Effects of Truck Traffic on Crash Injury Severity on Rural Highways in Wyoming using Bayesian Binary Logit Models

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Word Count
6,623 + (3 x 250 Figures and Tables) = 7,373

July 2014

Transportation Research Board
Washington, D.C.
ABSTRACT

Roadway safety is an integral part of a functioning infrastructure. A major use of the highway system is the transport of goods. The United States has experienced constant growth in the amount of freight transported by truck in the last few years. Wyoming is experiencing a large increase in truck traffic on its local and county roads due to an increase in oil and gas production.

This study explores the involvement of heavy trucks in crashes and their significance as a predictor of crash severity and addresses the effect that large truck traffic is having on the safety of roadways for various road classifications. Studies have been done on the factors involved in and the causation of heavy truck crashes, but none address the causation and effect of roadway classifications on truck crashes.

Binary Logit Models (BLM) with Bayesian inferences were utilized to classify heavy truck involvement in severe and non-severe crashes using ten years (2002-2011) of historical crash data in the State of Wyoming. From the final main effects model, various interactions proved to be significant in predicting the severity of crashes and varied depending on the roadway classification. The results indicated the odds of a severe crash increase to 2.3 and 4.5 times when a heavy truck is involved on state and interstate highways respectively. The severity of crashes is significantly increased when road conditions were not clear, icy, and during snowy weather conditions.
INTRODUCTION

The number of motor vehicle crashes is a primary concern in the study of transportation safety and crashes involving trucks tend to have the largest repercussions. Property damage, loss of goods, and loss of life are all heightened aspects when dealing with a heavy truck crash. The average cost of a heavy-truck related crash in 2005 was estimated to be more than $91,000 (1). Since 2009, the numbers of injuries and fatalities due to crashes that involved a heavy truck have been steadily increasing from the previous years (2).

The U.S. economy relies heavily upon the trucking industry for the movement of goods. Trucking was responsible for a total of 9.4 million tons of freight in America in 2012, which accounted for 68.5 percent of the total freight weight. This percentage is expected to continue to grow in the next ten years (3).

Not all roads were originally designed to handle the amount of heavy truck traffic that is becoming common on interstates, highways, bridges, and local roads. Large trucks not only contribute to prematurely deteriorated road structures, they also affect crash rates. In 2012, approximately 4,000 fatalities and 104,000 injuries occurred nationwide in crashes that involved at least one heavy truck. Of these fatalities, 83 percent were not the operators of the heavy truck (2). Roads are not always built wide enough or with the correct geometry needed to accommodate heavy trucks. Driver fatigue from long hours of operating also contributes to the number of crashes involving heavy trucks. Inclement weather can compound this issue.

With oil and gas extraction being a growing industry all around the United States, the amount of heavy trucks operating in rural locations is expected to increase. During a three year period from 2003-2006, a total of 404 fatalities occurred nationwide amongst extraction workers. Of these fatalities, 110 were highway related incidents and multi-vehicle collisions accounted for 36 percent of the highway related fatalities (4). Wyoming and North Dakota are both currently experiencing high oil and gas production. Crash rates for heavy trucks in these states were twice as high as the national average. The large truck crash rate in Wyoming has increased from 8.1% in 2009 to 16.8% in 2012 (5).

OBJECTIVES

The objectives of this paper are to explore if the involvement of a heavy truck in a crash is a significant predictor of crash severity, to identify factors combined with heavy truck involvement affecting the severity of a crash, and to discover if a relationship exists between the severity of a crash involving a heavy truck and the classification of the road on which the crash occurred. Together with a descriptive analysis of factors involved in heavy truck crashes, recommendations can be made to improve truck safety.

BACKGROUND

Crash causation can be examined from a variety of angles. Factors are generally broken down into a few different categories including: driver factors, external or road factors, and vehicle factors. In a large truck safety evaluation conducted in Wisconsin (6), driver factors and behaviors were shown to be the most significant variables in the outcome of severity of crashes in the state. In the study, many county officials agreed that large truck crash causations are due to driver decisions more so than the infrastructure’s design (6).

