, which is a probability sample of police-reported crashes that occurred in the United States.

FARS database has been categorized into three major files crash, vehicle and person, which is quite similar to that of the GES database. To be included in this census, a crash had to involve a motor vehicle traveling on a traffic way customarily open to public, and must result in the death of a person (occupant of a vehicle or a non motorist) within 30days of the crash.

The focus of this research is on the various collisions between the car and truck. Car-truck collisions may involve three or more vehicles. To simplify the assignment of driver culpability and easily identify crash roles of vehicle in the crash, analysis was restricted to two-vehicle collisions, in which the vehicle is either a car or truck. This study doesn't include the truck-truck collisions as main focus of the study is on the car-truck crash, which is compared to the base car-car crashes. Moreover the truck-truck sample (GES avg: 1.87%, and FARS avg: 1.74% over 2000-2004) was not sufficient enough to analyze. The type of collision, number of vehicles involved and body type of the vehicle are all mentioned in both FARS and GES databases. In this study a comparison was made between the car-truck crashes to that of car-car crashes. The data obtained from GES and FARS crash database over the years 2000-2004 is shown in the following Table 1 and Table 2.

Table 1: Details of collisions from GES (2000-2004)

| Type | 2000 | 2001 | 2002 | 2003 | 2004 |
|---|---|---|---|---|---|
| **All Collisions** | 57382 | 55964 | 54291 | 59156 | 60974 |
| **Collisions (Two Vehicles)** | 32083 | 33283 | 30998 | 33870 | 35038 |
| **2 Veh Collisions (Car or Truck)** | 19916 | 19229 | 18077 | 19702 | 20384 |
| **Car-Car** | 14427 | 13952 | 13294 | 14580 | 15285 |
| **Car-Truck** | 5085 | 4872 | 4466 | 4771 | 4753 |
| **Truck-Truck** | 404 | 405 | 317 | 351 | 346 |

Table 2 Details of collisions from FARS (2000-2004)

| Type | 2000 | 2001 | 2002 | 2003 | 2004 |
|---|---|---|---|---|---|
| **All Collisions** | 37526 | 37862 | 38491 | 38477 | 38253 |
| **Collisions (Two Vehicles)** | 13804 | 13720 | 13744 | 14062 | 13910 |
| **2 Veh Collisions (Car or Truck)** | 6323 | 6176 | 6204 | 6204 | 6146 |
| **Car-Car** | 4274 | 4247 | 4304 | 4278 | 4151 |
| **Car-Truck** | 1937 | 1826 | 1807 | 1809 | 1879 |
| **Truck-Truck** | 112 | 103 | 93 | 117 | 116 |

The two vehicle crashes were observed and percentage of car-car, car-truck and truck – truck collisions is shown in the below Table 3 and Table 4. The truck-truck crashes were not considered in our study because of its lowest percentage of two vehicle crashes involving a car and truck, which is shown in the Table 3 and Table 4.

Table 3: GES (% of car-car, car-truck, truck-truck w.r.t two vehicle (car/truck collision)

| Type | 2000 | 2001 | 2002 | 2003 | 2004 | Average |
|---|---|---|---|---|---|---|
| **Car-Car** | 72.4% | 72.56% | 73.54% | 74.00% | 74.99% | 73.50% |
| **Car-Truck** | 25.5% | 25.34% | 24.71% | 24.22% | 23.32% | 24.62% |
| **Truck-Truck** | 2.0% | 2.11% | 1.75% | 1.78% | 1.70% | 1.87% |

Table 4: FARS (% of car-car, car-truck, truck-truck w.r.t two vehicle (car/truck collision))

| Type | 2000 | 2001 | 2002 | 2003 | 2004 | Average |
|---|---|---|---|---|---|---|
| **Car-Car** | 67.59% | 68.77% | 69.37% | 68.96% | 67.54% | 68.45% |
| **Car-Truck** | 30.63% | 29.57% | 29.13% | 29.16% | 30.57% | 29.81% |
| **Truck-Truck** | 1.77% | 1.67% | 1.50% | 1.89% | 1.89% | 1.74% |

It can be observed from Table 3 and Table 4, car-truck percentages were higher in case of FARS when compared to that of GES crash database. It can be that the average car-car percentage was 73.50% in GES while it was 68.45% in FARS crash database. The average percentage of car-truck was 24.62% in GES and it was 29.81% in FARS database.

## 3.1 Crash classification and data preparation

Different methods were followed to analyze different kinds of collisions and the data was prepared accordingly to suit the analysis process.  The crashes were analyzed in the order of their ranking based on the crash frequency. Data preparation methods varied based on the crash type that was analyzed. GES is sampling database and the projected observations obtained by weights were calculated and used to find distributions of different types of car-truck collisions which is shown in Figure 2. It was observed that the angle collisions constituted of highest percentages of crashes which were followed by rear-end and sideswipe (same direction).Similar trend was observed when sample observations of GES crash database were considered which is shown in Figure 3. Angle crashes were followed by head-on and rear-end when FARS (census crash database) was used and is shown in Figure 4.

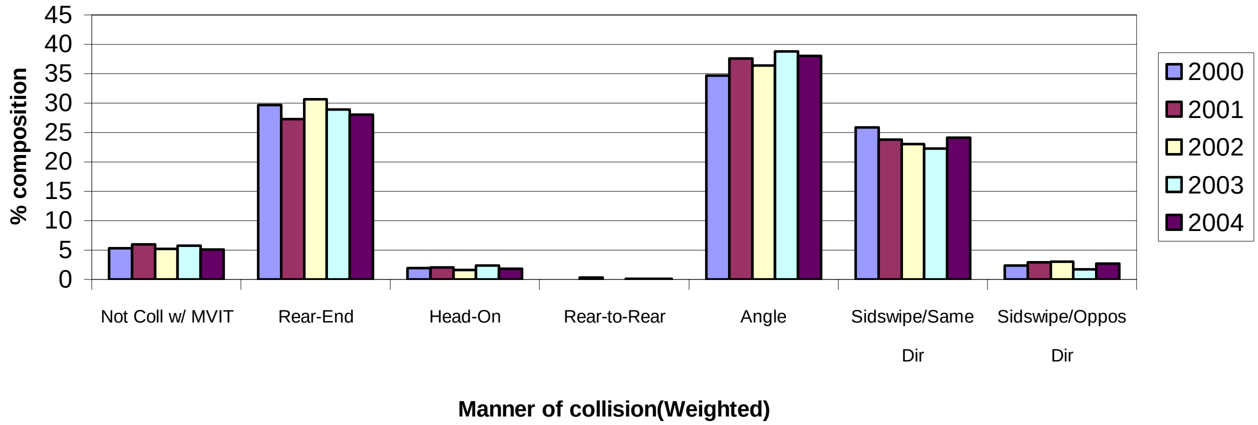


Figure 2: Composition of car-truck collisions (Projected data, GES 2000-2004)

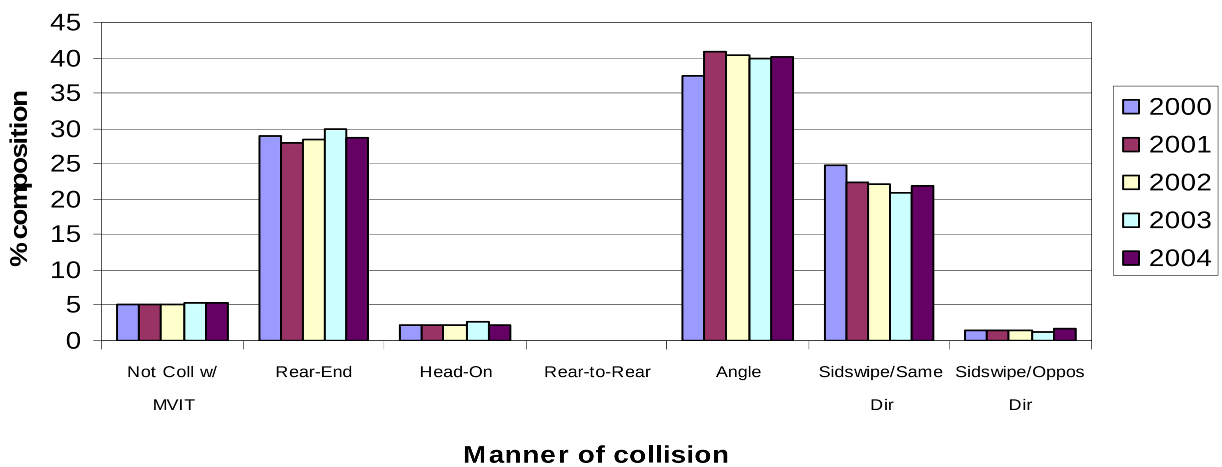


Figure 3: Composition of car-truck collisions (Sample data, GES 2000-2004)

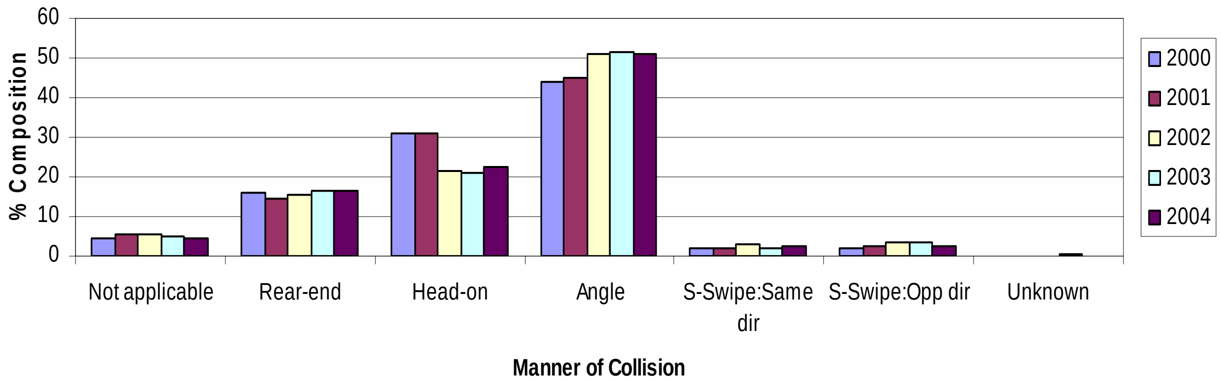


Figure 4: Composition of car-truck collisions (FARS 2000-2004, Census data)

Table 5 shows the ranking based on the crash percentage obtained using the GES and FARS crash databases. The current study being a an explanatory study, the sample GES database can be used rather than the estimated GES database observations which are obtained by multiplying the sample data with their corresponding weights. Abdel-Aty, M., and Abdelwahab, H., (2004b) used the sample GES database rather than the estimated weights for analyzing the effect of the lead vehicle's size on the rear-end crash configuration. In our study the GES sample cases were used for crash analysis.

Table 5: Crash ranking based on percentage composition (GES & FARS)

| **Rank** | **Crash Database Type** | |
|---|---|---|
| | **GES** | **FARS** |
| **1** | **Angle** | **Angle** |
| **2** | **Rear-end** | **Head-on** |
| **3** | **Sideswipe (same direction)** | **Rear-end** |

### 3.1.1 Angle

While analyzing angular car-truck collision, the fault drivers of either a car or truck in a car-truck crash was compared to a faulty car driver in a car-car crash and the well accepted Nominal Multinomial logistic model is used for the analysis. More over no-fault cases in which none of the vehicle was charged against any violation was also investigated.

#### <u>3.1.1.1 Fault cases</u>

As mentioned earlier, the current research took into consideration two-vehicle car truck crashes. The GES and FARS crash database over the years 2000 to 2004 were obtained and in GES each observation has a unique data row over the years and in case of FARS database each observation is unique over one year. Data was filtered to all the two-vehicle crashes and then all the crashes, which include either a car or truck were obtained by segregating the data using the vehicle type variable obtained in the vehicle dataset of each database. Once the two vehicular crashes including a car or truck (truck –truck crashes excluded) were obtained then that dataset was used to extract various kinds of car truck collisions. For angle car-truck collision analysis, the violations charged variable (from the Vehicle file) from the database is observed and the faulty vehicle is obtained. Only those cases involving driving activity, by the driver were taken into account. For example while dealing with violations in FARS database the violation charge “fail to give aid, info, wait for Police after crash” was not considered. Current study focused on the driving violations rather than non-driving violations hence all non-driving violations charged against the driver was not taken into account. Moreover only those observations were considered in which only one of two vehicles was at fault. This was done for better assignment of driver culpability and to easily identify crash roles of vehicle in the crash. All the fault driver observations were obtained and a separate dataset was created. This data set contains all the details of the crash from the crash, vehicle and person file. A fault variable is created in the dataset. The obtained dataset contains either a car-car crash or a car-truck crash. In case of a car-truck crash if the truck driver is at fault then the fault variable is set to '1' and if the car is at fault then it is set to '2'. In case of the car-car crashes which forms our base case if a car was at fault then the variable was set to '3'. Thus, through comparisons among the drivers/environmental factors, the distributions in 1, 2 and 3, one can find crash propensity of car-truck crashes that resulted from either a car or truck.  The data thus prepared for each year from 2000 to 2004 is appended to obtain one final data set. Figure 5 below shows the steps involved in dealing angle crashes.

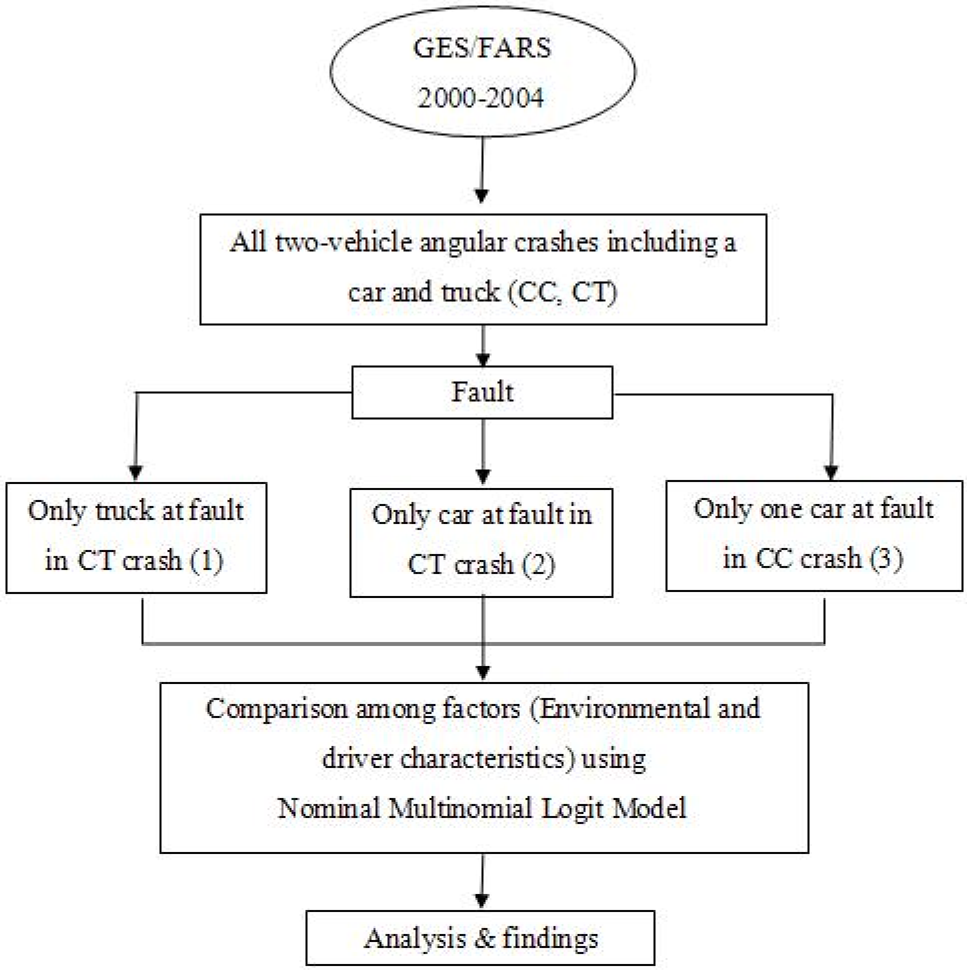


Figure 5: Methodology followed to obtain data and analyze fault angle car truck crashes

The data obtained using the above stated methodology is shown in the Table 6. It can be noticed that more percentage of trucks (11.25%) were found faulty in car-truck crashes when FARS database was considered when compared to that of GES database. It can be noticed that truck being at fault can cause more fatal crashes when compared to that of car being at fault in car-truck crash. When GES database was analyzed it was observed that more cars were found to be at fault in a car-truck crash than truck being at fault in a car-truck crash. 86.3% percentage of cars at fault in a car-car crash was observed in GES while 81.99% of car at fault in car-car crash were observed in FARS.

