CONFOUNDING FACTORS OF COMMERCIAL MOTOR VEHICLES IN SAFETY CRITICAL EVENTS

FINAL PROJECT REPORT

by

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16. Abstract

Recent quasi-experimental commercial motor vehicle (CMV) driver hours-of-service (HOS) studies published through the Federal Motor Carrier Safety Administration (FMCSA) in 2011 readily identified consistent increases in crash odds as driving time increased. These studies identified time-on-task as a significant indicator of the potential for a safety critical event (SCE) (crash, near crash, or crash-relevant event). However, while these studies may have provided indication of a relationship between HOS and the probability of an SCE, they largely failed to account for many potential confounding factors. The HOS relationship is frequently attributable to the fatigue of the driver. Confounding factors however, are those factors that may also contribute to the likelihood of an incident and potentially create a systematic bias or contribute to measured error. This study sought to uncover existing relationships between the HOS observations and a set of potential confounding factors related to time of day. These relationships were addressed by controlling for confounds. Conclusions drawn from HOS-related studies, such as those mentioned herein affect millions of people and have economic impacts in the billions. Faulty scientific inferences from these studies can have high human and economic costs. Therefore, the work described in this study was needed to validate the findings of these studies, as well as other studies using similar designs and variables. In addition, the work described could lead to deeper insights into commercial motor vehicle crash risk and causation, with safety implications and applications beyond HOS regulations. We foresee the following to benefit from this work: federal regulators, trucking industry groups, carriers, academia, insurance companies; anyone interested in understanding crash causation.

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List of Abbreviations

AIC: Akaike Information Criteria

ATRI: American Transportation Research Institute

CMV: Commercial motor vehicle

CPAP: Continuous positive airway pressure

DLC: Discretionary lane changing

EDS: Excessive daytime sleepiness

EHSR: Electronic hour of service recorders

FHWA: Federal Highway Administration

FMCSA: Federal Motor Carrier Safety Administration

HOS: Hours of service

LCA: Lane change assistance

LTCCS: Large Truck Crash and Causation Study

LTL: Less-than-truckload

MDU: Mobile device use

MLC: Mandatory lane changing

NHTSA: National Highway Transportation Safety Administration

NTDS: Naturalistic Truck Driving Study

OSA: Obstructive sleep apnea

PacTrans: Pacific Northwest Transportation Consortium

PDO: Property damage only

SCE: Safety critical event

TL: Truckload

TOD: Time of day

TPB: Theory of planned behavior

TSLDS: Trucker Sleep Disorders Survey

Executive Summary

Recent quasi-experimental commercial motor vehicle (CMV) driver hours-of-service (HOS) studies published through the Federal Motor Carrier Safety Administration (FMCSA) in 2011 readily identified consistent increases in crash odds as driving time increased. These studies identified time-on-task as a significant indicator of the potential for a safety critical event (SCE) (crash, near crash, or crash-relevant event). However, while these studies may have provided indication of a relationship between HOS and the probability of an SCE, they largely failed to account for many potential confounding factors. This study sought to uncover existing relationships between the HOS observations and a set of potential confounding factors related to time of day. To achieve this objective, the current study utilized a survey issued to large truck drivers that deliver goods in the Pacific Northwest.

Because of data heterogeneity, advanced econometric methods were applied, namely random parameters binary logit approaches and a multivariate probit approach to produce the most accurate estimates and to make inferences appropriately. In this study, three main questions of interest were used to better understand the effect of HOS on large truck drivers' safety. Of particular interest were questions related to issues of finding safe and adequate parking, using a cell phone while driving, and lane changing behavior. From a policy standpoint, agencies can enact policies at the strategic operating level for private carriers to address factors that influence large truck drivers' performance. For instance, this study showed that factors related to fatigue and driving hours management, such as restrictions on the number of hours worked or schedules that enable drivers to easily take breaks when fatigued, are effective at reducing the likelihood that a truck driver will be involved in SCEs. Moreover, CMV carriers can develop and enforce similar policies within their companies to reduce the occurrence of distracted driving among their truck drivers.

Conclusions drawn from HOS-related studies such as those mentioned herein affect millions of people and can have economic impacts in the billions. Faulty scientific inference from these studies can have high human and economic costs. Therefore, the work described in this study was needed to validate the findings of these studies, as well as other studies using similar designs and variables. In addition, the work described could lead to deeper insights into commercial motor vehicle crash risk and causation, with safety implications and applications beyond HOS regulations. We foresee the following entities benefiting from this work: federal regulators, trucking industry groups, carriers, academia, insurance companies, and anyone interested in understanding crash causation.

1.0 Introduction

1.1 Background

Recent quasi-experimental commercial motor vehicle (CMV) driver hours-of-service (HOS) studies published through the Federal Motor Carrier Safety Administration (FMCSA) in 2011 readily identified consistent increases in crash odds as driving time increased. These were observed by Jovanis et al. (2012) as gradual increases from 1-10 hours, followed by a marked jump after 10 hours. Blanco et al. (2011) similarly identified that time-on-task was a significant indicator of the potential for a safety critical event (SCE) (crash, near crash, or crash-relevant event). However, while these studies may have provided indication of a relationship between HOS and the probability of an SCE, they largely failed to account for many potential confounding factors. The HOS relationship is frequently attributable to the fatigue of the driver. Confounding factors, however, are factors that may also contribute to the likelihood of an incident and potentially create a systematic bias or contribute to measured error. Such factors include time of day (TOD), circadian status, time on task, total time awake, roadway infrastructure attributes, weather, and other driver behavior and traffic density factors related to both the driver and the external conditions experienced by the driver.

The Transportation Research Board's Committee on Truck and Bus Safety (ANB70) has identified driver performance and other causal mechanisms in quasi-experimental HOS studies as a key research need. In its needs statement, ANB70 suggested the need to validate and elucidate the findings from the above cited quasi-experimental studies. It identified limitations of the studies as stemming from their lack of controls for likely co-varying, confounding factors and failure to analyze underlying causal mechanisms. This study sought to correct several components of the omissions and to validate their findings. The works of Jovanis et al. (2012) and Blanco et al.

(2011), along with others, began with the premise that parameters associated with HOS, namely hours off duty, hours driving, hours working, breaks, and recovery are predictors of SCEs through fatigue. However, fatigue is a construct not directly observable. Rather, it is assumed to exist; consequently, it is presumed that the HOS effect on fatigue is mediated by observable changes in sleep time, time awake, or other physiologically based changes or biochemical intermediary

1.2 Confounding Factors

1.2.1 Time on Task

Analyzing Naturalistic Truck Driving Study (NTDS) data from 97 drivers using mixed-effect negative binomial regression, Blanco et al. (2011) found that the odds for an SCE are significantly higher in the eleventh driving hour than in the first or second driving hour. Also, a longer work day increases the odds of an SCE toward the end of a driver's workday, as the driver is exhausted by the performance of non-driving tasks earlier in the workday. In addition, taking a non-working break (rest during duty period or off duty) reduces the SCE rate by half, when the SCE rate is compared with the one-hour window immediately before the break and the one-hour window immediately after the break. However, the authors did not control for these confounding factors using econometric methods.

Chen and Xie (2015a) modeled heterogeneity among freight companies and individual drivers by using a discrete-time multilevel mixed logit model, which allowed drivers within the same company or the same driver operating in different hours to share the same unobserved risk factors. Consistent with the above finding, they found that the eleventh hour of driving was significantly riskier than other hours, but this may have been due to driving in peak hours on local roads when the driver was stressed toward the end of his shift because of HOS time limits, rather than the eleventh hour of driving itself. When the confounding effects were controlled for, uncertainty existed as to whether the last hour of driving, by itself, significantly contributed to increased odds, as Chen and Xie (2015a) mentioned that "all these factors may contribute to the higher crash odds for the 11^{th} driving hours." While their model identified daytime driving as causing more crashes (that is, 4:00 – 20:00 measured in 4-hour blocks), it is possible that such causality was noisy and susceptible to other confounding factors, such as higher traffic density during the daytime, rather than daylight itself causing the truck crashes to occur. Therefore, simply controlling for time-of-day as another explanatory variable, without allowing it to create differential impacts on the causal effects of driving hours on crash odds, is overly restrictive, and this is why stratification based on time-of-day has been called upon and tested for, as we shall see in the next section.

1.2.2 Time of Day

Pahukula et al. (2015) analyzed large truck crashes on urban roadways in Texas between 2006 and 2010 by using five separated random parameter, mixed logit models, which accounted for heterogeneous effects and correlation in unobserved factors and that were stratified by time of day (i.e., early morning, morning, mid-day, afternoon and evening). Using log-likelihood ratio tests, they found that the stratified time-of-day models provided more information than the unstratified full model with statistically different estimates, and each time-of-day strata had different contributing factors to large truck crashes. For example, indicator variables for changing lanes, median width, and speeding were only significant in the mid-day model, presumably because traffic density is lower in between the morning and afternoon rush hours, and drivers are more inclined to overtake other vehicles when shoulders are wide. Therefore, the authors called for planning tools to mitigate the impacts of severe truck crashes that addressed time-of-day differences. Other authors have also identified that although most large truck crashes occur during the daytime because most truck operations occur during the day (Belzer et al., 2002) and because traffic volume and density are higher (Hickman et al., 2014), truck crashes occurring at nighttime are, in general, more severe than those occurring during the daytime because higher traffic flow during the rush hours retards the speeds of trucks when traffic accidents occur (Islam and Hernandez, 2013).

1.3 Need for Study

This study sought to uncover existing relationships between HOS observations and a set of potential confounding factors related to TOD. These relationships were addressed by controlling for confounds. Within the TOD confound, we examined two primary competing factors: circadian rhythm and traffic density variation. Where a confound was not directly observable, a suitable instrument was sought and implemented. Following the development of the relationships between SCEs and the above factors, we explored opportunities for, and constraints to, the deployment of operational adjustments to reduce SCEs. These operational adjustments included actions by both industry and transportation agencies. Such actions included delivery schedule adjustments to avoid highest risk TOD and HOS interactions, should such interactions be demonstrated as significant.

Conclusions drawn from HOS-related studies may affect millions of people and have economic impacts in the billions. Faulty scientific inferences from these studies could have high human and economic costs. Therefore, the work described in this study is needed to validate the findings of these studies, as well as other studies using similar designs and variables. In addition, the work described could lead to deeper insights into commercial motor vehicle crash risk and causation, with safety implications and applications beyond HOS regulations. We foresee the following entities benefiting from this work: federal regulators, trucking industry groups, carriers, academia, insurance companies, and anyone interested in understanding crash causation.