The critical reasons behind large truck involvement in fatal and injury crashes were explored in a Large Truck Crash Causation Study (LTCCS) (7). A critical reason is defined as
the immediate reason for an unavoidable collision and is assigned to the vehicle responsible for the crash. Large trucks were assigned the critical reason in 55 percent of the study group. Of those crashes where the truck was the critical reason, 87 percent were driver-related, 10 percent were vehicle-related, and 3 percent were environment-related. A further look at the driver-related crashes revealed that 38 percent were caused by the decision of the driver, such as driving too fast, 28 percent were because the driver was inattentive or distracted, 12 percent were non-performance, such as falling asleep, and 9 percent were based on the performance of the driver, such as a panic or overcompensating(7).

The American Transportation Research Institute (ATRI) examined specific truck driver behavior and infractions as a way of predicting crash involvement (8). The study used data that was collected from 2008-2009. It was found that five different truck driver events cause an increase in crash likelihood of 80 percent or more. The greatest increase in crash likelihood occurred when a driver failed to use or improperly used a turn signal at 96 percent. If the driver had been involved in a previous crash or if the driver had been issued an improper passing violation, the likelihood of a future crash occurring increased to 88 percent. The increase in likelihood was 84 percent if a driver had been caught making an improper turn and 80 percent if convicted of an improper or erratic lane change (8).

Research presented at the International Driving Symposium (9) investigated the critical reasons behind single vehicle and multi-vehicle crashes using data from the LTCCS. The conclusions showed that single vehicle truck crashes were the result of driver choices such as driving too fast for conditions or lack of sleep, as well as roadway factors such as curves. Multi-vehicle crashes where fault was placed on the truck driver usually occurred in dense traffic when the driver was not paying adequate attention to the surroundings. Multi-vehicle crashes where the other vehicle was found at fault had similar reasons relating to vehicle interaction errors rather than loss of control (9).

Determining driver-related crash factors was the subject of a study that focused specifically on two-vehicle fatal collisions (10). This national study focused exclusively on crashes that involved one passenger vehicle and one heavy truck. These types of crashes make up about 60 percent of all truck involved fatal crashes, in which the truck driver survived 98 percent of the time and the passenger vehicle driver was killed in 83 percent. The dataset was separated into two files; one included all information about the truck involved in the crash, and the other file had the non-truck information. It was found that the truck driver was the main contributor to causing the fatal crash 34.1 percent of the time (10).

Another study which used data collected by the LTCCS examined the effect of large trucks on the severity of crashes (11). A specific focus was placed on long-combination vehicles, which are trucks pulling multiple trailers. The study’s model found that the probability increased for injury and fatal crashes if non-bright lighting conditions are present, the road surface is snowy or icy, and/or there is fog.

The road type that a crash occurs on lends important information to the nature and possible causations of the crash. In 1987, a national analysis on large trucks involved in fatal crashes on different road classifications was conducted (12). This early study considered four variables when predicting crash severity in its model: road class, truck type, truck gross weight, and year of the accident. Of the four types of roadways that were used, the largest amounts of crashes occurred on rural undivided roadways (12).
More recent national trends in fatal heavy truck crashes on various roadways were observed in 2011 (13). A descriptive analysis showed that an average of approximately 5,000 fatalities per year (2004-2008) occurred as a result of a truck-related crash. In a breakdown of crashes from 2008, 29.4 percent of fatalities occur on state highways, 27.1 percent on interstates, 23.8 percent on US highways, and 8.9 percent on county roads. Almost two-thirds of all the crashes occurred in rural areas. Of the truck drivers involved, 3.1 percent tested for alcohol and 1.2 percent for drugs (13). These facts do not take into account VMT which may be misleading.

With gas and oil extraction being a growing industry around the United States, the amount of heavy trucks is expected to increase. The National Institute for Occupation Safety and Health-(NIOSH) performs an annual study called the Census of Fatal Occupation Injuries (CFOI) examining the number of fatalities happening among workers in the field. Following a 15% increase in oil and gas extraction fatalities from 2003-2004 (14), a full investigation was done. During a three year period of the 2003-2006 NIOSH study, a total of 404 fatalities happened among extraction workers. 110 of those fatalities were highway- related incidents. Non-collision events accounted for 38 percent of fatalities, while collisions between vehicles accounted for 36% (15).