Table 6: Percentage of observations as per fault variable (200-2004)

| FAULT | GES | FARS |
|---|---|---|
| **Truck at fault in car-truck crash, fault-1** | 808 (5.09%) | 323 (11.25%) |
| **Car at fault in car-truck crash, fault- 2** | 1365 (8.61%) | 194 (6.76%) |
| **Car at fault in car-car crash, fault- 3** | 13686 (86.30%) | 2353 (81.99%) |
| Total | 15859 (100.00%) | 2870 (100.00%) |

### 3.1.1.2 No-fault cases

The cases in which none of the drivers were charged any violation were termed as no-fault cases. It was observed that a substantial number of observations were found were none of the two vehicles involved in the crash were at fault. The Table 7 shows the number of no-fault cases in both GES and FARS crash databases over five years (2000-2004). These cases in which none of the vehicles were charged of violation were analyzed to find a trend among these cases. In these cases the vehicle role of striking vehicle in car-truck and car-car crash was used to categorize the data into three categories. These categories are listed below

- Truck striking a car- (car-truck collision); strike =1
- Car striking a truck- (car-truck collision); strike =2
- Car striking a car- (car-car collision); strike =3

Figure 6 below explains the data preparation methodology to obtain the required data.

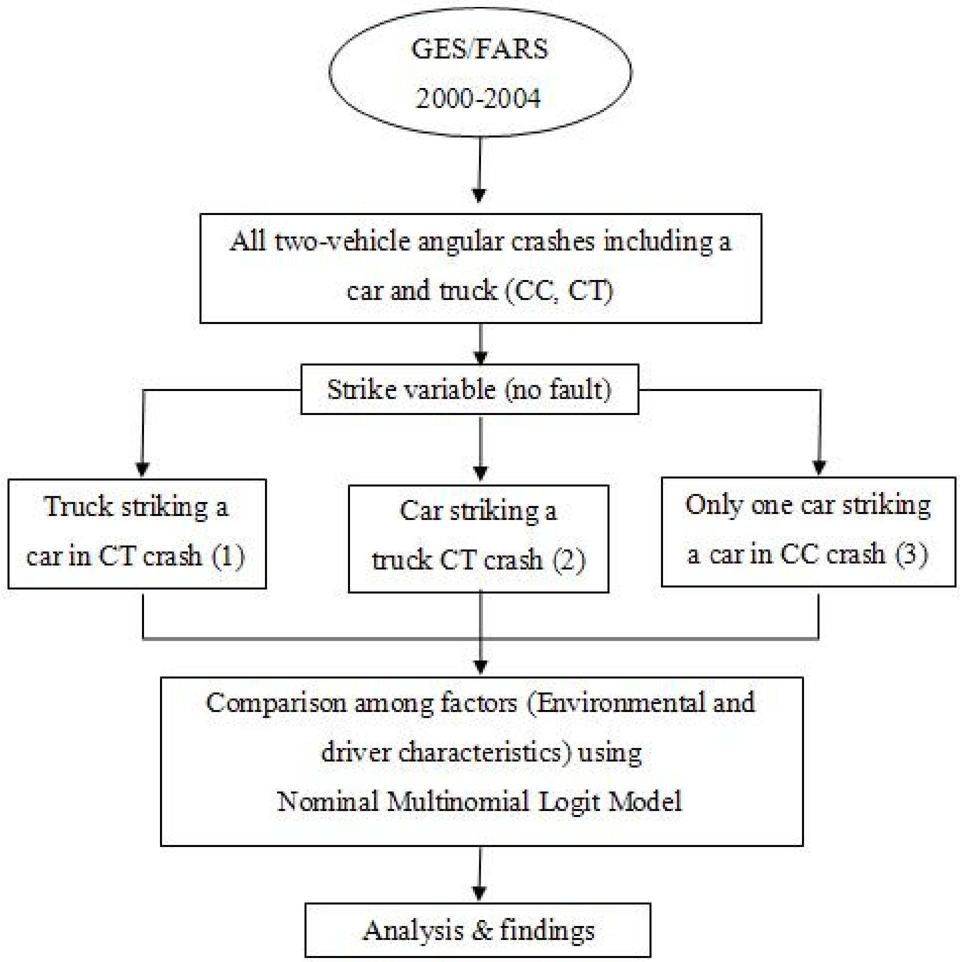


Figure 6: Methodology followed to obtain data and analyze no fault angle crashes

The number of observations is shown in Table 7 below.

Table 7: Observations of no-fault crashes (GES & FARS, 2000-2004)

| NO-FAULT | GES | FARS |
|---|---|---|
| **Truck striking a car (CT)-1** | 1846 (11.12%) | 2314 (20.99%) |
| **Car striking a truck (CT)-2** | 1851 (11.22%) | 1148 (10.41%) |
| **Car striking a car (CC)-3** | 12790 (77.57%) | 7560 (68.59%) |
| Total | 16487 (100.00%) | 11022 (100.00%) |

### 3.1.2 Rear-end

The dataset for the rear-end collision is obtained by considering all the two vehicle rear-end car truck crashes. Both GES/FARS crash databases were used to obtain the required data. Once all the rear-end car-truck collisions (excluding truck-truck collision) were obtained, they were then categorized into three categories based on the vehicle role of the vehicle. The three categories and the corresponding value of the strike variable for each case that were categorized as below

- Truck striking a car- (car-truck collision); strike =1
- Car striking a truck- (car-truck collision); strike =2
- Car striking a car- (car-car collision); strike =3

Figure 7 shows the steps involved in investigating the rear-end collisions

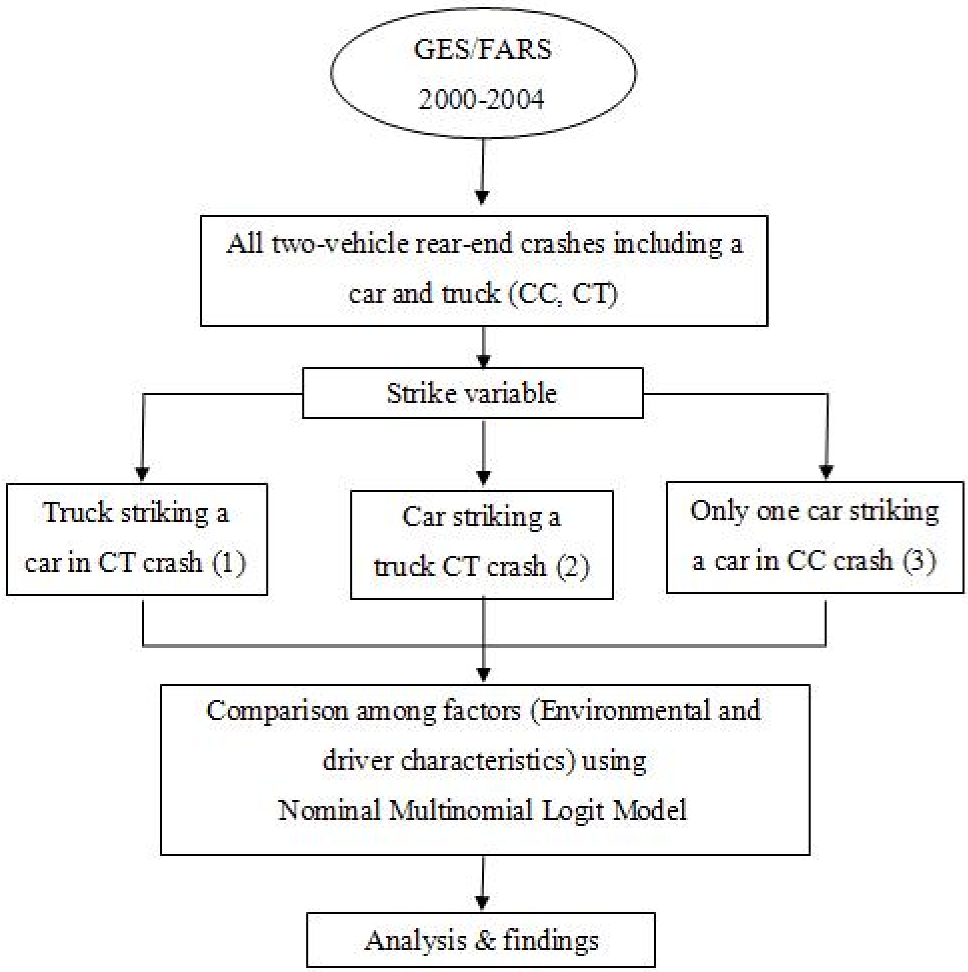


Figure 7: Methodology followed to obtain data and analyze rear-end Collision

The rear-end collisions (car-car or car-truck) were found to be the second largest composition in GES and third largest in FARS database. While considering the fault variable the number of observations from both the database GES and FARS are shown in the below Table 8.

Table 8: Observations for rear-end crash (GES & FARS, 2000-2004)

| Variable | GES | FARS |
|---|---|---|
| **Fault** | 3778 | 583 |
| **No-Fault** | 12115 | 1793 |

Table 9: Vehicle role (Fault cases, GES & FARS, 2000-2004)

| Vehicle Role | GES | FARS |
|---|---|---|
| Striking | ***3589*** | ***514*** |
| Struck | 189 | 69 |
| Total | 3778 | 583 |

For rear end crashes we need to differentiate between a leading vehicle and a following vehicle and then analyze the data. Moreover using the fault variable wouldn't suffice in rear end because only 5% (189 observations out of 3778) in GES and 11.8% (69 observations out of 583) in FARS database were leading vehicles (struck) at fault and the rest were preceding vehicles (striking) which is shown in the above Table 9.

Moreover the no-fault database had the strike variable, which took into consideration only the striking vehicles (preceding vehicle), which is of our main focus in a rear end crash analysis. Hence we would have just one database for each GES and FARS, which would include details of all the striking vehicles rather than the faulty vehicle (as followed in angular crash analysis). The Table 10 shows the details of the vehicle role in both the fault and no fault cases of rear-end crashes.

Table 10: Rear-end (striking vehicle-following vehicle)

| Striking | GES | | | FARS | | |
|---|---|---|---|---|---|---|
| | **Fault** | **No-Fault** | **Total** | **Fault** | **No-Fault** | **Total** |
| 1 | 283 | 1330 | 1613 | 73 | 247 | 320 |
| 2 | 512 | 1304 | 1816 | 78 | 811 | 889 |
| 3 | 2794 | 9481 | 12275 | 363 | 735 | 1098 |
| Total | 3589 | 12115 | 15704 | 514 | 1793 | 2307 |

Note: 1-Truck striking in CT crash, 2-Car striking in CT crash, 3-car striking in Car-Car striking

This configuration of striking and struck vehicle was considered in earlier studies by Abdel-Aty, M., and Abdelwahab, H., (2004) to analyze the effect of the lead vehicle's size on the rear-end crash configuration.

Moreover from the driver's perspective, Eby, D., and W., Kostyniuk, L. P. (1998) found that the action of the driver in the leading vehicle was the major contributing factor for rear-end crash (i.e., the leading vehicle stopped unexpectedly or did not move when it should have).

For rear-end crash analysis the driver characteristics of the striking vehicle driver was taken into consideration to create three categories.

### 3.1.3 Sideswipe (same direction)

For sideswipe collisions the two-vehicle (car-car and car-truck) sideswipe collisions were extracted from GES/FARS crash databases over the years 2000-2004.The obtained observations of the dataset were categorized into three various categories based on the vehicle role (striking/struck). The three various categories that were identified are listed below:

- Truck striking a car- (car-truck collision); strike =1
- Car striking a truck- (car-truck collision); strike =2
- Car striking a car- (car-car collision); strike =3

A multinomial logit model was used to study the effect of various significant factors and to run a comparison between the trucking striking a car and car striking a truck with the base case car striking a car. The Figure 8 shows the steps involved in obtaining the data and analyzing the sideswipe (same direction) crashes.

The sideswipe collisions were analyzed based on the concept of striking vehicle rather than the faulty vehicle. The vehicle configuration car-truck and car-car collisions were categorized into three categories based on the striking vehicle in the crash. Table 11 shows the number of observations involved in the analyzing these crashes using the GES database over the years 2000-2004.