2.0 Literature Review

2.1 Hours of Service

The FMCSA released a report on the final ruling of hours of service for drivers (Federal Motor Carrier Safety Administration, 2011). The goal of the ruling was to limit the hours of drivers to reduce driver fatigue, improve health conditions, and decrease crash risk. The rulings limit the use of a 34-hour rest period to once every 168 hours. Everyone using a 34-hour rest period must have two consecutive overnight periods, defined as 1:00 am to 5:00 am. Truckers may drive if they have had a 30-minute break in the previous 8 hours. The daily driving limit remains 11 hours, and the 60- and 70-hours limits are unchanged. Many studies have looked at the HOS rules specifically. Goel and Vidal created an optimization algorithm to minimize transportation costs that considered business hours and HOS (Goel and Vidal, 2014). The method assessed the impacts that different hours of service could have on a carrier. To determine the impacts of different HOS regulations on carriers, the research compared the HOS rulings in different countries.

The study noted the differences in HOS rules between the United States, Canada, the EU, and Australia. Canada has separate rules based on latitude, and in the southern region drivers cannot drive after accumulating 13 hours of driving, after 14 hours on duty, or after 16 hours have elapsed since the end of the last 8 hours of off-duty time. If one of these cases is met, then the driver must take 8 consecutive hours off duty. The driver must also drive no more than 13 hours and must be off duty at least 10 hours in the same 24-hour period.

In the European Union a driver must take a break of at least 45 minutes after 4.5 hours of driving. A rest period of at least 11 hours must be completed within 24 hours of completing the previous rest period, and driving time accumulation cannot exceed 9 hours between rest periods.

Driving time in one week cannot exceed 56 hours, and combined driving and working time cannot exceed 60 hours. These are the basic rules, but there are others as well.

In Australia motor carriers are either accredited or not. Carriers without accreditation must have drivers rest for at least 15 minutes and not work more than 5.25 hours in any period of 5.5 hours. In any 8-hour period a driver must not work more than 7.5 hours and have at least 30 minutes of rest in blocks of no less than 15 minutes. In any period of 11 hours, a driver cannot work more than 10 hours and must rest at least 60 minutes in no less than 15-minute blocks. In any 24-hour period drivers must not work more than 12 hours and must have at least seven continuous hours of stationary rest. In any period of seven days, a driver must work no more than 72 hours and have at least 24 hours of stationary rest time.

Accredited carriers in Australia must adhere to different rules. In a period of 6.25 hours, a driver must not work more than 6 and have at least 15 continuous minutes of rest time. In any 9-hour period, a driver must not work more than 8.5 hours and have at least 30 minutes rest time in blocks of no less than 15 minutes. In any period of 12 hours, a driver must not work more than 11 hours and must have at least 1 hour of rest time in blocks of no less than 15 minutes. In any 24-hour period, a driver must not work more than 14 hours and must have at least 7 hours of stationary rest time. In any period of seven days, a driver must not accumulate more than 36 hours of long/night work time.

In a more recent study Mansfield and Kryger completed a summary of hours of service regulations governing truck drivers in the United States, Canada, Australia, and the EU to assess the effectiveness of hours of service provisions in preventing fatigue and drowsiness (Mansfield and Kryger, 2015). The methodology of the work presented included summaries from the United States Federal Motor Carrier Safety Administration, Canada's Commercial Vehicle Drivers Hours of Service Regulations, the National Heavy Vehicle Regulator of Australia, and the European Commission summary of Regulation 561/2006. The study results found gaps across all the current provisions that could be associated with higher crash risk (a summary appears in table 2.1). There are no provisions for what a driver must be doing when not working, and thus s/he could return to work after not sleeping for 24 hours. In Australia, there are no provisions accounting for circadian rhythm by prohibiting driving at night.

Table 2.1 Fatigue, drowsiness, and the law summary of HOS regulations

Factors	United States	Canada	Australia	European Union
Work time per day	May work 14 hours but only 11 hours can be driving time	May drive 13 hours and work 14 hours a day	12 hours with 7 hours continuous rest	May drive 9 hours with 11 hours of continuous rest (some variation allowed)
Overall Schedule	May not drive after 60 hours on-duty in 7 consecutive days or 70 hours in 8 consecutive days	7-day cycle: 70 hours on-duty maximum 14-day cycle: 120 hours on-duty maximum	For any 7-day period, may not work more than a total of 72 hours For any 14-day period, may not work more than a total of 144 hours	Weekly driving time may not exceed 56 hours May not drive more than 90 hours in 2 weeks
Restart Periods	May restart schedule by taking 34 hours off-duty	7-day cycle: 36 hours off-duty 14-day cycle: 72 hours off-duty	For any 7-day period, must take 24 hours of continuous rest For any 14-day period, must take 4 night rests	Weekly 45 hours of continuous rest, but can be reduced every second week to 24 hours
Breaks	Must take a 30-min break after working 8 hours	2 hours off-duty per day may be taken in blocks of no less than 30 min (may defer)	5.5 hours: 15-min break 8 hours: 30-min breaks 11 hours: 60-min breaks	45 min every 4.5 hours can be broken to 15 and 30 min

Source: *(Mansfield and Kryger, 2015)*

Jovanis et al. (2011) performed an analysis to determine whether there was a relationship between crash odds and hour of service policy. The purpose of the study was to fill the gaps in knowledge regarding crash occurrences and driver characteristics. Data collected came from 15-minute interval, carrier-supplied logs entered one to two weeks prior to a crash occurrence. Comparable data were also collected from drivers that were not involved in a crash but were working for the same firm, at the same time, and driving out of the same terminal as the driver that was involved in a crash. Data were collected from multiple truckload (TL) and less-than-truckload (LTL) carriers during the years 2004-2005 and 2010. Data from the different years were tested by using a Chow test, and the researchers determined that they could be combined. The day the crash occurred was the day of interest and was designated as day 8, with the previous seven being checked to determine patterns.

The data were analyzed through a case control logistic regression formulation, with multiday driving, interaction terms for driving time and multiday driving main effects, time of day, driving breaks, and timing of recovery periods used as predictor variables. Additionally the relationship between 34-hr restart and crash probability was analyzed. Driving patterns could not be combined into the single model. Similar driving patterns were developed through cluster analysis to determine the driver behaviors more closely associated with high crash risk. Time of day was coded as a series of dummy variables in 2-hour blocks to indicate when drivers were driving. Driving breaks were accounted for in four groups: no breaks, one break, two breaks, and three or more breaks, with categorical covariates used to determine influence on crash odds. Extended recovery period variables were tested to determine the effects on crash rates. Interaction terms were used to determine whether there were significant effects of interaction terms for driving time and driving pattern. The 34-hr restart analysis was performed by using a comparison between a driver and themselves, using an approach creating crash outcome cases and non-crash controls to determine violations of the 70/8 rule. Also a predictor variable was created to investigate the implication of a pseudo-violation occurring for two consecutive days in a driving schedule.

In terms of TL carriers, cluster 5 was used as the baseline driving pattern, and others were compared to that. Clusters 1, 2, 6, and 7 had crash risks below .7, and clusters 3, 4, 5, and 8, 9, 10 were above .7. Cluster 1 had the lowest risk (driving early morning to early evening during days 4 to 7) with drivers being off duty on days 2 and 3. Pattern 5 had the highest crash risk and was based on a pattern of the driver being off during time in days 3 to 5, with 50 percent off duty on day 1 increasing to 70 percent by the end of day 2, 82 percent by the end of day 3 and 90 percent on day 4. Days 6 and 7 had peak usage of berths at 2:00 AM Driving hours 2, 5, and 9 showed fewer crashes than hour 1, and hour 11 showed increased crash risk. There was no real trend, but rates spiked at hour 11. The multiday pattern variable was statistically independent of the multiday driving variable. Most interaction terms had long driving hours as a common component. Another common component was driving in late afternoon. Time of day was dropped as a predictor.

In regard to LTL carriers, pattern 4 was chosen as the baseline, with patterns 7, 8, and 9 having high risk and patterns 1, 2, 3, 6, and 10 having low risk. Pattern 4 had 2 to 3 hours of duty/non-driving for days 1 through 5 and less than 1 hour for days 6 through 7. Pattern 2 had drivers with infrequent duty during days 1 through 4 and increased duty on days 6, 7, and 8, with on-duty time building gradually from noon to 10:00 pm. In comparing all patterns, crash risk was higher as the recovery period was closer to day 8. Crash odds as a function of driving time indicated that hours 6 through 11 increased the crash probability, spiking in hour 11 as with TL carriers. Interaction variables were perceived to be influenced by factors such as circadian rhythms or were traffic related and not correcting to extended time on task. Taking breaks resulted in lower crash odds. Returning from a 34-hr recovery showed increased odds of returning during the day. Results of the 34-hour restart models indicated that returning to work at night tripled the odds of a crash. Pseudo-violations occurring two and three days before a crash were significant in their effect on the model, quadrupling crash odds. The aggregate model results indicated that crash odds increased after hour 8, spiking as before in hour 11, with a 30 percent reduction if two driving breaks had been taken. A 34-hour recovery period was associated with a 50 percent increase in crash risk on the first day back.

Boris and Johnson (2015) investigated how hours-of-service rules affect parking, specifically to understand truck driver perspectives on parking reservation systems. To analyze driver perspectives, a survey was administered focusing on driver opinions of public vs private truck parking. Roughly 1,417 drivers completed the survey. Descriptive statistics indicated 76.8 percent for hire and 23.2 percent private drivers, with 66.8 percent truckload, 11 percent flatbed, 5.9 percent LTL, 4.1 percent Tanker, 1.5 percent express/parcel service, and 9.7 percent other. Approximately, 52.7 percent indicated they were employee drivers, 25.7 percent indicated they were independent contractors, and 21.6 percent were owner operators. Evaluation of carrier perspectives indicated that 62.1 percent of drivers thought parking was equally difficult to find at public and private rest stops, 23.7 percent thought private truck stops were more difficult for finding parking, and 14.2 percent thought public rest stops were more difficult for finding parking. Regarding payment of parking, 46.8 percent of respondents reported that they thought the carrier should be responsible for payment of the reservation fee, while, 20.7 percent thought the responsibility lay on both the carrier and driver. Additionally, 15.3 percent thought payment was the driver's responsibility, 5.8 percent thought it was the government's, and another 5.8 percent thought there should be no fees. 5.8 percent responded "other" responsibility. A possible limitation with this study was the lack of information regarding the time that parking was needed. Having this information could have illuminated the effects of fatigue and HOS rules on parking.