When examining all of the CFOIs done by the NIOSH in the past 10 years, highway crashes consistently have been one of the leading causes of worker fatalities (16). Mining had the second highest fatal work injury rate, the majority of which occur in the oil and gas extraction industries.

A safety survey was conducted examining the public view on the impact of increased oil drilling in Western North Dakota (17). Kubas & Vachal’s research has shown a significant increase in both the truck traffic and crashes within the most impacted counties which have seen the largest increase in production of oil drilling. The survey revealed that 88.8 percent of the drivers in the affected counties felt less safe driving on the roads than they did 5 years earlier, approximately when drilling started increasing (17).

Savolainen et al. (18) summarized the evolution of research and statistical analyses of traffic injury severities. From the review it can be seen that Binary Logit Model (BLM), Nested Logit Model (NLM), Ordered Logit Model (OLM) and Ordered Probit Model (OPM) and random parameters (Mixed) Logit Model (MLM) are among the most popular methods used in analyzing crash injury severities. Other non-traditional statistical models; data mining techniques such as Artificial Neural Networks (ANN) (19), Classification and Regression Tree (CART) (20), and Support Vector Machine (SVM) (21), are also used. Recently, Bayesian statistics are gaining momentum in traffic safety analysis, Huang et al. (22) introduced hierarchical Bayesian binomial logistic models to perform the multi-vehicle crash injury severity analysis. Lemp et al. (11) analyzed large truck crash severity using heteroskedastic ordered probit models with Bayesian inference approach. Their approach allowed for variations of unobserved components, the authors concluded that the Bayesian approach outperformed the traditional Maximum Likelihood Estimation (MLE). In this study, the BLM models with both the MLE and Bayesian inference techniques were estimated to investigate the effect of heavy vehicles on crash injury severity.
METHODOLOGY

This paper presents a statewide study on all roadway classifications in Wyoming. Once data was collected and organized, a descriptive analysis was conducted. Binary Logit Models (BLM) with both the maximum likelihood estimation and Bayesian inference approach were used to classify heavy truck involvement in severe and non-severe crashes, and to identify the effect of driver, roadway, and environmental factors.

Crash severity is used in this study to assess the effect of trucks on crashes. All crash records and roadway inventories for the state of Wyoming were obtained from the Wyoming Department of Transportation (WYDOT) and a master dataset was created for a 10-year period (2002-2011). The vehicle type and the estimated travel speed at the time of the crash for each vehicle involved was recorded in each crash report. The road surface, grade, horizontal alignment, and rumble strips were all items of data specific to the piece of roadway on which the crash occurred. Information on all drivers that were involved in each crash which included age, gender, and safety equipment use (seat belts) was also recorded. Data detailing the traffic volumes and geometric dimensions of the roadways was retrieved from WYDOT road inventories which included traffic volumes, miles travelled, road dimensions, the number of lanes, and shoulder material. However, traffic volumes were not available for many of the roadways, particularly the secondary and local roads.

Analysis of the statewide Wyoming dataset focuses on the relationships between different crash factors, namely vehicle type, road classification, road conditions, and driver influences. Using spreadsheets and various visual tools, relationships between variables were identified. Once trends were observed, factors that appear insignificant were ruled out, and factors that appear significant in affecting crash severity were used in the statistical analysis.

Upon completion of the descriptive analysis, a statistical analysis was used to verify the findings. A model was previously developed for the various road classifications in Wyoming to determine significant factors that affect crash severity. This research used those factors to build upon for the statistical analysis (23). First a univariate analysis was conducted to identify if trucks are significant crash predictors on each of the road types. Then a main effects model was used to test if trucks maintain their significance in the presence of other predictors. Finally, interactions were introduced into the model between trucks and other crash factors to better understand the effect of trucks on crash severity in the presence of these other variables.

DESCRIPTIVE ANALYSIS

The crash records from 2002-2011 were investigated. During that time period, a total of 160,613 crashes involving 253,531 vehicles were recorded. The main characteristics investigated included: severity, types of vehicles, number of vehicles, highway system, posted speed, vehicle speeds, road condition, weather condition, seat belt usage, drug usage, and alcohol usage.