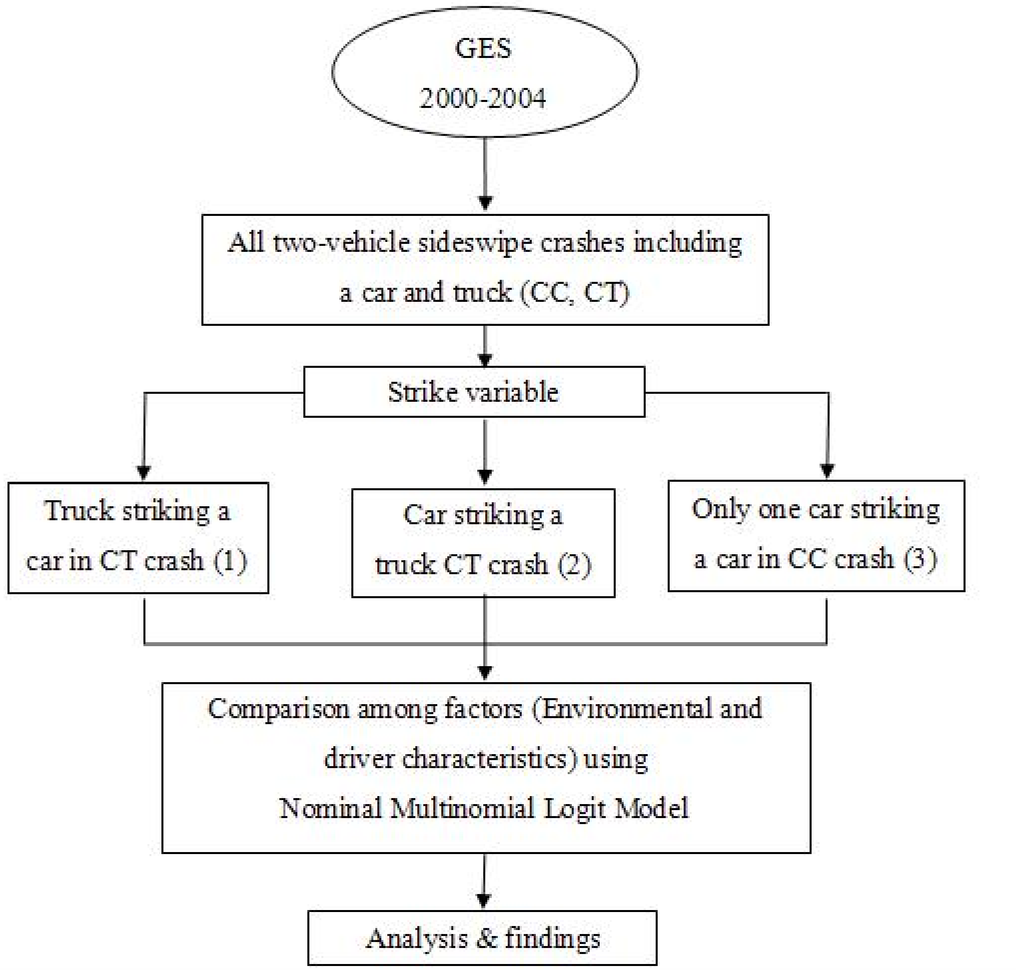


Figure 8: Methodology followed to obtain data and analyze sideswipe (same direction)

Table 11: Sideswipe (same direction), number of observations (GES)

| **Strike variable** | **No of Observations** |
|---|---|
| Truck striking car (1) | 1003 |
| Car striking truck (2) | 1201 |
| Car striking car (3) | 1485 |

### 3.1.4 Head-on

The dataset was obtained for this type of collision by extracting all the two vehicle (car-car, car-truck) collisions and picking up the head-on collisions from a FARS database over the year 2000-2004. In a car-truck head-on collision both car and truck would be striking each other and hence it was not divided based on the hitting roles of the vehicles involved in the crash. Categorizing the data based on the fault role lead to a lower sample size which made it difficult to analyze. The obtained observations were then categorized based on two categories namely car-car and car-truck collisions. Car-truck included the crashes which involved a car and a truck irrespective of their striking and hitting roles. Car-truck and truck-car were included in the first vehicle configuration (head-on collision between a car and a truck). The categories are shown below:

- Car-truck Head-on collision; vehicle configuration =1
- Car-car Head-on collision; vehicle configuration =2

The effect of various factors on these types of collision has been analyzed by considering the binary logit model. Car-car collisions form the base case for our study. The flow chart showing the methodology followed in studying head-on collisions is shown below:

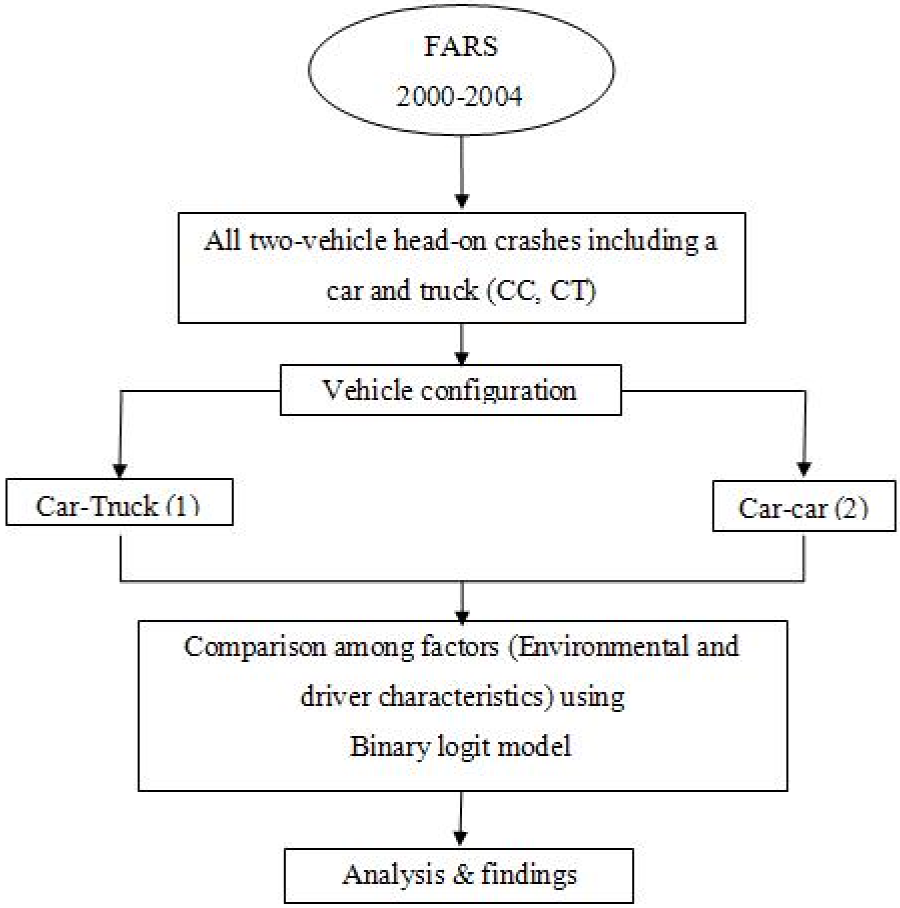


Figure 9: Methodology followed to obtain data and analyze head-on collisions

Head on collision constitute the second highest percentage of fatal crashes in car-car/truck crashes. In case of head on collision either of the vehicles was striking and it wouldn't make any sense if there were categorized by the vehicle role (striking or struck). The crashes were categorized into two categories car-truck and car-car crashes. Earlier studies by Abdelwahab, H., and Abdel-Aty, M., (2004) addressed the impact of crash configuration (car-car, car/LTV, and LTV-to-LTV) in analyzing head-on collisions. A similar approach is followed to analyse the head-on collisions between a car and truck.

The crash configuration followed here is car-car and car-truck head-on fatal crash.

The number of observations for this analysis is shown in the below Table 12.

Table 12: Head-on collisions (FARS, 2000-2004)

| HEAD-ON COLLISION | |
|---|---|
| **Car-Truck** | 1021 |
| **Car-Car** | 3361 |
| **Total** | 4382 |

A crash in this study is a dichotomous variable with two categories, car-truck head on car-car being represented by values 1 and 2 respectively. Because of the binary nature of this dependent variable, a logistic regression approach was found suitable. Earlier studies (Al-Ghamdi, A.S., 2002) used a logistic regression to estimate the influence of crash factors on crash severity. The detailed information of the logistic regression is given the earlier section 3.2.2.

## 3.2 Statistical modeling

Logistic regression is a proper tool to analyze categorical data. The following statistical models were used to analyze the various types of car-truck crash collisions.

- Multinomial Logistic model: Angle, rear-end and sideswipe (same direction)
- Binary Logistic model: Head-on Collision

### 3.2.1 Multinomial logit model

The dependent variable (fault/strike) has three categories (fault/strike=1, 2, 3) and there is no inherent ordering involved in it. A comparison is run between the various categories of the fault variable. The best suitable model for such cases is the multinomial logistic model. Allison, D.P., (1999) provided the details of the multinomial logit model.

The general form of a multinomial logit model is explained below. If y is the response variable with J nominal outcomes, then the assumption of the Multinomial logit model is that the categories one through J is not ordered. Also, let Pr(y= m/x) be the probability of observing outcome m given the set of independent variables x. The model for y is constructed as follows:

Assume that Pr(y = m|x) is a linear combination xβm. The vector βm = (β0m …βkm…βKm)' contains the intercept β0m and coefficients βkm for the effect of xk on outcome m. This is an opposing view from the ordinal response model because the parameter estimates are assumed different for each outcome.

• To ensure non-negativity for the probabilities, the exponential of xβm is taken.

• For the probabilities to sum to one, the following normalization is needed:

$$\Pr(y_i = m / x_i) = \frac{\exp(x_i \beta_m)}{\sum_{j=1}^{j} \exp(x_i \beta_j)} \tag{1}$$

To identify the set of parameters that generates the probabilities, a constraint must be imposed. It is common to impose the constraint that one of the parameter estimates equals zero (i.e., β1 = 0). Imposing such a constraint allows the model to be written as follows:

$$\Pr(y_i = 1 / x_i) = \frac{1}{1 + \sum_{j=2}^{j} \exp(x_i \beta_j)} \tag{2}$$

$$\Pr(y_i = m / x_i) = \frac{\exp(x_i \beta_m)}{1 + \sum_{j=2}^{j} \exp(x_i \beta_j)} \tag{3}$$

In our research we have three categories for the fault variable.

For a dependent variable let

pi1: prob. that the variable is 1 for observation i

pi2: prob. that the variable is 2 for observation i

pi3: prob. that the variable is 3 for observation i

Xi = [ 1 Xi1 Xi2 Xi3 Xi4. . …. X ij ]’

Where Xi=single explanatory variable

The equation can be written as the following

$$\log\left(\frac{p_{i1}}{p_{i3}}\right) = \beta_1 X_i \Rightarrow \frac{p_{i1}}{p_{i3}} = e^{\beta_1 X_i} \tag{4}$$

$$\log\left(\frac{p_{i2}}{p_{i3}}\right) = \beta_2 X_i \Rightarrow \frac{p_{i2}}{p_{i3}} = e^{\beta_2 X_i} \tag{5}$$

$$\log\left(\frac{p_{i1}}{p_{i2}}\right) = \beta_3 X_i \Rightarrow \frac{p_{i1}}{p_{i2}} = \frac{e^{\beta_1 X_i}}{e^{\beta_2 X_i}} \tag{6}$$

$$\beta_3 = \beta_1 - \beta_2 \tag{7}$$

Where β1, β2, β3 are the parameter estimates of the three categories respectively. The probabilities are calculated using the following equations respectively.

$$p_{i1} = \frac{e^{\beta_1 x_i}}{1 + e^{\beta_1 x_i} + e^{\beta_2 x_i}} \tag{8}$$

$$p_{i2} = \frac{e^{\beta_2 x_i}}{1 + e^{\beta_1 x_i} + e^{\beta_2 x_i}} \tag{9}$$

$$p_{i3} = \frac{1}{1 + e^{\beta_1 x_i} + e^{\beta_2 x_i}} \tag{10}$$

$$p_{i1} + p_{i1} + p_{i1} = 1 \tag{11}$$

The sum of these probabilities equals to one and hence it can be confirmed to be right.

### 3.2.2 Binary logit model

Binary logit model otherwise known as logistic regression model is used to analyze head-on collisions, which have two vehicle configuration types (car-truck and car-car, head on collision). Because of the binary nature of the dependent variable, a logistic regression approach is found suitable for analysis. The findings show that logistic regression as used in this research is a promising tool in providing meaningful interpretations. Allison, D.P., (1999) provided the details of the binary logit model.

For k explanatory variables and i=1,2…n individuals, the model is

$$\log\left[\frac{p_i}{1-p_i}\right] = \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} .... + \beta_k x_{ik} \tag{12}$$

Where pi is, as before the probability that yi=1. The expression on the left-hand side refers to as the logit or log-odds.

The logit-equation is solved for pi to obtain

$$p_i = \frac{\exp(\alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} \ldots + \beta_k x_{ik})}{1 + \exp(\alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} \ldots + \beta_k x_{ik})} \tag{13}$$

Further the above equation can be written as

$$p_i = \frac{1}{1 + \exp(-\alpha - \beta_1 x_{i1} - \beta_2 x_{i2} - \beta_3 x_{i3} \ldots - \beta_k x_{ik})} \tag{14}$$

This equation has the desired property that no matter what values we substitute for the β's and the x's, pi will always be a number between 0 and 1.

Maximum likelihood (ML) is a method to estimate the logit model for grouped data and the only method in general use for individual-level data. A dichotomous dependent variable for each individual along with measured characteristics of the individual is observed. Maximum likelihood is a very general approach to estimate that is widely used for all sorts of statistical models. There are a two reason for this popularity. First, ML estimators are known to have good properties in large samples. Under fairly general conditions, ML estimators are consistent, asymptotically efficient and asymptotically normal.

The other reason for ML's popularity is that it is often straightforward to derive ML estimators when there are no other obvious possibilities and ML handles data very nicely with categorical dependent variables.

The basic principle of ML is to choose estimates those parameter values, which, if true would maximize the probability of observing what we have in fact, observed. There are two steps to this: (1) write down an expression for the probability of the data as a function of the unknown parameters, and (2) find the values of the unknown parameters that make the value of the expression as large as possible.

# 4. MODELING RESULTS AND RELATED ANALYSIS

The datasets for running our statistical model obtained using both GES and FARS databases were analyzed using the multinomial and binary logit model. Various collisions were analyzed. GES database was used to analyze the angle, rear-end and sideswipe (same direction). FARS was used to analyze angle, head-on and rear-end collisions. The descriptions of the variables in GES and FARS database that have been used in modeling are shown in Table 13 and Table 14 respectively.

Table 13: Description of GES variables used in modeling

| Variable | Description | Sub levels |
|---|---|---|
| **AGE** | Age of the driver | |
| **ALCHL_I** | Hot deck imputed variable describing the alcohol involvement involved in crash | Alcohol involved, No alcohol involved |
| **ALIGN_I** | Alignment of the road section | Straight, curve |
| **INT_HWY** | Describes whether crash occurred on an Interstate Highway | No, yes, Unknown |
| **LGTCON_I** | Imputed variable indicating general light condtion at time of crash | Daylight, dark but lighted, dark |
| **LGTCON_I_S1** | Imputed variable for a striking vehicle indicating general light condtion at time of crash | Daylight, dark but lighted, dark |
| **SEX_H** | Hot deck imputed variable indicating the gender of the driver | Male, female |
| **SEX_H_S1** | Hot deck imputed variable for a striking vehicle indicating the gender of the driver | Male, female |

| Variable | Description | Sub levels |
| --- | --- | --- |
| **SPEEDREL** | Indicates whether speed was an contributing factor to the cause of crash | No, yes, no driver present, unknown |
| **SPEEDREL_S1** | Indicates whether speed was an contributing factor to the cause of crash in case of striking cases | No, yes, no driver present, unknown |
| **TRAF_WAY** | Indicates whether a roadway was divided or undivided | Divided, undivied |
| **TRAF_WAY_S1** | Indicates whether a roadway was divided or undivided ( striking cases) | Divided, undivied |
| **V_ALCH_I** | Imputed variable indicating alcohol use by the driver | Alcohol involved, No alcohol involved |
| **WEATHR_I** | Imputed variable that indicates general weather condition at the time of crash | Adverse, non-adverse |
| **WEATHR_I_S1** | Imputed variable that indicates general weather condition at the time of crash ( Striking cases) | Adverse, non-adverse |
| **WKDY_I** | Imputed variable indicating the day of the week in which crash occurred | Weekday, weekend |
| **WKDY_I_S1** | Imputed variable indicating the day of the week in which crash occurred ( striking cases) | Weekday, weekend |
| **TRAF_WAY*SPEEDREL** | Interaction between TRAF_WAY and SPEEDREL | Divided/undivi.ded & No/yes speed related. |
| **TRAF_WAY*V_ALCH_I** | Interaction between TRAF_WAY and V_ALCH_I | Divided/undivided & Alcohol involved/ No alcohol involved |
| **TRAF_WAY*WEATHR_I** | Interaction between TRAF_WAY and WEATHR_I | Divided/undivided & adverse, non-adverse |

| Variable | Description | Sub levels |
|---|---|---|
| **TRAF_WAY_S1*WEATHR_I_S1** | Interaction between TRAF_WAY_S1 WEATHR_I_S1 | Divided/undivided & adverse, non-adverse |
| **WEATHR_I*SPEEDREL** | Interaction between WEATHR_I and SPEEDREL | adverse, non-adverse & yes/no speed realted |

Table 14: Description of the FARS variable used in modeling

| Variable | Description | Sub levels |
|---|---|---|
| AGE | Age of the driver | Young aged, middle aged, old aged |
| DAY_WEEK | The day of week on which the crash occurred | Weekday, weekend |
| DR_DRINK | Involvement of alcohol(by driver) at the time of crash | No drinking, drinking |
| LGT_COND | Lighting conditions at the time of crash | Day light, Dark but lighted, Dark |
| NHS | Road section on National Highway system(NHS) or not. | NHS, Not NHS |
| SEX | Gender of the driver involved in the crash | Male , female |
| TRAF_FLO | Divided or undivided road section on which the crash occurred | Divided, Undivided |
| WEATHER | Weather Condition at the time of crash occurrence | Adverse, non-adverse weather conditions |
| NHS*WEATHER | Interaction between the NHS and weather conditions | NHS/Non-NHS & Adverse /Non adverse |

## 4.1 Angle

Angle crashes constituted the highest percentage in both the GES and FARS databases. The fault cases in which only one vehicle of the two vehicles was charged against a violation were analyzed. The no-fault cases in which there was no violation charged against the two vehicles involved in the crash were analyzed. Incase of no-fault cases the categories were based on the strike variable of the vehicle.