Murray and Short (2015) investigated the impacts of the 34-hour restart provisions in the 2013 HOS changes. Specifically, the changes to the 34-hour restart were examined to determine the influence on truck driving operations and any resulting safety consequences. Looking first at daytime driving operations, The American Transportation Research Institute (ATRI) gathered data from October 2012 and 2013 to compare pre- and post-final ruling changes. Data were standardized by month and highway locations. Using SAS algorithms and a GPS data set, truck activity was analyzed. Results of this daytime study indicated increased weekday operations after the HOS changes. Truck activity did increase, and Saturday mornings saw increased driving as well. The impacts on safety were determined by using chi-square tests on data prior to and after July 1, 2013. Results also revealed significant increases in injuries and towaways in a comparison of the 12 months and six months of pre- and post-July 1, 2013, data for all days. Weekend towaways significantly increased for all day and weekend mornings in comparison to weekday counterparts. Also of note were significantly higher injury and towaway crash rates on post-July 1 weekends, with Sunday morning fatalities increasing significantly. The study concluded that overall, crashes increased after the final rulings went into effect. One theory to explain these findings was that drivers used rolling recap rather than the 34-hour restart, which negated the safety benefits that would have been expected. Drivers may also have shifted their driving activity to occur early in the weekend.

Anderson et al. (2017) sought to determine the impacts of the 2013 hours of service changes on crash safety. Ohio Department of Safety Statistics crash data from 2002 to 2012 were regressed to extrapolate crash rates in 2013 and 2014 as if there had been no HOS rules changes.

A comparison of pre- and post-HOS data showed no significant difference between the periods with regard to injury and property damage. A decrease in fatalities was present but not significant, and an increase in fatal accidents caused by truck drivers was present but also not significant. In examining 12-month increments of data, the change in fatal accidents caused by truck drivers in pre- and post-HOS change years was not significant. The number of fatalities involving trucks was lower post-HOS, and the number of fatalities caused by trucks was higher post-HOS. Findings of the model indicated a downward trend in accidents involving and caused by trucks, and the post-HOW year was not significantly different from the previous year with regard to injuries or property damage. Anderson et al. (2017) suggested that HOW may not have improved safety significantly.

Matthews et al. (2012) sought to understand the role that pre-drive sleep and time of day have on driver performance. Driving simulations were performed by 14 male subjects who took a simulated 10-minute drive on a variable course. Subjects completed training drives during two training days. For testing, drives were completed two hours after waking and at 2.5-hour intervals after completing nine tests each day. Each 28-hour day lasted 4 hours longer than a circadian day to have multiple tests occurring at six separate circadian phases of each day. This process desynchronized the effects of time of day and previous wakefulness. ANOVA models were used to analyze the resulting data. Results indicated that time of day affected all dependent variables of speed, lane position, and lane violations. The worst performance coincided with early morning and best driver performance coincides with early evening. Performance declined with an increase in previous hours of wakefulness. Performance was high with low sleep debt and worsened with high sleep debt. If sleep debt was, then low circadian effects were low, and when sleep debt was high circadian effects were high. During circadian peak hours there was no effect from previous wakefulness. From this one can intuit an interaction among the variables, and the authors theorized that time of day influence depends upon the length of previous wakefulness. All factors were more influential the more that sleep was restricted, i.e., the effects were compounding.

2.2 Impacts of HOS on Truck Drivers

2.2.1 Fatigue

Williamson and Friswell (2013) investigated the link between fatigue and safety for truck drivers. To accomplish this the authors undertook an extensive literature review. For the study, “fatigue” was defined as “a biological drive for recuperative rest.” Evidence was observed suggesting that fatigue results in reduced performance and increased safety risks, and factors were looked at that are said to cause fatigue. This research investigated evidence for the effects of circadian rhythm and other factors on fatigue and driver safety outcomes, then examined the evidence for each of these factors on driver performance and safety. The risk of a person being involved in an accident was substantially higher at times they would normally be asleep. The peak of risk occurred shortly after 12:00 am, with factors including time since waking, time since starting work, timing of rest breaks and work quotas, occupation differences, difference in work task, and difference in lighting. Williamson and Friswell (2013) concluded that there was strong evidence for a circadian rhythm effect on the risk of truck driver crashes. Discrepancies could be explained by confounding factors contributing to fatigue.

The effects of restricted sleep and time since last sleeping on driver safety risks are confounded by circadian influences, as well as time on task. Time on task induces workplace fatigue and is often treated as a measure to evaluate safety risk in occupational settings. Studies have suggested that injuries and accidents peak in the first half of the workday. With regard to continuous time on task, there is increased crash risk from the first half-hour to the second while on task. While monotonous driving at night is a particular concern for long trips, no controlled studies featuring boredom or monotony as causal factors in fatigue-related crashes were found.

Research has consistently revealed a higher crash or accident risk with a higher frequency of driver sleepiness. However, there is a scarcity of findings available on the effects of circadian rhythms on performance, indicating a need for more research.

Research regarding homeostatic factors has demonstrated that the strength of their effects on fatigue and performance compromise road safety. With regard to homeostasis effects on performance, fatigue-inducing conditions such as sleep loss produce impairments in performance. Regarding time on task, the type of task performed can have negative effects on performance. Sustained attention and unstimulating or monotonous tasks have been identified as increasing the likelihood of poor performance. The link between performance and safety outcomes supports the hypothesis that performance decreases play a causal role in accidents and injury. Fatigue-caused performance shortcomings lead to adverse safety outcomes.

Chen and Zhang (2016) investigated background risk factors associated with fatigue-related truck crashes and injury severity. Data were compiled from two separate highways in China, analysis was performed on each separately, and the results were compared. Data from crashes in which fatigue was a factor from Jiangxi and Shaanxi over a 12-year period were compiled. Roughly, 9,168 records were used, with 5,447 cases from Jiangxi and the rest from Shaanxi. Injury severity was scaled as fatal, serious, moderate, or slight. Empirical results from both regions indicated that inexperienced male drivers were more likely to be involved in fatigue-related crashes. Being an employed driver increased the risk of fatigue-related crashes. Commercial goods transporting vehicles, unfit safety status, and poor brake performance are all had positive correlations with fatigue-related crash risk. Fatigue-related crashes were more likely to occur on curved roads, on grades, on bridges, in tunnels, and at urban intersections. Time of day was indicated to have a significant effect on fatigue, as crash risk probability was higher during the evening or at dawn. Fatigue-related crashes were more likely during adverse weather conditions. Speeding, overloading, risky following, and failure to use a seat belt all had positive correlations with fatigue-related crash risk. Head-ons, side-swipes, and rear-end crashes made up the majority of crash types caused by fatigue.

Risk factors related to truck crashes in Jiangxi suggested that a driver's gender, age, and experience level significantly affected fatigue-related crash risk, all other things being equal. A logistic regression model was used to analyze these data. Young, less experienced, male, employed truck drivers exhibited a higher probability of fatigue-caused crashes. Commercial transport vehicles and poor brakes were associated with higher crash risk, as were slippery roads, sharp curves, steep grades, and bridges. Also, crashes were more likely to occur on expressways. Results also indicated that speeding and overloading increased risk of a fatigue-caused crash. Crashes were more likely to happen between midnight and 6:00 am, during poor visibility, during adverse weather, and during winter. Fatal and serious crash types were more likely to occur. Head-on, sideswipe, and rear-end collisions were most likely to occur. Large trucks were more likely to be involved in fatal multi-vehicle crashes. Focusing on Shaanxi, results were very similar to those from Jiangxi, with few differences. Differences included summer and winter being associated with higher crash risk, as were run-off-the-road crashes. Results indicated that time of day was a very significant contributing factor to fatigue-related truck crashes. Most accidents coincided with sleepiness associated with circadian rhythms.

Chen and Xie (2014) investigated how many hours off-duty and how many rest breaks were sufficient in preventing driver fatigue. The study evaluated the impacts of time off-duty before a trip and short breaks on commercial truck safety. The methods of analysis included the Cox proportional hazards and Andersen-Gill models. The data consisted of 407 observations, featuring 136 crashes. Driving logs were included for the seven days leading up to a crash, as well as a crash. The Cox PH model was analogous to treatment groups composed of different rest break patterns represented by explanatory covariates. The PH model estimated a hazard ratio and a confidence interval, which was the probability of a driver being involved in a crash in the next moment. Each driver could have zero to multiple breaks. Each trip could consist of multiple segments with a start time, end time, duration, and status variable (i.e., an indicator that a crash had occurred). Results suggested that a brief rest break could reduce crash risk caused by fatigue. Increases in rest break duration reduced crash risk caused by fatigue. More than 2 hours of rest appeared to reduce crash risk. Having one rest break lowered the risk of a crash, two breaks reduced the risk further, but the reduction from three breaks was minor.

Taking a break after 1.25 hours was found to be more helpful than taking a break in the first 1.25 hours of the shift. It was better to take the second break after 2.5 hours. A third break should be taken after 3.25 hours of driving; however, it would not affect crash risk substantially unless the break was longer than 30 minutes. Thirty minutes was found to be adequate for a first and second rest break. The results of the Anderson-Gill model suggested that taking breaks reduced crash risks. Increasing rest-break durations could also reduce fatigue-related crash risk. Taking additional rest breaks could help reduce risk. Two rest breaks were considered enough for a 10-hour trip. Thirty minutes was an adequate time for a rest break. Taking rest breaks soon after a trip began lessened the effect of a break.

Zhang and Chan (2014) investigated whether truck drivers had a higher crash risk probability associated with fatigue than non-professional drivers. To accomplish this task, a comprehensive literature review was performed with regard to sleepiness and crash risk, and a meta-analysis was applied to summarize the effects. Each study of interest was coded according to study characteristics, sleep problem information, and accident information. The effects of each study were extracted and unified as part of an odds ratio analysis. Study quality was assessed according to the study's description of sleep problems, data collection methods, and control of confounding factors. All studies of interest clearly stated sleep problems and methods of investigation. Three of the studies considered crash severity in their data collection, and most were self-reported data. Half of the studies controlled for potential confounding factors. The most common confounders were age and driving experience. Risks associated with excessive daytime sleepiness (EDS), sleep apnea, acute sleepiness, and insomnia were summarized separately. EDS was concluded to be a predictor of higher crash rates. Sleep apnea and acute sleepiness had moderate impacts on crash risk. Results indicated that sleep apnea and EDS showed heterogeneity, and therefore the odds ratios were recalculated with random models. Publication bias was found to be present in the EDS studies. Professional drivers did not have more crash risk due to sleep apnea or EDS than non-professional drivers.