The severity level of a crash is dictated by the worst injury that was incurred by all passengers in the crash. Only one severity level is assigned to each crash, so the percentage is taken from the total number of crashes. Of 160,613 crashes that occurred in the 10 year span, less than 1 percent resulted in a fatality. Incapacitating injury crashes resulted in about 4 percent, and possible injury and non-incapacitating injury crashes were each about 10 percent.
Truck involvement refers to when there is at least one heavy truck weighing more than 26,000 pounds involved in a crash. Table 1 shows the percentage of crashes broken down by each severity level, and separated by whether or not one or more of the vehicles involved in the crash was a heavy truck. The percentages are slightly higher for more severe crashes when trucks are involved than when no truck is involved. The percentage of fatal crashes is almost twice as high when a truck is involved. The usage of safety restraints was evaluated and found that truck drivers were using their safety restraints 83.0 percent of the time. As seen in Table 1, truck drivers were using alcohol 2.1 percent of the time, which is less than the crashes where no heavy truck was involved. Truck drivers tested positive for drugs in 0.3 percent of the crashes, which is less than half of that for crashing not involving a truck.

Table 1. Crashes and Truck Involvement

<table>
<thead>
<tr>
<th>Severity</th>
<th>Truck Involved</th>
<th>No Truck Involved</th>
</tr>
</thead>
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<tr>
<td></td>
<td>Crashes</td>
<td>Percent</td>
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<tr>
<td>No Injury</td>
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<td>74.0%</td>
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<tr>
<td>Possible Injury</td>
<td>1161</td>
<td>8.8%</td>
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<tr>
<td>Non-Incapacitating Injury</td>
<td>1314</td>
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</tr>
<tr>
<td>Incapacitating Injury</td>
<td>709</td>
<td>5.3%</td>
</tr>
<tr>
<td>Fatal</td>
<td>205</td>
<td>1.5%</td>
</tr>
<tr>
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<td>65</td>
<td>0.5%</td>
</tr>
<tr>
<td>Total Crashes</td>
<td>13272</td>
<td>100%</td>
</tr>
</tbody>
</table>

| Alcohol Involved          |                |        |            |        |
|---------------------------|----------------|----------------|
| Yes                       | 280            | 2.1%   | 10387      | 7.0%   |
| No                        | 12992          | 97.9%  | 127185     | 86.3%  |
| No Answer                 | 1              | 0.0%   | 9768       | 6.6%   |
| Total Crashes             | 13273          | 100%   | 147340     | 100%   |

| Drugs Involved            |                |        |            |        |
|---------------------------|----------------|----------------|
| Yes                       | 46             | 0.3%   | 1069       | 0.7%   |
| No                        | 4961           | 37.4%  | 46890      | 31.8%  |
| No Answer                 | 8266           | 62.3%  | 99381      | 67.5%  |
| Total Crashes             | 13273          | 100%   | 147340     | 100%   |

Heavy trucks were involved in 13,273 crashes, which is 8.3 percent of the total crashes, but they only make up 6.0 percent of the total vehicle count. Cars are involved in 58.5 percent of the crashes, and make up 47.3 percent of the vehicles. Over 50 percent of crashes are multiple vehicle crashes and single vehicle crashes account for 46.2 percent of the crashes reported.

The road classifications were grouped into categories based on their ownership and maintenance. Most crashes took place on primary federal highways and interstates. This could be due to large traffic volumes and a high number of road miles, which is typical for these types of roads. Sixty-eight percent of heavy trucks were involved in crashes on
interstates. This is approximately double any of the other vehicle types on any of the other road types.

When comparing the posted speeds where the crashes occurred, 39.1 percent of heavy truck crashes occurred where the speed was posted at 75 mph. The second most occurred on roads where the posted speed was 30 mph at 19.3 percent of the truck crashes.

Weather and road conditions at the time of the crashes were also analyzed. Weather can affect visibility and roadway condition. Most crashes occurred when the weather was clear. However, snow was most common in crashes that occurred during inclement weather.

Inclement weather can lead to less-than-optimal road conditions, which affect handling of the vehicle. In Figure 1, the analysis shows that the next most common road condition to dry roads was ice and frost. Twenty-eight percent of truck involved crashes occurred on roads with ice and frost, compared to fifteen percent of non-truck crashes occurring on ice and frost covered roads.