### 4.1.1 Fault cases

Both GES and FARS crash databases are used to analyze the fault angle crashes. The results are explained in the below section 4.1.1.1 and 4.1.1.2

#### <u>4.1.1.1 Analysis: GES crash database</u>

Various variables were tested and the statistically significant (level of significance <0.05) variables were taken and were considered in the modeling. The traffic way (divided/ undivided), Weather conditions (good/adverse conditions), lighting conditions (dark/dark/ but lighted daylight/), speed related (variable describing whether the speed was a contributing factor in the crash), the involvement of alcohol, weekday, the gender of the driver were found significant.

The full modeling results are shown in Table 15 and

Table 16. The interactions of traffic way with lighting conditions, speeding and alcohol involvement, weather condition and the speeding are found statistically significant. Table 15 and

Table 16 show the analysis of the maximum likelihood variance and the maximum likelihood analysis of estimates.

Table 15: Maximum likelihood analysis of variance (GES, fault angle crashes)

| Maximum likelihood analysis of variance | | | |
|---|---|---|---|
| Source | DF | Chi-Square | Pr > ChiSq |
| Intercept | 2 | 744.68 | <.0001 |
| AGE | 4 | 284.11 | <.0001 |
| TRAF_WAY | 2 | 110.06 | <.0001 |
| WEATHR_I | 2 | 18.76 | <.0001 |
| LGTCON_I | 4 | 33.95 | <.0001 |
| SPEEDREL | 2 | 276.87 | <.0001 |
| V_ALCH_I | 2 | 69.17 | <.0001 |
| WKDY_I | 2 | 141.53 | <.0001 |
| SEX_H | 2 | 282.32 | <.0001 |
| TRAF_WAY*SPEEDREL | 2 | 26.96 | <.0001 |
| TRAF_WAY*V_ALCH_I | 2 | 24.96 | <.0001 |
| WEATHR_I*SPEEDREL | 2 | 16.51 | 0.0003 |
| Likelihood Ratio | 760 | 621.71 | 0.9999 |

Table 16: Analysis of maximum likelihood estimates ( GES, fault angle crashes)

| Analysis of Maximum Likelihood Estimates | | | | | | | |
|---|---|---|---|---|---|---|---|
| Parameter | Comparison | Function Number | Estimate | Std. Error | Chi-Square | Pr > Chi Sq | **Odds ratio(OR)** |
| Intercept | | 1 | -5.4245 | 0.2414 | 504.97 | <.0001 | |
| | | 2 | -1.382 | 0.081 | 290.86 | <.0001 | |
| AGE | Young vs Middle aged | 1 | -0.7787 | 0.0869 | 80.37 | <.0001 | 0.46 |
| | | 2 | -0.1444 | 0.0475 | 9.25 | 0.0024 | 0.87 |
| | Old vs Middle ages | 1 | -0.2666 | 0.0902 | 8.74 | 0.0031 | 0.77 |
| | | 2 | 0.0911 | 0.0551 | 2.73 | 0.0983 | 1.10 |
| TRAF_WAY | Divided vs undivided | 1 | 0.8174 | 0.1928 | 17.98 | <.0001 | 2.26 |
| | | 2 | 0.6325 | 0.0636 | 98.92 | <.0001 | 1.88 |
| WEATHR_I | Adverse vs Non-adverse | 1 | 0.1549 | 0.1135 | 1.86 | 0.1724 | 1.17 |
| | | 2 | 0.2283 | 0.0533 | 18.35 | <.0001 | 1.26 |
| LGTCON_I | Dark vs Daylight | 1 | -0.00627 | 0.1538 | 0 | 0.9675 | 0.99 |
| | | 2 | 0.2472 | 0.0897 | 7.59 | 0.0059 | 1.28 |
| | Dark but lighted vs Day light | 1 | -0.2953 | 0.1081 | 7.46 | 0.0063 | 0.74 |
| | | 2 | -0.2403 | 0.0678 | 12.56 | 0.0004 | 0.79 |
| SPEEDREL | Speed related vs Not related | 1 | -0.1637 | 0.1166 | 1.97 | 0.1604 | 0.85 |
| | | 2 | 0.8812 | 0.0545 | 261.9 | <.0001 | 2.41 |
| V_ALCH_I | Alcohol vs Non alcohol | 1 | -0.7456 | 0.1711 | 18.99 | <.0001 | 0.47 |
| | | 2 | 0.4071 | 0.0601 | 45.83 | <.0001 | 1.50 |
| WKDY_I | Weekday vs Weekend | 1 | 0.6204 | 0.0732 | 71.9 | <.0001 | 1.86 |
| | | 2 | 0.4161 | 0.0476 | 76.3 | <.0001 | 1.52 |

| Parameter | Comparison | Function Number | Estimate | Std. Error | Chi-Square | Pr > Chi Sq | **Odds ratio(OR)** |
|---|---|---|---|---|---|---|---|
| SEX_H | Male vs Female | 1 | 1.7438 | 0.105 | 276.03 | <.0001 | 5.72 |
| | | 2 | 0.1009 | 0.0333 | 9.18 | 0.0025 | 1.11 |
| TRAF_WAY*SPEEDREL | Divided speed related | 1 | 0.211 | 0.1048 | 4.05 | 0.0441 | 1.23 |
| | | 2 | 0.2366 | 0.0471 | 25.19 | <.0001 | 1.27 |
| TRAF_WAY*V_ALCH_I | Divided, alcohol involved | 1 | 0.4074 | 0.1694 | 5.78 | 0.0162 | 1.50 |
| | | 2 | 0.2532 | 0.0559 | 20.54 | <.0001 | 1.29 |
| WEATHR_I*SPEEDREL | Adverse weather, speed related | 1 | -0.0997 | 0.1134 | 0.77 | 0.3793 | 0.91 |
| | | 2 | 0.2001 | 0.0532 | 14.14 | 0.0002 | 1.22 |

***Age:***

The age was divided into three groups namely

- Young aged drivers (25 years or below)
- Middle aged drivers (25 years < and <55 years)
- Old aged drivers (55 years and above)

The young aged drivers and old aged drivers were compared to the middle aged drivers.

Young at fault car drivers in a car-truck crash are 13% less likely to be at fault when compared to middle aged at fault car drivers. One can speculate that young car drivers do not like to be in the vicinity of a truck and they tend to overtake a truck or would avoid following a truck which might result in the lower percentage of young car drivers being at fault. Moreover one can speculate that young drivers may tend to be cautious when driving in the vicinity of a truck rather than that of a car.

***Lighting condition:***

The lighting condition has been divided into three categories

- Dark
- Dark but lighted (dark but lighted, dawn, dusk)
- Daylight

Cases in dark and dark but lighted conditions are compared to that of daylight ones. In case of dark lighting conditions at fault cars are 28% (OR=1.28) more likely to result in a car-truck crash when compared to at fault cars in car-car collision. The rest cases were statistically insignificant. Due to improper visibility during dark lighting conditions more car drivers tend to be at fault in a car-truck crash when compared to that of car-car crash. Moreover car driver might need better lighting conditions to judge the lateral movement of the trucks running in front of their vision.

***Gender:***

This variable, gender was found significant in both at fault truck and at fault car in a car-truck collision. If the truck driver was a male then it is 472% more likely to be at fault. The reason for such a result might be that only very few females are truck drivers. The percentage of male drivers is very high and hence this might have resulted in such a result.

A male at fault car driver (when compared to a female) is 11% more likely to result in a car-truck collision when compared to that of a male at fault car driver in a car-car crash. Male drivers are more aggressive drivers when compared to that of female drivers. Moreover female drivers drive more cautiously when compared to male drivers when they drive in the vicinity of a truck.

***Weekday/weekend:***

The weekday/weekend variable has been found significant in both the car and truck in a car-truck collision. It has been observed that at fault trucks are 86% and at fault cars are 52% more likely to be resulting in a car-truck crash on a weekday when compared to a weekend. This might be due to the fact that more cars and trucks travel on weekdays when compared to weekends. This result might depend on the number of cars and trucks that travel on a weekday or a weekend.

***Speed related cases and divided/undivided section:***

The traffic way was divided into divided and undivided traffic way. Crashes at divided sections are compared to that of undivided section. At a divided sections it is found that car is 126% (OR = 2.26) more likely to be at fault in a car-truck crash. When the effect of speeding is considered on the traffic way condition it has been observed that only cars in car-truck case were statistically significant. It was observed that if there was speeding then the car is found to be 138% (OR=exp (0.2366+0.6325) =exp (0.8691) =2.38) more likely to be at fault when compared to a car fault in a car-car collision. It shows that divided section accompanied with the effect of speeding increases the likelihood of car resulting in a car-truck crash. It can be speculated that at a divided section truck would require more time to perform the turning maneuver and speeding would increase the likelihood of car running into the truck or being at fault.

***Divided/undivided section and alcohol involvement/non-involvement:***

The effect of alcohol on a divided traffic way can be studied by considering the interaction variable between the alcohol and the traffic way type. It was found that both the car fault cases and truck fault cases were found to be statistically significant. If only divided sections was considered then cars were 126% and trucks were 88% more likely to be involved in a crash but with alcohol involvement car is 142% (OR = exp (0.2532+0.6325) = exp (0.8857) = 2.42) and truck is 240% (OR = exp (0.4074+0.8174) =exp (1.22) =3.40) more likely to be at fault when compared to a car being at fault in a car-car collision. Involvement of alcohol increases the likelihood of car and trucks to be at fault in a car-truck crash. Involvement of alcohol might impact the decision-making ability of both the car and truck drivers, which might make them liable to be at fault and end up colliding each other.

Traynor, T.L., (2005) tried to investigate the effect of driver alcohol on crash severity. Ordered logit estimates from the study indicated that that crashes in which the at-fault drivers had been drinking are more likely to result in a severe injury or death than are crashes caused by sober drivers. It showed that at-fault driver alcohol use increases the expected highest degree of injury resulting from a crash.

***Adverse/non adverse Weather and Speed related:***

Weather condition was divided into adverse (rain, sleet, snow, fog, rain and fog, sleet and fog and others) and non-adverse conditions. Crashes were compared in adverse conditions to that of non-adverse conditions. Adverse weather increased the likelihood of car in car-truck being more likely at fault when compared to that of fault car in car-car collision. When speeding accompanied with adverse weather, at fault car was statistically significant. It was observed that if the crash in an adverse weather condition was accompanied by speeding, then the car is 194% (OR=exp (0.2001+0.8812) =exp (1.08) =2.94) more likely to be at fault when compared to a car at fault in a car-car collision. This means that weather increases the likelihood of at fault cars in speed related car-truck crashes when compared to that of the at fault car in car-car crashes.

Edwards, J.B., (1998) investigated the relationship between weather and road collisions in England and Wales. The weather information recorded on Police Crash Report Forms was taken as the prevailing weather at the time of the crash. At the local authority level, crash severity for the various adverse weather categories of rain, fog, and high winds is compared with the non-hazardous condition of fine weather. It was observed that crash severity decreases significantly in rain when compared with fine weather.

#### 4.1.1.2 Analysis: FARS crash database

The FARS database was used to study the trend of two vehicular angular car truck crashes and some trends were consistent with the results found using the GES database.

A multinomial model was run for the data set created using the FARS database and the results are shown in Table 17 and Table 18 below

Table 17: Maximum likelihood analysis of variance (FARS, fault angle crashes)

| Maximum likelihood analysis of variance | | | |
|---|---|---|---|
| **Source** | **DF** | **Chi-Square** | **Pr > ChiSq** |
| **Intercept** | 2 | 522.35 | <.0001 |
| **NHS** | 2 | 34.34 | <.0001 |
| **LGT_COND** | 4 | 46.44 | <.0001 |
| **WEATHER** | 2 | 14.32 | 0.0008 |
| **DR_DRINK** | 2 | 91.09 | <.0001 |
| **SEX** | 2 | 96.03 | <.0001 |
| **AGE** | 4 | 184.1 | <.0001 |
| **NHS*WEATHER** | 2 | 9.79 | 0.0075 |
| **Likelihood Ratio** | 216 | 182.05 | 0.955 |

Table 18: Analysis of maximum likelihood estimates (FARS, fault angle crashes)

| **Analysis of Maximum Likelihood Estimates** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | Comparison | **Function Number** | **Estimate** | **Standard Error** | **Chi-Square** | **Pr > ChiSq** | **Odds ratio(OR)** |
| **Intercept** | | **1** | -4.4336 | 0.2581 | 295.16 | <.0001 | |
| | | **2** | -2.3339 | 0.146 | 255.47 | <.0001 | |
| **NHS** | **NHS vs Non NHS** | **1** | 0.4014 | 0.1071 | 14.04 | 0.0002 | 1.49 |
| | | **2** | 0.5919 | 0.1186 | 24.9 | <.0001 | 1.81 |
| **LGT_COND** | **Dark vs Daylight** | **1** | 0.901 | 0.1395 | 41.71 | <.0001 | 2.46 |
| | | **2** | -0.1518 | 0.1767 | 0.74 | 0.3903 | 0.86 |
| | **Dark but lighted vs Day light** | **1** | -0.8768 | 0.1496 | 34.37 | <.0001 | 0.42 |
| | | **2** | 0.0675 | 0.1418 | 0.23 | 0.6343 | 1.07 |
| **WEATHER** | **Adverse vs Non adverse** | **1** | 0.3941 | 0.107 | 13.58 | 0.0002 | 1.48 |
| | | **2** | 0.1624 | 0.1184 | 1.88 | 0.1701 | 1.18 |
| **DR_DRINK** | **Drinking vs Non drinking** | **1** | -1.6277 | 0.1719 | 89.67 | <.0001 | 0.20 |
| | | **2** | -0.1667 | 0.108 | 2.38 | 0.1228 | 0.85 |
| **SEX** | **Male vs Female** | **1** | 1.698 | 0.1747 | 94.45 | <.0001 | 5.46 |
| | | **2** | -0.0703 | 0.0806 | 0.76 | 0.3833 | 0.93 |
| **AGE** | **Young vs Middle age** | **1** | -0.8542 | 0.1296 | 43.46 | <.0001 | 0.43 |
| | | **2** | -0.0356 | 0.106 | 0.11 | 0.7373 | 0.97 |
| | **Old vs Middle age** | **1** | -0.4258 | 0.128 | 11.06 | 0.0009 | 0.65 |
| | | **2** | 0.3026 | 0.1149 | 6.94 | 0.0084 | 1.35 |
| **NHS*WEATHER** | **NHS, Adverse** | **1** | 0.2104 | 0.1066 | 3.89 | 0.0485 | 1.23 |
| | | **2** | 0.3175 | 0.1183 | 7.2 | 0.0073 | 1.37 |

***Lighting Condition:***

Truck being at fault was statistically significant in case of lighting condition. Compared to car-car collision at fault truck drivers are more likely to result in truck-car collisions under dark conditions compared to day light conditions. In case of a dark condition when compared to daylight condition at fault truck is (OR = 2.46) 146% more likely to result in a car truck collision when compared to a car-car collision. Moreover if we considered the dark but lighted condition compared to the day light condition at fault truck was statistically significant and followed a decreasing trend (OR = 0.42<1.0). It can be understood that improving lighting conditions would reduce the number of at fault trucks resulting in a car truck collision.

