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The Open Transportation Journal

Content list available at: www.benthamopen.com/TOTJ/

DOI: 10.2174/1874447801812010128

RESEARCH ARTICLE

Predicting Truck At-Fault Crashes Using Crash and Traffic Offence Data

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Received: December 13, 2017 Revised: February 28, 2018 Accepted: March 19, 2018

Abstract:

Introduction:

The number of truck-related injuries and deaths can be reduced by understanding the factors that contribute to the higher risk of truck-related crashes and violations. Truck drivers are at fault of more than 80% of all the truck crashes on Wyoming interstates, and the literature review indicated that in order to identify appropriate countermeasure to crashes, each crash type should be analyzed individually. The literature review also revealed that relationships exist between driving records and driver culpability in crashes.

Method:

This study employed two approaches to identify contributory factors to truck-at-fault fatal and injury crashes, and truck-related violations. Interstate 80, a Wyoming corridor in a mountainous area with one of the highest truck crash rates in the US, was selected as a case study. Only truck-at-fault crashes and specific types of truck-related violations were considered in this study. The analyses include two approaches. First, the logistic regression model was employed to explore vehicle, driver, crash, and environmental characteristics that contribute to truck-at-fault fatal and injury crashes. Second, truck violations were used as a proxy for truck crashes to examine the tendency to violate truck-related traffic laws in relation to driver and temporal characteristics. Based on the literature, only violations associated with higher risk of severe crashes were included in the analyses. The included violations accounted for more than 70% of all the violations.

Result:

This study considered more than 30 variables and found that only 10 variables impact truck-at-fault crashes. These factors included: gender, history of past violation, crashes involving multiple vehicles, exceeding the speed limit, occupant distraction, driver ejection, fatigued driving, non-seat belt usage, overturn, and head-on collision. Results of the second analysis indicated that both residency and time of crash are factors that impact truck-related violations. Results of the analysis also indicated that both residency and time of the crash are factors that impact truck-related violations.

Keywords: Truck-at-fault crash, Severe crashes, Injury, Fatality, Logistic regression, Enforcement, Citation, Risky violation.

1. INTRODUCTION

A variety of businesses depend on the trucking industry to deliver products in a timely fashion. In the US, the trucking industry delivers more than 80 percent of all the transported freight which accounts for 10 billion tons of commodities consumed with $700.4 billion worth of goods [1].

The economic cost of the crashes in the United States during 2010 alone totaled $871 billion, which includes productivity loss, medical costs, insurance costs, Emergency Service Costs (EMS), workplace losses, and quality of life

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1874-4478/18 2018 Bentham Open

valuation [2]. The rate of truck-involved crashes has been consistently dropping since 2001. However, the involvement rate of trucks in crashes, is still higher than no-truck vehicles crashes, at a rate of 1.34 per Million Vehicle Mile Traveled (MVMT) compared with 1.28 MVMT [3]. Wyoming has one of the highest percentages of large truck involvement in fatal crashes in the US (23.6%), while the national average is 8.7% [4]. This high rate has resulted mainly from high truck traffic through I-80 and the mountainous areas of Wyoming [5]. According to the US Department of Transportation (DOT), truck drivers caused 87% of truck-related crashes, while only 13% of these crashes were due to other factors such as vehicle and adverse road/weather conditions [6]. Different reasons are attributed to the drivers, including recognition errors, decision errors and performance errors [7].

Traffic crashes can be prevented by legislation or enforcement which control speeding, alcohol consumption, and traffic safety mandates [8]. The countermeasures can be organized into the 4 E's of injury prevention: engineering (*e.g.* highway design), enforcement *(e.g.* local law enforcement agencies), education (*e.g.* advocacy groups), and emergency (*e.g.* fire rescue) [9].

This paper adopted two approaches to reduce truck-at-fault crashes by identification of the contributory factors to injury and fatal (injury/fatal) truck crashes on Interstate 80 (I-80). I-80 is a transcontinental highway in the US that runs from San Francisco in California to Teaneck in New Jersey. The Wyoming section of this interstate is chosen as a case study as this section has one of the highest truck crash rates in the US. The two approaches utilized different explanatory variables including driver, vehicle, environmental, temporal, roadway, and crash factors that are likely to affect injuries and fatalities in truck-related crashes and truck violations on I-80. First, factors contributing to truck crashes, when the truck driver was at fault, were considered. Second, groups that are more prone to the offenses which are more likely to lead to severe truck crashes were identified. The findings of the second analyses will help to evaluate the risk of different truck driver groups in violating traffic laws. Based on the literature review, these violations are associated with an increase of being involved in severe crashes.