![Weather Conditions Truck Involved Crashes](image1)

![Weather Conditions Non-Truck Involved Crashes](image2)

![Road Conditions Truck Involved Crashes](image3)

![Road Conditions Non-Truck Involved Crashes](image4)

**Figure 1. Weather and Road Conditions during Crashes**

**STATISTICAL ANALYSIS**

The descriptive data analysis suggested certain trends when trucks are involved in a crash compared to when they are not. Statistical analysis was performed on the data to learn about the effects of trucks on crash severity. Logistic regression models with both maximum likelihood estimation and Bayesian inference were used to examine all aspects of the data and the effect of trucks on crash severity. Models were constructed for each type of road classification.

**Bayesian Logistic Regression**

The study utilized a Bayesian logistic regression approach to estimate the probability of crash
Bayesian logistic regression has the formulation of a logistic equation and can handle both continuous and categorical explanatory variables. The classical logistic regression treats the parameters of the models as fixed, unknown constants and the data is used solely to best estimate the unknown values of the parameters. In the Bayesian approach, the parameters are treated as random variables, and the data is used to update beliefs about the behavior of the parameters to assess their distributional properties. The interpretation of Bayesian inference is slightly different than the classical statistics; the Bayesian derives updated posterior probability of the parameters and construct credibility intervals that have a natural interpretation in terms of probabilities. Moreover, Bayesian inference can effectively avoid the problem of over fitting that occurs when the number of observations is limited and the number of variables is large.

The Bayesian logistic regression models the relationship between the dichotomy response variable (severe/non-severe) and the explanatory variables of roadway geometry, traffic, and weather. Suppose that the response variable $y$ has the outcomes $y=1$ or $y=0$ with respective probability $p$ and $1-p$. The logistic regression equation can be expressed as:

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta X \quad (1)$$

Where $\beta_0$ is the intercept, $\beta$ is the vector of coefficients for the explanatory variables, and $X$ is the vector of the explanatory variables. The logit function relates the explanatory variables to the probability of an outcome $y=1$. The expected probability that $y=1$ for a given value of the vector of explanatory variables $X$ can be theoretically calculated as:

$$p(y = 1) = \frac{\exp(\beta_0 + \beta X)}{1 + \exp(\beta_0 + \beta X)} = \frac{e^{\beta_0 + \beta X}}{1 + e^{\beta_0 + \beta X}} \quad (2)$$

One advantage of the Bayesian approach over the classical model is the applicability of choosing the parametric family for prior probability distributions. There are three different priors that can be used: 1) informative prior distributions based on the literature, experts’ knowledge or explicitly from an earlier data analysis, 2) weak informative priors that do not supply any controversial information but are strong enough to pull the data away from inappropriate inferences, or 3) uniform priors or non-informative priors that basically allow the information from the likelihood to be interpreted probabilistically. In this study, uniform priors following normal distribution with initial values for the estimation of each parameter from the maximum likelihood method was used. Different types of prior distributions using the results from this study as prior could be considered for further research once more data become available to update the estimated models.

All models were estimated by Bayesian inference using the freeware Winbugs (24). For each model, three chains of 10,000 iterations were set up in Winbugs based on the convergence speed and the magnitude of the dataset. The Deviance Information Criterion DIC, a Bayesian generalization of Akaike Information Criterion AIC, is used to measure the model complexity and fit. DIC is a combination of the deviance for the model and a penalty for the complexity of the model. The deviance is defined as $-2\log(\text{likelihood})$. The effective number of parameters, $pD$, is used as a measure of the complexity of the
model, \( pD = D_{bar} - Dhat \), where \( D_{bar} \) is the posterior mean of the deviance, and \( Dhat \) is a point estimate of the deviance for the posterior mean of the parameters. DIC is given by DIC \( = Dhat + 2pD \) (25). Moreover, receiver operating characteristic (ROC) curve analysis was used to compare across models.

Specific crash variables were chosen for the model. First and foremost, truck involvement was tested. Light truck, medium truck, and heavy truck were each measured. A light truck is considered to weigh less than 10,000 pounds, a medium truck between 10,000 pounds and 26,000 pounds, and a heavy truck is more than 26,000 pounds (25). Other factors that were used in the model were based upon those that were identified in a previous study that analyzed crash severity for all rural roadways in Wyoming (26). A stepwise variable selection method was utilized to find significant predictors of crash severity (26). The factors identified from that model were the variables used for this analysis, in addition to the truck involvement variables.