***Age:***

Old at fault car drivers in car-truck collision were (OR = 1.35) 35% more likely to result in a car-truck crash when compared to that of at fault middle-aged drivers. The young truck drivers would be relatively low when compared to that of middle aged drivers and young aged drivers. Old aged at fault truck drivers are 35% more likely to result in car truck crashes. This wouldn’t be a fair comparison to be done. Even though the number of old truck drivers is pretty low, old aged truck drivers have a higher risk to be at fault and are more likely to end up in fatal car-truck crashes.

***NHS and adverse/non adverse weather condition:***

NHS variable is categorized into national highway system or non-highway system. An interaction of adverse weather condition on NHS (national Highway system) has been found statistically significant in both the car and truck being fault in a car-truck crash when compared to that of a car-car collision. On an NHS at fault car was (OR = 1.81) 81 % and at fault car was (OR = 1.49) 49% more likely to result in an angular car-truck collision. If the weather was adverse on a NHS at fault car was (OR = exp (0.3175+0.5919) = exp (0.9094) =2.48) 148% more likely to result in a car-truck collision when compared to that of a car-car collision while at fault truck was (OR = exp (0.2104+0.4014) = exp (0.6118) =1.84) 84% more likely to result in a car-truck collision when compared to that of a car –car collision. This shows that adverse weather condition on a NHS aggravates the likelihood of both the at fault car and at fault truck to result in a car-truck crash.

### 4.1.2 Non-Fault cases

The no-fault cases were analyzed and the methodology to obtain the datasets is shown in the methodology chapter. All the non-fault cases were further categorized by their vehicle role. Both GES and FARS crash databases were used to analyze these no-fault cases. In these cases none of the two vehicles was charged of any violation. Striking role was used to categories the data into three categories (1: Truck Striking a car 2: Car striking a truck and 3: car striking a car).

#### 4.1.2.1 Analysis: GES crash database

Table 19 and Table 20 show modeling results, which analyze the GES database.

Table 19: Maximum likelihood analysis of variance (GES, no-fault angle crashes)

| Maximum likelihood analysis of variance | | | |
|---|---|---|---|
| Source | DF | Chi-Square | Pr > ChiSq |
| Intercept | 2 | 1081.15 | <.0001 |
| LGTCON_I_S1 | 4 | 81.96 | <.0001 |
| SEX_H_S1 | 2 | 478.63 | <.0001 |
| SPEEDREL_S1 | 2 | 252.02 | <.0001 |
| TRAF_WAY_S1 | 2 | 262.59 | <.0001 |
| WEATHR_I_S1 | 2 | 28.56 | <.0001 |
| WKDY_I_S1 | 2 | 212.68 | <.0001 |
| TRAF_WAY_S1*WEATHR_I_S1 | 2 | 27.13 | <.0001 |
| Likelihood Ratio | 172 | 157.7 | 0.7756 |

Table 20: Analysis of maximum likelihood estimates (GES, no-fault angle crashes)

| **Analysis of Maximum Likelihood Estimates** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | Comparison | **Function Number** | **Estimate** | **Standard Error** | **Chi-Square** | **Pr > ChiSq** | **Odds ratio(OR)** |
| **Intercept** | | 1 | -3.7381 | 0.1334 | 785.37 | <.0001 | |
| | | 2 | -1.3726 | 0.0663 | 429.21 | <.0001 | |
| **LGTCON_I_S1** | **Dark vs Day Light** | 1 | 0.1259 | 0.1002 | 1.58 | 0.209 | 1.13 |
| | | 2 | 0.345 | 0.0804 | 18.4 | <.0001 | 1.41 |
| | **Dark but lighted vs day light** | 1 | -0.4196 | 0.0743 | 31.88 | <.0001 | 0.66 |
| | | 2 | -0.3243 | 0.0624 | 27.02 | <.0001 | 0.72 |
| **SEX_H_S1** | **Male vs Female** | 1 | 1.8607 | 0.0854 | 474.8 | <.0001 | 6.43 |
| | | 2 | 0.0939 | 0.0301 | 9.73 | 0.0018 | 1.1 |

| Parameter | Comparison | Function Number | Estimate | Standard Error | Chi-Square | Pr > ChiSq | Odds ratio(OR) |
|---|---|---|---|---|---|---|---|
| **SPEEDREL_S1** | **Speed related vs Not Related** | 1 | -0.3115 | 0.0877 | 12.61 | 0.0004 | 0.73 |
| | | 2 | 0.6674 | 0.0463 | 208.06 | <.0001 | 1.95 |
| **TRAF_WAY_S1** | **Divided vs Undivided** | 1 | 0.5335 | 0.046 | 134.56 | <.0001 | 1.7 |
| | | 2 | 0.5141 | 0.0386 | 176.96 | <.0001 | 1.67 |
| **WEATHR_I_S1** | **Adverse vs Non-Adverse** | 1 | 0.0822 | 0.046 | 3.19 | 0.0739 | 1.09 |
| | | 2 | 0.2063 | 0.039 | 27.92 | <.0001 | 1.23 |
| **WKDY_I_S1** | **Weekday vs Weekend** | 1 | 0.537 | 0.0494 | 118.08 | <.0001 | 1.71 |
| | | 2 | 0.4804 | 0.0453 | 112.36 | <.0001 | 1.62 |
| **TRAF_WAY_S1*WEATHR_I_S1** | **Divided* Adverse** | 1 | 0.221 | 0.0457 | 23.43 | <.0001 | 1.25 |
| | | 2 | 0.1079 | 0.0385 | 7.86 | 0.0051 | 1.11 |

***Lighting conditions:***

It can be observed that in a dark lighting condition when compared to the day light, a car is (OR = 1.41) 41% more likely to be striking a truck in a car-truck collision when compared to a car striking a car in a car- car collision. In other words it can be said that a striking car in a car-truck crash is 41%more likely to result in a car-truck crash. The truck striking a car is not statistically significant in the dark light conditions. But if we observe the comparison for the dark but lighted condition to that of day light condition the car striking (OR=0.66 <1) and a truck striking (OR = 0.72 <1) in a car-truck collision are less when compared to a car striking a car in car-car collision.

It can be noticed that in spite of none being at fault, the striking vehicle follows a similar pattern of that of a faulty vehicles under such lighting conditions. So lighting does have some impact on these crashes and improvements in the lighting conditions will help in reduction of the one vehicle striking the other.

***Gender:***

It is very likely that most of the truck drivers are males and hence so see higher likelihood of truck striking a car hence it would be an appropriate one to compare for the truck drivers. But if we consider the car-striking drivers, it can be observed that if the car driver was a male then it is 10% (OR = 1.10) more likely that the car strikes a truck. This might be because male drivers are more aggressive than the female drivers and female drivers tend to drive more carefully in the vicinity of the trucks. Even this pattern is similar to that of the faulty cases.

***Speed related*:**

It can be observed that if it is speeding was involved then car was (OR = 1.96) 96% more likely to be the striking vehicle in a car-truck collision when compared to a car in a car –car collision.

***Weekday/weekend:***

This variable has been found significant in both the car and truck in a car-truck collision. It has been observed that trucks are 71% and cars are 62% more likely to be at fault on a weekday when compared to a weekend. This might be due to the fact that more cars and trucks travel on weekdays when compared to weekends. This result might depend on the number of cars and trucks that travel on a weekday or a weekend.

***Divided/undivided section and adverse/non adverse weather condition:***

The interaction between the traffic way and the weather was statistically significant. To obtain the effect of weather on a divided section we need to take into effect the combined effect of both the variables and the traffic way variable as an individual. By doing so it has been that in a car-truck collision observed that truck was 112% (OR = exp (0.221+ 0.5335) = exp (.7545) =2.12) and car was 86% (OR = exp (0.1079+ 0.5141) = exp (0.622) =1.86) more likely when compared to a car striking in a car-car collision.

#### 4.1.2.2 Analysis: FARS crash database

The modeling results using FARS database for no-fault angle crashes are shown in Table 21 and Table 22 respectively.

Table 21: Maximum likelihood analysis of variance (FARS, no fault angle crashes)

| **Maximum likelihood analysis of variance** | | | |
|---|---|---|---|
| **Source** | **DF** | **Chi-Square** | **Pr > ChiSq** |
| **Intercept** | 2 | 500.65 | <.0001 |
| **NHS** | 2 | 39.33 | <.0001 |
| **LGT_COND** | 4 | 41.83 | <.0001 |
| **WEATHER** | 2 | 12.68 | 0.0018 |
| **DR_DRINK** | 2 | 75.9 | <.0001 |
| **SEX** | 2 | 87.47 | <.0001 |
| **NHS*WEATHER** | 2 | 11.63 | 0.003 |
| **Likelihood Ratio** | 78 | 69.16 | 0.7526 |

Table 22: Analysis of maximum likelihood estimates (FARS, no fault angle crashes)

| Analysis of Maximum Likelihood Estimates | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | Comparison | **Function Number** | **Estimate** | **Standard Error** | **Chi-Square** | **Pr > ChiSq** | **Odds ratio(OR)** |
| **Intercept** | | **1** | -3.8503 | 0.2428 | 251.41 | <.0001 | |
| | | **2** | -2.3969 | 0.1434 | 279.23 | <.0001 | |
| **NHS** | **NHS vs Not NHS** | **1** | 0.4305 | 0.0981 | 19.24 | <.0001 | 1.54 |
| | | **2** | 0.6089 | 0.1182 | 26.53 | <.0001 | 1.84 |
| **LGT_COND** | **Dark vs Daylight** | **1** | 0.7665 | 0.1267 | 36.57 | <.0001 | 2.15 |
| | | **2** | -0.1687 | 0.1765 | 0.91 | 0.3392 | 0.84 |
| | **Dark but lighted vs Daylight** | **1** | -0.7837 | 0.1408 | 30.97 | <.0001 | 0.46 |
| | | **2** | 0.0394 | 0.1409 | 0.08 | 0.7795 | 1.04 |
| **WEATHER** | **Adverse vs Non-adverse** | **1** | 0.3375 | 0.098 | 11.85 | 0.0006 | 1.40 |
| | | **2** | 0.1732 | 0.118 | 2.15 | 0.1421 | 1.19 |
| **DR_DRINK** | **Drinking/Non drinking** | **1** | -1.4324 | 0.1679 | 72.79 | <.0001 | 0.24 |
| | | **2** | -0.2233 | 0.1047 | 4.55 | 0.033 | 0.80 |
| **SEX** | **Male/Female** | **1** | 1.5915 | 0.1715 | 86.07 | <.0001 | 4.91 |
| | | **2** | -0.0594 | 0.0802 | 0.55 | 0.4589 | 0.94 |
| **NHS*WEATHER** | **NHS, Adverse** | **1** | 0.2442 | 0.098 | 6.21 | 0.0127 | 1.28 |
| | | **2** | 0.3199 | 0.118 | 7.35 | 0.0067 | 1.38 |

***Light condition:***

Trucks are (OR = 2.15) 115% more likely to be striking a car in dark conditions when compared to that of car striking a car in car-car crash. One can speculate that its is very hard for the truck driver to judge the actions of the car from an angle positions in dark lighting conditions which might misjudge the truck driver to lead him to run into an opposing car. Moreover in dark but lighted conditions trucks were 54% less likely to be striking.

***NHS/Non-NHS and adverse/non adverse weather condition:***

The interaction of adverse weather condition on NHS (national Highway system) is statistically significant in both the car striking and truck striking in a car-truck crash when compared to that of a car-car collision. If the weather was adverse on a NHS a striking car was (OR = exp (0.3199+0.6089) = exp (0.9288) = 2.53) 153% more likely to result in a car-truck collision when compared to that of a car-car collision. A striking truck is (OR = exp (0.2442+0.4305) = exp (0.6747) =1.96) 96% more likely to result in a car-truck collision when compared to that of a car–car collision. The other variables analyzed were not statistically significant.

It was observed that there were some similar trends in both fault cases and no-fault (striking) cases. Lighting condition was found significant in both fault and no-fault angle cases and showed a similar trend. Weather and interaction between NHS and adverse weather condition, had similar effect in both the fault and no-fault cases. It can be speculated that in no-fault cases there might be some reporting errors as no-fault cases showed similar trends to that of fault cases to few variables.

## 4.2 Rear end

The rear-end collisions (car-car or car-truck) were found to be the second largest composition in GES and third largest in FARS database. The rear-end crash has been analyzed using both GES and FARS crash databases. The striking role considered to categorize the data into three categories.

### 4.2.1 Analysis: GES crash database

The modeling results for the rear-end car-truck collisions are shown in Table 23 and Table 24 respectively.