2. LITERATURE REVIEW

A considerable amount of literature has been published on the identification of factors contributing to severe truck crashes. Dong *et al*. identified some of the factors contributing to the severity of truck-involved crashes [10]. Traffic characteristics, driver behavior, and environmental conditions were included in this study. The results revealed that traffic, segment length, the degree of horizontal curvature, and terrain type were some of the factors with effects on car-truck crashes. Woodrooffe and Blower studied truck driver injuries related to crashworthiness. Rollovers, ejection, and frontal impact were identified as the crash types associated with the most severe driver injuries [11]. Lemp *et al.* used the Large Crash Causation Study (LTCCS) to investigate the impact of occupant, driver, vehicle, and environmental characteristics on injury severity in heavy-duty trucks [12]. The results indicated that the number of trailers, truck length, and gross vehicle weight impact truck crash severity.

Naik *et al*. investigated the effects of weather condition on single-vehicle truck crash injury severity [13]. They found that rain, humidity, wind speed, and temperature have significant impacts on truck crash severity. Neeley and Richardson examined the effect of truck-specific regulations on fatality rate by considering truck-involved crashes [14]. They discovered that lower speed limit and truck-length limitations resulted in a reduction of truck-related fatalities. Zhu and Srinivasan evaluated factors affecting large-truck injury crashes [15]. The results indicated that truck driver distraction, alcohol use, and emotional factors of car drivers can contribute to higher severity crashes. Islam investigated contributory factors to injury severity for truck-at-fault crashes [16]. The results indicated that there are different contributory factors to single-vehicle and multiple-vehicle in large truck-at-fault crashes. The literature review also indicated that there are substantial differences between crash types, and therefore each crash type should be analyzed separately [5, 17].

It is believed that a significant percentage of crashes result from driver violation and errors [18]. Therefore, it is important to identify truck driver behavior in violating the traffic laws with the goal of developing effective crash countermeasures. Brace *et al.* examined the relationship between road safety, off-road criminal activity, and traffic offenses of the drivers [19]. They found a positive relationship between criminal activity, traffic offenses, and the likelihood of these drivers being involved in a fatal or serious injury crash. Ayuso *et al*. evaluated the impact of traffic violations on the associated cost of traffic crashes [20]. It was found that some traffic violations were associated with a higher risk of being involved in a serious or fatal crash. They also found out that the costliest traffic violations were speeding-related violations. Associations between traffic offenses and involvement in severe crashes were found in the previous studies [21]. Murray identified violations that were associated with an increase in truck crash likelihood [22].

The factors included risky driving, hours-of-service violation, speeding, and past crash records. Studies also included violation data, in addition to crash data, to improve traffic safety in a more efficient way [5, 17]. Khattak *et al.* evaluated risk factors for truck injury severity [23 - 25]. The results indicated that risk factors for single-vehicle truck crashes include: risky driving habits of a truck driver such as speeding, reckless driving, and Driving Under the Influence (DUI) as well as roadway geometry and trucks that haul hazardous materials.

Most studies investigated the effects of different variables on the probability of severe crashes. However, far too little attention has been paid to the effects of those variables on the probability of truck-at-fault crash severity. Moreover, no study included violation data, as a proxy safety indicator for crashes, to identify the groups that are at higher risk of involvement in injury/fatal truck crashes. Thus, the current study has two objectives:

- (Crash Analysis) Determine the factors impacting injury/fatal truck crashes when trucks are at fault.
- (Violation Analysis) Predict future severe truck-at-fault crashes using risky truck traffic offenses.

The findings of this second objective will help in identifying the risks of different truck driver groups in violating particular traffic laws. These traffic laws are shown to be some of those associated with increase in the probability of being involved in severe crashes.