A Bayesian binary logit regression approach was used to model the response that the crash is severe or not severe. A crash is considered severe if its outcome is a fatal or incapacitating injury. Severe crashes are coded with the value one (1). Not severe crashes consist of non-incapacitating injury, possible injury, and no injury and are given the value zero (0). Each value of a crash variable was also converted into a binary or dichotomous response of either one or zero (1 or 0). The key to these responses can be seen in Table 4. The All Trucks variable takes into account if any light, medium, or heavy truck was involved in the crash or not.

The purpose of the modeling is to identify variables which are significant predictors of crash severity. Since crash severity is the outcome being modelled, it is called the response variable. The response variable is the function of a set of predictor variables (27). A simple logistic regression analysis was performed first to examine the significance of truck involvement as a predictor by itself. This univariate analysis involved running the logistic regression model with only one predictor variable. The analysis was done separately for each roadway model with each weight of truck. A univariate analysis demonstrates if a variable is important by itself and its individual relationship with the response.

Next, an analysis was conducted to assess the main effects. The main effects model determined predictor variables when interaction terms aren’t present. The main effects model was done separately for each roadway model with each weight of truck. Once a main effects model was run, pairwise interaction terms were added to the model. Interaction terms occur when a variable has a different effect on the outcome, severity in this case, depending on the value of another variable. Each significant factor was paired with the truck variable and tested for significance. Interactions for the roadway models were removed based on an iterative process to arrive at a final model. These interaction factors were tested in of the roadway models. Insignificant interactions were removed from the model by an iterative process.

Odds ratios were estimated based on variables that showed up consistently in the models. These ratios explain the probability of a severe crash happening when certain conditions are present versus when they are not present. The odds of a single variable are calculated as \( \text{odds} = \frac{\pi}{1-\pi} \). For interaction terms, the odds of the two variables that make up the interaction must be taken into account. Odds ratios are computed using equation 2 shown below.
\[ \text{\(\hat{OR} = \left(\frac{\pi_1}{1-\pi_1}\right)\left(\frac{1-\pi_2}{\pi_2}\right)\)} \quad (3) \]

From the odds ratios that are calculated from interactions, the odds of a severe crash in the presence of two predictors can be estimated.

**Analysis**

A univariate analysis was first conducted to investigate whether trucks were a significant predictor of severity when no other factor was involved which helps to screen the initial variables to determine if they are statistically significant and should be considered for the more extensive model. Light trucks, medium trucks, heavy trucks, and all trucks were put into the model and run individually in each road classification model.

A p-value threshold of <0.05 is typically used in transportation engineering for deeming a variable to be significant. However, for this analysis, a p-value of less than 0.1 is used in order to encompass more of the data. The presence of trucks in a crash was shown to be a significant variable only on state and interstate roads, so a new global model was constructed which excluded county roads. This non-significance could be due the lack of crash data in the county system and the system may have too much variation that is not accounted for by truck involvement. The change in the global model reflected the significance of the involvement of heavy trucks and all trucks on severity. All models revealed that light trucks and medium trucks do not appear to be statistically significant in predicting crash severity.

The next step in analyzing the direct effects of truck involvement on crash severity in the presence of other crash variables in a model is to identify the main effects through a stepwise selection. The variables chosen for the main effects model originated from a previous study which analyzed crash severity for all rural roadways in Wyoming and determined what variables were significant for each roadway type (26). Each truck term was tested one at a time in each of the road models and the global models.

Trucks did not appear to be a significant predictor of severe crashes when used in the main effects models. The p-value of each truck involvement term on each type of roadway is greater than the threshold of 0.1 and therefore trucks are not significant in the presence of other crash factors. However, since the univariate model suggested trucks had some effect, the statistical modeling is continued to determine if trucks are significant if combined with another variable as an interaction term.

Because of the lack of data, and lack of significance of truck crashes on county roads, this road class was not tested in the interaction models. Also, since light trucks and medium trucks showed to be insignificant in both the univariate and main effects models, they were not tested in the interaction model.