Table 23: Maximum likelihood analysis of variance (GES, rear-end crash)

| Maximum likelihood analysis of variance | | | |
|---|---|---|---|
| **Source** | **DF** | **Chi-Square** | **Pr > ChiSq** |
| **Intercept** | 2 | 840.65 | <.0001 |
| **ALCHL_I** | 2 | 118.42 | <.0001 |
| **WKDY_I** | 2 | 127.64 | <.0001 |
| **WEATHR_I** | 2 | 6.6 | 0.0369 |
| **TRAFF_WAY** | 2 | 58.54 | <.0001 |
| **INT_HWY** | 2 | 511.23 | <.0001 |
| **LGTCON_I** | 4 | 46.35 | <.0001 |
| **SPEEDREL** | 2 | 55.71 | <.0001 |
| **SEX_H** | 2 | 349.79 | <.0001 |
| **AGE** | 4 | 330.31 | <.0001 |
| **TRAFF_WAY*WEATHR_I** | 2 | 8.3 | 0.0157 |
| **Likelihood Ratio** | 1.00E+03 | 1016.35 | 0.9998 |

Table 24: Analysis of maximum likelihood estimates (GES, rear-end crash)

| Analysis of Maximum Likelihood Estimates | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | Comparison | **Function Number** | **Estimate** | **Standard Error** | **Chi-Square** | **Pr > ChiSq** | **Odds ratio(OR)** |
| **Intercept** | | **1** | -4.7648 | 0.1889 | 636.04 | <.0001 | |
| | | **2** | -1.1876 | 0.0716 | 275.15 | <.0001 | |
| **ALCHL_I** | **Alcohol vs Non-Alcohol** | **1** | -0.9161 | 0.1401 | 42.78 | <.0001 | 0.40 |
| | | **2** | 0.402 | 0.051 | 62.09 | <.0001 | **1.49** |
| **WKDY_I** | **Weekday vs Weekend** | **1** | 0.4265 | 0.0527 | 65.4 | <.0001 | 1.53 |
| | | **2** | 0.3766 | 0.043 | 76.88 | <.0001 | 1.46 |
| **WEATHR_I** | **Adverse vs Non Adverse** | **1** | -0.1357 | 0.0528 | 6.6 | 0.0102 | 0.87 |
| | | **2** | -0.0154 | 0.0429 | 0.13 | 0.7201 | 0.98 |
| **TRAF_WAY** | **Divided vs Undivided** | **1** | 0.2644 | 0.0561 | 22.22 | <.0001 | 1.30 |
| | | **2** | 0.2973 | 0.0458 | 42.08 | <.0001 | 1.35 |
| **INT_HWY** | **Interstate vs Non Interstate** | **1** | 0.6464 | 0.0446 | 210.14 | <.0001 | 1.91 |
| | | **2** | 0.732 | 0.0363 | 407.69 | <.0001 | 2.08 |
| **LGTCON_I** | **Dark vs Day light** | **1** | -0.1809 | 0.1108 | 2.66 | 0.1026 | 0.83 |
| | | **2** | 0.2544 | 0.0694 | 13.46 | 0.0002 | 1.29 |
| | **Dark but lighted vs Day light** | **1** | -0.1273 | 0.0817 | 2.43 | 0.1192 | 0.88 |
| | | **2** | -0.1018 | 0.0556 | 3.35 | 0.0672 | 0.90 |
| **SPEEDREL** | **Speed related vs Not related** | **1** | -0.2438 | 0.0384 | 40.37 | <.0001 | 0.78 |
| | | **2** | 0.0817 | 0.0302 | 7.34 | 0.0067 | 1.09 |
| **SEX_H** | **Male vs Female** | **1** | 1.9468 | 0.1042 | 348.95 | <.0001 | 7.01 |
| | | **2** | 0.0585 | 0.0301 | 3.78 | 0.052 | 1.06 |

| Parameter | Comparison | Function Number | Estimate | Standard Error | Chi-Square | Pr > ChiSq | Odds ratio(OR) |
|---|---|---|---|---|---|---|---|
| **AGE** | **Young vs Middle age** | **1** | -0.996 | 0.0701 | 202.13 | <.0001 | 0.37 |
| | | **2** | -0.1718 | 0.0447 | 14.76 | 0.0001 | 0.84 |
| | **Old vs Middle age** | **1** | 0.2146 | 0.0709 | 9.16 | 0.0025 | 1.24 |
| | | **2** | 0.1432 | 0.0576 | 6.17 | 0.013 | 1.15 |
| **WEATHR_I*TRAFF_WAY** | **Divided, Adverse Condition** | **1** | 0.1288 | 0.0527 | 5.98 | 0.0145 | 1.14 |
| | | **2** | 0.0771 | 0.0427 | 3.27 | 0.0707 | 1.08 |

***Alcohol:***

When involvement of alcohol was considered, in a car-truck crash car striking a truck was found statistically significant and the striking car drivers are 49% (OR = 1.49) more likely result in a car-truck rear end crash when compared to a car striking in a car-car rear end crash. This result is consistent with the findings of Yan, X., et al. (2005) which was focused on rear-end collisions at signalized intersection except for that fact that the current study deals more specifically about a car and truck rear end crash. Alcohol involvement would reduce the alertness, interfere with judgment and impairs vision. Alcohol might impair the driving ability.

***Light Condition:***

When dark lighting condition was compared to the daylight condition car striking in a car-truck crash was found statistically significant. Cars are (OR = 1.29) 29% more likely to be striking in a car-truck crash when compared to a car striking in a car-car crash. The lighting provided on a truck might not be sufficient enough for the car driver to estimate the exact distance, he/she is away from the truck ahead of him and thereby would find it difficult enough to stop and end up in rear-ending the truck. Moreover it is speculated that different lighting conditions may affect perception times in this regard. Earlier studies (Wang, Y., et al., 2003) estimating rear-end crash probabilities at signalized intersections have had results showing an increasing likelihood of rear-end collisions traveling at night. In the current study cars are more prone to be striking a truck when compared to a car striking a car. A striking car in a car-truck collision is more likely to result in a car-truck crash.

***Speed Related:***

Striking cars in a car-truck crash are (OR = 1.09) 9% more likely to result in a car-truck crash when compared to a car striking in a car-car striking. Car drivers are more aggressive and they tend to feel that truck can maneuver in a similar fashion as the cars and hence follow the trucks too closely. It has been found that cars tend to follow trucks too closely and when the truck encounters an obstacle, the preceding car doesn't have enough time to adjust its speed thereby rear-ending the truck. A driver of a smaller car following a truck, might have a problem seeing the roadway beyond the truck, and therefore would not be able to adjust his/her speed accordingly, increasing the probability of a rear-end collision. Also, the probability of a car-truck rear-end crash increases when the lead vehicle stops suddenly. Abdel-Aty, M., Abdelwahab, H., (2004) explored the effect of the lead vehicle's size on the rear-end crash configuration. Trucks have a better view ahead of them hence the truck drivers are more aware of the situation ahead of them and hence can adjust their speed accordingly and avoid rear-ending a car.

***Age:***

The age was divided into three groups namely

- Young aged drivers (25 years or below)

- Middle aged drivers (25 years < and <55 years)
- Old aged drivers (55 years and above)

The young aged drivers and old aged drivers were compared to the middle aged drivers. When old age drivers were compared to middle aged drivers, striking truck drivers were (OR = 1.24) 24% more likely to result in a car-truck crash. The old aged truck driver population sample would be pretty low when compared to the old car driver population but in spite of that it is observed that truck drivers have a high likelihood of falling into rear-end crashes. Old aged drivers need more reaction time when compared to young and middle aged drivers. Old aged car drivers were (OR = 1.15) 15% more likely to be striking when compared to car striking in car-car rear-end crash. Past studies have resulted in similar results while studying the effect of driver age in crashes (Abdel-Aty, M., et al., 1999). It was concluded that elderly driver were over involved in collisions. One can speculate that older age group's driving ability is affected by vision impairment and other physical constraints. The results are consistent with those of Abdel-Aty, M., Radwan, E., (2000) that old aged drivers experience more collisions than middle aged drivers.

But it was found that young drivers were less likely to be striking when compared to the middle aged drivers in car striking (car-truck crash) when compared to that of car striking in a car-car crash. The young aged striking truck drivers are 63% and young aged striking car drivers are 16% less likely to result in a car-truck crash when compared to that of car-car crash. These results were not consistent with earlier studies which showed that young aged drivers were more likely to be striking when compared to middle aged drivers. Earlier studies revealed that very young aged drivers face up to three times the risk of being at fault compared to middle-aged drivers (Kim, K., et al., 1998).

Previous studies assessing the age related changes in drivers' crash risk and crash type (Ryan, G. A., et al., 1998) have revealed that young aged drivers were more involved in crashes when compared to that of middle aged drivers. But in our current study it was found that young aged drivers followed a decreasing trend in a car-truck crash when compared to that of car-car crash when compared to the middle aged drivers.

***Divided/undivided traffic way and adverse/non-adverse weather:***

The interaction terms were studied and it was observed that traffic way (divided /undivided) interacted with the weather (Adverse / Non-adverse) and is statistically significant. Earlier studies on estimating rear-end crash probabilities at signalized intersections (Wang, Y., et al., 2003) revealed that median fence would lower the probability of encountering an obstacle and there by reduce the chance of a rear-end collision.

The report on rear-end large truck crashes (FMCSA) revealed that rear-end truck crashes are more likely to occur on divided roads than other truck crashes. About 45% of all truck striking rear-end crashes occurred on a divided road. The results of the current study comply with the results of the earlier studies.

Some studies related to effect of weather conditions of the injury severity have been done earlier (Edwards, J.B., 1998) revealed that crash number increases in wet conditions. In the current study adverse condition is compared to that of a non-adverse condition. Adverse conditions include the rain, sleet snow, fog rain and fog, sleet and fog and other. The unknown were not considered in the following study. The effect of weather conditions was observed on a divided section of the roadway, and trucks were (OR = exp (0.1288+0.2644) = exp (0.3932)

=1.48) 48% more likely to be striking when compared to that of car striking in a car-car rear-end crash. These are consistent with the results of earlier studies.

### 4.2.2 Analysis: FARS crash database

The modeling results obtained for the rear end crashes using FARS database are shown in Table 25 and Table 26 respectively.

Table 25: Maximum likelihood analysis of variance (FARS, rear end crashes)

| Maximum likelihood analysis of variance | | | |
|---|---|---|---|
| **Source** | **DF** | **Chi-Square** | **Pr > ChiSq** |
| **Intercept** | 2 | 242.79 | <.0001 |
| **TRAF_FLO** | 2 | 26.44 | <.0001 |
| **LGT_COND** | 4 | 25.02 | <.0001 |
| **DR_DRINK** | 2 | 64.82 | <.0001 |
| **SEX** | 2 | 56.57 | <.0001 |
| **AGE** | 4 | 74.83 | <.0001 |
| **DAY_WEEK** | 2 | 125.61 | <.0001 |
| **Likelihood Ratio** | 240 | 242.52 | 0.4424 |

Table 26: Rear-End: Analysis of maximum likelihood estimates (FARS, rear end crashes)

| Analysis of Maximum Likelihood Estimates | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | Comparison | **Function Number** | **Estimate** | **Standard Error** | **Chi-Square** | **Pr > ChiSq** | **Odds ratio(OR)** |
| **Intercept** | | 1 | -4.6331 | 0.3307 | 196.28 | <.0001 | |
| | | 2 | -0.5939 | 0.0733 | 65.74 | <.0001 | |
| **TRAF_FLO** | Divided vs Undivided | 1 | 0.3601 | 0.0832 | 18.74 | <.0001 | 1.43 |
| | | 2 | 0.2082 | 0.0524 | 15.78 | <.0001 | 1.23 |
| **LGT-COND** | Dark vs Daylight | 1 | 0.3258 | 0.1176 | 7.68 | 0.0056 | 1.39 |
| | | 2 | 0.2131 | 0.0737 | 8.36 | 0.0038 | 1.24 |
| | Dark but lighted vs Daylight | 1 | -0.5648 | 0.1383 | 16.69 | <.0001 | 0.57 |
| | | 2 | -0.0841 | 0.0769 | 1.2 | 0.274 | 0.92 |
| **DR_DRINK** | Drinking vs Non-Drinking | 1 | -1.5941 | 0.1985 | 64.51 | <.0001 | 0.20 |
| | | 2 | -0.0351 | 0.0576 | 0.37 | 0.5428 | 0.97 |
| **SEX** | Male vs Female | 1 | 1.8682 | 0.2557 | 53.39 | <.0001 | 6.48 |
| | | 2 | 0.1426 | 0.0563 | 6.41 | 0.0113 | 1.15 |
| **AGE** | Young vs Middle aged | 1 | -0.9154 | 0.1517 | 36.4 | <.0001 | 0.40 |
| | | 2 | -0.2546 | 0.076 | 11.22 | 0.0008 | 0.78 |
| | Old vs Middle aged | 1 | 0.0941 | 0.1317 | 0.51 | 0.4749 | 1.10 |
| | | 2 | 0.1806 | 0.084 | 4.62 | 0.0316 | 1.20 |
| **DAY_WEEK** | Weekday vs Weekend | 1 | 0.3705 | 0.0865 | 18.34 | <.0001 | 1.45 |
| | | 2 | 0.6366 | 0.0575 | 122.66 | <.0001 | 1.89 |

***Divided/undivided traffic way:***

Trucks were found to be (OR = 1.43) 43% and car was found (OR = 1.23) 23% more likely to be striking in a car-truck rear–end crash when compared to that of a car-car crash. So divided section increases the likelihood of both the car and truck to strike the vehicle ahead. These results are consistent with eth earlier studies shown in the Report" Rear-end large truck crashes (FMCSA)" in which it was found that trucks were more likely to be in a rear-end crash.

The increase in the car striking a truck can be related to the vision obscuring of the car driver by the truck in front of him/her. These results confirm with the results of the studies done by Mohamed Abdel-Aty, M., Abdelwahab, H., (2004).

***Light Condition:***

In dark conditions truck is (OR = 1.39) 39% more likely and car is (OR = 1.24) 24% more likely to be striking when compared to that of a car-car crash.

Earlier analysis done by the FMCSA (Rear-end large truck crashes) showed that in fatal rear-end crashes where the truck is striking vehicle, about 31% occurred in dark or dark but lighted conditions. The proportion of dark or dark but lighted raised to 46 percent when the truck was struck. Similar results were obtained in this study except that truck striking (39%) was more likely than the car striking (24%) when compared to car striking car. We might speculate that during totally dark conditions trucks might not be able to judge properly the distance between them and the car ahead of them and are unable to adjust the speed according to avoid rear-ending a car. Moreover the huge body of the truck makes it more difficult as they need more time to react and apply brakes to get the vehicle to a halt.

The car striking can be a result of lack of proper visibility. Earlier, study by Abdel-Aty, and Abdelwahab, H., (2004) showed that cars vision is obscured by the heavy vehicle ahead of them resulted in an increase in rear-end collisions. Dark lighting conditions adds to the problem and increase the likelihood of a car driver to strike a truck ahead of him/her.

But one interesting fact was observed when dark but lighted condition was analyzed. Truck striking a car follows a lower trend (43% less likely to be striking) which implies that if lighting conditions were improved the likelihood of a truck striking takes a lower trend thereby resulting in lowering of truck striking rear-end crashes. In other words we can say any extra lighting condition added to the lighting provided by truck headlights would give the truck drivers a better view of situation ahead of them and hence help them adjust their speed accordingly to avoid rear-ending.

***Gender:***

Gender variable was analyzed and the male driver was compared with that of a female driver. Gender was found statistically significant in both the truck striking and car striking. It wouldn't be fair enough to study this variable in the case of truck striking a car because majority of truck drivers tend to be males rather than females and this might make the results biased towards a higher likelihood of males being involved in truck striking cases.

Both males and female were more likely to be striking in both the car and trucks. But since major percentage of trucks drivers are males it wouldn't be justifiable to compare this variable in case of truck striking.

Whereas in case of cars striking, males are (OR = 1.15) 15% more likely to be striking when compared to that of females and it can be understood that males drive more aggressively when compared to females. The results comply with earlier studies (Kim, K., et al., 1998), which showed that males are found to be at fault when compared to that of females and are more likely involved in crash. But the study was not limited to just the rear-end collision. It took into account all kinds of collisions.

***Age:***

When old age drivers were compared to the middle aged drivers it was observed that this variable was significant in case of cars. Old aged car drivers are (OR = 1.20) 20% more likely to be striking in a car-truck crash when compared to car-car crash. It is consistent with results of earlier studies (Abdel-Aty, M., Abdelwahab, H., 2004), which showed that vision of the car driver was obscured by the truck ahead of him/her.

An interesting finding that was found which was quite different from earlier studies was that young drivers were less likely to be striking in car striking cases when compared to that of middle aged drivers. Young car driver are 22% are less likely to be striking when compared to that of middle aged drivers in case of car-car crashes.

Light condition, age and traffic way showed a similar kind of effect on the three categories in both the FARS and GES database.

## 4.3 Sideswipe (same direction)

GES database over the years 2000-2004 was used to analyze sideswipe (same direction) crashes. The modeling results obtained using the multinomial logit model are shown in the below Table 27 and Table 28.

