CHARACTERISTICS AND CONTRIBUTORY CAUSES ASSOCIATED WITH FATAL LARGE TRUCK CRASHES

by

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Abstract

One-ninth of all traffic fatalities in the United States (U.S.) in the past five years have involved large trucks, although large trucks contributed to only 3% of registered vehicles and 7% of vehicle miles travelled. This crash overrepresentation indicates that truck crashes in general tend to be more severe than other crashes, though they constitute a smaller portion of vehicles on the road. To study this issue, fatal crash data from the Fatality Analysis Reporting System (FARS) was used to analyze characteristics and factors contributing to truck-involved crashes. Driver, vehicle, and crash-related contributory causes were identified, and as an extension, the likelihood of occurrence of these contributory causes in truck-involved crashes (with respect to non-truck crashes) was evaluated using the Bayesian Statistical approach. Likelihood ratios indicated that factors such as stopped or unattended vehicles and improper following have greater probability of occurrence in truck crashes than in non-truck crashes. Also, Multinomial Logistic Regression was used to model the type of fatal crash (truck vs. non-truck) to compare the relative significance of various factors in truck and non-truck crashes. Factors such as cellular phone usage, failure to yield right of way, inattentiveness, and failure to obey traffic rules also have a greater probability in fatal truck crashes. Among several other factors, inadequate warning signs and poor shoulder conditions were also found to have greater predominance in contributing to truck crashes than non-truck crashes. By addressing these factors through the implementation of appropriate remedial measures, the truck safety experience could be improved, which would eventually help in improving overall safety of the transportation system.

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I would like to convey my heartfelt thanks to my advisor Dr.Sunanda Dissanayake for providing me the oppurtunity to carry out this research study, and for her guidance and continous support throughout the course of my study which lead to great success in this research as well as my academic career.

Also, I would like to thank all my colleagues, friends, and family members for their continuous encouragement and support.

Dedication

I would like to dedicate my thesis to my parents, B.A.Naveen Kumar and B.Indira, who gave me tremendous support to make everything in my life a success. Also, I would like to dedicate this to my teachers from the school, and the university, who gave me the courage and support to rise in my academic career so far.

CHAPTER 1 - INTRODUCTION

1.1 Background

Of the 41,059 fatalities related to motor vehicle crashes in 2007, 12 % or 4,808 deaths involved large trucks. Seventeen percent of those fatalities involving the large trucks were the occupants of said trucks. Though large trucks contribute to only 8% of vehicles involved in fatal crashes over the last five years, their impact in terms of severity appears to be a major concern.

Large trucks (of gross body weight greater than 10,000 pounds) have different performance characteristics than smaller vehicles. The large size of the vehicles makes it difficult for drivers to maneuver smoothly on roadways. Drivers might face vehicle control challenges while traversing large trucks on interstate or state highways at high speeds or at intersections while making turns. Also, the element of blind spots, as shown in Figure 1.1, makes it even more challenging for the truck driver and surrounding vehicle drivers to avoid the heavy crash risk.

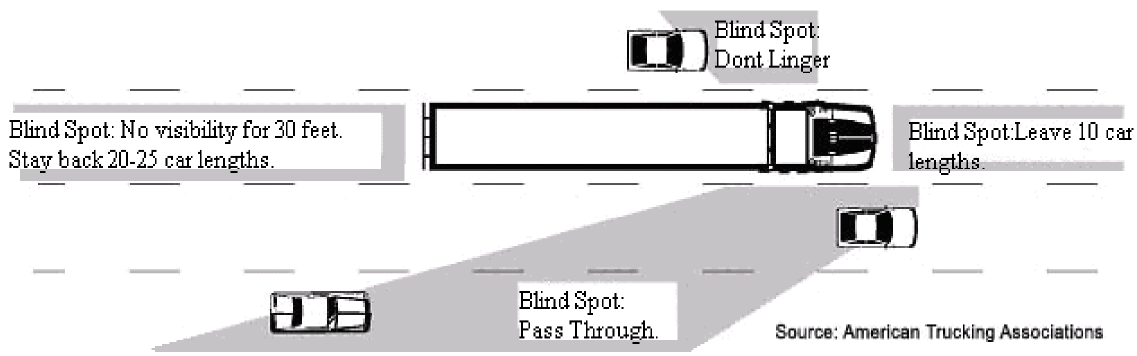

Figure 1.1 No a Zones or Blind Spots around Large Truck

When considering the past 10 years of data, it can be observed that frequency of fatal truck crashes varies between 4400 and 4800 crashes per year (Figure 1.2). Each of these crashes results in major destruction of human life and property, which is many times worse than other passenger car crashes in most cases. As it is evident that frequency of these crashes is remaining consistent between the range of 4500 to 5000 crashes per year, it becomes crucial to identify methods to mitigate this issue.

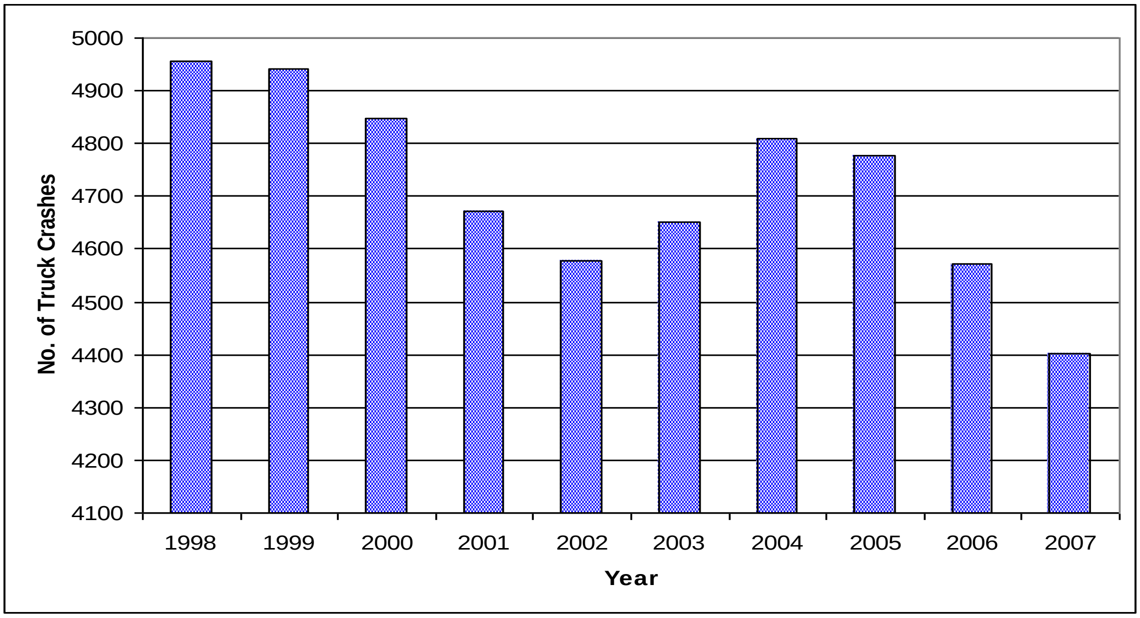

Figure 1.2 Number of Fatal Large Truck Crashes from 1998-2007

Trucks, when involved in crashes, can rollover or jackknife at high speeds and result in exponentially increasing the severity of the crash. Many factors such as roadway geometry, environmental conditions, driver mental and physical conditions, and vehicle conditions affect the possibility of occurrence of the crash.

Research has also shown (Figure 1.3) that large trucks cause more fatalities to other (non-truck) vehicle occupants than those in trucks. On average, 84% of fatalities related to large truck crashes in the country are not occupants of trucks. This reinforces the threat large trucks impose on other motor vehicles, pedestrians, and pedal cyclists.

Even though the number of fatal truck crashes has generally been decreasing with some ups and downs over the past 10 years, the amount of truck travel is increasing, which in turn requires continued attention in order to find ways of reducing truck crash risk. The Federal Motor Carrier Safety Administration (FMCSA) has set a goal of a 50% reduction in commercial truck-related fatalities by the year 2010 *(1)*.

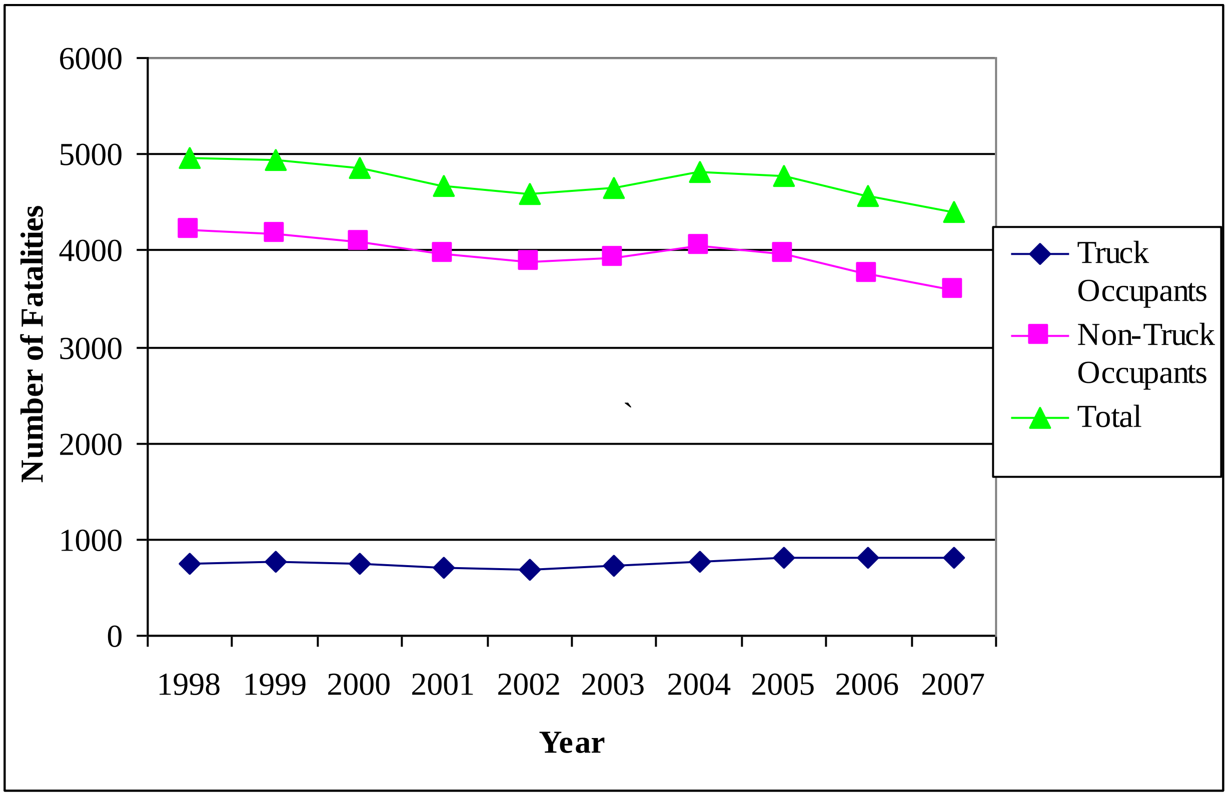

Figure 1.3 Number of Vehicle Occupants Killed in Large Truck Crashes

The FMCSA wants to reduce the number and severity of large truck- and bus- involved crashes through more commercial motor vehicle and operator inspections and compliance reviews; stronger enforcement measures against violators; expedited completion of rulemaking proceedings; scientifically sound research; and effective Commercial Driving License (CDL) testing, recordkeeping, and sanctions. All these measures can be enhanced by analyzing large truck crashes. Accordingly, it is important for the safety community to identify characteristics related to large truck-involved fatal crashes.

1.2 Objectives

Truck crashes can be mitigated by identifying characteristics and contributory causes involved and mitigating them with suitable countermeasures. The data provided by the Fatality Analysis Reporting System data was used to the maximum extent to conduct this analysis. The primary objectives of this study are as follows.

- To analyze and evaluate various crash characteristics that prevailed at the time of occurrence of fatal truck crashes.
- To identify various crashes, vehicle, and driver related contributory causes prevalent to fatal truck crashes.
- To evaluate relative significance of various contributory causes in fatal truck crashes as compared to fatal non-truck crashes through the calculation of likelihood ratios.
- To model the type of fatal crash (truck vs. non-truck) in terms of crash characteristics and other factors to compare the relative significance of these factors in truck and non-truck crashes.

1.3 Outline of the Report

This report consists of five chapters, covering the background and objectives in the first. The second chapter consists of a review of prior research related to the study area. In the third chapter, methodologies used in the analysis are presented along with descriptions of data used in the study. The fourth chapter covers the results from characteristic study and the comparative study done between truck and non-truck crashes using statistical analysis, and a detailed discussion is presented. In the final chapter summary and conclusions are presented and by addressing these issues the overall truck crash rate can be reduced, which can help in improving overall safety of the transportation system.

CHAPTER 2 - LITERATURE REVIEW

Fatal truck crash-related research studies have an extended history in addressing different safety aspects using a variety of databases and surveys. Past researchers have used various statistical modeling techniques to predict or explain the nature of truck crashes, and many study results are listed under this area. Furthermore, different types of crashes have been examined by these researchers, to identify more specific factors related to selected states. In this chapter, an elaborate discussion of past studies are presented under the following subsections: truck crash characteristics, rates and trends, contributory factors involved, crash types and related maneuvering difficulties, intersection-related crashes, human factors, risk to self and risk to others, countermeasure evaluations, medication and risk of injuries, decision to stop driving, vehicle design, and statistical methodologies.

2.1 Characteristic Comparisons, Rates, and Trends

Blower *(2)* conducted a study by collecting detailed data on the causes of truck crashes in the U.S and developed suitable countermeasures that would be effective in reducing the number and severity of the crashes. The Large Truck Crash Causation Study (LTCCS), used in this study, was developed by the Federal Motor Carrier Safety Administration (FMCSA) in co-operation with the National Highway Traffic Safety Administration (NHTSA). The study took three years and involved investigation teams at 24 locations around the country. Each crash was investigated in the field and a detailed analysis was conducted by experienced crash investigators.

The second study was conducted by the University of Michigan Transportation Research Institute's (UMTRI) Trucks Involved in Fatal Accidents (TIFA) project *(3)*. In contrast to the LTCCS, a telephone survey was conducted on fatal truck crashes in the country. Also, police reports were acquired for all crashes as a part of the survey. The variables coded in each study *(2, 3)* were compared by developing an algorithm to analyze the most significant factors in truck crashes and their accuracy. While studying both sets of data and referring to the "parent" FARS file, some cases could not be matched when defined as per the search protocol. As a result, the LTCCS proved to be the most elaborate database in truck crash reporting.

Using the LTCCS database, Krishnaswami et al. *(4)* analyzed the causes of heavy truck aggressiveness in two-vehicle, truck/light vehicle crashes and also derived detailed models which would help propose the required truck, structural countermeasures to mitigate collision severity. In this study, three years of data from 1996 to 1998 was used from FARS, TIFA, and GES databases. Collision and injury models were constructed using lumped parameter models in a two-stage manner. The first stage was a physical representation of the collision process using collision variables, acceleration levels, total velocity change, and crush levels experienced by the vehicle occupants as inputs. In the second stage, the previous outputs were used in the injury models to predict occupant injury outcomes. From results of the collision and injury models, it was consistently shown that by reducing peak vehicle deceleration, injury risk can be decreased. Another important observation from the simulations was that for a particular deceleration level, almost constant injury level criterion could be seen irrespective of the change of velocity.

As an extension of his earlier work Blower *(5)* identified the issues that contribute most to commercial motor vehicle crashes, fatalities, and injuries in the state of Michigan. This was done by conducting a detailed analysis of the available data, which included the Michigan vehicle crash files, trucks involved in fatal accidents file, and Motor Carrier Management Information System Inspection and Carrier files, for the period 2001-2005. From the analysis, it was seen that angle, rear-end, and head-on crashes appeared to be the most predominant crash patterns among commercial motor vehicles. Also it was observed that in almost all cases, brake defects were associated with fatal rear-end, head-on, and angle collisions, and lighting defects were associated with fatal rear-end crashes. Hence it was concluded that brake and lighting system violations were the most frequent causations. To address these issues, countermeasures such as preventive maintenance programs, training, consultation, and public information and education programs were proposed.

Another report by the United States Government Accountability Office to the Federal Motor Carrier Safety Administration (FMCSA) addressed the importance of reducing the number of commercial vehicle crashes and identifying carriers that pose a high risk for crashes *(1)*. Presently FMCSA decides which carriers to inspect primarily by using an automated data-driven analysis system called SafeStat. This system uses data on crashes, vehicle and driver violations, and other information to develop a priority list of high-risk-posing carriers. Though this has proved to be highly useful compared to the conventional random inspection of carriers, a recent study suggested a better and a more accurate way of analysis. For this purpose, a number of regression methods have been developed using crash data from the Motor Carrier Management Information System (MCMIS) for the year 2004. The accident, driver, vehicle, and safety management sections have been taken as independent variables to predict crash risks. Results were compared to those obtained from the SafeStat system and were found to be 9% more accurate.

Daniel et al. *(6)* proposed an accident prediction model which had been built for analyzing factors effecting truck crashes on roadways with intersections. Truck crash data for this project was developed by including all crashes in 1998 and 1999, in the state of New Jersey, from police accident report files. This database was used to conduct an initial analysis of truck crashes at signalized intersections along Route 1 in New Jersey. Poisson regression and negative binomial models were applied using LIMPID software to obtain the analysis results. Variables considered in modeling the crashes were segment length, AADT, type of intersection, degree of curve for horizontal curves, length of horizontal curve; crest curve grade rate, length of vertical curve, posted speed on main road, number of interchanges within the segment, and pavement width. From the analysis, it was concluded that signalized intersections have a significant impact on truck crash rate.

Vap and Sun *(7)* analyzed truck and passenger car interactions for the state of Missouri on its urban and rural freeways. The urban data was collected from the Portable Overhead Surveillance Trailers (POSTS) and the rural data was obtained from digital videos set up at the desired locations. Apart from these, the MoDOT Transportation Management System (TMS) was also used. Using this data, an analysis of trucks-at-fault crash rates versus passenger vehicles-at-fault crash rates, or RSEC ratios, were estimated. These results showed that on urban freeways the percentage of trucks-at-fault ratio was high. By contrast, the rural data in general showed that truck crashes were not disproportionate to the crash rates of passenger vehicles. Hence, it was concluded that a greater safety concern coefficient value developed by their model was attributed to truck-passenger vehicle interactions on urban freeways.

Apart from these studies, which particularly focused on truck-involved crashes, many more reports on general fatal crash data were reviewed *(8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18)* to acquire a larger idea of what these crashes have in common.