Williamson and Friswell (2013) explored the effects on long distance truck drivers' experience of fatigue. The objective was to gain an understating of the connection between external non-driving factors and fatigue outcomes for long distance truck drivers. The method of analysis employed was a cross-sectional survey with questions regarding factors such as employment status, fatigue management, payment, wait and queue times, and working hours. The data analyzed consisted of 475 New South Wales drivers recruited at rest stops between November 2009 and February 2010. Descriptive statistics indicated that 98.3 percent were male, and 67.3 percent self-administered the survey while the rest were interviewed. Survey questions focused on demographics, characteristics of the working arrangement, information about the driver's last trip, and safety outcomes. PASWStatistics were used to determine whether the self-administered and interview survey data could be combined. Descriptive analysis, Chi square tests, and logistic regression were further used for analysis. An analysis of drivers' work characteristics indicated that the average age was 45.3 years. 67.4 percent were married or in a de facto relationship, 57.9 percent had one or two children aged 18 or less living with them, and 47.8 percent felt that their work often or always interfered with their family. The average experience level was 21 years. 81.9 percent were employees and the rest owner operators. 24.6 percent were organized, and 21.5 percent were unionized. 96.4 percent were based in Australia's eastern seaboard states. 32.8 percent drove articulated trucks and 49.9 percent drove b-double, while 4.8 percent drove rigid and 1.7 percent drove road train trucks. 65.2 percent were paid by incentive for trip, 22.7 percent were paid by time spent working, and 12.8 percent responded "other" or gave multiple answers.

A comparison of drivers who worked under trip- or time-based payment found that drivers paid by the trip drove longer distances, for longer times, slept less, and more likely experienced fatigue than drivers paid by time. Drivers who were paid by the trip also drove heavier loads, drove longer, and drove for more time than time-based drivers. Drivers paid by trip were more likely to usually experience fatigue on half of their trips or more, and reported work interfering with family life more than time-paid drivers. Drivers who waited worked longer hours and more likely experienced fatigue. They also were less likely to be usually paid for non-driving tasks. Drivers who waited on a last trip were more likely to experience fatigue on that trip and to experience fatigue on half or more of their trips. Drivers paid to wait usually were paid for non-driving tasks and worked fewer hours per week and were less likely paid per trip. These drivers usually drove smaller trucks and drove less distance and spent less time driving on their last trip. It is interesting to note these drivers were less likely to report fatigue on more than half their trips and less likely to have work interfere with family.

Results of the multivariate analysis indicated that the amount of sleep a driver had in the 10 hours before the trip was associated with experiencing fatigue on the last trip. Those who slept less were more likely to be fatigued on their last trip. Fatigue odds were 11 percent higher for each hour of reduced sleep in the 10 hours before driving and roughly 4 percent lower for every year of work experience. Drivers who waited but were not paid for waiting on the last trip reported higher fatigue. Fatigue odds were more than 2.5 times higher for drivers who were not paid for waiting than for drivers who did not wait. Analysis showed that fatigue could be predicted by payment type and whether the driver was paid to wait. Those paid by trips were twice as likely to be fatigued as those paid by time, and there was an 80 percent increase of feeling usually fatigued among those who were not paid to wait than those who were.

Lemke et al. (2016) investigated how sleep affects safety performance among drivers and evaluated sleep quality as a predictor of safety performance. Survey and biometric data were collected from 260 male drivers in North Carolina. The Trucker Sleep Disorders Survey (TSLDS) was created to determine work environment, health factors, sleep quality, health consequences, and comorbidities. Analysis was performed to determine correlations between predictor variables and sleep duration and quality. A series of linear regression analyses was performed to determine predictive relationships. The results indicated longer and better sleep on non-workdays than on workdays. Drivers often operated trucks while sleepy, and sleepiness impacted safety performance. Sleep quality was found to be more significantly related to driving sleepy and job performance and concentration than sleep duration. Sleep duration was significantly related to crashes and crash risk.

2.2.2 Driver Health

Edwards et al. (2014) sought to understand factors that affect the health and safety of truck drivers. To accomplish the task, an in-depth literature review was performed. The review consisted of 104 peer-reviewed articles on a range of topics. The review found the behaviors that increase injury severity and likelihood relevant to truck crashes included fatigued driving, drunk or drugged driving, speeding, seatbelt infractions, and errors and violations. Factors were categorized according to government departments, transport organizations, customers, and road/work environment. The review found government departments focused on policies and enforcement. A large amount of research has focused on fatigued driving and work hours. External factors such as sleep quality have an effect on fatigue, but compliance with rules may be more important, and an unsafe culture can worsen effects.

Factors were categorized as general organizational, employee management, and management practices. All were related to hours-of-service rules with a relationship to crash risk. The review found that heterogeneity may be contributing to the influence of factors on safety. Particularly, subcultures may exist that influence safety-related behaviors. Driver beliefs, attitudes, and values may interact with management to determine the driver's response. Customers play a contextual part on the influence of safety within the commercial trucking industry. Environmental factors include other vehicles, time of day, weather, and road design and condition. The review found that private road design can affect not just crashes but injury severity as well. Vehicle factors were generally associated with mechanical faults and vehicle emissions.

Boris and Brewster (2016) highlighted issues related to truck driver screening and treatment of obstructive sleep apnea (OSA). Boris and Brewster (2016) surveyed commercial drivers on a number of OSA-related issues. One group comprised commercial motor vehicle (CMV) drivers who had undergone a sleep study and another was CMV drivers who had not. Among those who had not been referred to a study, daytime fatigue and high blood pressure were identified as potential complications of OSA by many respondents (91 percent and 67 percent, respectively), and among drivers who were referred to a study, 53 percent had paid some or all of the costs. 61 percent of drivers with no health care coverage of their sleep study incurred out-of-pocket costs, compared to 32 percent of drivers whose health insurance did cover some portion of the sleep study, with costs exceeding $1,000.

Survey results indicated that the continuous positive airway pressure (CPAP) machine was the most common treatment prescribed for drivers diagnosed as having sleep apnea, including those with mild sleep apnea. Drivers with severe OSA had experienced positive effects from CPAP treatment, reporting increased amounts of sleep (71 percent), feeling better when they woke up (84 percent), and lower blood pressure (75 percent). Half of drivers with severe OSA also reported losing weight after treating their OSA with a CPAP device (50 percent). Drivers with moderate and severe OSA in the sample were more likely to find their CPAP treatment effective (74 percent and 87 percent, respectively) than drivers with mild OSA (48 percent). Less than a third (32 percent) of those diagnosed with mild sleep apnea experienced improved sleep as a result of CPAP treatment.

2.2.3 Driver Sleep

Hanowski et al. (2007) investigated whether drivers got more sleep under the HOS regulations and the relationship between sleep quality and safety critical events. Data were collected through a naturalistic study in which 73 drivers were analyzed. The research method included monitoring sleeping or waking moments, as well as monitoring occurrences of safety critical events.

Mean sleep quantity was calculated through two methods. The first was calculated over full days and the second over weeks. Method 1 contained 73 drivers and method 2 contained 62 drivers. Both produced similar findings, with drivers averaging 6.15 and 6.28 hours of sleep, respectively. A matched-pairs t-test was conducted to compare mean sleep to mean sleep before the occurrence of a safety critical event. Matched-pairs t-tests were conducted on data when the truck driver was at fault for causing the crash. Results indicated that drivers may receive more sleep under the 2003 HOS regulations. The results also indicated fatigue-related critical events. Sleep quantity was found to be less before a critical event than overall mean sleep quantity.

Chen et al. (2016) examined the sleep patterns of truck drivers during non-working periods and evaluated the relationships between sleep patterns and truck driving performance. The authors believed the results of the study could be used to inform hours-of-service policy and to benefit safety in the trucking industry. The study utilized the Naturalistic Truck Driving Study (NTDS) data for its analysis. The study contained data from 96 truck drivers driving approximately 735,000 miles. The analysis included the four types of SCEs used in Blanco et al. (2011): crashes, near-crashes, crash-relevant conflicts, and unintentional lane deviations. For analysis, activities in the data set were categorized into work and non-work periods. Off-periods lasting less than 3 hours were reclassified as on-duty. On-duty periods lasting less than 7 hours were reclassified into adjacent on-duty work periods. The newly formed periods were created by merging consecutive off-duty periods and on-duty rest periods as working periods. 1,397 shifts (shifts shorter than 27.5 hours) were focused on having one period of sleep in a non-work period.

Four measures for sleep patterns were used: sleep duration, sleep start/end point in a non-work period, and percentage of sleep. To identify sleep patterns, k-mean generated clusters were used. A negative binomial regression was used to model the association between SCEs and sleep patterns. Demographic results indicated that the average age was 44.4 years, and the average driver experience was 9.3 years. Cluster analysis results indicated that cluster 4 had the highest sleep percentage and sleep duration, followed by 3, 2, and 1, with 2 and 1 having similar durations. Clusters 3 and 4 had longer average working periods and driving durations than clusters 1 and 2.

Drivers worked and drove longer after having slept longer before work or tended to sleep longer before work knowing that they had to drive and work longer than usual. Analysis of sleep involvement between 1:00 and 5:00 am indicated that cluster 2 had a lower proportion of shifts with non-work periods between 1:00 and 5:00 am than cluster 1, cluster 3, and cluster 4. Cluster 2 also had a lower proportion of shifts with sleep between the hours of 1:00 and 5:00 am. When taking shifts in clusters 3 and 4, drivers were more likely to sleep between 1:00 and 5:00 am. Assessing the impacts of sleep pattern on driving performance and risk indicated that shorter sleep periods at early stages of non-work periods were associated with higher SCE risk than longer sleep periods. Male drivers' SCE rate was twice that of females. More experience was associated with a decreased SCE risk. Higher body mass index was associated with an increased SCE risk.

2.2.4 Driving Style

Hickman et al. (2014) aimed to determine whether or not trucks equipped with electronic hours of service recorders (EHSRs) had a higher crash risk and HOS violations that those without. Driving data from 11 carriers during a five-year period were used for the analysis, with 82,943 crashes, 970 HOS violations, and 224,034 truck-years that drove a total of 15.6 billion miles. Carriers with EHSR devices were compared to carriers without EHSR devices to determine whether those that enforced HOS rules had fewer crashes. The analysis was divided into two cohorts, one examining the crash frequency and miles of trucks with EHSR and the other examining trucks without. The count-based Poisson regression model was utilized to model crash count data. Equipped trucks were found to have a 51 percent lower risk of driving-related HOS violations and a 49 percent lower risk of non-driving-related HOS violations. Interesting data included the fact that HOS violations were lower for the EHSR cohort, and the majority of violations for both cohorts were non-driving related. Fatigue-related crash rates were similar among EHSR and non-EHSR trucks. EHSR-equipped trucks had 12 percent and 5 percent lower crash rates and preventable crash rates, respectively.