3. DATA PREPARATION

Crash data was obtained from the Wyoming Department of Transportation (WYDOT) using the Critical Analysis Reporting Environment (CARE) package from 2011 through 2014. This study used crash, driver, and Commercial Motor Vehicle (CMV) data. The crash data contains information on reported crashes such as the location, crash circumstances, involved vehicles, and vehicle maneuvering. Driver data includes information on driver attributes such as demographic characteristics, residency of the CMV driver, drug use, and mental condition at the time of a crash. The commercial motor vehicle data contains information related to the CMV itself and driver information such as safety equipment use, driver distraction, and CMV driver violation history. The road geometry characteristics were also obtained from WYDOT. At the scene of the crash, driver condition and crash severity were designated by the police officer according to prescribed categories. Crashes were screened to only include the crashes for at-fault trucks, which weighed at least 10,000 pounds. The resulting dataset for this rural setting had too few fatal crashes for valid statistical modeling. Thus, injury and fatal crashes were included as one category (injury/fatal). The other category is Property Damage Only (PDO), which does not result in any type of injury or fatality.

The citation data was originally obtained from the Wyoming Courts reported violation database from the years 2011- 2014. The data was filtered from the original file to include only truck-related violations. Initially, there were about 85,000 violations on the corridor, I-80, filtered to about 10,661 truck-related violations. About 1000 truck-related violation types were categorized into 7 groups including speeding, seat belt, DUI, Crash Predictor (CP), Hours-Of-Service (HOS), and vehicle-related violations. If a violation did not belong to any of these seven categories, it was grouped under the other violation category. The HOS regulation has been imposed on drivers of commercial vehicles violating maximum driving limits, 14 consecutive hours, or daily off-duty requirements. Violating HOS could result in fatigued driving. Crash Predictor violation includes mostly risky or reckless driving which can result in a crash [26]. DUI violation is related to the drivers who operate a vehicle under the influence of alcohol or drugs.

4. METHODS

Logistic regression is commonly used in many research studies involving binary crash outcomes [27 - 29]. Logistic regression models were used to identify factors contributing to crash severity for truck-at-fault crashes. The response (Y) had two possible values: the value 1 if a truck-at-fault crash resulted in an injury or fatality and the value 0 if a truck-at-fault crash resulted in no injury.

Logistic regression was also used for the violation analyses. The purpose of these analyses were to identify truck drivers who were more at risk of committing particular traffic law violations, which may increase the probability of truck crashes that could result in injury/fatality. In this case, the response (Y) had two possible values: the value 1 if a truck driver received a citation of a particular type and the value 0 if a truck driver did not receive a citation of a particular type. The types of citations examined in this study included speeding, DUI, risky driving (Crash Predictor), fatigued driving or Hours Of Service (HOS), and failure to use a seatbelt. Based on the literature review presented previously, speeding, DUI, risky driving (crash predictors), HOS violations and failure to use a seat belt are likely to be associated with increased probability of a crash being severe. Vehicle-related citations were also included in the analysis due to the high percentage of citations in this category (25% of the total number of citations). The violations included in the analyses accounted for 73% of all violations. The probability that a truck driver received a citation is examined in relation to driver characteristics such as age, gender, and residency, as well as temporal characteristics such as time of day and day of week. As described in Kutner *et al.*, the response *Y* is assumed to have a Bernoulli distribution with probability π [30]. For the crash analysis, this is the probability that a truck-at-fault crash resulted in a fatality or injury. For the citation analysis, this is the probability that a truck driver receives a citation of a particular type. The probability was allowed to depend upon a collection of *n* predictors ($\boldsymbol{x}$) of interest using the logit link in which

$$\pi(\boldsymbol{x}) = \frac{e^{g(x)}}{1+e^{g(x)}} \text{ or } g(\boldsymbol{x}) = \ln\frac{\pi(\boldsymbol{x})}{1-\pi(\boldsymbol{x})} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n$$

To develop a final logistic regression model, stepwise model selection was used with all possible explanatory variables. Wald based Chi-square tests were conducted using the logistic procedure in SAS. A significance level of 0.10 was specified for entering the model and a significance level of 0.05 was specified for staying in the model. Effects remaining in the model were interpreted using the estimated odds ratio and 95% confidence intervals for the true odds ratio. A standard test for goodness-of-fit in logistic regression is the Hosmer-Lemeshow test [30, 31]. This test was used to assess the fit of the logistic regression model. The overall prediction ability of the model was assessed using the area under the Receiver Operating Characteristic (ROC) curve [32].