2.2 Truck Crash Study on LTCCS, TIFA, and GES

Blower *(3)* explained the significance of mirror-relevant crash types which occur due to a driver's restricted direct field of view in trucks. Mirror relevant crashes are those in which the truck driver would have needed to use mirrors to maneuver safely. For this purpose, a study has been conducted to evaluate the types of crashes which could have occurred due to insufficient field of view for drivers. These crash types include lane change/merge (LCM) left, LCM right, and left and right turn with conflict vehicles approaching from rear. The observational fatal data for this purpose was taken from the Large Truck Causation Study (LTCCS) and the Trucks Involved in Fatal Accidents (TIFA) study compiled by the University of Michigan Transportation Research Institute (UMTRI). Injury and property damage data files were taken from the National Automotive Sampling System, General Estimates System (NASS GES), which is a nationally representative sample of police-reported crashes compiled by NHTSA. From the results, it was summarized that mirror-relevant crashes account for almost 20% of truck crash involvements and serious measures need to be taken to minimize these by providing better facilities that give drivers a broader view of their surroundings.

The second study was undertaken by the University of Michigan Transportation Research Institute's (UMTRI) *(2)* Trucks Involved in Fatal Accidents (TIFA) project. In contrast to the LTCCS, a telephone survey was conducted on fatal truck crashes in the country. Also, police reports were acquired for all crashes as a part of the survey. Another project *(5)* was conducted with an objective to identify the issues that contributed most to commercial motor vehicle crashes, fatalities, and injuries in the state of Michigan. This was done by conducting a detailed analysis of the available data, which included the Michigan vehicle crash files, Trucks Involved in Fatal Accidents file, and Motor Carrier Management Information System Inspection and Carrier Files, for the period 2001-2005. Results showed that fatigue-related CMV crashes tended to be severe single-vehicle crashes in which the CMV ran off the road, or rear-end crashes. Most CMV fatigued driver crashes occurred at night, between midnight and 6 a.m. on Interstate roads, and involved tractor-semitrailers or doubles operated by interstate carriers. Another study *(4)* analyzed the causes of heavy truck aggressiveness in two-vehicle truck/light vehicle crashes and also derived detailed models which will help propose the required truck structural countermeasures to mitigate collision severity. Three years of data from 1996 to 1998 were used from FARS, TIFA, and GES for this project.

Another report *(19)* was submitted to the Congress on the Large Truck Crash Causation Study conducted by the FMCSA and NHTSA. This study has a unique database which not only covers the descriptive data of the crashes occurring but also incorporates pre-crash factors such as driver fatigue and distraction, vehicle condition, weather, and roadway condition. Unlike FARS (which only deals with fatal crashes) and NHTSA's GES (which considers only probability-based sample data), the LTCCS focuses on a larger spectrum of variables (approximately 1,000 per crash) in crashes. Coding of the events surrounding each crash is categorized as "critical event," "critical reason" for the critical event, and "associated factors" present. This study involved three crash severity levels: fatal, capacitating injury, and non-incapacitating injury. The primary protocol for the truck body type is the same as in FARS. The data has been categorized into 12 different crash types. From the analysis, it was concluded that rear-end crash type is one of the most predominant cases observed among truck crashes. The LTCCS database has been made electronically available to the public since 2006. However, this data doesn't contain information from interviews. The full database, inclusive of interview data, will be made available to researchers, private groups, universities, etc. upon request.

Blower et al. *(20)* conducted yet another study by applying the definition NHTSA uses to define trucks, for the TIFA project with one exception. Trucks in the TIFA file have all the trucks with a GVWR over 10,000 pounds, but emergency vehicles such as ambulances or fire trucks are excluded. As will be seen below, exclusion of fire trucks and ambulances accounts for only a small part of the difference between FARS and TIFA. Other than the exclusion of emergency vehicles, both FARS and TIFA count the same types of vehicles as trucks. The comparison of data files is based on the 1999 data years for both FARS and TIFA. Using NHTSA'a definition of large trucks in FARS, the 1999 FARS file identified 4,898 trucks involved in fatal accidents in 1999. The TIFA file for that year has 5,233 trucks, a difference of 335 trucks or about 6.8% more trucks in the TIFA file than FARS. The difference of 335 is the result of 40 cases that were counted in FARS as trucks but do not qualify as trucks in the TIFA file, and 375 cases identified as trucks in TIFA but which were classified as some other type of vehicle in the FARS file

2.3 Contributory Causes for Large Truck Crashes

Rau *(21)* conducted a study about drowsy driver detection and the effects of employing a warning system for commercial vehicle drivers. The research was conducted since 1996, by NHTSA and its partners, in order to quantify the loss of alertness among commercial vehicle drivers. By experimentation, it was concluded that a valid measure of loss of alertness among drivers can be made by the percentage of eyelid closure over the pupil over time (Perclos). Drowsiness was consistently identified in trucking summits as the number one safety concern of commercial vehicle drivers. The Perclos index is a measure of latency between a visual stimulus and a motor response, which is collected using the Psychomotor Vigilance Task (PVT). Drowsiness is measured using a three-minute running average of slow eyelid closures, as assessed by the Drowsy Driver Warning System (DDWS) during nighttime driving. It depends on the capability of the camera to detect infrared light reflected back to the source at the camera from the driver's retina. Also, the measures of performance at braking, closing, lane changing, lane keeping, and speed maintenance were observed. The first objective was to find drowsiness-level distributions and the differences between them with and without the DDWS. The second objective was to see the variations in drowsiness with a number of independent factors like age, nights of sleep, etc. From the experimental analysis, it was concluded that further understanding was needed about highway safety benefits, fleet acceptance, operational utility, and fatigue management practices so that the fatigue crash problems can be minimized.

Garber et al. *(22)* compared the safety effects of a uniform speed limit (USL) for all vehicles as opposed to a differential speed limit (DSL) for cars and heavy trucks. Crash and volume data were synthesized from 17 states to obtain the sample of interstate highways. A modified empirical Bayes framework was used to evaluate crash frequency changes with speed limit changes. The basic approach of the modified Bayes approach was conducted in four steps. Initially, the number of crashes at each site within a certain state as a function of related independent variables (in this case traffic volume and segment length) was created. Then the number of expected after-period crashes at each site was determined and their summation 'π' was calculated. Then the sum of the actual crashes that did occur at each site was computed as 'λ'. Next the ratio of total actual crashes to the total expected after-period crashes was determined and checked to see if the ratio of effectiveness 'θ' was significantly different from unity by using appropriate confidence intervals. From the experimental analysis, it was concluded that the modified Bayes approach showed no consistent safety impacts attributable to differential or uniform speed limit policies for rural interstate highways. In most cases, it was found that actual number of crashes for the after period was larger than the predicted expected after-period crashes

Daniel et al. *(23)* described the use of Poisson regression and negative binomial accident prediction models for truck accidents on an urban arterial with heavy truck volumes and a large number of signalized intersections. The research had a twofold objective. First was to identify the factors that impact the occurrence of truck crashes on urban arterials with signalized intersections. This was done by developing an accident prediction model. The second objective was to determine an approach which would account for signalized intersections in one unified prediction model. For these objectives, a prediction model was developed for truck crashes on a truck route in New Jersey on Route 1. A truck accident database for the state of New Jersey from 1998-2000 was collected for the study. Two models were developed for the selected roadway: unified (including both intersection and non-intersection locations) and separate models. For both models, the goodness of fit between the expected number of accidents and explanatory variables was evaluated based on both Pearson $R_p^2$and deviation R_D^2 values. It was concluded from the model that horizontal and vertical curvature were critical factors in determining the safety of the roadway. A reduced model derived from the above two models proved to be more efficient in both types of roadway segments.

Dick et al. *(24)* presented a comprehensive evaluation of the federal interstate commercial driving hours-of-services (HOS) rules implemented in January 2004. The rules that had been largely unchanged for more than 65 years were revised by the Federal Motor Carrier Administration (FMCSA). The new HOS rules included a number of prominent changes designed primarily to promote greater daily sleep and to encourage more regular daily work-rest cycles. Some of the changes included a daily minimum off-duty requirement of 10 hours, a maximum 11 hours of driving prior to going off duty, and also, a maximum of 14 hours tour-of-duty (beyond which driving is not permitted) in a 24 hour period, etc. Features of the old rule that did not support or promote driver alertness were considered in this amended version. The results were based on the opinions expressed by a diverse people and there was a consensus, positive view of the new rules. They also enabled the drivers to regularize their work timings more optimally.

Kostyniuk *(25)* analyzed two-vehicle crashes in the 1995–98 Fatality Analysis Reporting System (FARS) database to compare car-car crashes with car-truck crashes. A limitation of the study is that it did not address nonfatal crashes, single-vehicle crashes, or crashes involving more than two vehicles. This is important to keep in mind because fatal and injury crashes are not always similar in their causes or in the numbers of people they affect. The research was conducted in three stages. The first stage sought to identify driving maneuvers or actions of cars and large trucks that have a higher chance of resulting in fatal car-truck collisions than fatal collisions with a similar vehicle. The second stage involved discerning patterns associated with these driving actions through a detailed examination of actual crash reports. The third stage involved exploring ways that the risks associated with the identified driving actions can be effectively communicated to motorists, paying special attention to the fit between study findings and potential instructional approaches.

2.4 Drowsy Driver Effect and Hours of Service

Khattak and Targa *(26)* explored the elements of "injury severity" and "total harm" in cases of truck-involved work zone crashes. Their characteristics were empirically compared to those of non truck-involved collisions. For this study, a unique dataset from the Highway Safety Information System (HSIS), with additional variables coded from narratives in police reports, was used. Also, the year 2000 HSIS data for the state of North Carolina was used to develop the work-zone-related crashes. Using this data, ordered probit models were estimated for the most seriously injured occupant in the crash, and linear regression models for "total harm" in the crash were estimated. The linear model contained the variables of frequency and severity of injuries by transforming them into numerical values. From the results, certain situations which seemed to enhance the probability of work-zone-truck collisions were observed. The case where the road was completely closed with a detour in the opposite direction seemed to be the most predominant case for truck crashes in these areas. Also, two-way undivided roads and places where the traffic moved out of normal paths were other scenarios which seem to enhance the probability of a crash.

Rau *(21)* observed that drowsiness was consistently identified in trucking summits as the number one safety concern of commercial vehicle drivers. The Perclos index is a measure of latency between a visual stimulus and a motor response which was collected using the

Psychomotor Vigilance Task (PVT). Drowsiness was measured using a three-minute running average of slow eyelid closures, as assessed by the Drowsy Driver Warning System (DDWS) during nighttime driving. It depended on the capability of the camera to detect infrared light reflected back to the source at the camera from the driver's retina. By this, the measures of performance at braking, closing, lane changing, lane keeping, and speed maintenance were observed.

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2.5 Speed Limit, Rear-End/Angle Collisions, and Roadway Parameters

Dabbour et al. *(28)* analyzed radius requirements for reverse horizontal curves so as to attain better vehicle stability for trucks travelling on freeway interchanges. For this purpose, several models developed on vehicle stability were studied and finally, the most advanced extension of these models, which is a computer program called, "vehicle dynamic models roadway analysis and design" (VDM RoAD), was used. This program has a built-in vehicle library that contains most of the AASHTO-designed trucks. Two different alignment combinations were used: one with the effect of introducing reverse curvature and the other by introducing vertical alignment in the reverse curves. Geometric alignment data of the curves were the data input for the program. By using the different optimum models suggested by the program, it was analyzed that an increase is required in the minimum radius of horizontal curves to compensate for both effects of reverse curvature and vertical alignment. This change was shown to reduce skidding and rollover accidents on highways.

Miaou and Lum *(29)* illustrated ways in which the Poisson regression model can be used to evaluate the effects of highway geometric design on truck accident involvement rates. The model applied in this study can also be applied to any roadway class, vehicle configuration, and accident severity type of interest. From the model, an estimate for reduction in truck accident involvement caused by improvement in geometric design elements was also calculated. The percentage of reduction for the model could be specified to estimate the required variations in the geometric properties. For this analysis, the Highway Safety Information System was used to gather data from Utah from 1985 to 1989.

Aty and Abdelwahab *(30)* presented an analysis of the effect of the geometric incompatibility of light truck vehicles(LTV) on driver's visibility of other passenger cars involved in rear-end crashes. The objective of this paper was to explore the effect of the lead vehicle's size on rear-end crash configurations. Four types of rear-end crash configurations were taken, namely: car-car, car-truck truck-car, and truck-truck. The General Estimates System (GES) databases were used in this analysis. Nested logit models were calibrated to estimate the probabilities of the four crash configurations. These were created as a function of the driver's age, gender, vehicle type, vehicle maneuver, light conditions, driver's visibility, and speed. It was concluded from the results that the driver's visibility and inattention in following a vehicle had the largest effect on being involved in a rear-end collision. Also, the possibilities of a car-truck rear-end crash increased in cases where the lead vehicle stopped suddenly.

Diener and Richardson *(31)* studied truck-involved fatalities in Missouri, where nearly 70 percent of those who die in traffic crashes are not wearing seatbelts. NHTSA determined a vehicle involvement rate by dividing the number of vehicles involved in fatal rural/ urban crashes by the vehicle miles traveled. As to laws regarding seat belts, Missouri is a secondary enforcement state, meaning that drivers and passengers in violation of the law can only be cited when the vehicle has been stopped by a police officer for a separate offense. In other words, a police officer in Missouri cannot stop and cite a driver or passenger solely for not wearing a seat belt. A survey was conducted in several districts and truck drivers were asked questions such as "*If I were in a crash, I would want to have my seat belt on,"* and the number drivers who agreed to the questions and their level of agreement was noted and studied.

Burgess *(32)* studied data from the Fatality Analysis Reporting System (FARS) for the period 1994 – 2003 to compare characteristics of fatal rural and urban crashes. The study found that there are approximately 42 percent more fatal crashes in rural areas compared to urban areas; however, there are fewer vehicle miles traveled in rural areas than urban areas. In addition, fatal rural crashes are more likely to involve multiple fatalities, rollovers, and more trucks. Fatal rural crashes more often occur on curved roadways and have greater vehicle damage. Head-on crashes are more prevalent in rural areas than in urban areas. Finally, the length of time for emergency medical services to arrive at the scene is longer in rural areas than in urban areas.

2.6 Bayesian and Other Modeling Techniques

Majid *(33)* investigated the effect of heavy commercial vehicles on the capacity and overall performance on congested freeway section conditions. This seems to be an important situation because the mixed traffic flow on the freeways has different impacts. This poses a problem for freeway operations and safety, especially when the truck traffic percentage is on the higher side compared to passenger cars. For this purpose, traffic surveys were performed at two freeway sites in Tokyo and one freeway site in Melbourne. Video data was filmed using six cameras for six hours at each site by tracking a vehicle for a distance of 700m. The data was microscopically analyzed and variables like the truck's position (lead or lag vehicle), relative speed time gap, and space headways were estimated. Using this data, various mathematical models were developed and nonlinear regression techniques were performed in order to calibrate parameters for different probability values in the models. Among these, the most optimum models having optimum response variables, like the acceleration rate of the trucks at different times, were estimated. The framework uses a stimuli-response psychophysical concept as in its basic formulation. The collected data are used to calibrate the proposed model. The results showed a significant difference in the following behavior of heavy vehicles compared to other vehicles.

Duncan et al. *(34)* illustrated the impact of the variable injury severity in truck-passenger car rear-end collisions. For this, two objectives were targeted. The first objective was to understand the factors that influence the passenger vehicle occupant injury severity in car-truck rear-end collisions on divided roads. The second was to illustrate the application of the ordered probit model application on particular factors of injury severity levels. For this project, the Federal Highway Administration's Highway Safety Information System (HSIS) database was used along with police reports and roadway inventory data. The state of North Carolina was chosen for this analysis at it has a large number of truck routes. The ordered probit model proposed for the given analysis had the dependent variable (injury severity) coded as 0, 1,2,3,4. The independent variables were factors such as speed limit, light conditions, weather conditions, age, gender, etc. The interaction effects of cars being struck to the rear with high speed differentials and car rollovers were significant. Variables decreasing severity include snowy or icy roads, congested roads, being in a station wagon struck to the rear (as opposed to a sedan), and using a child restraint. With injuries ordered in five classes from no injury to fatalities, the marginal effects of each factor on the likelihood of each injury class were reported.

Pickrell *(35)* demonstrated in his study that while the overall proportion of passenger vehicle drivers with alcohol involvement in fatal crashes is lower in older age groups, the median blood alcohol concentration (BAC) was generally higher for those age groups. However, for motorcycle operators, age groups with the highest levels of alcohol involvement also had the highest median BAC levels. In order to understand the relationship between alcohol involvement in fatal crashes and median BAC levels of the drivers involved, this study examined FARS data at several different levels, including level of alcohol involvement, median driver/operator age, median BAC by age group within vehicle type, and median BAC by year and vehicle type, across all age groups. Data from 2004 are presented in the main body of the report, and data from 2000-2003 are included as a comparison for trends at the end of the report. This research work identifies differences between age groups and within vehicle types, based on the proportion of drivers with positive BACs (BACs greater than or equal to 0.01) by showing differences between passenger vehicle (passenger cars, SUVs, pickup trucks, and vans) driver and motorcycle operator BAC levels across age groups. Passenger vehicle drivers in the age groups 20-29 and 30-39 had the highest proportion of drivers with positive BAC levels. However, motorcycle operators in the age groups 30-39 and 40-49 had the highest proportion of drivers with positive BAC levels.

2.7 Multinomial Logistic Regression

Yan et al. *(36)* conducted a study on rear-end collisions in trucks using two national crash databases (2000-2004), the Fatality Analysis Reporting System (FARS) and the General Estimates System (GES). Overall and fatal truck-involved rear-end collisions were both investigated in this paper. Three groups were used to classify two-vehicles rear-end collisions in this study. Using the vehicle's striking/struck role as a basis, crash categories were car-car (car hitting car), car-truck (car hitting truck), and truck-car (truck hitting car). There was comparison of occurrence conditions of the three rear-end crash types so that potential risk factors associated with the truck-involved crashes, such as driver characteristics, highway designs, and road environments, could be identified. Multinomial logistic regression results showed a significant association between overall truck-involved rear-end crashes and factors such as gender, driver age, alcohol use, speed, day of week, interstate, weather condition, divided/undivided highway, and lighting condition. There was also a significant association between fatal truck-involved rear-end collisions and gender, driver age, alcohol use, day of week, divided/undivided highway, and lighting condition. The multinomial logistic regression results show that factors including lighting condition, divided/undivided highway, weather condition, interstate, day of week, speed related, alcohol use, driver age, and gender are significantly associated with overall truck-involved rear-end crashes. More information regarding effective crash countermeasures and a better understanding of track-related rear-end crash risk are provided by this study.