Chen and Xie (2015b) explored the relationship between multiday driving activity patterns and crash risk. The purpose was to determine how work schedules influence the risk of a crash, through which the goal was to determine which driving pattern was the safest. Data from large-truck drivers were collected and included both temporal and crash records, in 15-minute blocks over several days, from two carriers. To perform this analysis, k-means clustering was used to group different driving patterns into strata, which could then be analyzed. Discrete-time logistic regression models were used for this analysis to quantitatively determine the crash odds associated with each driving pattern. The results of the study indicated that longer driving hours were associated with higher crash risk, and a 34-hr restart might increase risks. Crashes were more likely to occur during periods in the early morning and late afternoon, times associated with high on-duty proportions, and corresponded to driving patterns 8 and 10 in the study. Another interesting result was that the eighth day had the highest crash risk. The driving patterns associated with the lowest crash risk had drivers working during the early morning (4:00 am) to noon. The driving patterns with the highest crash risk corresponded to having a long off-duty period and starting work in the late morning. Risk increased with driving in peak hours or with long hours.

2.2.5 Distracted Driving

Toole (2013) investigated the relationship between mobile device use (MDU), fatigue, through driving time and time on duty, drowsiness,and through time of day and amount of sleep, for commercial motor vehicle drivers. The purpose of the investigation was to determine whether any of the mentioned relationships could be used to evaluate policy, such as HOS rules. Toole (2013) performed an analysis of naturalistic driving data collected by Blanco et al (2011). Odds ratios were used to calculate SCE risk for six mobile device use subtasks and each of the factors, which were divided into smaller bins of hours for more specific information. A generalized linear mixed model (GLMM) was used to model the probability of the SCE/BL of interest with or without mobile device use as a function of driving time, time on duty, and time of day. Results indicated that MDU was higher in the early morning hours. Drivers had higher percentages of MDU during the circadian rhythm low morning bin than any other bins, which could indicate that drivers were drowsier at that time. Visual-manual subtasks were found to increase SCE risk. Visually demanding subtasks had an association with increased SCE risk; however, conversation using hands-free cell phone devices decreased SCE risk. An increase in SCE risk occurred for visual manual subtasks in all bins.

Dingus (2014) sought to understand the risk associated with inattention and distracted driving among drivers. Data were from the Naturalistic Driving Study, Naturalistic Teen Driving Study, and Heavy Vehicle Drowsy Driver Warning System Field Operational Test, and The Impact of Hand-Held and Hands-Free Cell Phone Use on Driving Performance and Safety-Critical Event Risk. Safety critical events were recorded for all three studies. Odds ratios or linear regressions were created to determine relative risk for the four data sets. Tasks that caused drivers to take their eyes off the road were found to significantly increase risk. Teens had a significant increase in risk when eating and driving. Light-vehicle adults and teens had an increased risk when looking at external roadside objects, in contrast to truckers. External distractions for truckers and teens had the highest frequencies. Truckers ate, drank, and used tobacco frequently, while teens spent significant time eating. No notable relationship existed between frequency of task and odds ratio for the task. For all drivers, handheld cell phone use was risky and frequent, not including handheld or hands-free conversations. For truckers, conversations had protective effects.

Swedler et al. (2015) investigated how truck drivers decided whether to undertake distractions while driving. Data were collected through interviews and online surveys with truck drivers. A bivariate analysis was used to examine the correlation of norms, perceived behavioral control, and attitudes to intentions separately for both texting and dispatch device use. Bivariate analysis was used to examine the association of each of the four theory of planned behavior (TPB) constructs for texting and distracted driving with the four crash and near-crash outcomes. Multivariate regressions were initially conducted without intentions, then including intentions to determine whether they attenuated the effects of the other three TPB constructs. Qualitative data analysis results indicated that most surveyed drivers reported being concerned regarding driving performance while distracted. Supervisors were most frequently named as the outside factor that would most influence driver decision making. Drivers mentioned the benefits of using devices, such as staying in touch with family, contacting emergency services, and contacting management. Respondents also noted the usefulness of using devices to combat fatigue. Drivers also mentioned negative outcomes from taking eyes off the road to interact with devices.

Drivers mentioned they felt there was a lot of personal control in whether or not to become distracted. Quantitative analysis results indicated that over half of the subjects in the texting and dispatch group reported crashing on the job; less than 20 percent reporting distraction-caused crashes. Regression analysis results for the texting group indicated that attitudes, norms, and perceived behavior control were significant in association with texting and dispatch device use. Significant multivariate results were present for the texting population with regard to distraction-involved hard braking and distraction-involved swerving. All four TPB constructs had associations with crashes, hard braking, and swerving. In regression analyses, drivers' intentions toward texting mediated the effects of the other TPB constructs for distraction-involved near-crashes; intentions toward dispatch devices did not have the same effects.

3.0 Data Collection

To uncover the potential confounding factors that might affect the relationship between HOS and SCEs of commercial motor vehicle drivers, a representative stated-preference survey was conducted and distributed to operators of commercial motor vehicles. The stated-preference survey was administered via the Qualtrics platform through Oregon State University. In total, the survey consisted of 511 responses representing CMV drivers that delivered goods in the Pacific Northwest. To ensure we got a random population sample, the origins of the surveyed drivers were included in the survey, and they are presented in figure 3.1.

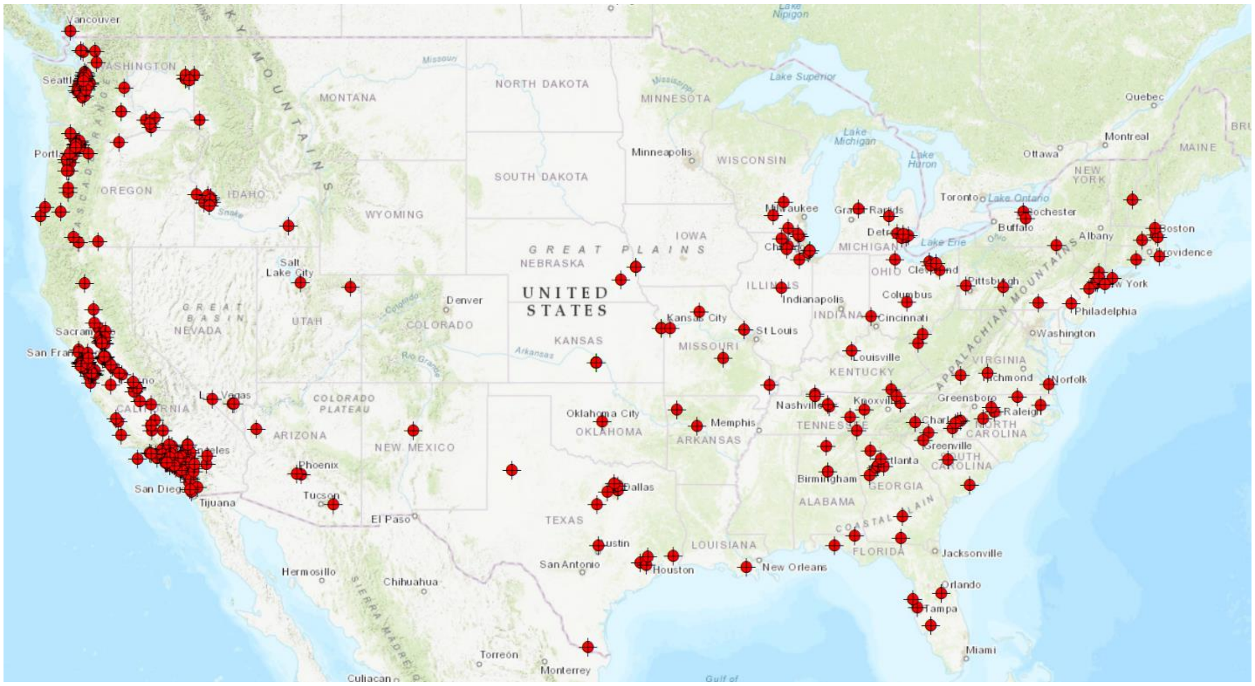

Figure 3.1 Origins of truck drivers who deliver goods in the Pacific Northwest

3.1 Survey Results

The survey's 63 questions were developed to help achieve the objective of the current study, including socioeconomic characteristics of drivers (e.g., age, gender, income, marital status, education status, etc.), the company characteristics (e.g., type of company, total number of trucks operating in the company, etc.), and so forth. In this section, a description of each question and the answers are provided.

3.1.1 Do You Drive a Commercial Grade Truck for Your Profession?

Figure 3.2 clearly shows that 100 percent of surveyed drivers drove their trucks for their own profession. This distribution of drivers' responses were anticipated because the survey was developed to unveil the confounding factors in the relationship between HOS and SCE for CMV drivers. Therefore, all respondents drove their trucks for their own profession.

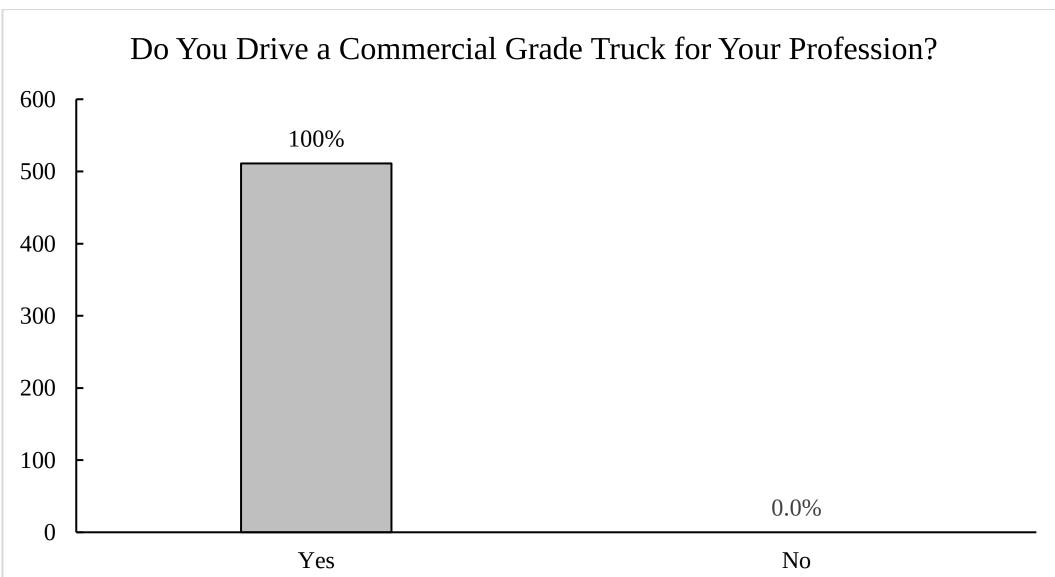

Figure 3.2 Do you drive a commercial grade truck for your profession?