Three final models were estimated including the main effects and interaction terms. Interaction terms help describe the effect that two variables occurring together have on an outcome. Interaction terms were formed between the truck variable and each variable from the main effects model and added to those interactions previously determined to be of importance.

All of the interactions were put into the main effects model. A stepwise process was then used where interactions were removed if their p-value did not fall below the desired threshold. The model was run again after those interactions were removed. The threshold
began at 0.5 and decreased by 0.1 each time the model was re-run. The last run of the model eliminated any interactions that were left with p-values higher than 0.05. This value is consistent with other cited work such as Andreen (28) and Shintine (26). These interactions, combined with the main effects variables, comprised the final model for each of the road systems.

The truck variables that were run were reduced to only “all trucks”, since the light trucks and medium trucks were shown to be insignificant in the preliminary analysis. Logistic regression models with the Bayesian inference approach were used for each specific data and the estimate coefficients, credible intervals and model fits are shown in Table 2. The three final models show similar classification ability since the ROC areas are almost the same.

Some of the interactions that were significant on all road types were all trucks with multi-vehicle crashes and all trucks with undesirable road conditions. Since these terms showed to be significant, it prompts further investigation into their effects on crash severity.
<table>
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<th>Model</th>
<th>State Mean 2.5%</th>
<th>State 97.5%</th>
<th>State Intercept Mean 2.5%</th>
<th>State Intercept 97.5%</th>
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<tr>
<td>Animal (FHE)</td>
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<td>-0.074</td>
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<td>-0.076</td>
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<td>All Trucks</td>
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<td>-0.860</td>
<td>-0.341</td>
<td>-0.231</td>
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<td>Motorcycle</td>
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<td>2.502</td>
<td>2.877</td>
<td>2.592</td>
<td>2.478</td>
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<tr>
<td>Rollover*All Trucks</td>
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<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Mean Speed*All Trucks</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<td>-</td>
</tr>
<tr>
<td>Grade*All Trucks</td>
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<td>-</td>
<td>-</td>
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Modeling Results and Discussions

State Model
The state model included the road classifications of state highway, primary federal highway, and secondary federal highway. Heavy trucks and all trucks were shown to be significant in the univariate analysis with p-values close to zero. In the main effects model, no weight of truck was shown to be significant in the presence of other variables. This lack of significance did not rule out the chance that trucks would be involved in significant interaction terms. The final model showed that the presence of a truck in a crash is significant when combined with any of the following terms: multiple vehicles, inclement road conditions, and curvy alignment.

The odds ratios can be used to interpret the presence of a truck in a crash on the severity of a crash when multiple vehicles are involved. The odds ratio is interpreted as the odds for when one or both interaction terms are present and comparing it to the odds when they are not present. When a multi-vehicle crash occurs but there is no truck involved, the estimated odds that the crash will be severe is 1.8 times as likely as when the crash is single vehicle with no truck. However, when the crash involves multiple vehicles and there is a truck involved, the estimated odds of a severe crash increase to 2.3 times as likely.

Interstate Model
The all trucks variable (light, medium, or heavy truck) was significant in the univariate analysis, but no trucks showed up in the main effects model. In the final interaction model the significant factors were shown to be interactions of truck and guardrail (FHE), truck and fixed object (FHE), truck and number of vehicles, truck and impaired, truck and road condition, and truck and grade.

In collisions where a truck was involved and the first harmful event was striking the guardrail, the estimated odds of a severe crash were 2.2 times as likely as when there was no truck involved the first harmful event was not striking a guardrail. These high odds could be due to how common guardrails are along interstates, and high speed limits. When an impaired driver gets into a collision where no truck is involved, the estimated odds of a severe crash are 2.7 times as likely as a non-impaired driver where no truck is involved. When there is a truck involved in a crash with an impaired driver, the odds almost double to being 5 times higher than with a non-impaired driver and no truck. And finally, on the interstate where a truck is involved in a multi-vehicle collision, the estimated odds are 4.5 times greater of a severe crash occurring than when a truck is not involved in a single vehicle crash.