Yan et al. *(37)* conducted another study by considering data from FARS for the years 2000-2004. Only two-vehicle angular crashes were considered. The crashes were then divided into truck-car and car-car categories. The at-fault parameter in these categories was considered. The category of truck-truck crashes was excluded from the analysis. The dataset was further filtered citing as two-vehicle crashes in which only one driver was at fault and the other was not. Multi-logistic regression modeling was used in this project. The dependent variable is y, which describes the type of crash. Pr(y=m|x) is the probability of observing outcome m given the set of independent variables x. Based on the results, it was suggested that truck-involved angle collisions should be considered as an important scenario design for retraining or education programs for the purposes of reducing older drivers' fatality rate; improving either the conspicuity of truck trailers or lighting design of the highway would reduce the frequency and severity of truck-involved angle crashes; to improve incompatibilities between truck, car, and highway design, further studies should conduct in-depth analyses of geometric factors related to driver performances and behaviors in the car-truck conflicts at intersections.

Venkataraman and Mannering *(38)* conducted a research study on motorcycle accident severity which focused on univariate relationships between severity and an explanatory variable of interest (e.g., helmet use). The potential ambiguity and bias that univariate analyses create in identifying the causality of severity has generated the need for multivariate analyses in which the effects of all factors that influence accident severity are considered. This study attempts to address this need by presenting a multinomial logit formulation of motorcycle rider accident severity in single-vehicle collisions. Using 5-year statewide data on single-vehicle motorcycle accidents from the state of Washington, they estimated a multivariate model of motorcycle-rider severity that considers environmental factors, roadway conditions, vehicle characteristics, and rider attributes. Their findings show that the multinomial logit formulation used was a promising approach to evaluate the determinants of motorcycle accident severity.

Moonesinghe et al. *(39)* conducted a binary response model for rollovers (jackknifes), and stated that the probability of a rollover (jackknife), given a single-truck fatal crash has occurred, is a function of selected explanatory variables. If Y denotes the dependent variable in a binary-response model for rollovers (jackknifes), Y is equal to 1 if there is a rollover (jackknife) and 0 otherwise. The statistical problem was to estimate the probability that Y=1, considered as a function of the explanatory variables. TIFA data were analyzed using a logit model, which is a widely used binary-response model. The explanatory variables used in the models were weather, light, speed limit, curve, weight, length, and width. Results showed that as the weight of the large truck and its cargo increases, the odds of a rollover increase, but the odds of a jackknife decrease. Conversely, as the length of a large truck increases, the odds of a rollover decrease, while the odds of a jackknife increase.

2.8 Countermeasure Ideas

Samuel et al. *(40)* conducted a study about drowsy driver detection and the effects of employing a warning system for commercial vehicle drivers. The research was conducted by NHTSA and its partners, since 1996, in order to quantify the loss of alertness among commercial vehicle drivers. By experimentation, it was concluded that a valid measure of loss of alertness among drivers can be made by the percentage of eyelid closure over the pupil over time (Perclos). Drowsiness was consistently identified in trucking summits as the number one safety concern of commercial vehicle drivers. The Perclos index is a measure of latency between a visual stimulus and a motor response, which was collected using the Psychomotor Vigilance Task (PVT). Drowsiness was measured using a three-minute running average of slow eyelid closures, as assessed by the Drowsy Driver Warning System (DDWS) during nighttime driving. It depended on the capability of the camera to detect infrared light reflected back to the source at the camera from the driver’s retina. By this, measures of performance at braking, closing, lane changing, lane keeping, and speed maintenance were observed. The first objective was to find drowsiness-level distributions and differences between them with and without the DDWS. The second objective was to see variations in drowsiness with a number of independent factors like age, nights of sleep, etc. From the experimental analysis, it was concluded that further understanding was needed about highway safety benefits, fleet acceptance, operational utility, and fatigue management practices so that fatigue crash problems could be minimized.

Cate et al. *(41)* presented results of an evaluation of truck lane restrictions conducted using the VISSIM microscopic traffic simulation software package as an analysis tool. The objective of this application was to study truck lane restriction at a very detailed level. The VISSIM traffic simulation model has a number of user-adjustable parameters such as lane usage, free-flow speeds, lane changing behavior, vehicle power, weight, braking characteristics, and traffic composition. The focus is on lane restrictions where large trucks are prohibited from using the far-left travel lane on freeway sections with three or more lanes of travel in a single direction. In order to make results of the testing as realistic as possible, field traffic data was utilized to create volumes and truck percentages representative of actual freeway operations. The simulations were done in two situations. In the first scenario, all vehicles were free to travel in any lane. In the second simulation, large trucks were restricted to the two right lanes of travel. After the simulations were completed, the output files generated were used to calculate the performance statistics on factors such as vehicle density, level of service, and average travel time. The “aggressiveness” of lane changes was seen to have increased by reducing the minimum distance and maximum speed differential between vehicles. Another important measure that allowed for an evaluation of the safety impact of truck lane restrictions was the frequency of lane changes. As the number of lane changes decreased, the opportunity for collision was reduced by limiting the interaction between the vehicles.

Reich et al. *(42)* proposed an idea of exclusive highway facilities for trucks as a countermeasure to reduce congestion, enhance safety, and improve free flow of freight. The Florida Department of Transportation (FDOT) contracted with the Center for Urban Transportation Research (CUTR) to lead this research project. The methodology used was to select sites in Florida that warranted consideration for truckways or reserved truck lanes. Important factors such as truck crash rates, truck volumes, and percent of trucks in traffic mix were evaluated based on FDOT data. Then GIS models were constructed and experimented in selected roadway segments to evaluate the considered parameters. It was concluded that most of the interstate system is suitable for consideration of exclusive truck facilities. Truck congestion in some areas appeared to have decreased by 15% by introducing this model. Crashes were also estimated to decrease considerably.

Reiskin *(43)* studied the proposal made by Stephen Kratzke, NHTSA's associate administrator for rule making, at a truck-part makers meeting in Las Vegas in February 2008. In view of reducing truck-involved fatalities, NHTSA was planning to release rules on brake stopping distance, brake hose materials, and electronic and roll-stability control. The agency wanted to use technology for this situation, not by proposing larger drum brakes or disc brakes, but by setting a distance-based standard on the trucks. They also published a rule in April mandating electronic stability control on all vehicles with gross vehicle weight ratings of less than 10,000 pounds by 2011. That would affect Class 2 trucks. Apart from these rules, the agency was also planning to put out regulations on brake hose standards and upgraded tire standards towards the end of the year.

Murray et al. *(44)* conducted a study in collaboration with the American Transportation Research Institute, focusing on driver-specific behaviors and events, and their relationship to future truck crash involvement. Driver-specific data were used by the research team to design and test a logistic regression model. The data was collected from the Motor Carrier Management Information System (MCMIS) and the Commercial Drivers License Information System (CDLIS). Initially, statistical tests, including Chi-square analyses, were done to assess the significant difference between future crash rates and driver's behavior. The regression model included specific violations discovered during roadside inspections, driver traffic conviction information and past accident involvement. These were taken as the independent variables and through the model, the probability of occurrence of crash were obtained as the dependent variable. The variables named intercept, reckless driving violation, serious speeding conviction, and hours of service violation seemed to be the topmost crucial factors in reducing the crash scenario. From the analysis, several countermeasures were recommended, which when effectively enforced, could bring the required results.

CHAPTER 3 - METHODOLOGY

3.1 Data

Data for the study were procured from the National Highway Traffic Safety Administration's Fatality Analysis Reporting System (FARS) database. FARS database documents detailed data on vehicles, drivers, roadways, and environmental conditions recorded in police crash reports, emergency medical service reports, hospital records, and coroner's reports of all fatal crashes in the United States. It contains details of fatal crashes in all 50 states, District of Columbia, and Puerto Rico. This database was conceived, designed, and developed by the National Center for Statistics and Analysis (NCSA) to aid the traffic safety community in identifying traffic safety problems and providing countermeasures for better driving standards *(45).* NCSA is a division of the National Highway Traffic Safety Administration (NHTSA), providing a wide range of analytical and statistical support to NHSTA. NCSA responds to requests for data from various sources like state and local governments, research organizations, private citizens, auto and insurance industries, Congress, and the media.

NHTSA has a contract with an agency in each state to obtain information on fatal crashes. This information is compiled and put into a standard format by FARS analysts who are state employees specially trained for this job. Fatal motor vehicle traffic crash data obtained from various state agencies are assembled and coded on standard FARS forms. Various forms used in assembling the information are Police Accident Reports (PARS), state vehicle registration files, state driver licensing files, state highway department data, vital statistics, death certificates, coroner/medical examiner reports, hospital medical records, and emergency medical service reports. FARS was established in 1975 and data since then is available in several formats. It is broadly used within NHTSA to answer many queries on the safety of vehicles, drivers, traffic conditions, and roadways. Fatal crash reports can be accessed at national and state levels by a FARS analyst acting in response to overall traffic safety issues.

In order to make an entry into the database, a crash must involve a motor vehicle traveling on a trafficway customarily open to the public, and result in the death of an occupant of a vehicle or non-motorist within 30 days of the crash. The FARS database includes details of each and every such fatal crash reported. Each crash is characterized in terms of crash, vehicle, roadway, and people involved with the help of more than 100 coded variables. All these variables are reported on accident, vehicle, driver, and person forms. The accident form contains information such as time and location, first harmful event, weather conditions under which the crash occurred, number of vehicles, and people involved. Vehicle and driver forms record details like vehicle type, impact points, most harmful event, and driver's license status. The person form contains details about each individual involved in the crash such as age and gender of the person; whether the person is the driver, passenger, or non-motorist; injury severity; and restraint use. Individual privacy is maintained by protecting details such as name, address, and any other personal information. Overall alcohol estimates, which describe the contribution of the alcohol factor in fatal crashes, as well as driver and non-occupant blood alcohol content (BAC) estimates, are present in the FARS alcohol file, which is an add-on to the data files when no alcohol information would otherwise be available.

FARS Encyclopedia is a web-based tool that facilitates in downloading the data and generating results through queries. It also consists of reports and fact sheets drawn from published FARS data for the relevant year and state. The reports are classified under trends, crashes, vehicles, and people sections. The trends section covers motor vehicle crashes and fatalities over a range of years. Reports under crashes present statistics about motor vehicle crashes based on injury severity of the person, and those under vehicles present details about kinds of vehicles involved in fatal motor vehicle crashes. Reports under the people section provide data on the kinds of people, i.e. drivers, passengers, or non-motorists involved in motor vehicle crashes. FARS Query System is a web interface that allows users to perform their own custom queries such as case listings and univariate and cross tabulations. FARS data files are available in an archive as a public resource to download in file transfer protocol (FARS FTP). This website enables users to process the data using their own computer systems.

From this database, truck and non-truck crashes were the two categories examined in the comparative study. In this study, a truck crash was defined as a crash which involved at least one truck whose gross body weight was greater than 10,000 pounds. A non-truck crash was defined as a crash which did not involve a truck. In the FARS database, trucks were divided into different categories depending on their Gross Vehicle Weight Rating (GVWR). Trucks considered for this study were vehicles with body type codes 61 (single-unit straight truck with GVWR greater than 10,000 lbs. and less than or equal to 19,500 lbs.), 62 (single-unit straight truck with GVWR greater than 19,500 lbs. and less than or equal to 26,000 lbs.), 63 (single-unit straight truck with GVWR greater than 26,000 lbs.), 64 (single-unit straight truck with unknown GVWR), 66 (truck/tractor with any number of trailing units and any weight), 67 (medium/heavy pickup truck with GVWR greater than 10,000 lbs.), 71 (any unknown single-unit or combination unit medium truck with GVWR greater than 10,000 lbs. and less than 26,000 lbs.), 72 (any unknown single-unit or combination-unit heavy truck with GVWR greater than 26,000 lbs.), 78 (any unknown medium/heavy truck type), and 79 (unknown truck type) in the FARS database. These specific body types were considered as they included trucks which had a gross body weight greater than 10,000 pounds. All other motor vehicles, other than those body types and ones which had a gross body weight less than 10,000 pounds, were considered as non-truck vehicles.

Files from the database were merged using unique crash, person, and vehicle identification codes employing SAS computing software *(46).* The merged files were checked so as to obtain a unique, unduplicated crashes, people, and vehicles list to retrieve frequencies or counts of different characteristics. Various crash characteristics were obtained using filtering techniques in Microsoft Excel and Access. After suitably merging and filtering accident, person, and vehicle files, fatal truck crash data for five-year time period from 2003 to 2007 was combined and truck and non-truck crash cases were categorized to obtain consolidated results with respect to several parameters.

Further, the values obtained were compared at various levels to analyze trends and patterns of specific crash parameters with respect to time or type of crash, or the extent of fault of the drivers involved. Also, certain pairs of parameters were selected to observe differences in the combination of conditions prevailing during higher crash-occurrence levels. Eventually driver, crash, and vehicle-related factors were extracted to compare the existence of these factors in both truck and non-truck crashes.

3.2 Analysis Methods

3.2.1 Bayesian Statistical Approach

The Bayesian statistical approach is an effective tool in recognizing the predominance of crash-related factors while comparing truck and non-truck crashes in the given data set. The computation of likelihood ratios, using Bayesian posterior probabilities, is valid and useful. It makes good logical sense, while producing significant results from projected analysis of crash factors.

Equation (1) describes the conditional probability of the occurrence of a driver, vehicle, or crash-related contributory cause (CC), given that it is a truck crash.

$$P(CC/Truck) = \frac{P(Truck/CC) \ * \ P(CC)}{P(Truck)} \tag{1}$$

where,

P(Truck/CC) = Probability that the crash was a truck crash, given that a specific contributory cause was reported. As shown in Equation (2), this value is estimated from the data by considering total number of crashes and those in which a truck crash and its contributory factor were coded together.

P(CC) = Overall probability of the specific driver, vehicle, or crash-related cause being reported as a contributing factor, and as shown in Equation (4), is estimated from the numbers of cases in which the CC was reported in the dataset.

P(Truck) = Overall probability that a crash was a truck crash and was estimated from the data as shown in Equation (3).

$$P(Truck/CC) = \frac{Number\ of\ Truck\ Crashes\ with\ that\ Contributory\ Factor}{Number\ of\ \ All\ (Truck\ and\ \ Non\text{-}Truck)\ Crashes\ with\ that\ Factor} \tag{2}$$

$$P(Truck) = \frac{Number\ of\ Truck\ Crashes}{Number\ of\ \ All\ (Truck\ and\ \ Non\text{-}Truck)\ Crashes} \tag{3}$$

$$P(CC) = \frac{Number\ of\ Crashes\ with\ that\ Contributory\ Factor}{Number\ of\ \ All\ (Truck\ and\ \ Non\text{-}Truck)\ Crashes} \tag{4}$$

Similarly, the conditional probability of a contributory cause for a given non-truck crash is estimated, and the ratio of these probabilities generates the likelihood ratio of that contributory factor as shown in Equation *(5).*

$$Likelihood\ Ratio = \frac{P(CC / Truck\,Crash)}{P(CC / Non\text{-}Truck\,Crash)} \quad (5)$$

The likelihood ratio of a given contributory factor being recorded in a truck crash as compared with a non-truck crash was assessed from crash records. This likelihood ratio is the probability of a crash being a truck crash when the contributory factor was recorded, as compared with the probability of a crash being a non-truck crash when the same contributory factor was identified. The larger the likelihood ratio, the greater the association between the contributory factor and truck crashes relative to non-truck crashes.

3.2.2 Multinomial Logistic Regression

Multinomial logistic regression modeling, which was also used in this study, is an efficient tool to analysis crash data (*36, 37, 38,* and *47*). The dependent variable in this modeling technique is denoted as y which describes the type of crash. Pr(y=m|x) is the probability of observing outcome m given the set of independent variables x. It is assumed to be a linear combination $x\beta_{m.}$

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

where,

Y=1: Truck Crash

Y=2: Non-Truck Crash

For the dependent variable let,

Pi1= Probability that the crash type is 1 for observation i.

Pi2= Probability that the crash type is 2 for observation i.

As, Pi1+Pi2=1, the probabilities can be calculated as follows:

$$Pi1 = \exp(x_i \beta_1) / (1 + \exp(x_i \beta_1) + \exp(x_i \beta_2))$$

$$Pi2 = \exp(x_i \beta_2) / (1 + \exp(x_i \beta_1) + \exp(x_i \beta_2))$$

In this study, the SAS LOGISTIC procedure was used to perform the multinomial logistic regression. The dependent variable was the type of crash which took the binary form depending on whether it was a truck crash or non-truck crash. The independent variables included several crash, driver, vehicle, and environmental factors which were combined using statistical modeling software SAS version 9.1. The independent variables considered were driver age, gender, national highway, light condition, weather condition, alcohol use, and 35 other factors. As the selection criteria of variables to be included in the model, a 95% confidence level was used in which the p-value should be less than 0.05. Co-linearity of individual variables was also checked before considering variables into the model and if such a relationship existed, one of the two correlated variables was discarded based on the lowest mean value criterion.

The LOGISTIC procedure used in developing this model fits linear logistic regression models for binary or ordinal response data by the method of maximum likelihood. The maximum likelihood estimation is carried out with either the Fisher-scoring algorithm or the Newton-Raphson algorithm *(47).*

The LOGISTIC procedure provides four variable selection methods: forward selection, backward elimination, stepwise selection, and best subset selection. The best subset selection is based on the likelihood score statistic. This method identifies a specified number of best models containing one, two, three variables and so on, up to a single model containing all the explanatory variables *(47).*

Odds-ratio estimates are displayed along with parameter estimates in the output generated by the LOGISTIC procedure. You can also specify the change in the explanatory variables for which odds-ratio estimates are desired. Confidence intervals for the regression parameters and odds ratios can be computed based either on the profile likelihood function or on the asymptotic normality of the parameter estimators.

The Wald Chi-Square and Pr > ChiSq are the test statistics and p-values, respectively, for the hypothesis test that an individual predictor's regression coefficient is zero given that the rest of the predictors are in the model. The Wald Chi-Square test statistic is the squared ratio of the estimate to the standard error of the respective predictor. The probability that a particular Wald Chi-Square test statistic is as extreme as, or more so, than what has been observed under the null hypothesis is given by Pr > ChiSq.

The "Model Fit Statistics" in Table 4.8 contain the Akaike Information Criterion (AIC), the Schwarz Criterion (SC), and the negative of twice the log likelihood (-2 Log L) for the intercept-only model and the fitted model. AIC and SC can be used to compare different models, and the ones with smaller values are preferred *(47)*.

Other goodness-of-fit parameters, which the LOGISTIC procedure gives in the output, are described as follows *(47)*:

- Percent Concordant-A pair of observations with different observed responses is said to be concordant if the observation with the lower ordered response value has a lower predicted mean score than the observation with the higher ordered response value.
- Percent Discordant-If the observation with the lower ordered response value has a higher predicted mean score than the observation with the higher ordered response value, then the pair is discordant.
- Percent Tied-If a pair of observations with different responses is neither concordant nor discordant, it is a tie.
- Pairs-This is the total number of distinct pairs.
- Somer's D-Somer's D is used to determine the strength and direction of relation between pairs of variables. Its values range from -1.0 (all pairs disagree) to 1.0 (all pairs agree). It is defined as $(n_c-n_d)/t$ where n_c is the number of pairs that are concordant, and n_d the number of pairs that are discordant, and t is the number of total number of pairs with different responses.
- Gamma-The Goodman-Kruskal Gamma method does not penalize for ties on either variable. Its values range from -1.0 (no association) to 1.0 (perfect association). Because it does not penalize for ties, its value will generally be greater than the values for Somer's D.
- Tau-a-Kendall's Tau-a is a modification of Somer's D to take into the account the difference between the number of possible paired observations and the number of paired observations with different response. It is defined to be the ratio of the difference between the number of concordant pairs and the number of discordant pairs to the number of possible pairs $(2(n_c-n_d)/(N(N-1))$.
- c-Another measure of rank correlation of ordinal variables is c. It ranges from 0 to (no association) to 1 (perfect association).