5. VARIABLE DESCRIPTION

Table (**1**) presents descriptive statistics of truck-at-fault crashes and truck-related violations. Since there were more than 30 variables examined in this study, summary statistics are only provided for the significant variables in Table (**1**). Of the 2,042 truck-at-fault crashes, there were 1,695 no injury (PDO) (83%) and 352 were injury/fatal crashes, which include 150 non-incapacitating crashes (7%), 122 unknown and possible crashes (6%), 61 incapacitating crashes (3%), and 19 fatal crashes (<1%). About 95% of truck-at-fault crashes involved male drivers and just 5% involved female drivers. Only 100 (5%) drivers at fault were residents of Wyoming. About 65% of truck-at-fault crashes involved a single vehicle. Over-turn crashes accounted for about 21% of all the truck crashes and front-side crashes comprised one-third of all the truck crashes. Less than 1% of the truck-at-fault crashes involved drivers under the influence and 4% of the drivers showed some sign of fatigue at the time of crashes. Most of the crashes (66%) occurred at higher speed limits (>65) compared with lower speed limit zones (<65). Only 2% of the truck drivers had more than 1 traffic violation on their record before the crashes. Just 41 (2%) of the truck drivers did not use seat belts at the time of the crash. In addition, 551 (27%) of the truck drivers had some types of distraction such as TV, cell pager, or wireless communication inside the cabin at the time of crashes.

For the violation data, the majority of the violations were speeding (26%), vehicle-related (25%), and other violations (26%). About 97% of the drivers violating the traffic laws were male, and the majority of the violators (93%) were non-residents of Wyoming.

6. RESULTS

6.1. Factors Associated with Higher Risk of Truck-at-Fault Injury/Fatal Crashes, Crash Data

The significance of the predictors of crash severity was examined using binary logistic regression. Table (**2**) presents the estimated odds ratios and 95% confidence intervals for the true odds ratio of those predictors that had p-values less than 0.05. The predictors are categorized according to various characteristics and driver behaviors. The models were developed based upon 2,042 truck-at-fault crashes along the I-80 corridor in Wyoming. However, there were missing values in the crash record for some of the predictors. The reduced model was based upon 1,643 truck-at-fault crashes.

Table 1. Summary statistics of the significant explanatory variables.

Truck crashes				
Variable name			**Number**	**%**
Gender		Male	1,898	95
		Female	101	5
Residency		Resident of Wyoming	102	5
		Non resident	1,940	95
Crash characteristics		Single vehicle involved in a crash	1,327	65
		Multiple vehicles involved in a crash	715	35
		Frontal crash	668	33
		Overturn crash	425	21
Driver ejection		CMV Driver is ejected at the crash scene	48	2.35
Driver behavior		suspicion of DUI	10	1
		Fatigued	84	4
Posted speed limit		Less than 65	691	34
		Greater than 65	1,342	66
Violation record		CMV driver received 1 or less ticket in the past	1,652	98
		CMV driver received more than 1 violation	34	2
Safety equipment in use		No safety equipment used	41	2
		Some types of safety such shoulder or lap belt used	2,001	98
Distraction at the time of the crash		CMV driver had some distraction at the time of the crash	551	27
		CMV driver had no distraction at the time of the crash	1,491	73
Crash severity	PDO	PDO	1,695	83
	Injury /fatality	Non-incapacitating injury	150	7
		Unknown/possible injury	122	6
		Incapacitating injury	61	3
		Fatal crashes	19	1
		Truck violation		
Violation Type		Speeding	2,800	26
		Vehicle-related	2,711	25
		Crash predictor	1,454	14
		HOS violation	385	4
		Seatbelt	277	3
		DUI	123	1
		Others	2,815	27
Driver demographic		Male	10,335	97
		Female	326	3
Residency		Resident of Wyoming	783	7
		Non resident	9,898	93

As can be seen in Table (**2**), a few driver and roadway characteristics were identified as significant predictors. Female truck drivers had higher odds of injury/fatal crashes by an estimated 261 percent compared with male truck drivers. O'Donnell and Connor suggested that females are generally less able to sustain different levels and types of physical trauma [33]. Females are not more likely to be involved in a crash, but when they are involved in a crash, it is more likely to be injury/fatality [17]. Truck drivers who had more than one violation are estimated to be 48 percent more likely to be involved in injury/fatal crashes than truck drivers with at most one violation. This result is consistent with previous studies, which indicated drivers with more previous traffic offenses are more likely to be involved in a crash [34, 35]. Results also showed that when the speed limit increased from less than 65 to greater than 65 miles per hour, the estimated odds of an injury/fatal crash increased by 48 percent. The present finding is in contrast with Malyshkina and Mannering, which indicated that speed limit has no effect on crash severity on interstate highways in Indiana [36].