3.1.2 Do You Pick Up or Deliver Goods in the Pacific Northwest (Northern California, Idaho, Oregon, Washington, or British Columbia)?

Responses to this question are illustrated in figure 3.3, which clearly shows that 100 percent of surveyed drivers positively responded to this question by confirming that they di pick up and deliver goods in the Pacific Northwest.

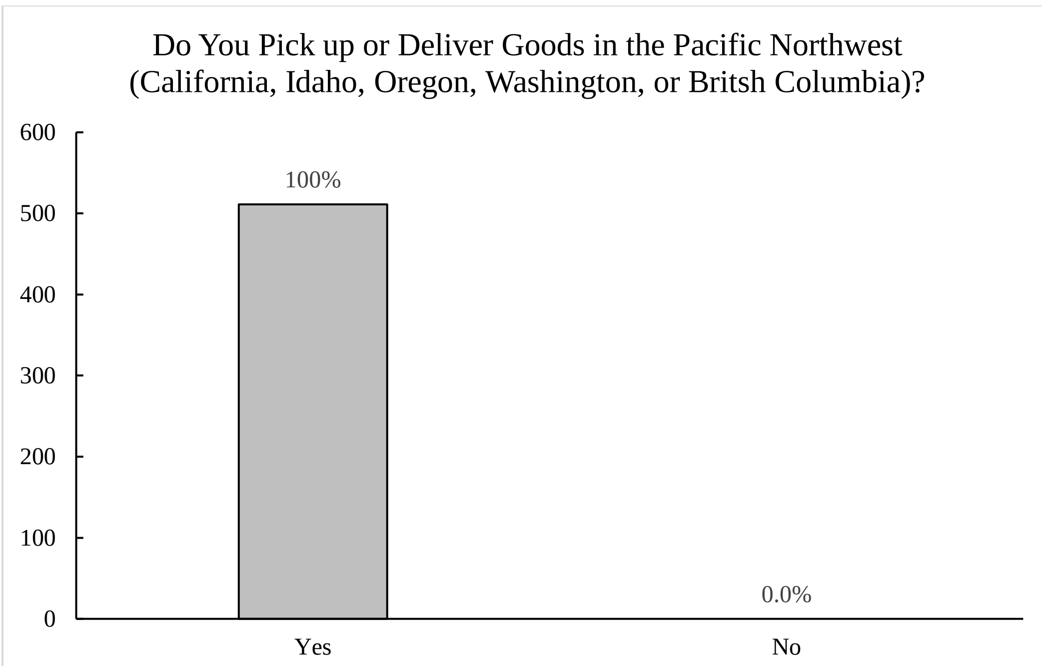

Figure 3.3 Do you pick up or deliver goods in the Pacific Northwest (Northern California, Idaho, Oregon, Washington, or British Columbia)?

3.1.3 Do You Commit to Thoughtfully Providing Your Best Answers to Each Question in This Survey?

Because we cared about the quality of our data, the surveyed drivers were asked that they thoughtfully provide their best answers to each question in this survey so that we got the most accurate measures of drivers' opinions, as shown below in figure 3.4. Nearly 100 percent of drivers selected "I will provide my best answers." Therefore, the quality of our data was proved to be accurate.

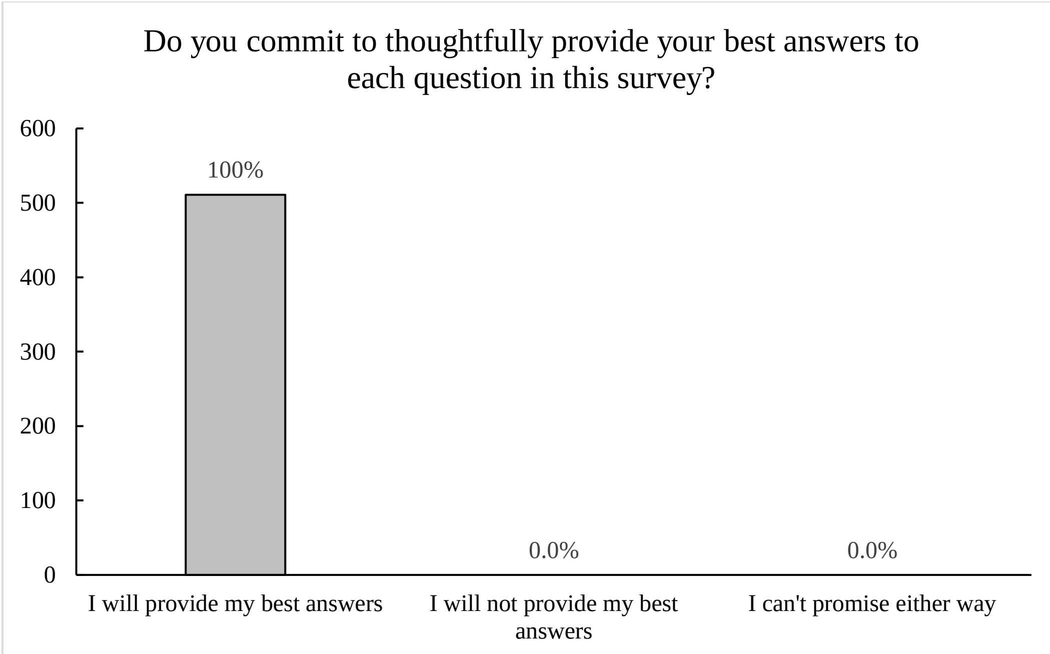

Figure 3.4 Do you commit to thoughtfully providing your best answers to each question in this survey?

3.1.4 Are You Male or Female?

Figure 3.5 demonstrates that 77 percent of the surveyed drivers were male and female drivers constituted 23 percent of the observations.

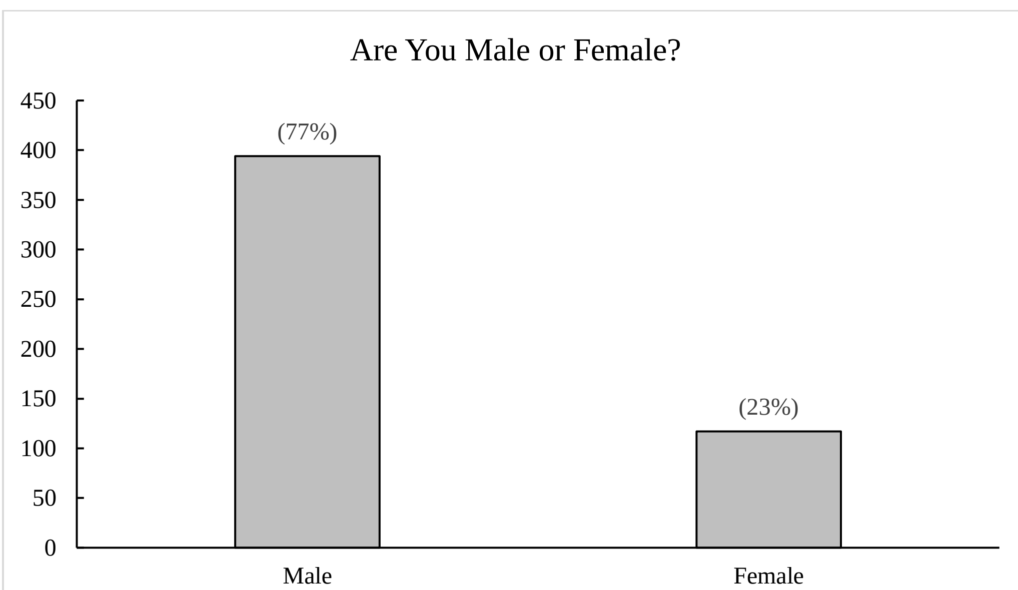

Figure 3.5 Are you male or female?

3.1.5 How Old Are You?

Figure 3.6 shows the age distribution of surveyed drivers. Age was categorized into ordered age groups to easily visualize the age distribution. The drivers with ages between 30 and 39 years encompassed about 34 percent of the total sample. Younger drivers with ages between 20 and 29 years were the second largest category with 26 percent of total surveyed drivers. Therefore, approximately 60 percent of drivers were between 20 and 39 years old. Other age categories were distributed with less frequencies than the first two categories.

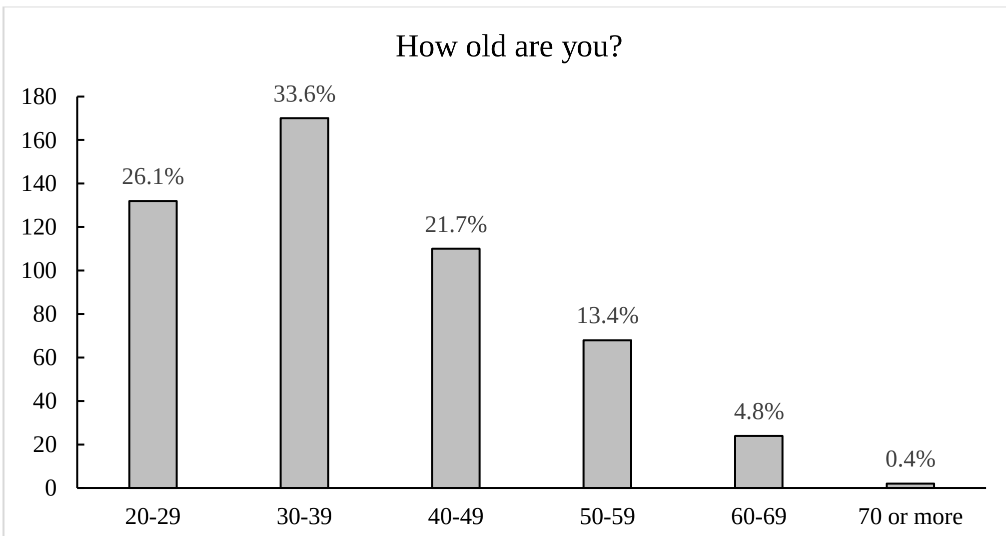

Figure 3.6 How old are you?