These goodness-of-fit parameters could be used to evaluate the robustness of a developed multinomial logistic regression model.

CHAPTER 4 - RESULTS AND DISCUSSION

4.1 Characteristics of Fatal Truck Crashes

Analysis of the data showed that large trucks contribute to more fatalities in other (non-truck) vehicles than in trucks themselves. On average, 84% of fatalities occurring in large truck crashes in the United States are not occupants of trucks. This section elaborates the characteristic analysis done on fatal truck crashes in the United States using five years of crash data from 2003 to 2007.

4.1.1 Initial Point of Impact for the Truck

One observation made from fatal truck crash data was the direction of impact, which is the initial point on the truck where the other vehicle collides. As shown in Figure 1.1, trucks have blind spots in all directions, and initial impact point helps in showing which zone is more crucial for a higher crash risk. By observing the initial point of impact on the truck, the position of the colliding vehicle with respect to the truck was estimated. From this, the blind spot which results in a higher crash rate was interpreted. From the Figure 4.1, it is seen that almost 62.5% of the cases resulted in trucks having the initial impact on their front. This might weaken the argument that poor visibility range for trucks on their rear side leads to a majority of rear-ends crashes in trucks. It is possible that other vehicle drivers need to be more vigilant when driving in front of a truck rather than the rear. Around 15.5% of the crashes were on the left-hand side of the truck driver. This could be a significant observation because from Figure 1.1, it was observed that the left-hand side of the truck driver has the smallest blind spot zone when compared to all other directions.

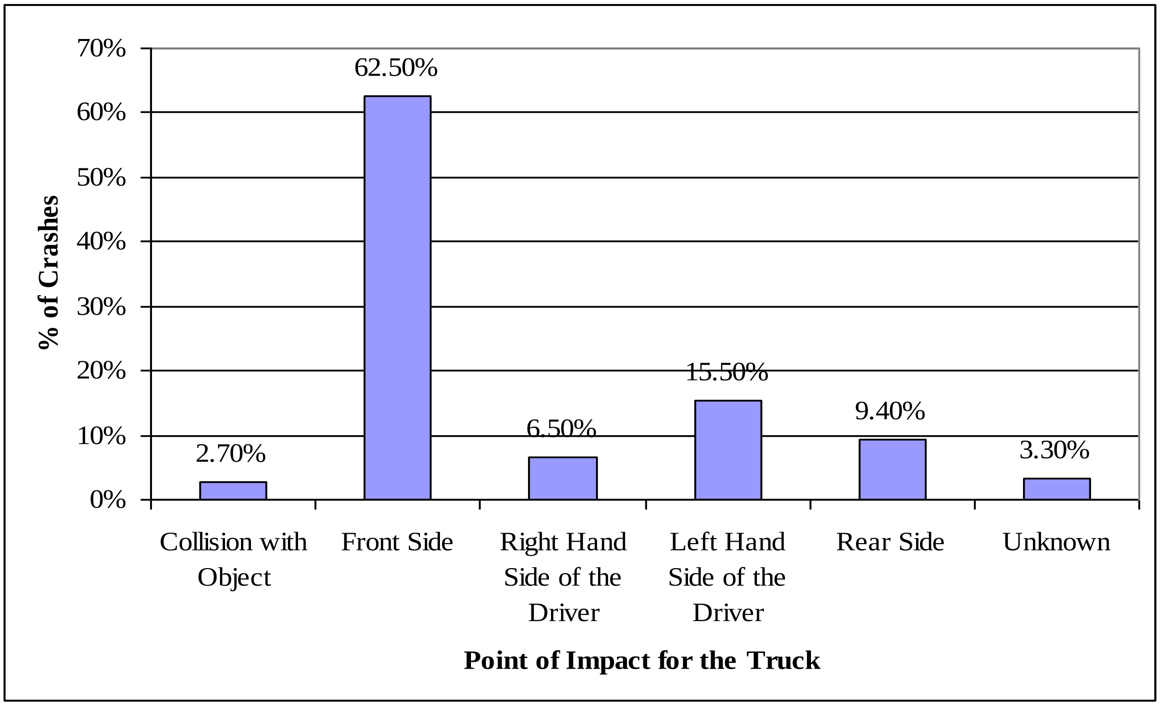

Figure 4.1 Point of Impact for Trucks in Fatal Crashes

4.1.2 Alcohol Involvement

Alcohol involvement of drivers has the potential to be one of the most important contributory factors resulting in all crashes, which could also be the case in truck crashes. Analysis showed that of all drunken drivers involved in fatal truck crashes, only 12.7% were truck drivers with blood alcohol levels higher than the 0.08 mg/ml limit and the rest of the 87.3% were non-truck drivers. This indicates that a larger percentage of truck drivers are under influence of alcohol/drugs leading to fatal crashes. Hence, it can be deduced that in fatal truck crashes with alcohol involvement, non-truck drivers are more likely to be under the influence of alcohol than truck drivers.

4.1.3 Manner of Collision

The manner of collision of the trucks in fatal crashes was observed from the combined dataset for the period of 2003-2007, and the results are shown in Figure 4.2. Angle crashes have the highest proportion of 34.2%, followed by 23.7% of cases where the vehicles collided with a fixed object like a tree, guardrail, etc. Head-on and rear-end crashes also form a significant portion of crashes resulting in fatalities.

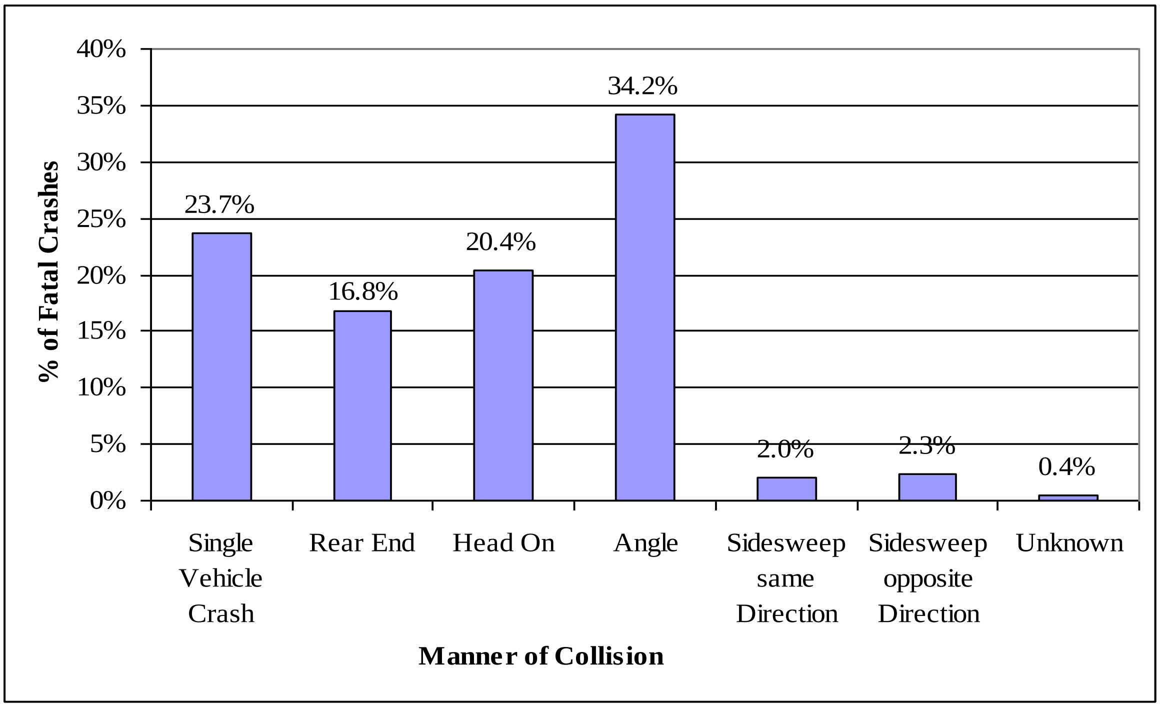

Figure 4.2 Manner of Collision of Fatal Truck Crashes

4.1.4 Speed Limit

Trucks are more difficult to maneuver smoothly as compared to smaller vehicles, and at higher speeds they have a higher risk of losing control. This can also be one of the factors contributing to higher crash risk involving trucks. The speed limit of the roadway where the truck is traversing before succumbing to a fatal crash can approximately show the speed of the truck. As seen in Figure 4.3, the percentage of fatal crashes increases with increase in speed limit up to 60 mph. The range of 51-60 mph has the highest number (an average of 5,280 crashes per year) of fatal truck crashes in the past five years. The drop in the number of crashes from 51-60 mph to 61-70 mph may be because of the smaller number of roadways with the later speed range.

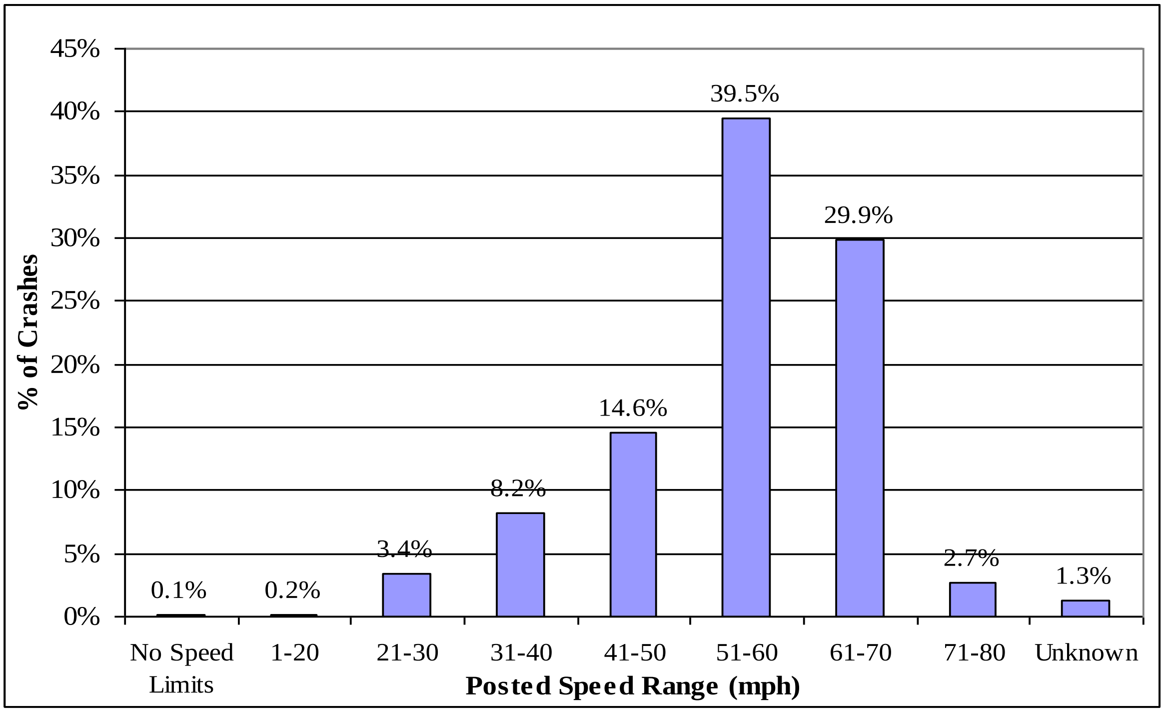

Figure 4.3 Fatal Truck Crashes in Different Speed-Limit Ranges

4.1.5 Truck Driver Age

A number of driver-related parameters can be responsible for influencing the crash risk, especially for trucks which travel on commercial basis for longer and more strenuous hours. In a study made by Crum and Morrow *(48)*, they explain that truck driver fatigue plays a major role in the occurrence of a crash. They investigated and established a driver fatigue model to test various carrier scheduling practices with other driver parameters. Another study was done by Williams et al. *(49)*, to scale the amount of responsibility in drivers by age and gender for all motor vehicle crashes. Here, they compared the number of drivers at fault in different age groups and gender. From their analysis, they proved that the element of "responsibility" declined with age until about age 63 years, and then increased as a function of age.

From Figure 4.4, it is seen that the number of drivers involved in fatal truck crashes is higher in the age range of 41-50 yrs than other groups. With the highest percentage of 29% being in this range, the graph has an overall normal distribution. Until the range of 41-50 yrs, the percentage of fatal truck crashes has an increasing curve and after that range, the percentage of crashes takes a decreasing trend.

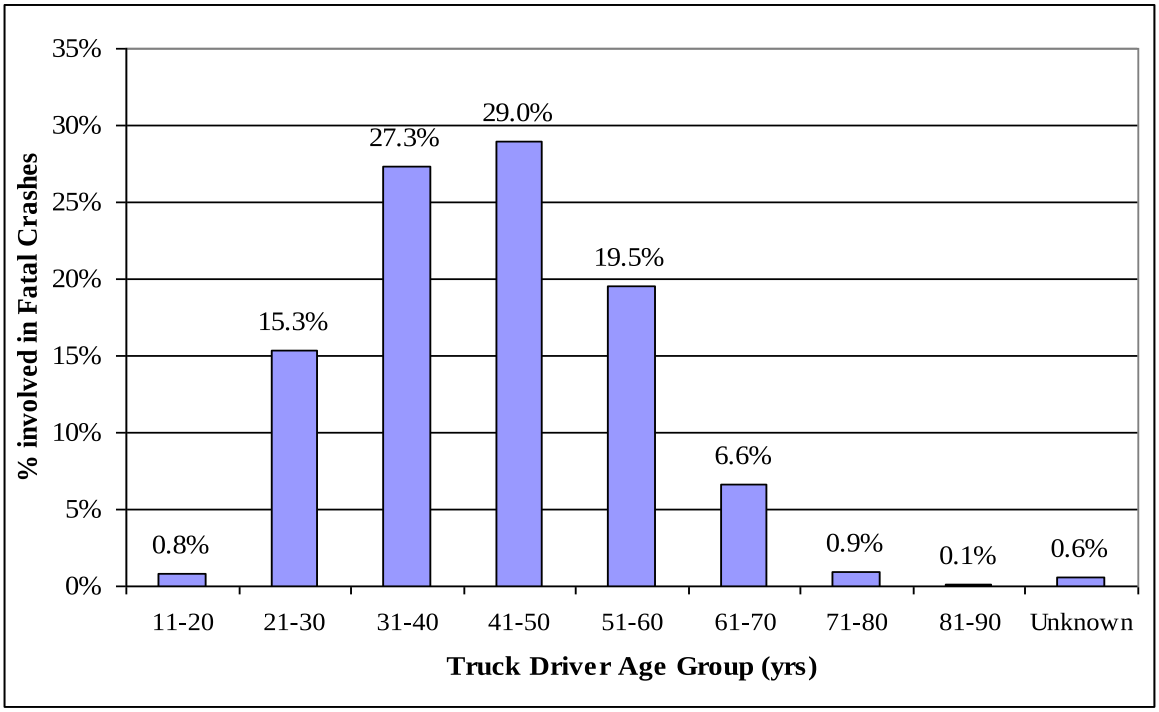

Figure 4.4 Age of Truck Drivers Involved in Fatal Truck Crashes

4.1.6 Types of Trafficways

Truck maneuverability may become more challenging depending on the type of roadway. Depending on these roadway characteristics, even actions like lane changing and lane merging can sometimes become critical factors in leading to a crash. Also, presence of physical dividers is likely to affect the number of fatal crashes, because they have the potential to reduce the severity of a crash and sometimes may even prevent fatalities.

A majority of almost 55.2 % of fatal truck crashes, as shown in Figure 4.5, have occurred on two-way trafficways with no physical division. This shows that this kind of roadway has a greater tendency in the occurrence of fatal crashes. Traffic flowing in opposite directions with no physical division in between can be one of the high-risk situations where the smallest of human errors can result in highly severe crash scenarios. Roadways of this type should be improved by providing the necessary divisions so as to minimize the frequency of fatal truck crashes.

Number of lanes on two-way trafficways with 55.2 % of crashes was analyzed, and it has been observed that almost 77.3% of those crashes occurred on two-lane two-way roadways. Difficulty in controlling the large size of the vehicle in narrow or smaller roadways can be the reason for this high frequency. Two-lane roadways are often congested and cannot be easily traversed. This situation, in conjunction with the two-way trafficway without any physical division, can be the scene causing the occurrence of a fatal truck crash.

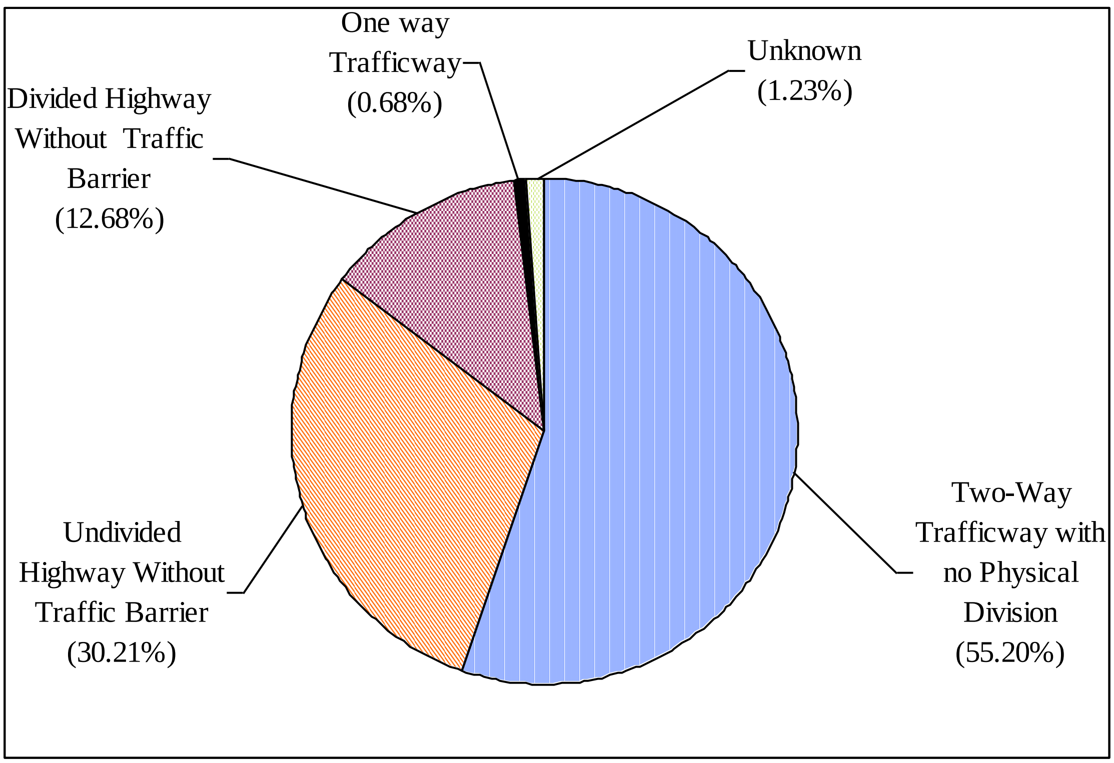

Figure 4.5 Proportion of Fatal Truck Crashes on Different Traffic Flowways

4.1.7 Level of Deformation on Urban and Rural Roadways

As seen in Figure 4.6, the level of deformation of the vehicles involved in fatal truck crashes is severely disabling in most cases, which is consistent in both urban and rural roadways. As large trucks are heavy in weight and volume and also, as was observed in Figure 4.3, a majority of fatal truck crashes occur at high speed levels, it is evident that consequences of such conditions result in severe damages to the collided vehicles. However, the percent of severely disabled vehicles is proportionally smaller in urban areas when compared to rural areas.