Table 2. Estimated Odds ratio for at fault truck collision with other vehicles, 2011-2014.

Collision Characteristic	Predictors	Odds ratio	95% CL
Driver Characteristics	**Gender:** Male truck driver (0 if true; 1 otherwise)	2.61*	1.54-4.44
	Age group[1]: Younger driver: age <45 years (1 if true; 0 otherwise)		
	Violation record: Traffic record of one ticket or less (0 if true; 1 otherwise)	1.48*	1.10-1.99
	Residency: State of Wyoming (0 if true; 1 otherwise)	-	-
Environmental Characteristic	**Weather condition[1]:** Clear (0 if true; 1 otherwise)	-	-
	Road condition[1]: Dry (0 if true; 1 otherwise)	-	-
Vehicle characteristic	**CMW weight:** Truck greater than 26000 pounds (1 if true; 0 otherwise)	-	-
Temporal characteristic	**Day of week[1]:** Weekends (1 if true; 0 otherwise)		
	Time[1]: Peak hours 6< <22: (0 if true; 1otherwise)	-	-
Roadway characteristic	Delta[1]	-	-
	Radios[1]	-	-
	Horizontal Length[1]	-	-
	Sag A[1]: Less than 2.0 (0 if true; 1 otherwise)	-	-
	Crest A[1]: Greater than -2 (0 if true; 1 otherwise)	-	-
	Posted speed limit: Speed limit less than 65 (0 if true; 1 otherwise)	1.48*	1.07-2.03
Crash characteristic	**No of vehicle:** 1 (0 if true; 1 otherwise)	3.15*	2.37-4.18
	Pre-collision vehicle actions[1]: Straight-ahead (0 if true; 1 otherwise)	-	-
	Manner of collision		
	Rear-end[1] (1 if true; 0 otherwise)	-	-
	Sidewipe[1] (1 if true; 0 otherwise)	-	-
	Others[1]	-	-
	Head-on (1 if true; 0 otherwise)	1.83*	1.35-2.46
	Rollover (1 if true; 0 otherwise)	4.35*	3.08-6.13
	Occupant ejection: Driver is partially or totally ejected (1 if true; 0 otherwise)	4.55*	1.62-12.83
Driver behavior	**Driver distraction:** No distraction in truck (0 if true; 1 otherwise)	2.57*	1.76-3.75
	DUI suspicion: Driver was suspected of driving under the influence condition (1 if true; 0 otherwise)	-	-
	Sign of fatigue: Driver was fatigued (1 if true; 0 otherwise)	3.69*	2.281-5.990
	CMV driver safety technology in use: Safety equipment was used (1 if true; 0 otherwise)	9.64*	3.03-30.65

Severity (response): no injury=0, injury or fatality=1
*indicates p<0.05
[1] indicates insignificant variable included in the initial model

A number of significant crash characteristics were identified by the analyses. Crashes involving multiple vehicles were estimated to be more than three times more likely to result in an injury or fatality compared with single-vehicle crashes. This finding was in agreement with previous research by Khorashadi *et al*., in which large truck crashes were investigated [37]. Head-on collision increased the odds of injury/fatal crashes by an estimated 83 percent compared with other types of crashes. Rollover crashes led to increased odds of injury/fatal crashes by an estimated 435 percent compared with crashes with other point of impacts. This finding supports the study by Rezapour *et al*., who analyzed contributory factors of truck crashes [17]. In their study, higher odds of severe crashes in rollover crashes were linked to an increased contact of a driver with road and vehicle. The odds of involvement in an injury/fatality when the driver was ejected from the vehicle was estimated to be about 455 percent higher than when the driver was not ejected.