Global Model
The final global model consisted of all the crashes occurring on the interstate and state systems. In the univariate analysis, heavy trucks and all trucks were significant predictors. However, trucks were not significant when introduced into the main effects model. The final model included all possible interactions between the main effects variables and all trucks. The truck interactions that remained included the variables: trucks*guardrail (FHE), trucks*number of vehicles, trucks*FHE location, trucks*impaired, trucks*road condition, trucks*grade, and trucks*median. Using the estimated beta coefficients obtained from the final model, the estimated odds ratios of these interactions were calculated to gain insights of how trucks affected the global model.
The trends in odds ratios were similar to those of the state and interstate models. For example, when there is a truck involved and more than one vehicle is involved, the estimated odds of a crash being severe is 4.7 times higher than when there is no truck involved and it is a single vehicle crash. An impaired driver in a truck crash was an estimated 6.7 times as likely to be in a severe crash as a non-impaired driver in a crash with no truck. Also, when the first harmful event was off the roadway, or there was no median, the estimated odds were around 2 times higher of a severe crash when a truck was involved in the crash.

CONCLUSIONS

Although Wyoming is considered to be primarily a rural state, crashes have different causes and effects on the various road classifications. Of particular importance in this research is the effect of truck involvement on the severity of crashes.

A descriptive analysis was completed which investigated crashes for the entire state of Wyoming. In the 10 year study period (2002-2011), fatal crashes made up less than 1 percent of the total crashes. However, truck involved crashes had 1.54 percent fatalities. At 68 percent, heavy trucks had a higher observed percentage of vehicles that were involved in crashes that occurred on interstates. Truck involved crashes occurred 19 percent more often when there is inclement weather such as severe wind or snow than no truck-involved crashes. In addition, when the road conditions were not dry, truck involved crashes occurred more often when there was ice or frost. Safety belt use in trucks was higher than that of drivers of other vehicles. Alcohol and drug involvement in truck drivers were both lower than that of drivers of other vehicles as well.

An extensive analysis has been conducted in this study to explore if the involvement of a heavy truck in a crash is a significant predictor of crash severity, and to identify roadway and weather factors affecting crash severity. The analysis was also performed at various roadway classifications. A Bayesian Binary Logit Models were calibrated to verify results from the statewide data analysis and to further study the relationship between truck involvement and crash severity. Bayesian approach accounts for the uncertainty associated with parameter estimates and provide exact measures of uncertainty on the posterior distributions of these parameters and hence overcome the maximum likelihood methods’ problem of overestimating precision because of ignoring this uncertainty. From the final main effects model, where truck interactions were introduced into the model, various interactions proved to be significant in predicting the severity of crashes. The state system model showed that trucks involved with multi-vehicle crashes were more significant in estimating severity. In interstate models, the effect of truck crashes where striking the guardrail, impairment, or multiple vehicles was higher. In the global model, off roadway crashes, impaired driver crashes, and multiple vehicle crashes all caused the impact of truck involvement to be higher. Moreover, the involvement of trucks in crashes results in higher severity. The odds of a severe crash increases to 2.3 and 4.5 times when a heavy truck is involved on state and interstate highways respectively.

RECOMMENDATIONS

Based on the analysis, weather and road conditions play a major role in truck related crashes. Improvements such as enhanced advanced warning systems will provide vital information to the truckers about the existing conditions. WYDOT is currently in the process
of implementing such a program where monitors will be installed at truck stops, restaurants
and gas stations that will provide real time visual information on the existing weather and
road conditions.

The trucking industry has done an outstanding job of training truckers concerning the
use of seatbelts and the dangers of drug and alcohol use as can be seen from the analysis.
However, training should be expanded to include the risks involved in driving in inclement
weather. Providing advanced warning systems and targeted training, improved roadway
safety can be realized and fatal crashes involving trucks can be reduced. The higher serious
and fatal crash rates of truck related crashes are not unique to Wyoming and thus these
improvements could be implemented to reduce these types of crashes throughout the country.

ACKNOWLEDGEMENTS

The WYT2/LTAP center at the University of Wyoming provided extensive resources to assist in
the compilation of the data sets used and the development of the models. WYDOT was
extremely helpful and responsive to provide the needed bulk crash data, inventories and traffic
data. Special acknowledgement goes to WYDOT and FHWA that provided the resources to
make this research possible.

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