Availability of more space for maneuvering on urban roads and higher traffic volumes leading to lower speeds could probably be the reasons for this observation.

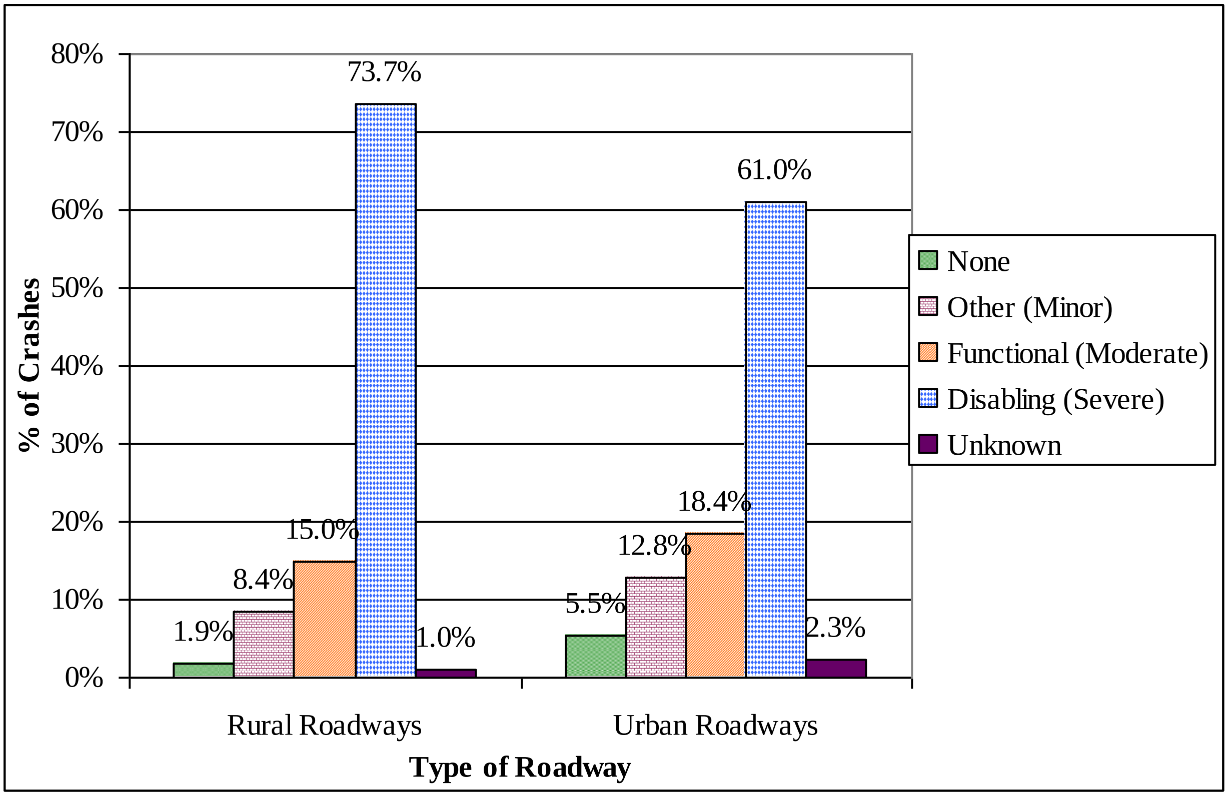

Figure 4.6 Level of Deformation of all Vehicles Involved in Fatal Truck Crashes

4.1.8 Truck Driver At-Fault Factors

Various types of truck driver-related factors have contributed to fatal crashes as shown in Figure 4.7. Around 28.1 % of the truck drivers have contributed to fatal truck crashes due to non-compliance with traffic regulations. Improper driving is another factor, which in 24.6% of cases has contributed to fatal truck crashes. These categories will include factors like running off the road, erratic lane change, following improperly, failure to keep in lane properly, etc. Also, the figure shows that 15.8 % of truck drivers involved in fatal truck crashes had some type of mental/physical condition such as fatigue, drowsiness, inattentiveness, drugs, etc. that contibuted to the occurance of a fatal truck crash.

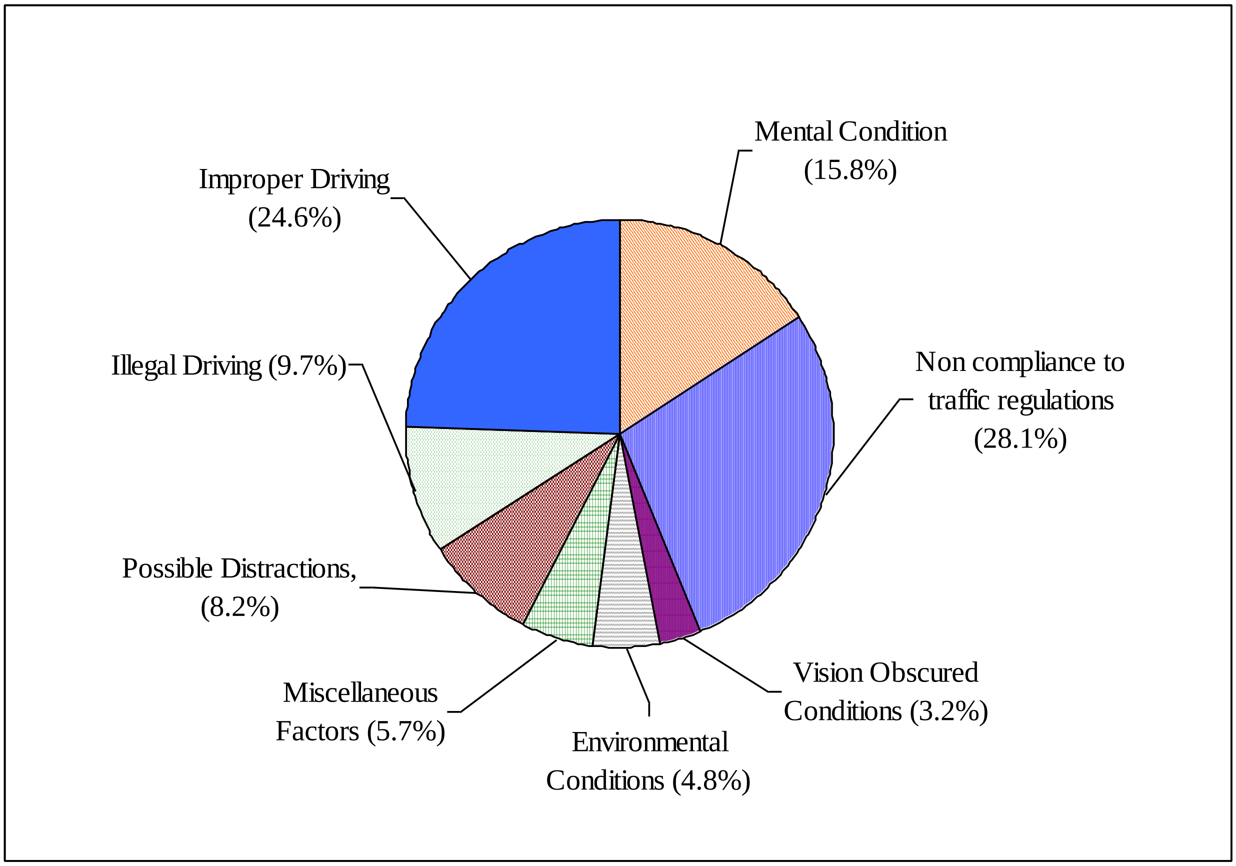

Figure 4.7 Truck Driver-Related Contributory Factors in Fatal Crashes

4.2 Truck Striking/Struck Comparison

4.2.1 Truck Striking/Struck on Different Roadways

In this section, fatal truck crashes are divided into two categories, one where the truck strikes another vehicle first in the crash and the other in which the truck is struck first by another vehicle resulting in a crash. The analysis was done by comparing these two categories where the truck was the striking vehicle and those where the truck was the struck vehicle. A similar framework was adapted to the currant data set, as shown in Figure 4.8, to observe the crashes on different types of roadways over the past five years.

It was observed that the truck-striking and truck-struck categories have a high number of crashes on state highways contrasting with other crashes which have a high number of crashes on interstates rather than other types of roadways. A truck striking another vehicle results in a higher number of crashes than a truck being struck, on both interstates and state highways, but this comparison has equal proportions in the case of U.S. highways.

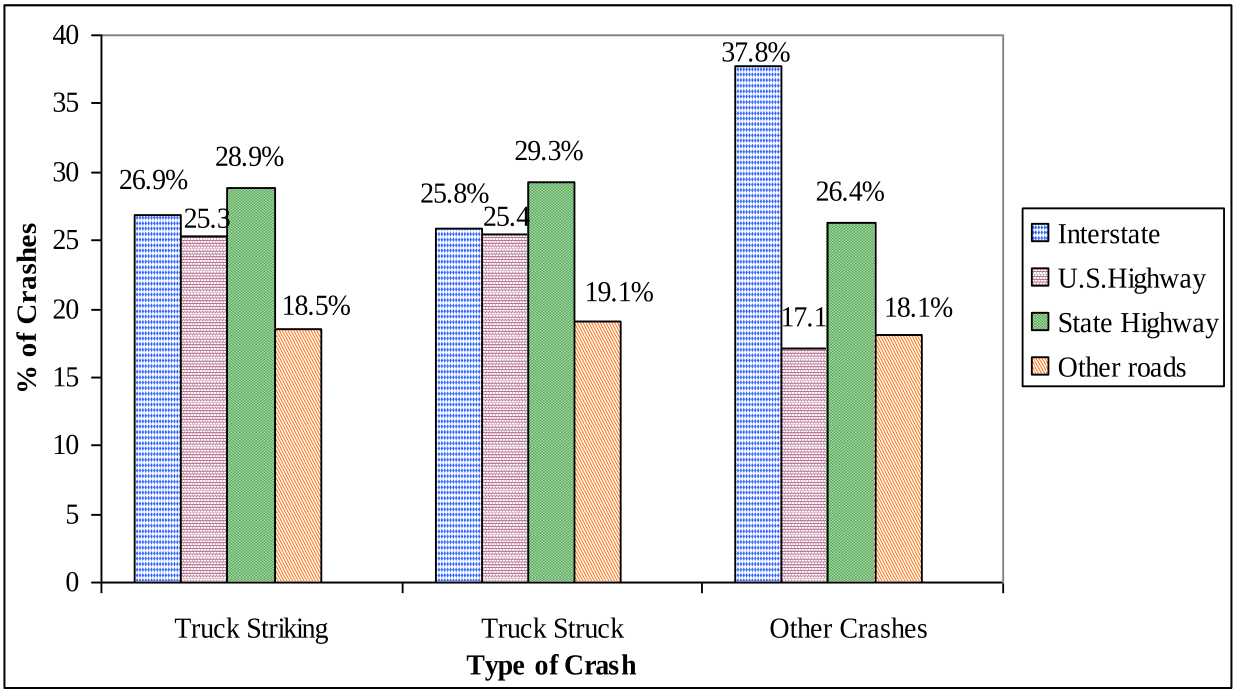

Figure 4.8 Fatal Truck Crashes by Roadway Type in Truck Striking/Struck Conditions

4.2.2 Truck Striking/Struck under Different Light Conditions

When truck striking and truck struck were studied under different light conditions, it was observed that the proportion of cases where trucks are struck was smaller under daylight conditions than cases where the truck strikes other vehicles as shown in Figure 4.9. In constrast, the percentage of trucks being struck is higher in dark or dark but lighted conditions when compared to cases where the trucks are striking other vehicles.

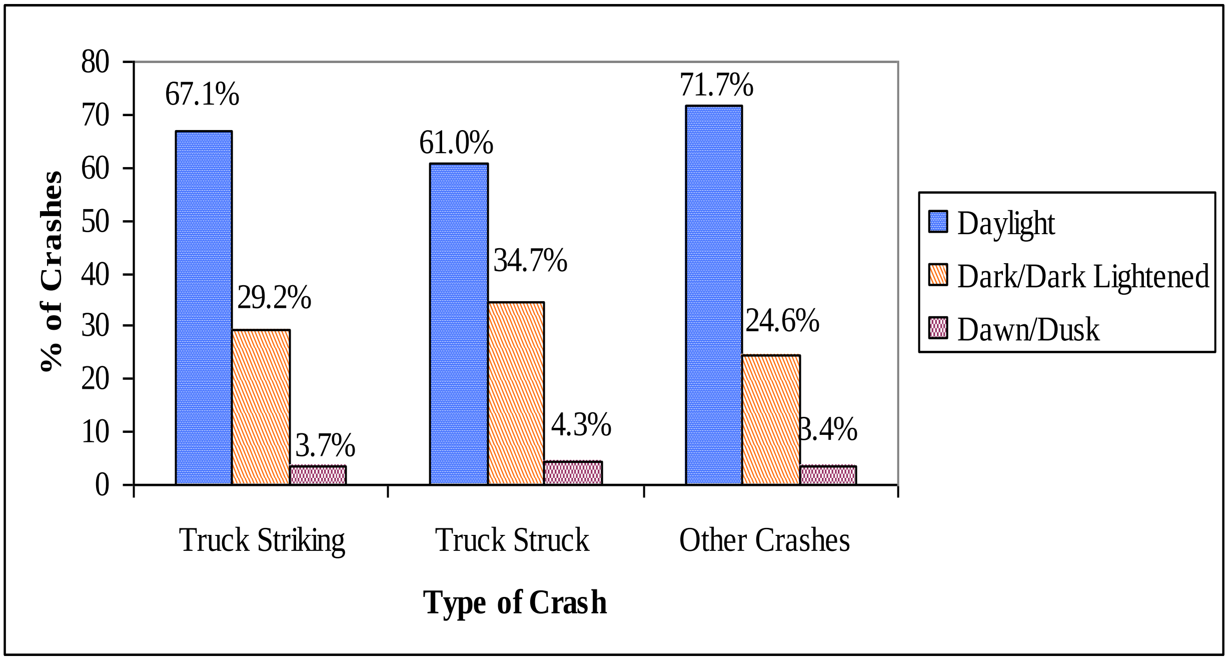

Figure 4.9 Truck Crashes in Different Light Conditions under Striking/Struck Types

4.3 Comparison of Characteristics of Fatal Truck and Non-Truck Crashes

Fatal crash data for the period of 2003-2007 was divided into crashes which involved trucks and those which did not involve trucks, or non-truck crashes. Different characteristic factors such as initial point of impact, driver age, posted speed limits, manner of collision, level of deformation, rural/urban split, types of traffic flowways, and roadway categories were compared between truck and non-truck crashes. Percentages in each sub-category were calculated by taking the total number of truck or non-truck crashes as the base value.

It can be seen from Figure 4.10 that initial impact point for vehicles in both truck and non-truck fatal crashes were mostly on the front side. Although all other categories had lower proportions in both truck and non-truck crashes, left-hand side of the driver as the impact point had a comparatively larger proportion of fatal crashes in trucks than in non-trucks.

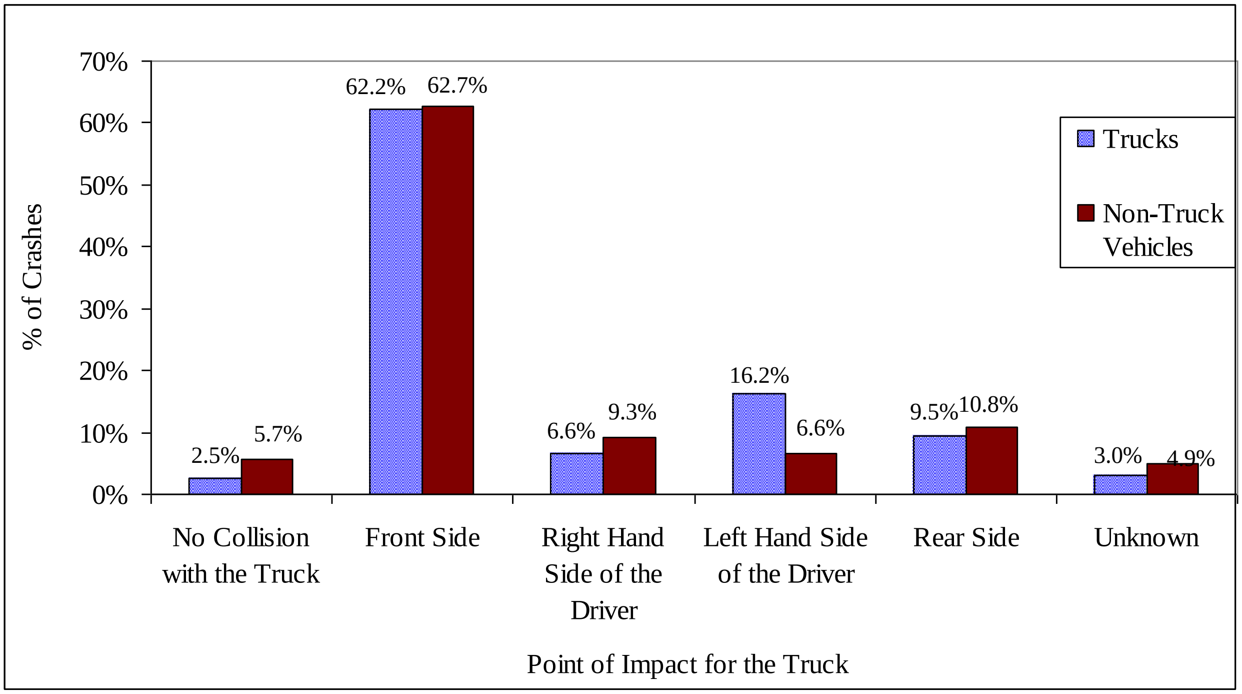

Figure 4.10 Initial Impact Point for Truck and Non-Truck Crashes

Also, a larger proportion of truck drivers involved in fatal crashes seemed to be of the age group 41-50 yrs, whereas the non-truck drivers were mostly in the 21-30 yrs age group. Figure 4.11 shows that starting from the age group of 31-40 yrs, truck drivers had larger involvement than non-truck drivers in fatal crashes.