A number of important driver behaviors were identified as important predictors of injury/fatal truck-at-fault crashes. Distraction is defined by the National Highway Traffic Safety Administration (NHTSA) as any distraction, including in-vehicle technologies, which takes the eyes or mind of a driver off the road [38]. Distraction was identified as the most common cause of traffic crashes [39]. Driver distraction caused by in-vehicle technologies increased the odds of injury/fatal crashes by an estimated 257 percent compared to that of the non-distracted truck drivers, confirming the previous study conducted on truck crashes [17]. The results also indicated that being fatigued at the time of crash increased the odds of injury/fatal crashes by an estimated 369 percent. This finding was consistent with the study conducted by McCartt *et al*., who indicated that fatigue was one of the significant factors behind serious truck-involved crashes [40]. Not having any type of CMV safety in use at the time of crashes increased the odds of injury/fatal crashes by an estimated amount of more than 964 percent. This finding confirmed research carried out by Chen *et al.* showing that truck drivers without any use of seat belts are at increased risk of injury and death [41].

The factors presented in Table (**2**) can be classified into three categories based on the estimated odds ratios. However, the uncertainty should also be noted in these comparisons. As can be seen from Table (**3**), the factor with the highest impact on injury/fatal crashes included the usage of driver safety technology. Number of vehicles, roll-over, occupant ejections, and sign of fatigue were factors that affected truck injury/fatal crashes moderately. Lower impact was observed for factors such as gender, violation record, posted speed limit, head-on collision and driver distraction.

Table 3. Significant contributory factors to truck crash severity.

Degree of Impact	Factors
High (odds ratio estimate >9)	CMV driver safety in use
Medium (3< odd ratio estimate <5)	No of Vehicle
	Rollover
	Occupant ejection
	Sign of fatigue
Low (odd ratio estimate <3)	Gender
	violation record
	Posted speed limit
	Head-on collision
	Driver distraction

The Hosmer-Lemeshow test did not an indicate lack-of-fit for this reduced model of truck-at-fault crash severity (Chi-square = 6.82, df = 9, p-value = 0.5561). The area under the ROC curve for this reduced model was 0.75, which indicates acceptable prediction ability (38).

6.2. Factors Associated with Higher Odds of Truck Severe Crashes, Violation Data

This section was set forward to identify the groups that are more likely to be involved in risky violations and, consequently, severe crashes. These violations accounted for more than 70% of all violations. The results of the speeding violation analysis indicated that being a non-resident of Wyoming increased the odds of being involved in a speeding violation by an estimated 68 percent. Two predictors were significant for vehicle-related violations. Wyoming residents were more often exposed to this violation than out-of-state drivers. Drivers were also less likely to violate vehicle-related regulation during off-peak hours, possibly due to lack of visibility by patrols. For crash predictor violations, three predictors were significant. Non-resident drivers were estimated to be more than two times more likely to receive these types of citations. In addition, these violations had an estimated 35% higher odds of occurring during off-peak hours and an estimated 18% higher odds of occurring during weekends. Only peak hours was significant for modeling DUI violations. Three predictors were significant for HOS violations. Both non-residents and off-peak drivers had a higher probability of violating HOS regulation, with estimates of 302% and 78%, respectively. Driving at night decreased the odds of violating the seat belt law by about an estimated 22%.

The Hosmer-Lemeshow test did not provide an indication of lack-of-fit for any of these full models as all p-values exceed 0.25. Therefore, the models provide an indication of the driver and temporal characteristics pertaining to these types of violations. (Table **4**)

Table 4. Adjusted odds ratio for tuck related violation, 2011-2014.

Groups		Speeding	Vehicle-related	Crash Predictor	DUI	HOS	Seat Belt
Driver characteristics	**Driver gender** Male truck driver (0 if true; 1 otherwise)	-	-	-	-	-	-
	Age of driver: <45(0 if true; 1 otherwise)	-	-	-	-	-	-
	Residence group: Non residence(1 if true; 0 otherwise)	1.68*	0.37*	2.11*		3.02*	-
Temporal characteristics	**Time:** peak 6< <22(0 if true; 1 otherwise)	-	0.71*	1.35*	1.82*	1.78*	0.67*
	Date: weekends(1 if true; 0 otherwise)	-	-	1.18*	-	0.78	-

*indicates p<0.05

- indicates insignificant variables

7. DISCUSSION

Crash data from WYDOT was used to investigate the effects of different variables on truck-at-fault injury/fatal crashes. The literature review indicated that there are substantial differences in contributory factors by crash types, so crash types should be analyzed separately. Also, trucks are at fault in more than 80% of all truck- related crashes. Therefore, it is important to identify the underlying causes of these types of crashes as contributory factors to this types of crashes are unique. The literature review was an indication that there are associations between previous violations and future crashes. Therefore, violation data, in addition to crash data, were used in this study to identify the contributory factors to truck-at-fault crashes.