3.1.6 Which of the Following Annual Income Categories Best Describes You?

This question was asked to figure out the annual incomes of the drivers surveyed in this study. Notably, an annual income of more than $60,000 had the highest share among other annual income categories, with approximately 40 percent of the drivers, as shown in figure 3.7. Figure 3.7 shows that the annual income distribution was as follows: 50,000 to 59,999 (27.6 percent), 40,000 to 49,999 (14.5 percent), 30,000 to 39,999 (8.4 percent), 20,000 to 29,999 (6.3 percent), and less than 19,999 (3.3 percent).

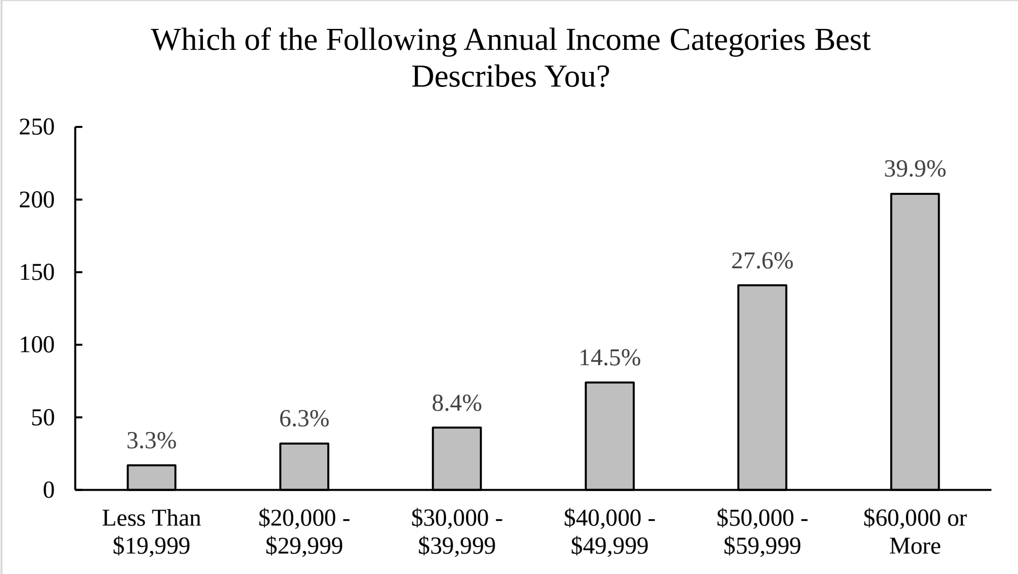

Figure 3.7 Which of the following annual income categories best describes you?

3.1.7 How Are You Normally Paid?

As indicated in figure 3.8, approximately 37 percent of drivers were paid hourly, whereas 17.4 percent of them were paid as a flat rate for every container or truck load carried. Other payment categories were fairly consistent. Note that being paid hourly has some advantages, such as it is more appropriate for local and light duty drivers, and it gives drivers more time to stay with their families. However, hourly paid drivers are not able to get some benefits that drivers with per-mile payment have ,such as sleeper pay, layover pay, and inconvenience pay.

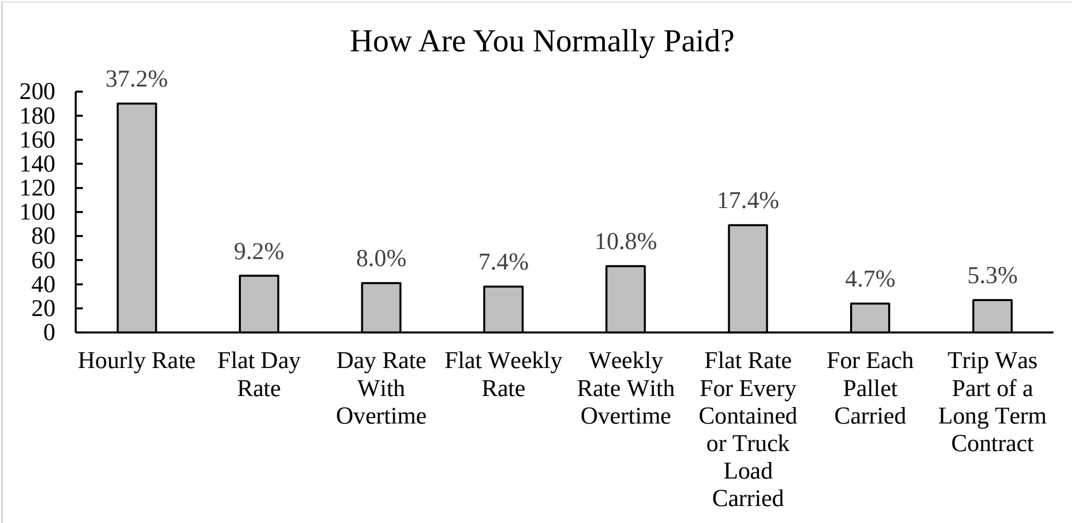

Figure 3.8 How are you normally paid?

3.1.8 Which of the Following Categories Best Describes Your Marital Status?

Roughly, 67.3 percent of drivers were married or had a defacto relationship, and 25.6 percent were single, as shown in figure 3.9. Separated or divorced drivers were 6.3 percent of surveyed drivers.

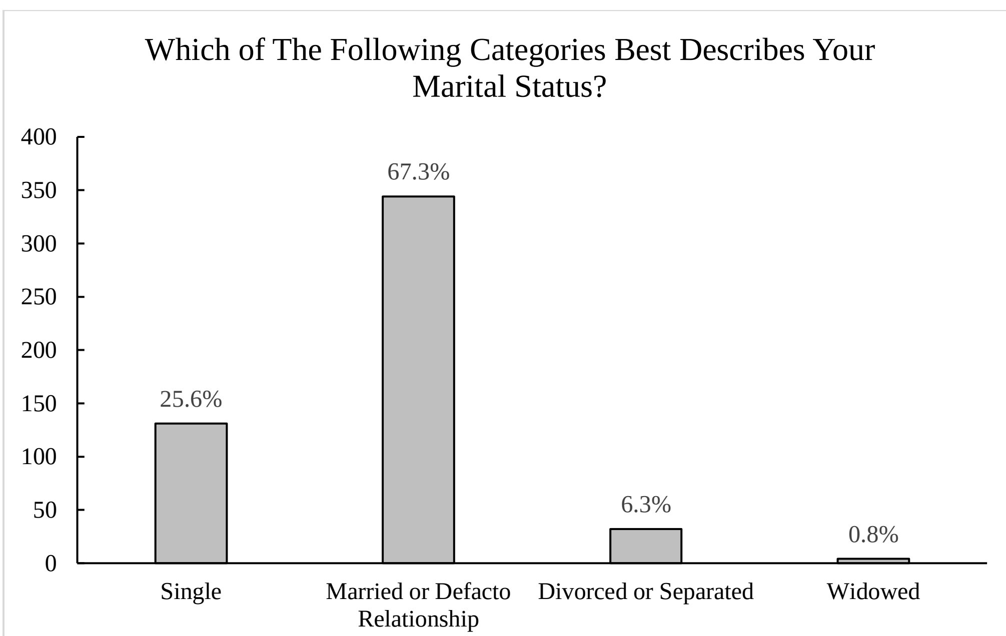

Figure 3.9 Which of the following categories best describes your marital status?

3.1.9 What Is Your Highest Completed Level of Education?

Figure 3.10 illustrates the highest completed level of education that drivers had. The majority of responses were that they had completed high school/technical school (28.4 percent), secondary diploma/degree (25 percent), and trade or technical certificate (23.5 percent). Also, nearly 16.2 percent of drivers had some secondary education, whereas drivers who had some high school/technical school and primary or elementary/middle school encompassed only 5.9 percent and 1 percent , respectively.

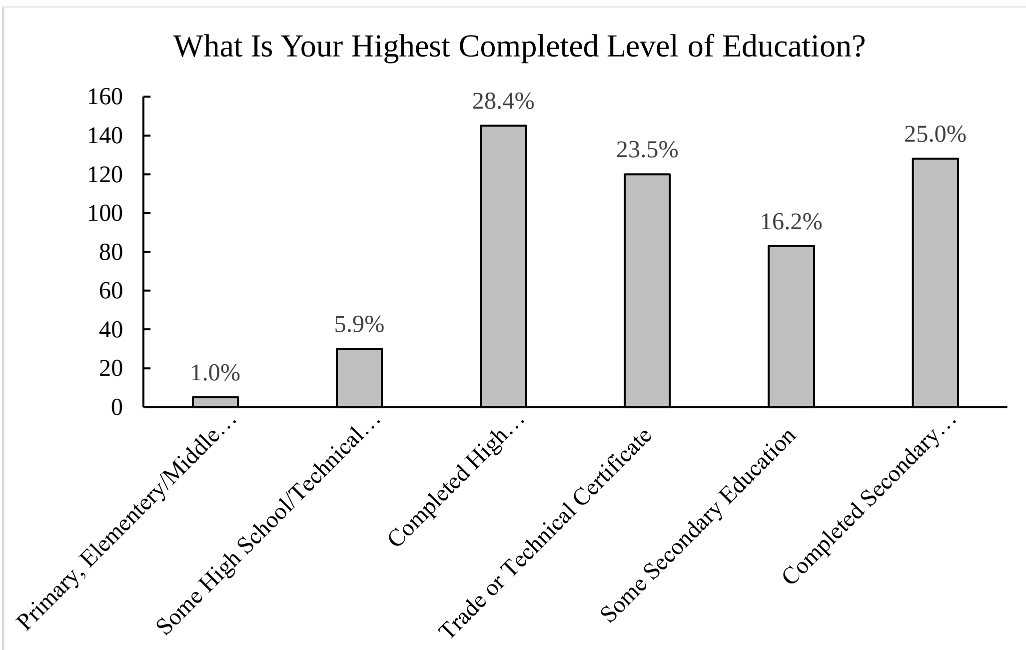

Figure 3.10 What is your highest completed level of education?

3.1.10 What Type of Company Do You Work or Contract For?

In order to determine the type of company that drivers' worked or contracted for, this question was developed, as shown in figure 3.11. This figure shows that three choices were available. These choices were for-hire (28.2 percent), private carriage (34.6 percent), and both for-hire and private (35.8 percent). Noted that about 1.4 percent of drivers did not know the type of company that they worked or contracted for or refused to respond.