When the overall trend lines in both truck and non-truck drivers was observed, there was a difference in the pattern. Truck drivers had almost a normal distribution with the line, peaking at the age range of 41-50 yrs, whereas non-truck drivers had the trend line skewed towards the younger population with the peak at the 21-30 yrs. This showed that younger drivers have a larger proportion of involvement in non-truck crashes and middle-aged drivers have a larger involvement in truck crashes.

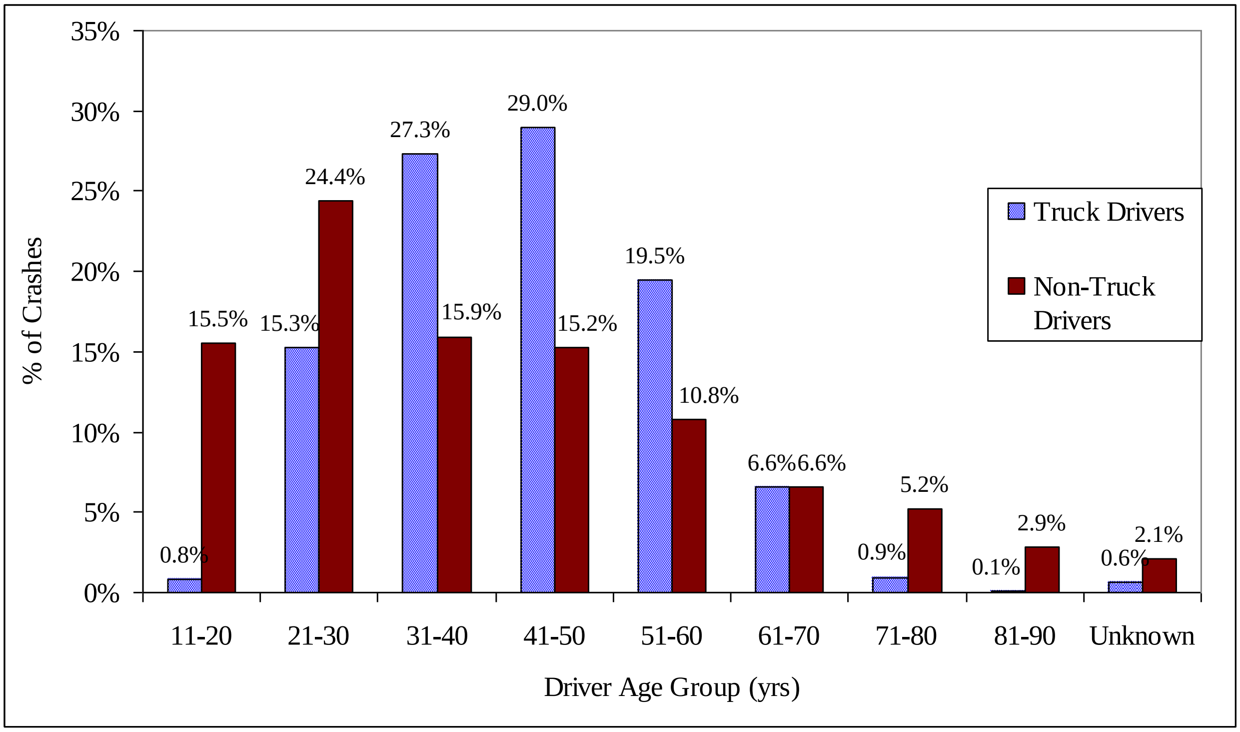

Figure 4.11 Driver Age for Truck and Non-Truck Drivers

Distribution of truck and non-truck crashes in different speed limit ranges is shown in Figure 4.12. In both truck and non-truck crashes, the maximum number of crashes are in the 51-60 mph range. In the speed-limit range of 21-50 mph, non-trucks had more fatal crashes than trucks, whereas between 51-70 mph, trucks seemed to have more fatal crashes than non-trucks. This shows that in lower speeds non-trucks have a higher proportion of fatal crashes, and in higher speeds trucks have a higher proportion of crashes.

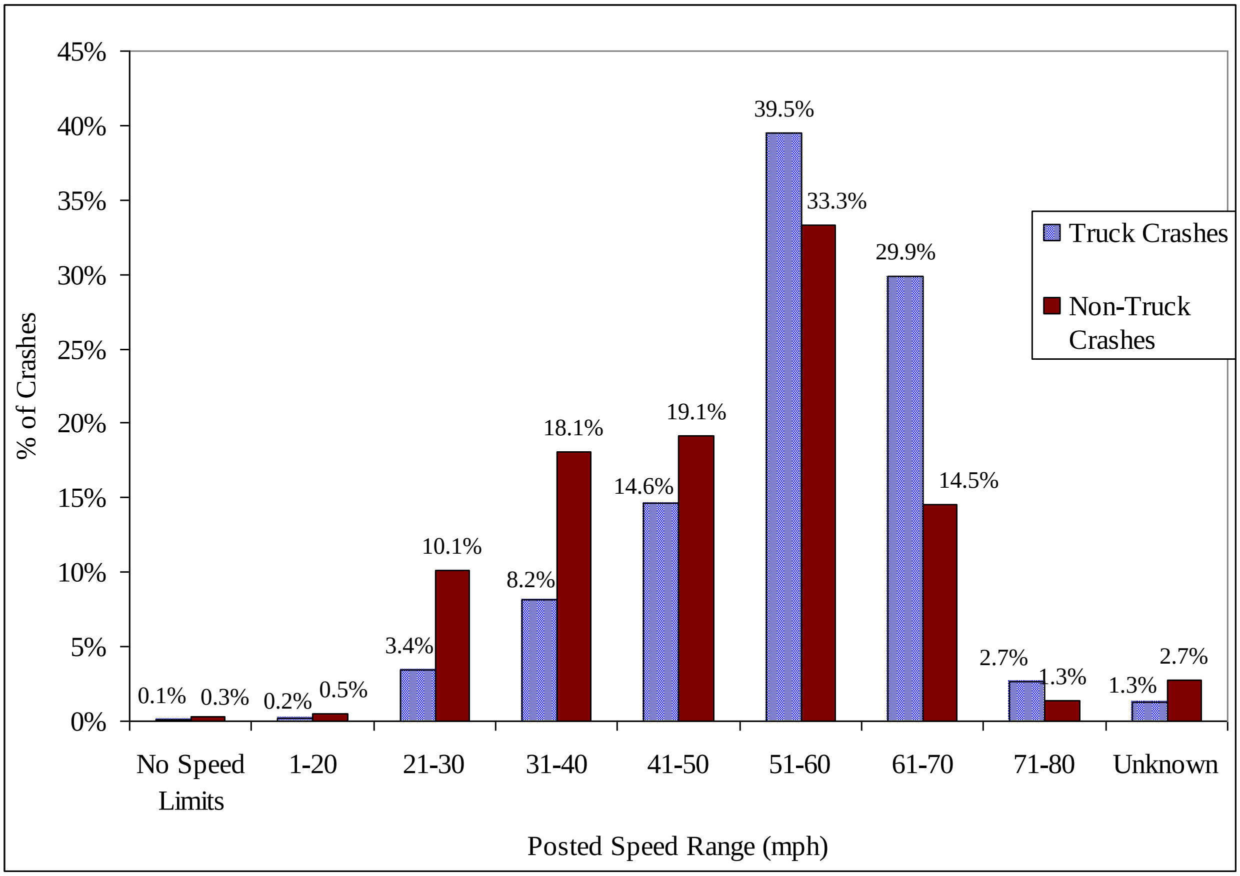

Figure 4.12 Posted Speed Limit for Truck and Non-Truck Crashes

In most fatal crashes, as observed from Figure 4.13 a majority of fatal non-truck crashes were single-vehicle crashes but most of the fatal truck crashes were angle crashes. Also proportionately, there were more rear-end, head-on and angle crashes involving trucks than non trucks.

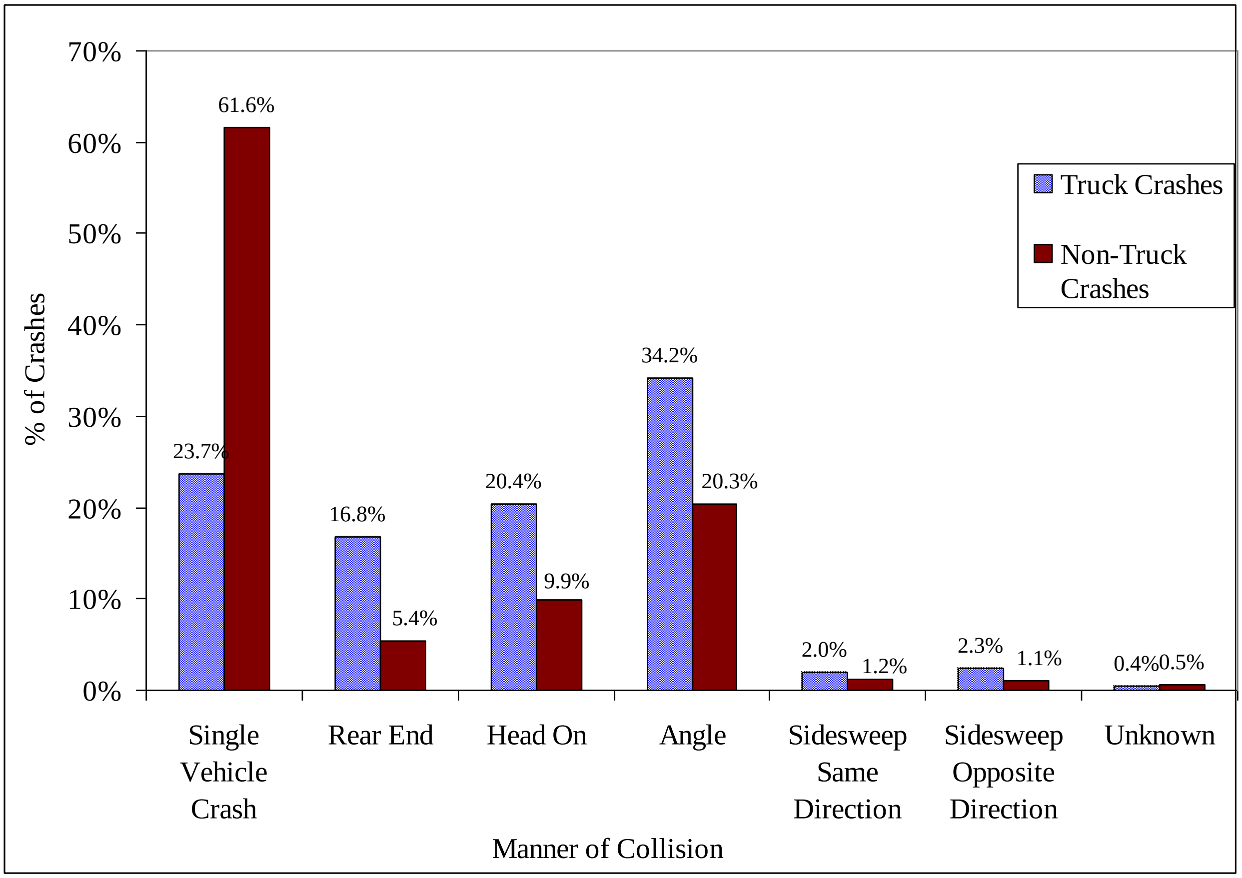

Figure 4.13 Manner of Collision for Truck and Non-Truck Crashes

Both truck and non-truck fatal crashes most commonly resulted in disabling vehicle deformations as shown in Figure 4.14. However, fatal non-truck crashes had a higher percentage (78.4%) of severe/disabling vehicle deformations than fatal truck crashes. Also, it was observed from Figure 4.15 that more than half of the crashes in trucks and non-trucks occurred on two-way trafficways with no physical division. Fatal non-truck crashes had a higher percentage (69.9%) of occurrence on two-way traffic ways with no physical division than fatal truck crashes. Other types of traffic flowways, such as divided highways with or without traffic barriers, were observed to have a larger proportion of truck crashes than non-truck crashes.

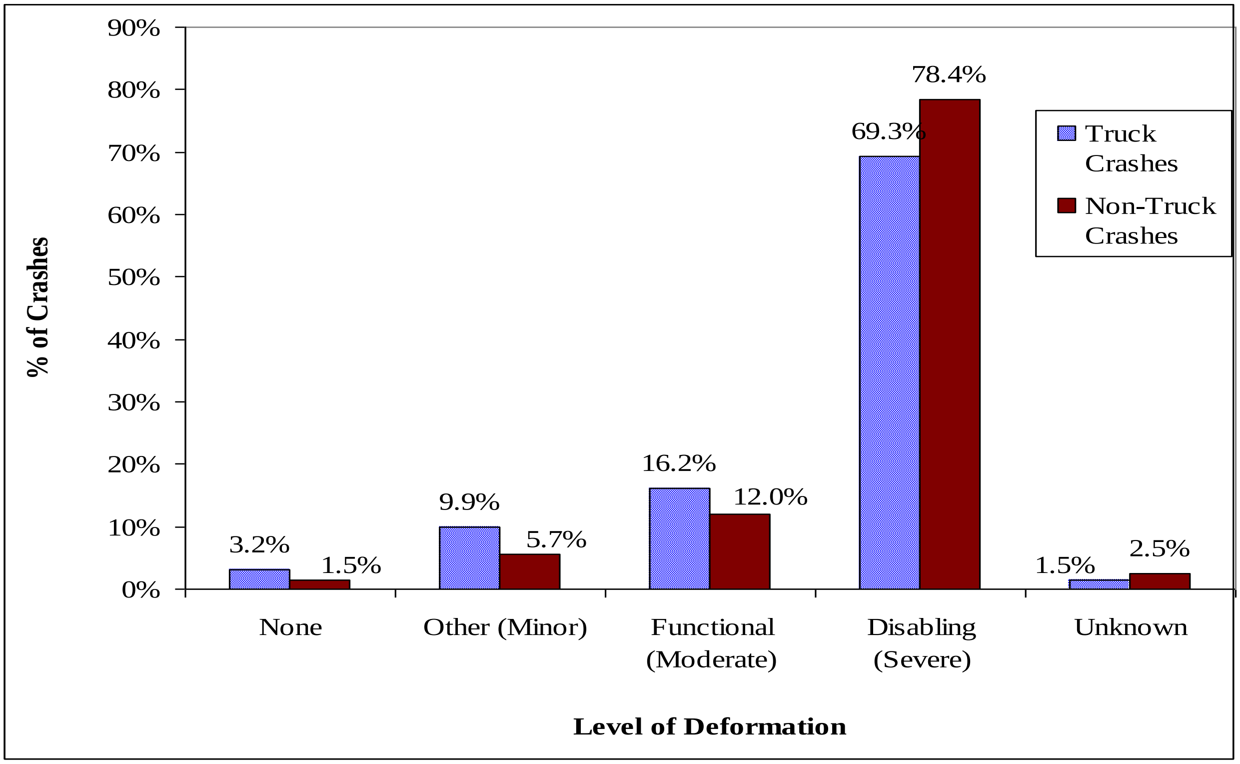

Figure 4.14 Level of Deformation for Truck and Non-Truck Crash Vehicles

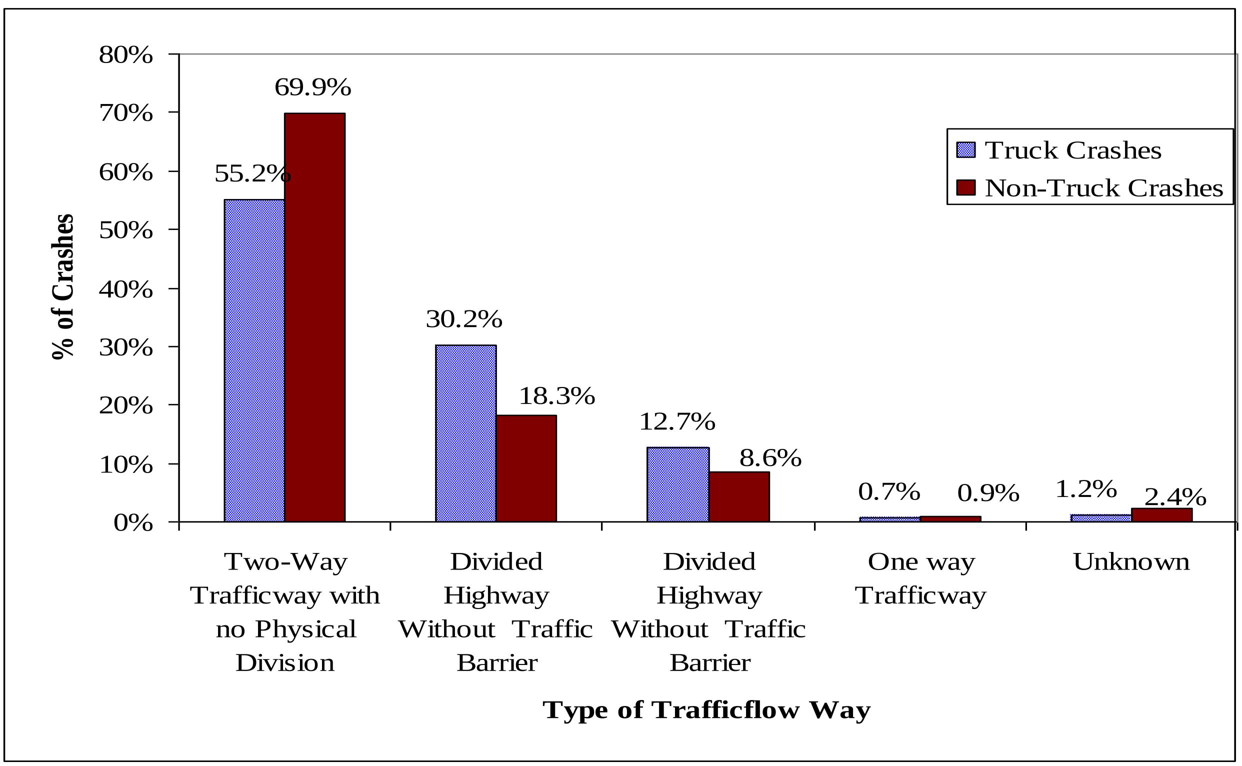

Figure 4.15 Trafficway Type for Truck and Non-Truck Crashes

Arterial roadways in both urban and rural sectors had a higher predominance of fatal truck crashes, whereas collector and local roads had a higher predominance of non-truck crashes, as shown in Figure 4.16.