While much research has been done to evaluate factors contributing to truck crash severity, this work focuses on the rural mountainous interstate of I-80 in Wyoming, which has one of the highest truck crash rates in the country. Moreover, the majority of previous studies used all types of truck crashes while this study just included truck-at-fault crashes. In addition, no study used violation data as a proxy safety measure for crashes to identify groups at higher risk of involvement in truck-at-fault crashes. Truck-at-fault crashes were analyzed in this study instead of all types of truck crashes due to the following considerations. First, the literature review indicated that there are substantial differences between contributory factors across different crash types. Second, trucks are at fault in more than 80% of truck-related crashes on Wyoming interstates.

The results of crash data analysis showed that a variety of factors affect the odds of a truck-at-fault injury/fatal crashes. In particular, these predictors included violation record, posted speed limit, occupant ejection, driver distraction, fatigued driving, and the use of safety equipment. This current study is unique as it used violation data in addition to crash data. Although any type of violation can increase the odds of crashes, the literature review indicated that some violations are more likely to result in crashes, especially severe crashes. Speeding-related, crash predictor, DUI, HOS, seatbelt violations were included in the analyses. Factors associated with these types of violations could increase the odds of involvement of future truck violations and severe truck crashes. Vehicle-related violations also were included in the analyses due to the high percentage of citations in this category. In addition, only truck-related violations were included in the analyses as the objective was to identify factors associated with truck-at-fault crashes. The included violations accounted for the majority of all the violations (73%), which may justify the included groups of violations.

CONCLUSION

Overall, the results of violation analyses indicated that Residency plays a dominant role in truck-related violations. Non-residents of Wyoming had higher odds of receiving speeding, risky driving and HOS violations, but lower odds of receiving a vehicle-related violation. The odds of receiving the risky truck violations and consequently truck crashes, could be due to a lack of familiarity with driving conditions in Wyoming. However, residents of Wyoming were more likely to violate vehicle-related laws. Time of violation was another important predictor of truck violations. The odds of being involved in risky driving and violating HOS regulations were higher at off-peak hours compared with peak hours. However, night-time truck drivers had smaller odds of receiving a citation for not using a seat belt. The results of the violation analyses can help in understanding tendencies in involvement in risky traffic offenses. The results showed which groups of drivers were more prone to violate the laws that increased the possibility of being involved in severe truck crashes.

8. RECOMMENDATION

Based on crash and violation analyses, a number of countermeasures could be recommended to Wyoming Highway Patrol (WHP) to reduce the number of injury/fatal truck crashes. These countermeasures included educating truck drivers on the hazards associated with distraction and fatigued driving. A strategy should be employed for truck drivers who have more than one traffic violation due to the fact that these drivers were more susceptible to being involved in injury/fatal crashes. Regarding violation analysis, non-residents of Wyoming are more likely to violate those traffic laws, which could result in injury/fatal truck crashes. This may be due to lack of familiarity of non-residents with the mountainous road conditions of Wyoming highways.

Therefore, it is recommended that WYDOT educate non-residents about the hazards associated with these roads. On the other hand, residents were more likely to violate the laws related to truck weight, size regulations, or issues related to truck vehicles. Stronger enforcement is also recommended between 10 PM and 6 AM to stop HOS violators as these drivers were more likely to violate this law during this time period. Crash predictors or risky driving were also more likely to occur during off-peak hours.

CONSENT FOR PUBLICATION

Not applicable.

CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

ACKNOWLEDGEMENTS

The Wyoming Technology Transfer (WYT2/LTAP) center at the University of Wyoming provided extensive resources to assist in the compilation of the data sets used. WYDOT provided the funding for this study. Special acknowledgement goes to WHP and WYDOT for providing the data used in this research.

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