Table 27: Maximum likelihood analysis of variance (GES, sideswipe (same dir) crashes)

| Maximum likelihood analysis of variance | | | |
|---|---|---|---|
| **Source** | **DF** | **Chi-Square** | **Pr > ChiSq** |
| **Intercept** | 2 | 151.95 | <.0001 |
| **WKDY_I** | 2 | 37.83 | <.0001 |
| **INT_HWY** | 2 | 270.41 | <.0001 |
| **TRAF_WAY** | 2 | 52.24 | <.0001 |
| **LGTCON_I** | 4 | 16.24 | 0.0027 |
| **ALCHL_I** | 2 | 36.84 | <.0001 |
| **SPEEDREL** | 2 | 52.23 | <.0001 |
| **SEX_H** | 2 | 311.21 | <.0001 |
| **AGE** | 4 | 179.44 | <.0001 |
| **ALIGN_I** | 2 | 11.1 | 0.0039 |
| **Likelihood Ratio** | 698 | 615.39 | 0.9889 |

Table 28: Analysis of maximum likelihood estimates (GES, sideswipe (same dir) crashes)

| Analysis of Maximum Likelihood Estimates | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | Comparison | **Function Number** | **Estimate** | **Standard Error** | **Chi-Square** | **Pr > ChiSq** | **Odds ratio(OR)** |
| **Intercept** | | **1** | -3.5756 | 0.3015 | 140.65 | <.0001 | |
| | | **2** | 0.0127 | 0.1424 | 0.01 | 0.929 | |
| **WKDY_I** | **Weekday vs Weekend** | **1** | 0.4137 | 0.0793 | 27.23 | <.0001 | 1.51 |
| | | **2** | 0.32 | 0.0641 | 24.95 | <.0001 | 1.38 |
| **INT_HWY** | **Interstate vs Non Interstate** | **1** | 0.7471 | 0.0729 | 105.13 | <.0001 | 2.11 |
| | | **2** | 0.9588 | 0.0596 | 258.64 | <.0001 | 2.61 |
| **TRAF_WAY** | **Divided vs Undivided** | **1** | 0.2703 | 0.0778 | 12.08 | 0.0005 | 1.31 |
| | | **2** | 0.4966 | 0.0714 | 48.42 | <.0001 | 1.64 |
| **LGTCON_I** | **Dark vs Day light** | **1** | 0.0371 | 0.1618 | 0.05 | 0.8188 | 1.04 |
| | | **2** | 0.1081 | 0.1209 | 0.8 | 0.371 | 1.11 |
| | **Dark but lighted vs Day light** | **1** | -0.3208 | 0.1208 | 7.05 | 0.0079 | 0.73 |
| | | **2** | -0.1703 | 0.0935 | 3.32 | 0.0684 | 0.84 |
| **ALCHL_I** | **Alcohol vs Non-Alcohol** | **1** | -1.4069 | 0.2436 | 33.34 | <.0001 | 0.24 |
| | | **2** | 0.0323 | 0.1028 | 0.1 | 0.7533 | 1.03 |
| **SPEEDREL** | **Speed related vs Not related** | **1** | -0.6291 | 0.1073 | 34.37 | <.0001 | 0.53 |
| | | **2** | 0.0945 | 0.072 | 1.72 | 0.1898 | 1.10 |
| **SEX_H** | **Male vs Female** | **1** | 1.4268 | 0.0927 | 236.66 | <.0001 | 4.17 |
| | | **2** | -0.1776 | 0.0532 | 11.14 | 0.0008 | 0.84 |

| Parameter | Comparison | Function Number | Estimate | Standard Error | Chi-Square | Pr > ChiSq | Odds ratio(OR) |
|---|---|---|---|---|---|---|---|
| AGE | Young vs Middle age | 1 | -1.2802 | 0.1202 | 113.47 | <.0001 | 0.28 |
| | | 2 | -0.1893 | 0.0768 | 6.07 | 0.0137 | 0.83 |
| | Old vs Middle age | 1 | 0.2861 | 0.1115 | 6.58 | 0.0103 | 1.33 |
| | | 2 | 0.1321 | 0.0933 | 2.01 | 0.1565 | 1.14 |
| ALIGN_I | Curve vs Straight | 1 | 0.1886 | 0.1057 | 3.18 | 0.0743 | 1.21 |
| | | 2 | 0.2946 | 0.0884 | 11.1 | 0.0009 | 1.34 |

***Divided/undivided traffic way:***

Striking cars are 31% and striking trucks are 64% more likely to result in a car-truck sideswipe crash when compared to that of car-car sideswipe crash at a divided section. One can speculate that at a divided section a truck might take a left turn or a right turn and would try to get into the inner lane and while doing so

***Lighting condition:***

Dark light condition was not statistically significant whereas dark but lighted conditions were found to be statistically significant in truck striking in car-truck crash when compared to that of car striking in a car-car crash. In dark but lighted condition the striking trucks are 27% less likely to result in a car-truck crash when compared to that of a car striking in a car-car sideswipe crash. Any improvement in the lighting conditions would help in reducing the truck-striking sideswipe crashes.

***Age:***

Old aged striking truck drivers are 33% more likely to result in a sideswipe crash when compared to middle aged drivers. The sample for old aged trucks drivers is pretty less than the number of old aged car drivers and yet old aged car drivers are more likely to be involved in striking a car in sideswipe crashes which is a major concern. These results are consistent with those studies carried out by Abdel-Aty, M., et al., (1999). But young aged striking truck drivers are 72% less likely to result in a car-truck crash when compared to the middle aged drivers striking drivers.

Kim, K., et al., (1998) revealed that very young and very old drivers face up to three times the risk of being at fault compared to middle-aged drivers. Ryan, G. A., and Legge, M., Rosman, D., (1998) revealed that young aged drivers were more involved and constituted of higher percentages of crashes. It was found that drivers aged 17- 19 and 20 -24years were the largest single groups with approx. 12.0% and 14.2% of the 237,235 car drivers involved in crashes.

The results of the current study are consistent with earlier studies when old aged drivers are compared to the middle aged drivers and follow a complete anti pattern in case of young aged drivers.

***Alignment (curve/straight section):***

Curved section was compared to that of straight road section and it was found that this variable was statistically significant in case of truck striking. Striking trucks are 34% more likely to result in a car-truck crash when compared to that of striking car in a car-car crash on a curved portion. It can be speculated that on a curved section it is difficult to adjust the speed of the vehicle thereby end up side swiping the other vehicle. It is difficult to maneuver a truck due to its large size and is difficult in maneuvering which result in an increase in the likelihood of it striking the other vehicle.

## 4.4 Head-on

FARS database over the years 2000-2004 was used for head-on crashes. The modeling results are shown in the below Table 29 and Table 30.

Table 29: Type III analysis of effects (FARS, head-on crashes)

| Type III Analysis of Effects | | | |
|---|---|---|---|
| **Effect** | **DF** | **Wald Chi-Square** | **Pr > ChiSq** |
| **LGT_COND** | 2 | 21.9411 | <.0001 |
| **DR_DRINK** | 1 | 41.4408 | <.0001 |
| **GENDER** | 1 | 53.6682 | <.0001 |
| **NHS** | 1 | 51.2608 | <.0001 |
| **AGE** | 2 | 70.15 | <.0001 |
| **DAY_WEEK** | 1 | 97.2651 | <.0001 |

Table 30: Head-on: Analysis of maximum likelihood estimates (FARS head-on crashes)

| Analysis of Maximum Likelihood Estimates | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Parameter** | | **DF** | **Estimate** | **Standard Error** | **Wald Chi-Square** | **Pr > ChiSq** | **Odds ratio(OR)** |
| Intercept | | 1 | 568.9 | 79.7157 | 50.929 | <.0001 | |
| LGT-COND | Dark vs Daylight | 1 | -0.011 | 0.0662 | 0.0277 | 0.868 | 0.99 |
| | Dark but lighted vs Daylight | 1 | -0.2649 | 0.0818 | 10.481 | 0.001 | 0.77 |
| DR_DRINK | Drinking vs Non-Drinking | 1 | -0.3192 | 0.0496 | 41.441 | <.0001 | 0.73 |
| SEX | Female VS Male | 1 | -0.317 | 0.0433 | 53.668 | <.0001 | 0.73 |
| NHS | Nhs vs Non-Nhs | 1 | -0.5704 | 0.0797 | 51.261 | <.0001 | 0.57 |
| AGE | Young vs Middle aged | 1 | -0.3267 | 0.0596 | 30.058 | <.0001 | 0.72 |
| | Old vs Middle aged | 1 | -0.071 | 0.0678 | 1.0964 | 0.295 | 0.93 |
| DAY_WEEK | Weekday vs Weekend | 1 | 0.4667 | 0.0473 | 97.265 | <.0001 | 1.59 |

***Lighting Condition:***

Car-truck head on collisions are 33% (OR = 0.77) less likely to happen than the car-car head-on collision in a dark but lighted conditions when compared to daylight. It can be speculated that car drivers and truck drivers drive safely in vicinity of a truck and hence account for less percentage when compared to a car-car collisions. Moreover during totally dark conditions car drivers might drive cautiously in the vicinity of a truck.

***Alcohol involvement:***

It has been observed that car-truck collisions are 27% (OR = 0.73) less likely to happen than a car-car head on collision when alcohol involvement is compared to that of non-involvement. It can be speculated that drivers in vicinity of a truck tend to drive more cautiously when compared to driving in the vicinity of another car.

***Gender:***

It is found that females are 27% (OR = 0.73) less likely to be involved in a car-truck crash when compared to a male. Males generally drive more aggressively and tend to take more risk when compared to females. Some studies done by Gregersen, N.P., and Berg, H.Y., (1994) deal with effect of age gender and vehicle type in a crash and it was observed that young male drivers were found to be more aggressive and risk taking.

***Age:***

It was observed that young age drivers are 28% (OR = 0.72) less likely than middle aged drivers to be involved in a car-truck head-on collision when compared to that of car-car head on collision. An anti pattern has been observed when young aged drivers were compared to that of middle aged drivers in car-car and car-truck head-on collisions. Earlier research revealed results by Kim, K., et al., (1998), and Abdel-Aty, M., et al., (1999).

Ryan, G. A., et al., (1998) dealt with age factor and found that young age drivers had more involvement when compared to middle aged drivers.

But in the current study it was found that young age drivers were less likely to be in car-truck head-on collision when compared to the car-car head-on collision when compared to that of the middle aged drivers. One can speculate that young drivers drive more safely in the vicinity of trucks and are more cautious when they encounter a truck when compared to that of driving in the vicinity of a car. The summary of the odds ratio for various car-truck crashes obtained using the census FARS database is shown in Table 31.

Table 31: Summary of the odds ratio (OR) for car-truck crashes (FARS)

| Variable | Description | Comparison | Odds Ratio | | | | |
|---|---|---|---|---|---|---|---|
| | | | Angle | | Rear-end | Head On | |
| | | | Fault Role | Strike Role | Strike role | Crash Configuration | OR |
| **AGE** | Young vs Middle age | TC | 0.43 | - | 0.4 | C/T | 0.72 |
| | | CT | - | - | 0.78 | | |
| | Old vs Middle age | TC | 0.65 | - | - | C/T | |
| | | CT | 1.35 | - | 1.2 | | 0.93 |
| **DR_DRINK** | Drinking vs Non Drinking | TC | - | - | - | C/T | |
| | | CT | - | - | - | | 0.73 |
| **LGT_COND** | Dark vs Daylight | TC | 2.46 | 2.15 | 1.39 | C/T | |
| | | CT | - | - | 1.24 | | - |
| | Dark but lighted vs daylight | TC | 0.42 | 0.46 | 0.57 | C/T | |
| | | CT | - | - | - | | 0.77 |
| **SEX** | Male vs Female | TC | 5.46 | 4.91 | 6.48 | C/T ( Female vs male) | |
| | | CT | - | - | 1.15 | | 0.73 |
| **TRAF_FLO** | Divided vs Undivided | TC | - | - | 1.43 | C/T | |
| | | CT | - | - | 1.23 | | - |
| **NHS*WEATHER** | NHS, Adverse weather | TC | 1.84 | 1.28 | - | C/T | |
| | | CT | 2.48 | 1.38 | - | | - |

Note

1) The default case here is car-car. Truck-car (TC), car-truck(CT) are compared to car-car. Car/truck (C/T) means the crash involving car and a truck.

2) "-" implies that the variables were statistically insignificant at significant level of 0.05

# 5. CONCLUSION

Angular, rear-end, head-on and sideswipe (same directions) car-truck crashes were analyzed using multinomial logit and binary logit models and it was found that several different environmental factors (divided/undivided, lighting condition and highway character, speed related, weekday/weekend), factors related to driver (age, gender, alcohol) and speeding are significantly associated with the risk of car-truck collisions.

Based on the types of crashes the maximum likelihood estimate varied accordingly. Two different databases namely GES and FARS over the years 2000-2004 were used to prepare datasets for analysis of these car-truck crashes. While considering the GES database, angle collisions constituted the highest percentage of the two vehicle car-truck crashes (truck –truck crashes excluded due to its lower sample percentage) and was followed by rear-end then sideswipe (same direction). When FARS database was used, it was found that angle collisions constituted the highest percentage and were followed by head-on and rear-end type of crashes.

The angle, rear-end, and sideswipe (same direction) were analyzed based on multinomial logit models while the head-on collision was analyzed using a binary logit model. In this study the car-truck crash is compared to that of the base car-car crash.

Angle crashes were categorized into fault and no fault cases and each was separately analyzed. When fault angle cases using GES database were analyzed, dark lighting condition increased the likelihood of car to be at fault in a car-truck crash by 28% when compared to that of car-car crash. In dark but lighted conditions truck was 26% and car was 21% less likely to be at fault. This shows that if the lighting conditions are improved the chance of either of car and truck being at fault in an angle crash can be reduced resulting in a reduction in angle crash.

When the age was studied the young aged at fault truck drivers are 54% and young aged at fault car drivers are 13% less likely to result in a car-truck crash when compared to that of middle-aged drivers. Moreover old aged truck drivers were found to be 33% less likely to be at fault when compared to that of middle aged drivers. These results do not follow the pattern of earlier studies, which revealed that young and old aged drivers were more likely to be prone to be involved in crashes. One can speculate that young drivers wouldn't like to be in the vicinity of a truck and hence are less likely to be involved in a car-truck crash. If speeding accompanied a divided traffic way, car was 138% likely to be at fault. Involvement of alcohol at a divided traffic way makes the cars 142% and trucks 240% more likely to be at fault when compared to that of a car-car crash. Speeding and alcohol would aggravate the likelihood of a car or a truck to be involved in a crash. Cars are 194% more likely to be at fault if speeding accompanied adverse weather conditions in a crash.

FARS database was used to find the trend among the fatal car-truck angle crashes. Adverse weather condition on national highway system (NHS) was found statistically significant. Truck was 84% and car was 158% more likely to be at fault in car-truck crash. In dark lighting condition truck was 146% more likely to be at fault. In dark but lighting conditions the fatal crashes showed the similar decreasing trend, truck was 58% less likely to be at fault when compared to that of a car-car crash. Moreover young aged car drivers followed an anti pattern when compared to previous studies and they were 57% less likely to be at fault when compared to middle aged drivers. One can speculate that young drivers wouldn't like to be in the vicinity of a truck and hence would result in reducing the likelihood of involving in a car-truck crash. While old aged truck drivers are 35% more likely to be at fault when compared to middle aged drivers.

When no-fault cases of the GES database were analyzed a similar trend as in the case of fault cases was found except for few variations in the likelihood estimates. It was observed that gender was found significant and male drivers who tend to drive aggressively are 10% more likely to be striking a truck when compared to that of car striking in a car-car crash. Striking cars are 43% more likely to result in car-truck crashes in dark lighting conditions when compared to day light conditions. In dark but lighting conditions car was 34% and truck was 28% less likely to be striking. This shows that any improvement in lighting conditions would result in less striking cases of cars and trucks in angle collisions. When speeding was involved in a crash then cars were 96% more likely to be striking a truck. At a divided roadway section, in an adverse weather condition, it was found that, truck was found to be 112% and car was 86% more likely to be striking in a crash.