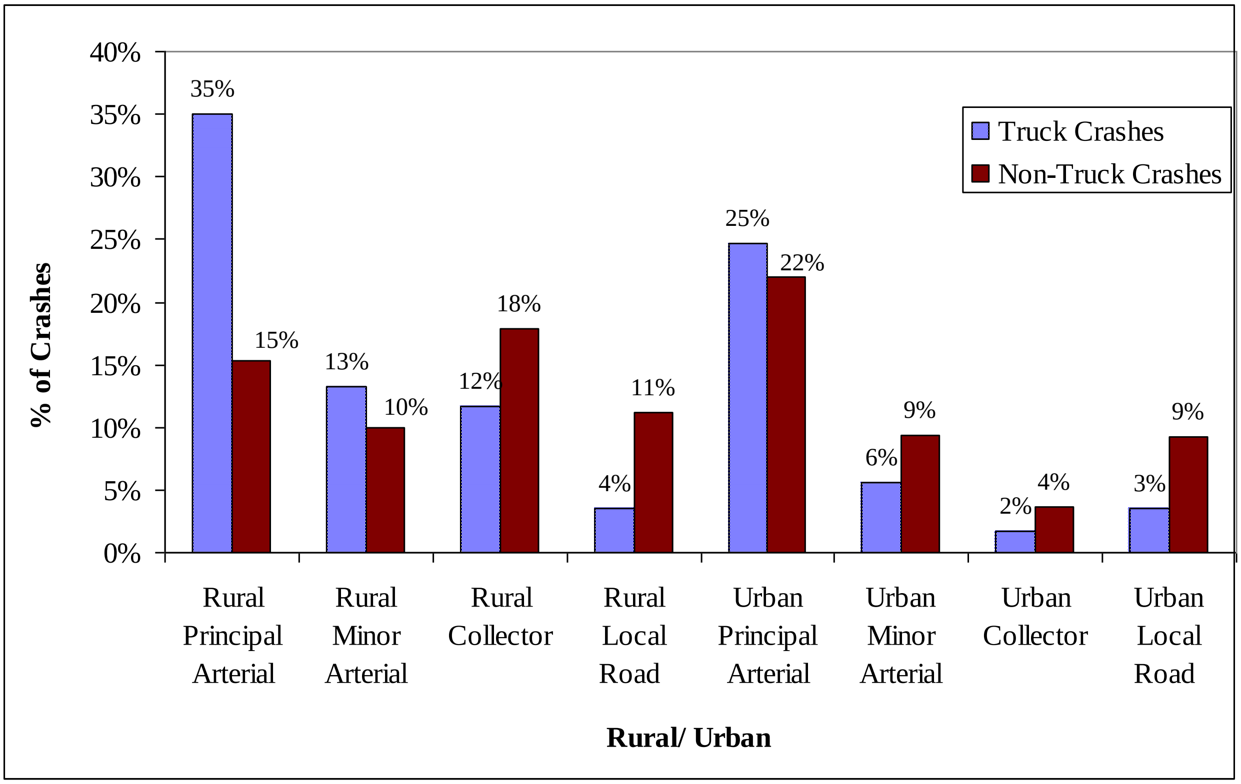

Figure 4.16 Rural Urban Contrast for Truck and Non-Truck Crashes

Different types of roadways on which truck and non-truck crashes occurred are shown in Figure 4.17. Trucks had a larger proportion of fatal crashes on interstates and highways, whereas other county and municipality roads had a higher proportion of fatal non-truck crashes. A larger presence of trucks on these major arterials and roadways might be one of the causes for this high proportion of fatal truck crashes.

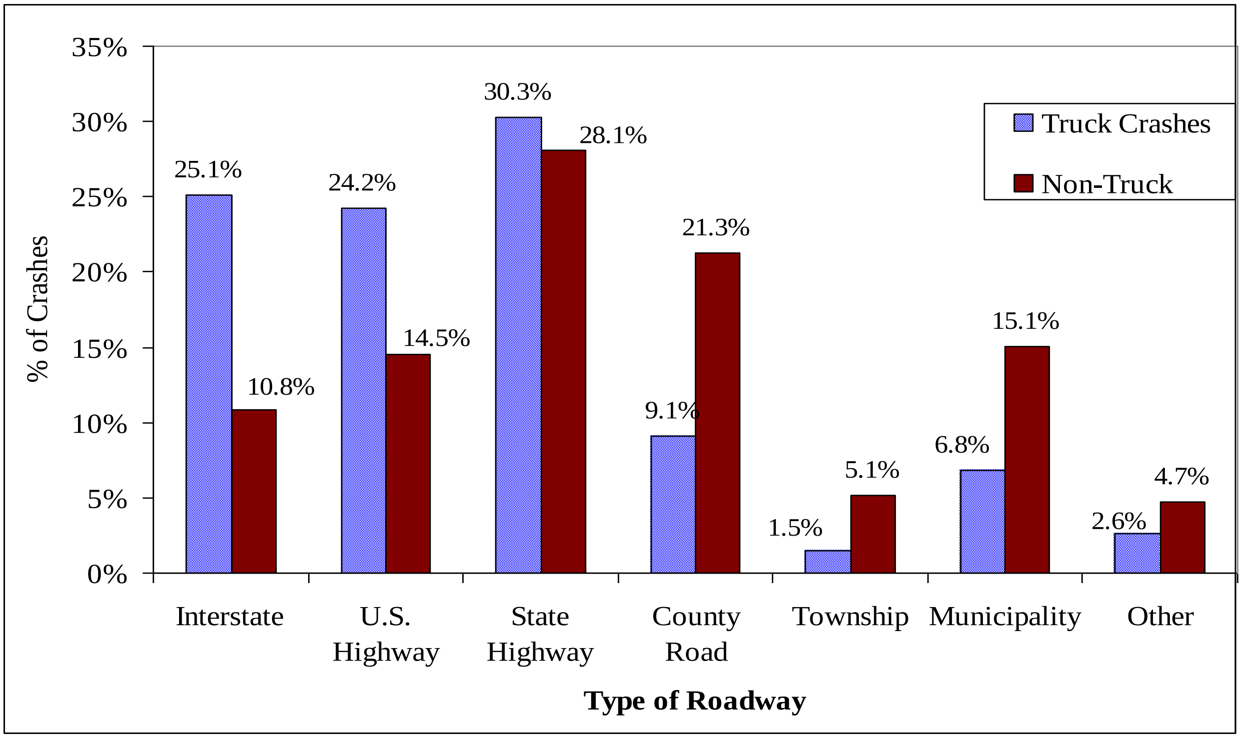

Figure 4.17 Type of Roadway for Fatal Truck and Non-Truck Crashes

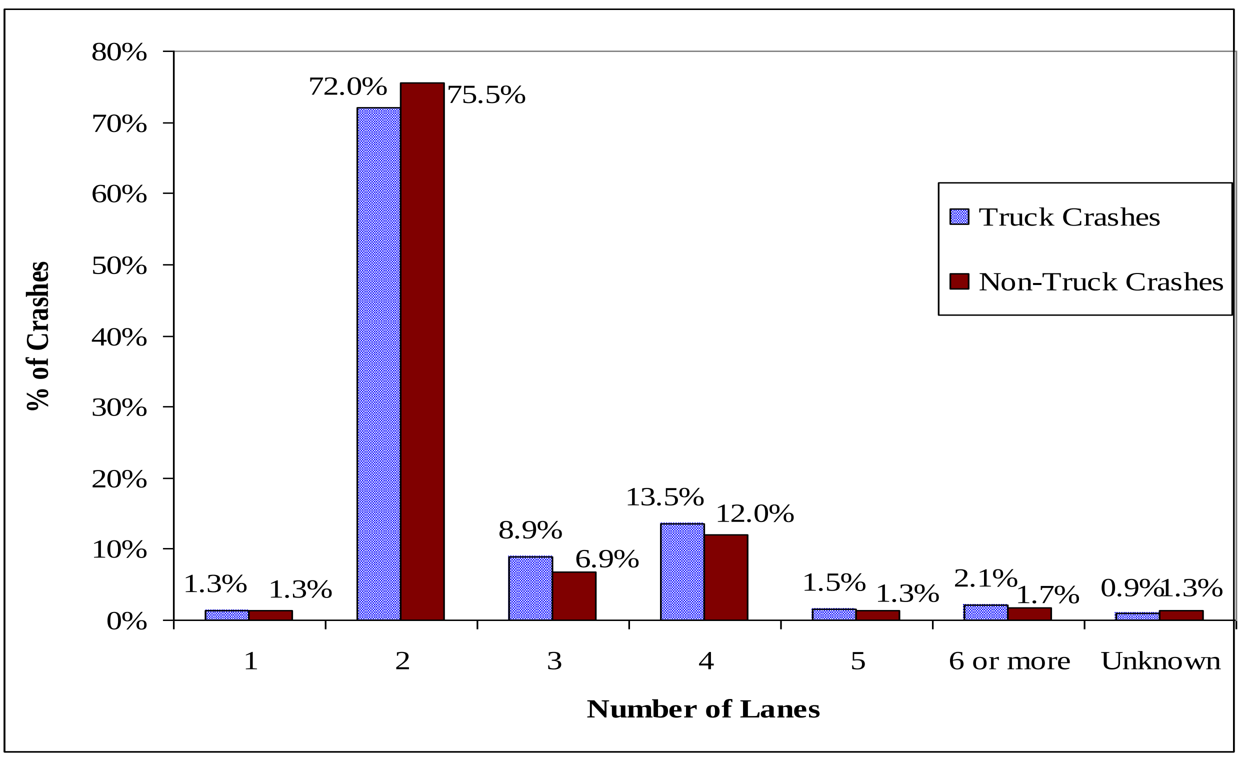

Figure 4.18 Number of Lanes on Roadways Where Truck/ Non-Truck Crashes Occurred

In addition, factors such as alcohol involvement and cellular usage were also analyzed. Of all fatal truck crashes which had some alcohol involvement, it was seen that in 87% of cases, non-truck drivers were the ones involved in alcohol consumption and in only 12% of cases truck drivers were under the influence of alcohol. Also, cellular usage was one among the top 10 driver-related contributory factors for truck drivers involved in fatal crashes.

4.4 Bayesian Statistical Analysis: Contributory Causes for Truck and Non-Truck Crashes

The following section shows the likelihood of occurrence of contributory factors in fatal truck crashes when compared to fatal non-truck crashes. If probability of the factor is greater than one, it indicates the factor was more predominant in fatal truck crashes than those involving fatal non-truck crashes. Factors in the tables belong to categories of driver-related, vehicle-related, or crash-related issues. The likelihood ratios are recorded in descending order of predominance in each category. Each crash might have more than one contributory factor leading to the crash, as FARS records up to four driver-related, three crash-related, and two vehicle-related factors per crash. Hence, the sum of the number of crashes in truck and non-truck categories will not be equal to the number of crashes that occurred in the time considered.

Table 4.1 shows crash-related contributing factors in 11 different categories as defined by the FARS database. Crash data for the period of 2003-2007 was considered for this analysis. Recent previous crash nearby/ vehicle set in motion by a non-driver, work area conditions, poor shoulder conditions, and inadequate warning signs are the topmost factors which have more likely contributed to truck crashes than to non-truck crashes. Providing sufficient signs at all places, including work areas, and improving shoulder conditions might help reduce fatal truck crashes.

Table 4.1 Conditional Probabilities and Likelihood Ratios for Crash-Related Factors

Crash-Related Factor(CF)	Number of Truck Crashes	Number of Non-Truck Crashes	Conditional Probability of This CF Given a Fatal Truck Crash	Conditional Probability of This CF Given a Fatal Non-Truck Crash	Likelihood Ratio
Recent Previous Crash Nearby/ Vehicle Set in Motion by a Non-Driver	416	1025	0.01901	0.00602	3.15
Motor Vehicle Struck by Falling Cargo	558	1496	0.02550	0.00879	2.90
Construction/ Work Area Condition	122	342	0.00557	0.00201	2.77
Inadequate Warning of Exits, etc.	15	57	0.00069	0.00033	2.04
Aggressive Driving or Road Rage of Non-Contact Vehicle Driver	102	391	0.00466	0.00230	2.02
Poor Shoulder Condition	22	158	0.00101	0.00093	1.08
Within Designated School Zone	6	51	0.00027	0.00030	0.91
Poor Roadway Condition	33	443	0.00151	0.00260	0.57
Speed Limit Is a Statutory Limit but Is not Posted	61	1004	0.00279	0.00590	0.47
Police Pursuit Involved	57	1557	0.00260	0.00915	0.28

Vehicle-related contributory factors between fatal trucks and non-truck crashes are listed in Table 4.2. As most of the utility vehicles are trucks rather than other motor vehicles, this cannot be considered as a contributory cause, but defective brake systems having the second highest likelihood ratio seems to be more predominant in truck crashes rather than other vehicle crashes. Defective lights, mirrors, and engines also appear to have more likelihood because of the severe wear and tear trucks undergo as a result of long miles traveled.

These factors, recorded as vehicle-related factors, are subjective with respect to police officers present at crash sites. As officers are not professional vehicle inspectors, these records might not be precise to the maximum extent.

Table 4.2 Conditional Probabilities and Likelihood Ratios for Vehicle-Related Factors

Vehicle-Related Factor (VF)	Number of Truck Crashes	Number of Non-Truck Crashes	Conditional Probability of This VF Given a Fatal Truck Crash	Conditional Probability of This VF Given a Fatal Non-Truck Crash	Likelihood Ratio
Vehicle Identified as Utility/Emergency/Other Working Vehicle	188	80	0.00859	0.00047	18.27
Defect in Brake System	445	421	0.02033	0.00247	8.22
Defects in Lights/Horn/Mirror/Wiper	89	260	0.00407	0.00153	2.66
Defects in Steering/Suspension/Engine/ Exhaust System	77	263	0.00352	0.00155	2.27
Other Vehicle Defects(Wheels/Doors/Safety Belts/Air Bags)	124	499	0.00567	0.00293	1.93
Defective Tires	358	2501	0.01636	0.01470	1.11
Identified Vehicle Registration as Handicapped	65	581	0.00297	0.00341	0.87
Identified as a Hit-and-Run Vehicle	306	7727	0.01398	0.04540	0.30
Vehicle Went Airborne During Crash	57	1489	0.00260	0.00875	0.29
Vehicle Set in Motion by Another Vehicle/Non-Motorist	9	316	0.00041	0.00186	0.22

FARS records 94 different driver-related factors which include mental, psychological, vision obscured, environmental, and other miscellaneous factors. Of these 94 factors, only those which reasonably reflect the truck driver contributing to the occurrence of the crash were included here. As shown in Table 4.3, the conditional probability of each driver's contributory factor in truck and non-truck crashes and their likelihood ratios were estimated. Factors having considerable number of frequencies were selected, and results were listed in descending order of their likelihood ratios.

Table 4.3 Conditional Probabilities and Likelihood Ratios for Driver-Related Factors

Driver-Related Factor(DF)	Truck Crashes	Non-Truck Crashes	Conditional Probability of This DF Given a Fatal Truck Crash	Conditional Probability of This DF Given a Fatal Non-Truck Crash	Likelihood Ratio
Stopped or Unattended Vehicle	501	1019	0.02289	0.00599	3.82
Following Improperly	903	1902	0.04126	0.01118	3.69
Starting or Backing Improperly	147	349	0.00672	0.00205	3.27
Overloading or Improper Loading of the Vehicle	111	309	0.00507	0.00182	2.79
Making Improper Exit or Entry	76	287	0.00347	0.00169	2.05
Erratic Lane Change	525	2129	0.02399	0.01251	1.91
Cellular Telephone in Use in Driving	765	3488	0.03496	0.02049	1.70
Signal Inattention/Unfamiliar Roadway	128	643	0.00585	0.00378	1.54
Passing with Insufficient Distance or Inadequate Visibility or Failing to Yield to Overtaking Vehicle	283	1700	0.01293	0.00999	1.29
Driving on Wrong Side of the Road	557	3379	0.02545	0.01985	1.28
Failure to Yield Right of Way	2968	18801	0.13562	0.11047	1.22
Failure to Obey Traffic Rules	1688	10899	0.07713	0.06404	1.20
Drowsy ,Sleepy, Fatigued	683	4499	0.03121	0.02644	1.18
Tire Blow Out or Flat Tire	134	887	0.00612	0.00521	1.17
Inattentive(Talking, Eating)	2569	17407	0.11739	0.10228	1.14
Driving/Passing in Prohibited or Wrong Direction	83	701	0.00379	0.00412	0.92
Passing Where Prohibited by Posted Signs	104	900	0.00475	0.00529	0.89
Failing to Dim Lights or Have Lights When Required	39	338	0.00178	0.00199	0.89
Other Non-Moving Traffic Violation	745	6690	0.03404	0.03931	0.86
Operating without Required Equipment	285	2648	0.01302	0.01556	0.83
Failure to Keep in Proper Lane	5921	61914	0.27056	0.36379	0.74
Making Improper Turns	664	7085	0.03034	0.04163	0.72
Non-Traffic Violation Charged-Manslaughter or Homicide, etc.	286	3540	0.01307	0.02080	0.62
Reckless Driving	1040	13141	0.04752	0.07721	0.61
Driving Over the Posted Speed Limit	4070	54837	0.18598	0.32221	0.57
Driver Inexperienced or Impaired Health or Physical Condition	328	4683	0.01499	0.02752	0.54
Illegal Driving on Road Shoulder	54	912	0.00247	0.00536	0.46
Over Correcting	657	11656	0.03002	0.06849	0.43
Running Off the Road	587	11815	0.02682	0.06942	0.38
Other Drugs (Cocaine etc.)	1520	33954	0.06946	0.19951	0.34
Hit-and-Run Vehicle Driver	264	6807	0.01206	0.04000	0.30

Stopped or unattended vehicles, improper following, and starting and backing the vehicle improperly are factors with the highest likelihood ratios, which show they may contribute to fatal truck crashes more often than fatal non-truck crashes. Erratic lane change, cellular phone usage, and signal inattention are also factors significantly contributing to fatal crashes. Truck drivers appear to be more fatigued, drowsy, and inattentive when compared to other vehicle drivers, having a likelihood ratio of greater than one.

4.5 Multinomial Logistic Regression Analysis for Truck Crashes

The multinomial logistic regression technique was used on a subset of the FARS data in this study to elaborately analyze factors which have a higher rate of occurrence in fatal truck crashes than in non-truck crashes. The subset data consists of only single-vehicle fatal crashes that occurred in the United States from 2003-2007. The dependent variable for this model is dichotomous, as it can either be a truck crash or a non-truck crash.

There were 35 independent variables which included several crash, driver, vehicle, and environmental factors using statistical modeling software SAS version 9.1 (53). As the selection criteria of variables to be included in the model, a 95% confidence level was used in which the probability should be less than 0.05. Co-linearity of individual variables was also checked before considering variables into the model and if such relationship existed; one of the two correlated variables was discarded based on the lowest mean value criterion.

The independent variables considered in this model are shown in Table 4.4. Also, the odds-ratio values are presented along with parameter estimates in Table 4.5. One can also specify the change in the explanatory variables for which odds-ratio estimates are desired. Confidence intervals for the regression parameters and odds ratios can be computed based either on the profile likelihood function or on the asymptotic normality of the parameter estimators.

Table 4.4 Description of the Variables Used in the Model

Variable	Notation	Value	Description	Frequency	%
Month of the Year	month	1	Winter	26,571	24.0
		2	Spring	24,549	22.2
		3	Summer	29,430	26.6
		4	Fall	30,006	27.1
Day of a Month	day	1	<14	54,696	49.5
		2	>=14	55,860	50.5
Hour in a Day	hour	1	<10	54,583	49.4
		2	>10	55,973	50.6
Road Function Class	road_func	1	Rural	62,965	57.0
		2	Urban	47,591	43.1
Route	route	1	Interstate/US and State Highway/County Road	81,311	73.6
		2	Local Roads	29,245	26.5
Special Jurisdiction	sp_jur	1	No Special Jurisdiction	109,212	98.8
		2	Under Special Jurisdiction	1,344	1.2
First Harmful Event	harm_ev	1	Overturn/Rollover	19,783	17.9
		2	Pedestrian	20,473	18.5
		3	Motor Vehicle in Transport on Same Roadway	105	1.1
		4	Tree (Standing Tree Only)	15,424	14.0
		5	All Other Categories	54,771	49.5
Manner of Collision	man_coll	1	Not a Collision with a Motor Vehicle	109,051	98.6
		2	Rear End	744	0.7
		3	Head On Collision	133	0.1
		4	Angle	61	0.1
		5	Other	628	0.6
Traffic Flowway	traf_flo	1	Not Physically Divided	75,299	68.1
		2	Divided Highway/One way/Ramp/Other	35,257	31.9
No. of Lanes	no_lanes	1	Two Lane Or Less	88,232	79.8
		2	More than Two Lanes	22,324	20.2
Posted Speed Limit	sp_limit	1	<40	27,536	24.9
		2	40<=x<50	21,644	19.6
		3	50<=x<60	35,693	32.3
		4	60<=x<70	13,928	12.6
		5	>=70	11,755	10.6
Road Alignment	alignmnt	1	Straight	73,044	66.1
		2	Curved/Unknown	37,512	33.9
Road Profile	profile	1	Level	76,923	69.6
		2	Grade, Hillcrest, Sag, Unknown	33,633	30.4
Pavement Type	pave_typ	1	Blacktop	95,673	86.5
		2	Concrete and Other	14,883	13.5
Light Condition	lgt_cond	1	Day Light	44,192	40.0
		2	Poor Light Conditions/Other	66,364	60.0
Surface Condition	sur_cond	1	Dry	92,610	83.8
		2	Wet/Snow/Slush/Ice/Sand, Dirt	17,946	16.2

Table 4.4 Description of the Variables used in the Model (contd.)

Variable	Notation	Value	Description	Frequency	%
Weather Condition	weather	1	No Adverse Condition	98,290	88.9
		2	Rain/ Sleet/ Snow/Fog/Rain/Sleet/Smog	12,266	11.1
Crash-Related Contributory Factor	cf1	1	No Factor	106,415	96.3
		2	Some Factor Present	4,141	3.8
No. of Fatalities	fatals	1	One Fatality	104,411	94.4
		2	More than One Fatality	6,145	5.6
Day of the Week	day_week	1	Fri,Sat,Sun	58,728	53.1
		2	Mon-Thur/Unknown	51,828	46.9
Age of the Driver	age	1	Young	47,267	42.8
		2	Middle	26,392	23.9
		3	Older	36,897	33.4
Sex of the Driver	sex	1	Male	83,345	75.4
		2	Female	27,211	24.6
Ejection Type of the Driver	ejection	1	Not Ejected	82,586	74.7
		2	Totally or Partially Ejected	27,970	25.3
Alcohol Involvement	drinking	1	NO	38,905	35.2
		2	YES	27,542	24.9
		3	Not Reported/Unknown	44,109	39.9
Alcohol Detection	alc_det	1	Test Conducted	31,212	28.2
		2	Not Reported	79,344	71.8
Drugs Involvement	drugs	1	NO	26,259	23.8
		2	YES/Unknown	17,895	16.2
		3	Not Reported	66,402	60.1
Injury Severity of the Driver	inj_sev	1	No Injury	23,448	21.2
		2	Fatal Injury	68,300	61.8
		3	Other Injury	18,808	17.0
Rollover	rollover	1	No Rollover	68,659	62.1
		2	Happened as a First/Subsequent Event	41,897	37.9
Jacknife	j_knife	1	Not an Articulated Vehicle	107,554	97.3
		2	No/Other	3,002	2.7
Travelling Speed	trav_sp	1	Between 0 and 45 mph	15,927	14.4
		2	Between 45 and 60 mph	22,224	20.1
		3	Above 60 mph	6,161	5.6
		4	Not Reported/Unknown	66,244	59.9
Initial Impact Point	impact1	1	Front Side/Other	95,931	86.8
		2	Rear Side	14,625	13.2
Extent of Deformation	deformed	1	Severe Disabling Deformation	80,688	73.0
		2	Functional and Other Deformation	29,868	27.0
Vehicle-Related Contributory Factor	veh_cf1	1	No Vehicle factor	98,818	89.4
		2	Some Vehicle Factor	11,738	10.6
Driver Contributory Factor	dr_cf1	1	None	16,091	14.6
		2	Improper Physical/Mental Condition	29,333	26.5
		3	Improper Following of Traffic Regulations	53,919	48.8
		4	Other Miscellaneous factors	11,213	10.1

From the output parameters shown in Table 4.5, those response variables which are significant in the model are identified by setting the alpha level at 0.05 value. For all variables which have a p-value greater than 0.05, the model fails to reject the null hypothesis that the coefficient of that variable is zero. Hence, all those variables become insignificant in the model.

Therefore, the variables of *month*, *day, sp_jur, harm_ev, no_lanes*, *alignment, pave_typ,* and *drugs* become insignificant in the model as they have a p-value greater than the assumed cutoff value. All 27 other response variables remain in the model as they have a p-value less than 0.05 and hence, the null hypothesis is rejected and it's concluded that the regression coefficient for all these variables has been found to be statistically different from zero in estimating the model.

From the sign of the significant variables in the model when the coefficient estimates are observed, their sign shows the kind of proportionality the response variables have with the type of crash is known. While analyzing this aspect, it should be noted that the analysis is done with respect to the occurrence of a fatal single-vehicle truck crash. All variables with respect to their estimate value and point estimate (odds ratio) are explained in the following categories.

4.5.1 Roadway Characteristics

The negative coefficient for the response variable *route* would explain there are a larger proportion of fatal single-vehicle truck crashes on interstates than on local roads, as compared to non-truck crashes. Similarly, the coefficient of *road_fnc* explains that fatal truck crashes are more frequent on rural roads than on urban roads.

The variable *traf_flo* was also found to be significant in the model. As the sign of the estimate value is positive it shows that truck crashes have 1.98 times greater odds of occurring on roadways which are not physically divided when compared to non-truck crashes. Also, the variable *profile* has a positive estimate value. This shows that the type crash has a direct relationship with the roadway profile at the crash. Truck crashes tend to have 1.26 times greater odds of occurring on level roadway profiles than when compared to non-truck crashes. Similarly, when the surface condition at the crash site was analyzed it had a negative estimate value in the model. This implies that non-truck crashes have 0.76 times lesser odds of occurring on dry surfaces when compared to truck crashes.

4.5.2 Crash Characteristics

In the case of manner of collision, the estimate suggests that fatal single-vehicle truck crashes have 1.24 times higher odds of resulting in angle crashes than rear-end or head-on collisions. Also, they have 1.21 times greater odds of occurrence at speed limits greater than 60 than on roadways with lower speed limits. Similarly, the variable *hour* shows that truck crashes have 0.461 times lesser odds of occurring in morning and dawn hours of the day than in non-truck crashes. The variable *fatals* in the model which shows the number of fatalities in the crashes was found to have a negative estimate value in the model. This implies that fatal truck crashes have 0.647 times lesser odds of resulting in more than one fatality in a crash when compared to non-truck crashes.

Further, it was observed that truck crashes have 2.096 times higher odds of resulting in rollover crashes and 1.035 times higher odds of having a travelling speed above 60mph than non-truck crashes. Also, it was seen that truck crashes have 1.45 times higher odds of having a rear side initial impact point in a single vehicle crashes and 1.601 times higher odds of suffering functional deformation of the vehicle than when compared with non-truck crashes.

4.5.3 Environmental Characteristics

The light condition variable explains that truck crashes have 0.44 times lower odds of occurrence in dark light conditions, and in case of weather variables, they have 1.22 times higher odds of occurrence than in no adverse weather conditions.

4.5.4 Driver Characteristics

The *age* variable has a positive coefficient which shows that truck drivers are mostly in the middle and older population, whereas non-truck drivers tend to be mostly in the younger population. Also truck drivers have 1.906 times higher odds of being middle or older aged than being younger aged. From the alcohol involvement variable, it can also be derived that truck drivers have 0.88 times lesser odds of involvement in fatal crashes when compared to non-truck drivers.

Table 4.5 Parameter Estimates and Odds Ratio of Fatal Truck Crashes in the Model

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Sq	Odds Ratio	95% Wald Confidence Limits For Odds Ratio
intercept	-1.5899	0.3494	20.7004	<.0001		
month	0.0138	0.0154	0.7958	0.3723	1.014	0.984 , 1.045
day	-0.0178	0.0341	0.2716	0.6023	0.982	0.919 , 1.050
hour*	-0.7747	0.0357	470.137	<.0001*	0.461	0.430 , 0.494
road_func*	-0.3144	0.0442	50.6108	<.0001*	0.73	0.670 , 0.796
route*	-0.225	0.0485	21.5353	<.0001*	0.799	0.726 , 0.878
sp_jur	-0.2132	0.1807	1.3916	0.2381	0.808	0.567 , 1.151
harm_ev	0.0141	0.011	1.6281	0.202	1.014	0.992 , 1.036
man_coll*	0.2173	0.0404	28.8839	<.0001*	1.243	1.148 , 1.345
traf_flo*	0.6831	0.0418	266.572	<.0001*	1.98	1.824 , 2.149
no_lanes	-0.0395	0.0438	0.8136	0.3671	0.961	0.882 , 1.047
sp_limit*	0.1947	0.016	148.621	<.0001*	1.215	1.178 , 1.254
alignmnt	0.0234	0.0418	0.3136	0.5755	1.024	0.943 , 1.111
profile*	0.2384	0.0388	37.86	<.0001*	1.269	1.176 , 1.369
pave_typ	-0.0011	0.0487	0.0005	0.9825	0.999	0.908 , 1.099
lgt_cond*	-0.8113	0.0357	517.257	<.0001*	0.444	0.414 , 0.476
sur_cond*	-0.2735	0.071	14.8527	0.0001*	0.761	0.662 , 0.874
weather*	0.1993	0.0788	6.4037	0.0114*	1.221	1.046 , 1.424
cf1*	0.2813	0.0805	12.2242	0.0005*	1.325	1.132 , 1.551
fatals*	-0.436	0.1002	18.9312	<.0001*	0.647	0.531 , 0.787
day_week*	0.8383	0.0362	535.453	<.0001*	2.312	2.154 , 2.483
age*	0.645	0.0219	870.743	<.0001*	1.906	1.826 , 1.989
sex*	-2.5808	0.0921	785.063	<.0001*	0.076	0.063 , 0.091
ejection*	-0.517	0.0496	108.486	<.0001*	0.596	0.541 , 0.657
drinking*	-0.1237	0.0218	32.0713	<.0001*	0.884	0.847 , 0.922
alc_det*	0.2171	0.0436	24.8166	<.0001*	1.242	1.141 , 1.353
drugs	-0.0011	0.0218	0.0024	0.9608	0.999	0.957 , 1.042
inj_sev*	-1.0785	0.0418	664.734	<.0001*	0.34	0.313 , 0.369
rollover*	0.7401	0.047	247.666	<.0001*	2.096	1.912 , 2.299
trav_sp*	0.0342	0.0149	5.2619	0.0218*	1.035	1.005 , 1.065
impact1*	0.373	0.0504	54.8538	<.0001*	1.452	1.316 , 1.603
deformed*	0.4706	0.0473	99.1199	<.0001*	1.601	1.459 , 1.756
veh_cf1*	0.3514	0.055	40.8397	<.0001*	1.421	1.276 , 1.583
dr_cf1*	-0.097	0.0194	25.0645	<.0001*	0.908	0.874 , 0.943

* – Significant at 0.05 level

The variable representing the gender of the driver had a negative estimate value in the model. This shows that truck drivers have 0.076 lesser odds of being female drivers than in non-truck crashes. Also, when the *ejection* variable was observed it showed that truck drivers had 0.596 times lesser odds of ejecting out of the vehicle during the crash than when compared to non-truck drivers in fatal crashes.

4.5.5 Other Contributory Factors

When the overall crash-related factor, *cf1* is observed, the positive coefficient shows that truck crashes tend to have some significant factor which has been identified in the police report. Also, the vehicle-related factor shows there is 1.42 times higher odds of a truck having a significant vehicle contributory factor than a non-truck vehicle.

The "Model Fit Statistics" in Table 4.6 contain the Akaike Information Criterion (AIC), the Schwarz Criterion (SC), and the negative of twice the log likelihood (-2 Log L) for the intercept-only model and the fitted model. AIC and SC can be used to compare different models, and the ones with smaller values are preferred.

The AIC value of 34,527 is the smallest value obtained in the repeated trials performed in this dataset, which shows that this model is the most optimum result. The SC and the -2 Log L values were also observed to be the least, therefore reinforcing the above statement.

Table 4.6 Model Fit Statistics of the Multinomial Logistic Regression Analysis

Criterion	Intercept Only	Intercept and Covariates
AIC	34527.4	27107.59
SC	34537.0	27434.44
-2 Log L	34525.4	27039.59

The three independence tests of likelihood ratio, overall score, and Wald's Chi-Square have a p-value less than .0001 as shown in Table 4.7, therefore showing that results are very significant.

Table 4.7 Tests of Independence for the Multinomial Logistic Regression Analysis

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	7485.8133	33	<.0001
Score	6963.1703	33	<.0001
Wald	5397.167	33	<.0001

Table 4.8 shows other goodness-of-fit parameters values obtained from the LOGISTIC procedure performed on the dataset. Descriptions of those parameters are as follows:

- Percent Concordant-This has a value of 85.1% which shows a high rate of concordance between the pairs of observations with different observed, and the observation with the lower ordered response value has a lower predicted mean score than the observation with the higher ordered response value.
- Percent Discordant-If the observation with the lower ordered response value has a higher predicted mean score than the observation with the higher ordered response value, then the pair is discordant.
- Percent Tied-If a pair of observations with different responses is neither concordant nor discordant, it is a tie.
- Somer's D-This is used to determine the strength and direction of relation between pairs of variables. Its values range from -1.0 (all pairs disagree) to 1.0 (all pairs agree). The value of 0.71 is closer to 1 which therefore shows that all pairs of variables agree to a large extent.
- The Goodman-Kruskal Gamma-This has a value of 0.717 which also signifies the perfect association of the variables in the model. This method does not penalize for ties on either variable. Its values range from -1.0 (no association) to 1.0 (perfect association).
- Tau-a-This has the value of 0.05, which is a modification of Somer's D to take into account the difference between the number of possible paired observations and the number of paired observations with different responses.
- Another measure of rank correlation of ordinal variables (c) has a value of 0.855 which reinforces the perfect association between the data variables and the observed variables. This value usually ranges from 0 to (no association) to 1 (perfect association).

Table 4.8 Associations of Predicted Probabilities and Observed Responses

Percent Concordant	85.1	Somers' D	0.71
Percent Discordant	14	Gamma	0.717
Percent Tied	0.9	Tau-a	0.05
Pairs	428,069,684	c	0.855

Hence, multinomial logistic regression provides useful goodness of fit measures which help analyzing the significance of various parameters with truck crashes in comparison with non-truck crashes.

CHAPTER 5 - CONCLUSIONS AND SUMMARY

This study explored the characteristics of trucks involved in fatal crashes and evaluated the fatality risk posed for them in relation to some of the selected driver, vehicle, environmental, and roadway-related variables. Fatal crash data obtained from NHTSA was used for this analysis.

Several significant characteristics of fatal truck crashes have been observed from this analysis. Fatal crash frequency was observed to be greater with the initial impact point for the vehicle in the front end of the truck rather than anywhere else. All fatal truck crash cases which had alcohol involvement indicated that in 87% of cases, non-truck drivers were the ones under this influence. Trucks seemed to have a majority of fatal crashes at higher posted speed levels, which might also be due to a larger presence of trucks at higher speed ranges. Fatigue, drowsiness, and inattention were observed to be more predominant in truck drivers than in other motor vehicle drivers. The majority of fatal truck crashes occurred on two-way two-lane traffic flowways with no physical divisions. Such roadways could be altered by providing necessary changes in the roadway design. Improper driving and non-compliance to traffic regulations were observed to be the main driver-related contributory factors in cases of fatal truck crashes. In comparing the overlapping effect of two fatal crash characteristics, truck striking and truck being struck seemed to have similar proportions on all roadway types. Also, this proportion remained consistent even under different light conditions.

From the likelihood ratios, stopped or unattended vehicles or improper following had greater probabilities of occurrence in fatal truck crashes than in non-truck crashes. Recent previous crash nearby/ vehicle set in motion by a non-driver, work area conditions, poor shoulder conditions, and inadequate warning signs are the topmost factors which have more likelihood in fatal truck crashes than non-truck crashes. Other factors like cellular usage, failure to yield right of way, inattentiveness, and failure to obey traffic rules are more likely to contribute to fatal truck crashes. Also, truck drivers appear to be more fatigued, drowsy, and inattentive when compared to other vehicle drivers, having a likelihood ratio of greater than one.

From the Multinomial Logistic Regression Modeling performed on the single-vehicle fatal crashes, several factors were concluded such as, that single-vehicle, fatal truck crashes are more frequent on rural roads than on urban roads. The manner of collision coefficient estimate suggests that fatal, single-vehicle truck crashes have 1.24 times higher odds of resulting from angle crashes than rear-end or head-on collisions. Also, they have 1.21 times greater odds of occurrence at speed limits greater than 60 than on roadways with lower speed limits. The light condition variable explains that truck crashes have 0.44 times lower odds of occurrence in dark light conditions and in the case of the weather variable, they have 1.22 times higher odds of occurrence in no adverse weather conditions. Finally, the overall 85.1% concordance value of the model has shown the level to which it fits the given data, hence proving to be a decent model fit.

The results provide a deep understanding of the various factors which have greater association with truck crashes when compared to non-truck crashes. By addressing these issues the overall truck crash rate can be reduced, which can help in improving overall safety of the transportation system.

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