When no-fault cases of FARS database were used, it was found that trucks were 115% more likely to be striking in dark lighting conditions when compared to that of car-car crashes. Weather, traffic way and lighting conditions had similar effect in both the fault and no-fault cases (categorized based on striking vehicle)

In case of rear-end GES cases, it was found that cars were more likely to be striking a truck when alcohol was involved (49% more likely), in dark lighting conditions (29%) and in speed related crashes (9%), when compared to that of car-car crashes. Old aged drivers were 24% and 15% more likely to be striking which was found to be consistent with earlier studies (Abdel-Aty, M., Abdelwahab, H., 2004). A similar result was found when divided section was accompanied by adverse weather condition. Trucks were 48% more likely to be striking at divided section in an adverse weather condition.

When fatality cases were used to analyze the rear-end crashes it was found that at a divided section, truck was 43% and car was 23% more likely to be striking while in dark conditions, truck was 39% and car was 24% more likely to be striking. In dark but lighted conditions, truck was 43% less likely to be involved in striking. Young aged car drivers were 60% and young aged truck drivers 22% less likely to be striking where as old aged car drivers were 20% more likely to be striking.

In case of sideswipe (same direction), trucks are 64% and cars were 31% more likely to be striking. In dark but lighted conditions trucks were 27% less likely to be striking when compared to that of car-car crash. Old aged truck drivers were 33% more likely while young truck drivers were 17% and young truck drivers were less likely to be striking when compared to middle aged drivers. On a curve section trucks were 34% more likely to be striking a car in car-truck crash.

In case of head-on car truck collisions binary logit model was used. Dark but lighted conditions were found significant in the case of car-car collisions. It was found that car-car head-on was 30% more likely to happen when compared to that of car-truck collisions.

Alcohol involvement was found to be significant and car-car collisions were 27% more likely than a car-truck collision. It means car-car head-on collisions had higher chance of being in head-on collisions. Females were 27% less likely to be involved in car truck head-on collisions. These results were consistent with the results of earlier studies. Whereas when age was considered, unlike the results of previous studies the young aged drivers were 28% less likely to be involved when compared to middle aged drivers.

In all the car truck crashes it was found that lighting conditions, traffic way, age had similar kind of effects on these car-truck crashes. Divided section, curve section, male drivers, old aged drivers, alcohol involvement, dark lighting condition, speeding, adverse conditions increase the likelihood of car or truck in a car-truck collisions when compared to that of car-car collisions. Dark but lighted condition reduced the likelihood of involvement (at fault, striking) of car or truck in car-truck collision when compared to that of car-car collision.

Based on the above results it is found that divided sections need to be improved. Providing wider turning radii would help the cars and trucks make safe turning movements. This can reduce the chance of angular collisions. The sight distance also might play an important role at intersections as well which might help in reducing car-truck angle and rear-end crashes. A strict check on the involvement of alcohol can act as a remedy to reduce the chance of either a car or truck to be involved in a car truck crash. Cautious driving in adverse weather conditions can also help in lowering the car-truck crashes. Improving the lighting conditions can as well make the car-truck collisions follow a decreasing trend. Installing street lights and improving the lighting conditions associated with the trucks might improve the lighting conditions. Providing better lighting conditions at intersections would help in reduce in crashes at intersections.

It was observed that speeding in adverse weather conditions increases the likelihood of a car-truck crash. A better way to tackle this would be to reduce the speed limits in adverse weather conditions. This can be done by installing variable message signs displaying the varied speed limits in adverse weather conditions.

In field it was observed that a car ran into a truck that was maneuvering a turn in spite of observing it at a safe distance. This study revealed that just analyzing various variables of crash databases wouldn’t be sufficient enough to understand such a scenario. Sophisticated tools like the driving simulator and more field data or other surrogate measures are required for better understanding of such scenarios.

# APPENDIX: SAMPLE SAS CODING

**Coding for one year of GES database (2000)**

```
data ges00.all2veh(keep = casenum VEH_INVL);
set ges00.accident;
where VEH_INVL=2 ;
run;
proc sort data = ges00.all2veh;
by casenum;
run;
proc sort data = ges00.vehicle;
by casenum;
run;
data ges00.veh2;
   merge ges00.all2veh ges00.vehicle;
   by  casenum;
   if VEH_INVL=. then delete;
run;
data ges00.veh2data;
set ges00.veh2;
i=mod(_N_,2);
run;
data ges00.D1;
set ges00.veh2data;
where i=0;
run;
data ges00.D2;
set ges00.veh2data;
where i=1;
run;
proc sql;
create table ges00.ALLCT as
select d1.casenum  from ges00.d1,ges00.d2
where d1.casenum=d2.casenum and (d1.Body_typ <20 or (d1.body_typ>59 and
d1.body_typ<80) )
and (d2.Body_typ <20 or (d2.body_typ>59 and d2.body_typ<80) );
quit;

proc sql;
create table ges00.CCcases as
select d1.casenum  from ges00.d1,ges00.d2
where d1.casenum=d2.casenum and (d1.Body_typ <20 and d2.Body_typ<20);
quit;
proc sql;
create table ges00.CTcases as
select d1.casenum  from ges00.d1,ges00.d2
where d1.casenum=d2.casenum and ((d1.Body_typ <20 and (d2.body_typ>59 and
d2.body_typ<80))
or (d2.Body_typ <20 and (d1.body_typ>59 and d1.body_typ<80)));
quit;
proc sql;
create table ges00.ttcases as
select d1.casenum  from ges00.d1,ges00.d2
where d1.casenum=d2.casenum
and ((d1.body_typ>59 and d1.body_typ<80)and (d2.body_typ>59 and
d2.body_typ<80));
```

```
quit;

data ges00.cccases;
set ges00.cccases;
gen=1;
run;
data ges00.ctcases;
set ges00.ctcases;
gen=1;
run;
data ges00.ttcases;
set ges00.ttcases;
gen=1;
run;
/* merging Car truck cases with the accident file CTAC=car-Truck accident
set*/
data ges00.CT_AC;
 merge ges00.ctcases ges00.accident;
   by  casenum;
    if gen=. then delete;
run;
data ges00.CC_AC;
 merge ges00.cccases ges00.accident;
   by  casenum;
    if gen=. then delete;
run;
data ges00.TT_AC;
 merge ges00.ttcases ges00.accident;
   by  casenum;
    if gen=. then delete;
run;
/* Frequencies of various accidents*/
proc freq data=ges00.CC_AC;
tables Man_Col;
run;
proc freq data=ges00.CT_AC;
tables Man_Col TRAF_WAY PROFILE ALIGN REL_RWY NUM_LAN REL_JCT LGHT_CON
ALCOHOL SPD_LIM MAX_SEV  NUM_INJ   ;
run;
proc freq data=ges00.TT_AC;
tables Man_Col;
run;

/* angular collisions car-car, car-truck and truck-truck*/
proc sql;
create table ges00.CC_ANG as
select accident.*  from ges00.cccases ,ges00.accident
where cccases.casenum=accident.casenum and (accident.MAN_COL=4);
quit;
proc sql;
create table ges00.CT_ANG as
select accident.*  from ges00.ctcases ,ges00.accident
where ctcases.casenum=accident.casenum and (accident.MAN_COL=4);
quit;
```

```
proc sql;
create table ges00.TT_ANG as
select accident.*  from ges00.ttcases ,ges00.accident
where ttcases.casenum=accident.casenum and (accident.MAN_COL=4);
quit;

/*Frequencies car truck collisions-angular*/
proc freq data=ges00.CT_ANG;
tables Man_Col TRAF_WAY PROFILE ALIGN REL_RWY NUM_LAN REL_JCT LGHT_CON
ALCOHOL SPD_LIM MAX_SEV  NUM_INJ TRAF_CON  ;
run;

/*Frequencies car car collisions-angular*/
proc freq data=ges00.CC_ANG;
tables Man_Col TRAF_WAY PROFILE ALIGN REL_RWY NUM_LAN REL_JCT LGHT_CON
ALCOHOL SPD_LIM MAX_SEV  NUM_INJ  TRAF_CON ;
run;

/*Frequencies car car collisions*/
proc freq data=ges00.CC_AC;
tables Man_Col TRAF_WAY PROFILE ALIGN REL_RWY NUM_LAN REL_JCT LGHT_CON
ALCOHOL SPD_LIM MAX_SEV  NUM_INJ  TRAF_CON ;
run;

/* Truck violations in car-truck collisions*/
proc sql;
create table ges00.VIO_TRK as
select d1.* from ges00.ct_ang, ges00.d1, ges00.d2
where (d1.casenum = ct_ang.casenum and d1.casenum=d2.casenum)
and ((d1.body_typ<20 and d1.VIOLATN=0 and d2.VIOLATN>0 and d2.VIOLATN<8)
or ((d1.body_typ>59 and d1.body_typ<80) and (d1.violatn>0 and d1.violatn<8)
and (d2.violatn=0)));
quit;
/* Car violations in car -truck collisions*/
proc sql;
create table ges00.VIO_CAR as
select d1.* from ges00.ct_ang, ges00.d1, ges00.d2
where (d1.casenum = ct_ang.casenum and d1.casenum=d2.casenum)
and ((d1.body_typ<20 and (d1.VIOLATN>0 and d1.VIOLATN<8) and d2.VIOLATN=0)
or ((d1.body_typ>59 and d1.body_typ<80) and (d1.violatn=0) and (d2.violatn>0
and d2.violatn<8)));
quit;
/* None violations in car-truck collisions*/

proc sql;
create table ges00.VIO_NONE as
select d1.* from ges00.ct_ang, ges00.d1, ges00.d2
where (d1.casenum = ct_ang.casenum and d1.casenum=d2.casenum)
and d1.violatn=0 and d2.violatn=0;
quit;

/* Both violations (name of this data set from vio_bothct to vio_boct)*/

proc sql;
create table ges00.VIO_BOCT as
```

```
select d1.* from ges00.ct_ang, ges00.d1, ges00.d2
where (d1.casenum = ct_ang.casenum and d1.casenum=d2.casenum)
and (d1.violatn>0 and d1.violatn<8) and (d2.violatn>0 and d2.violatn<8);
quit;

/* check for the first event for cases with none at fault in car-truck
collisions*/
proc sql;
create table ges00.VIOE1 as
select accident.* from ges00.VIO_NONE, ges00.accident
where VIO_NONE.casenum=accident.casenum;
quit;
proc freq data=ges00.vioe1;
table EVENT1 REL_JCT REL_RWY TRAF_CON REL_JCT*TRAF_CON;
run;
/* Car- car fault cases (name of the dataset has been changed from CFault_ang
to CF_ANG)*/

proc sql;
create table ges00.CF_ang as
select d1.* from ges00.cc_ang, ges00.d1, ges00.d2
where (d1.casenum = cc_ang.casenum and d1.casenum=d2.casenum)
and (( d1.Violatn=0 and d2.violatn>0 and d2.violatn<8)or (d2.violatn=0 and
d1.violatn > 0 and d1.violatn < 8));
quit;

/* frequencies for various datasets*/
proc freq data=ges00.CF_ang;
table VIOLATN;
run;
proc freq data=ges00.ct_ac;
tables Man_col*Traf_way;
run;
proc freq data=ges00.cc_ac;
tables Man_col*Traf_way;
run;
/*
datasets
VIO_TRK- truck violation in CAR_TRUCK CRASHES angular
VIO_CAR- CAR violation in CAR_TRUCK CRASHES angular
VIO_NONE-NONE violation in CAR_TRUCK CRASHES angular
VIO_BOTH-BOTH violation in CAR_TRUCK CRASHES angular
CF_ang- car fault in  the car car angular crashes*/

/* CLUBBING ALL THE ACCIDENT, VEHICLE, PERSON FILES INTO ONE DATA SET*/
/* Data Set for the truck violations car truck collisions*/
/* STEP1: clubbing all the accident and  vehicle  files into one data set*/
/*NOTE: the name of the dataset has been changed from VIO_TRK_ACC_VEH to
VTAV*/

proc sql;
create table ges00.VTAV as
select accident.*, vehicle.* from ges00.accident, ges00.vehicle,ges00.Vio_Trk
```

```
where (vio_trk.casenum=accident.casenum) and
(vio_trk.casenum=vehicle.casenum) and (vehicle.violatn > 0 and
vehicle.violatn < 8);
quit;

/* STEP2: Clubbing VTAV with the person file*/
/* Note The dataset name has been changed from VIO_TRK_ALL to VTALL*/
proc sql;
create table ges00.VTALL as
select VTAV.*, person.* from ges00.VTAV, ges00.person
where VTAV.casenum=person.casenum and VTAV.vehno=person.vehno and
person.per_type=1;
quit;

/* Final dataset for the truck violation in car truck collisions is VTALL*/

/* Data Set for the CAR violations car truck collisions*/
/* STEP1: Clubbing all the accident and vehicle files into one data set*/
/*NOTE: The name of the dataset has been changed from VIO_CAR_ACC_VEH to
VCAV*/

proc sql;
create table ges00.VCAV as
select accident.*, vehicle.* from ges00.accident, ges00.vehicle,ges00.Vio_CAR
where (vio_car.casenum=accident.casenum) and
(vio_car.casenum=vehicle.casenum) and (vehicle.violatn > 0 and
vehicle.violatn < 8);
quit;
/* STEP2: Clubbing VCAV with the person file*/
/* NOTE: The name of the dataset has been changed from VIO_CAR_ALL to VCALL*/
proc sql;
create table ges00.VCALL as
select VCAV.*, person.* from ges00.VCAV, ges00.person
where VCAV.casenum=person.casenum and VCAV.vehno=person.vehno and
person.per_type=1;
quit;

/* Final data set for the car violations in car truck crashes is VCALL*/

/* Data Set for the CAR violations CAR_CAR collisions*/
/* STEP1: clubbing all the accident and  vehicle  files into one data set*/
/* NOTE : The name of the dataset has been changed from Vio_CAR_CC to
VCARCC*/
proc sql;
create table ges00.VCCC as
select accident.*, vehicle.* from ges00.accident, ges00.vehicle,ges00.CF_ang
where (CF_ang.casenum=accident.casenum) and (CF_ang.casenum=vehicle.casenum)
and (vehicle.violatn > 0 and vehicle.violatn < 8);
quit;
/* STEP2: Clubbing VCCC with the person file*/
/* The dataset name has been changed from VIO_CAR_CC_ALL to VCCCALL*/
proc sql;
create table ges00.VCCCALL as
select VCCC.*, person.* from ges00.VCCC, ges00.person
```

```
where VCCC.casenum=person.casenum and VCCC.vehno=person.vehno and
person.per_type=1;
quit;

/* Final data set for the car violations in car truck crashes is VCCCALL*/

/*SO final DATA SETS
VTALL- Truck fault in CT (fault=1)
VCALL-car fault in CT (fault=2)
VCCCALL-car fault in CC (fault=0)*/

/* Setting an fault variable for various faults*/

data ges00.VCCCALL;
set ges00.VCCCALL;
fault=0;
run;
data ges00.VTALL;
set ges00.VTALL;
fault=1;
run;
data ges00.VCALL;
set ges00.VCALL;
fault=2;
run;
/* Final Data set including the fault variable*/

data ges00.FIN2000;
set ges00.VTALL ges00.VCALL ges00.VCCCALL;
run;

/* Final Data set is Fin2000*/

proc sort data=ges00.fin2000;
by fault;
run;
proc freq data=ges00.fin2000;
table fault;
run;
proc contents data=ges00.fin2000;
run;

proc contents data=ges00.fin2001;
run;
/* end of the dataset formation*/
```

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