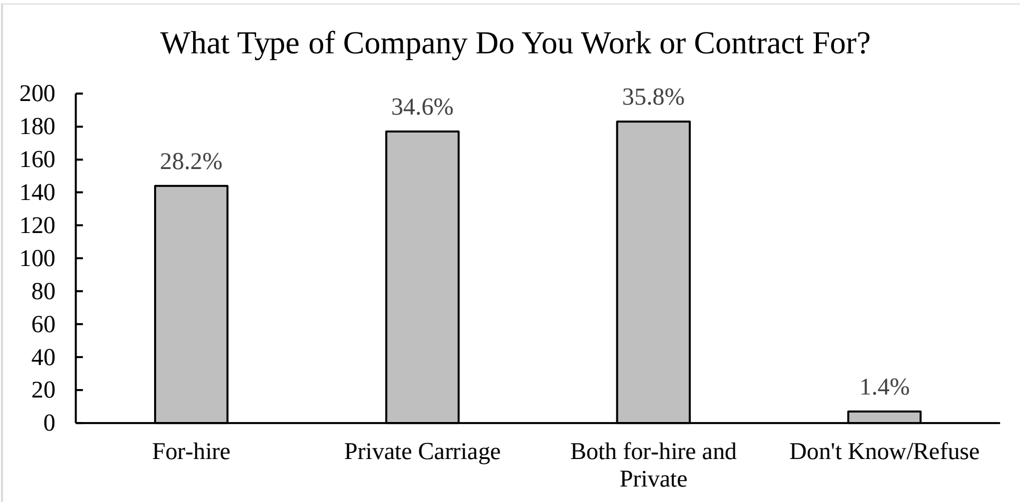

Figure 3.11 What type of company do you work or contract for?

3.1.11 What Is the Total Number of Drivers Operating in Your Company?

In this question, drivers were asked to provide an estimate of the total number of trucks operating in their companies. The driver responses ranged from 0 to 50,000, with a mean of 508 trucks. The answers were dependent on the type and size of the company that the drivers worked with. For example, some companies had a small fleet of trucks, whereas others operated a large fleet of trucks.

3.1.12 What Is the Total Number of Drivers Operating in Your Company?

In an attempt to figure out the total number of trucks operating in their companies, surveyed drivers were asked this question. The driver responses ranged from 0 to 50,000 with a mean of 652 truck drivers. The idea underlying this question was to determine whether there was a shortage in truck drivers and how that affected truck companies.

3.1.13 On Average, How Many Freight-Related Trips Do You Make Weekly?

Then, drivers were asked about the number of freight-related trips that they made weekly. The responses were disproportionate, as drivers' responses ranged from 0 to 500,000 trips, with a mean of 1,428 trips. This variation in drivers' responses reflected the importance of the companies that they worked with.

3.1.14 On Average, How Many Miles Do You Drive Trucks Each Week?

In this question, surveyed drivers were asked about the total number of miles they drove each week. The responses to this question had extreme variation, ranging from 1 to 25,000,000 miles. Some responses were deemed outliers because some drivers reported that they drove 25,000,000 miles each week. In fact, these responses contradicted FMCSA rules regarding HOS, in which drivers are limited to work no more than 70 hours within any period of eight consecutive days.

3.1.15 About What Percentage of Your Total Freight-Related Trips (e.g,. Trips Loaded or Empty) Are within the Following Ranges (must add up to 100%)?

The distribution of total freight related trips is shown in figure 3.12. Obviously, freight-related trips of greater than 500 miles constituted the majority of drivers' responses, with 25.9 percent. Other categories regarding freight related trips are distributed as follows: trips between 250 to 500 miles (23.2 percent), trips between 100 to 249 miles (20.7 percent), trips between 50 to 99 miles (15.1 percent), and trips of fewer than 50 miles (15.3 percent).

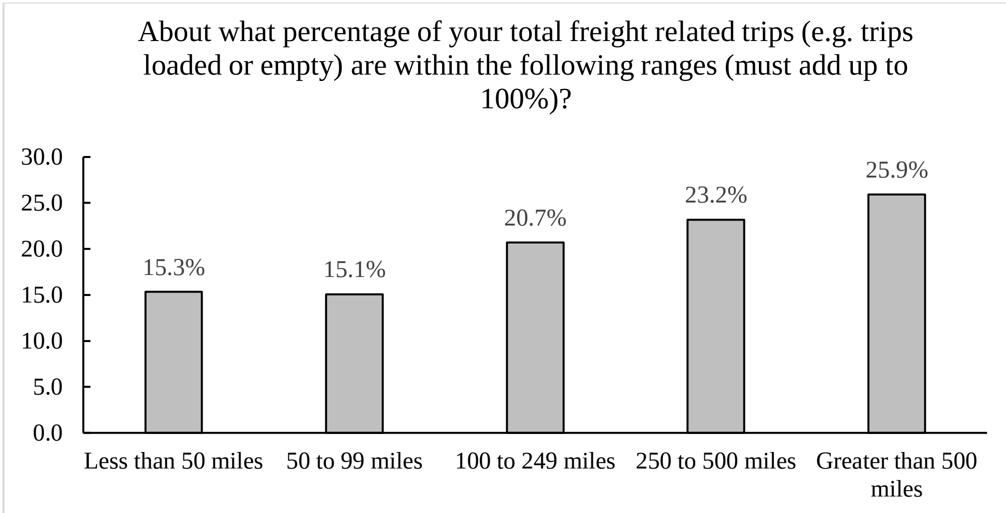

Figure 3.12 About what percentage of your total freight related trips (e.g. trips loaded or empty) are within the following ranges (must add up to 100%)?

3.1.16 On Average, What Type of Shipments Do Your Trips Consist of?

Figure 3.13 illustrates the types of shipments that drivers' trips consisted of. Nearly, 81.6 percent of shipments were truckload, whereas 12.7 percent of surveyed drivers responded that their shipments are less-than-truckload and 4.5 percent said parcel. In this study, 1.2 percent of drivers did not know what their shipments were or refused to respond.

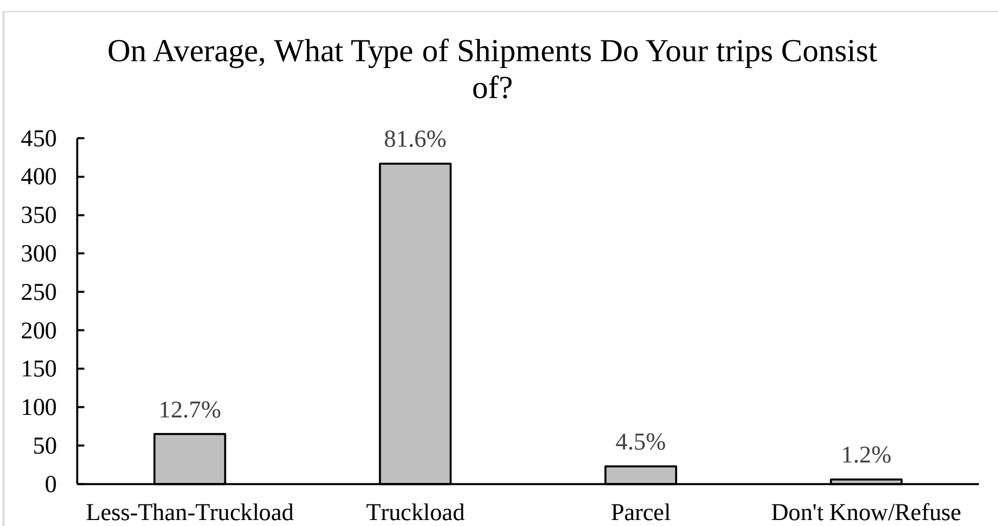

Figure 3.13 On average, what type of shipments do your trips consist of?

3.1.17 How Many Years Have You Been Driving Commercial Motor Vehicles?

The majority of surveyed drivers, nearly two-thirds (66 percent), had been driving commercial vehicles for fewer than 10 years, while other responses were distributed a follows: 11 to 20 years (21 percent), 21 to 30 years (9.3 percent), and more than 31 years (3.5 percent). Figure 3.14 shows the distribution of the number of years that drivers had been commercial truck drivers. Drivers' responses for this question ranged from 1 to 50 years of being truck drivers, with a mean of 10.58 years.

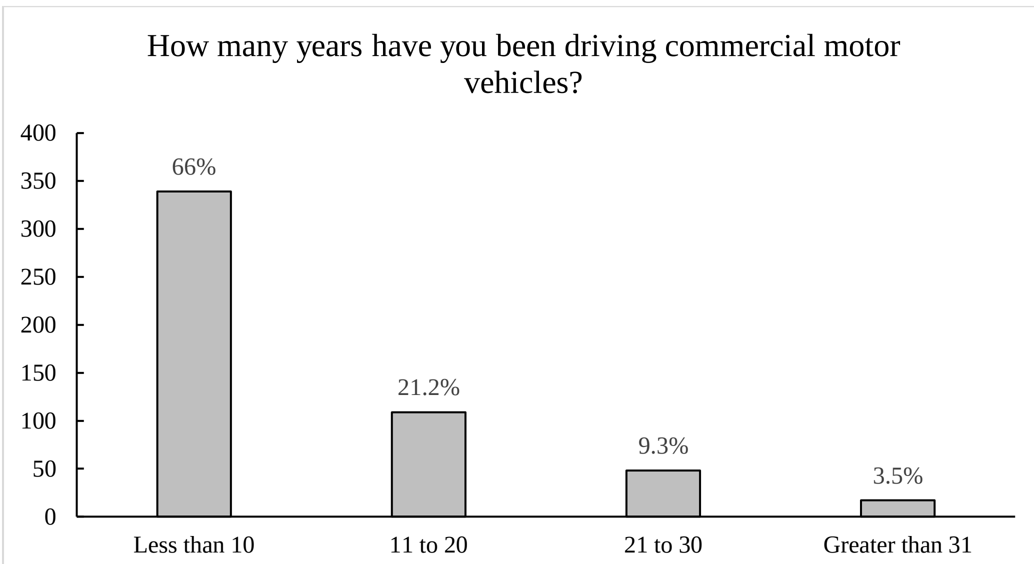

Figure 3.14 How many years have you been driving commercial motor vehicles?

3.1.18 How Did You Learn to Drive the Semi-Truck You Drive?

Figure 3.15 illustrates how surveyed drivers learned to drive a semi-truck. About 43 percent of drivers' responses indicated that they learned to drive semi-trucks in driving schools, whereas 18.2 percent of drivers reported that they learned by themselves. Drivers who learned with help from their friends and relative accounted for 7.4 percent and 11.9 percent, respectively. Military services and being a previous or present employer also played a role in teaching some drivers and accounted for 2.9 percent and 16.5 percent, respectively.

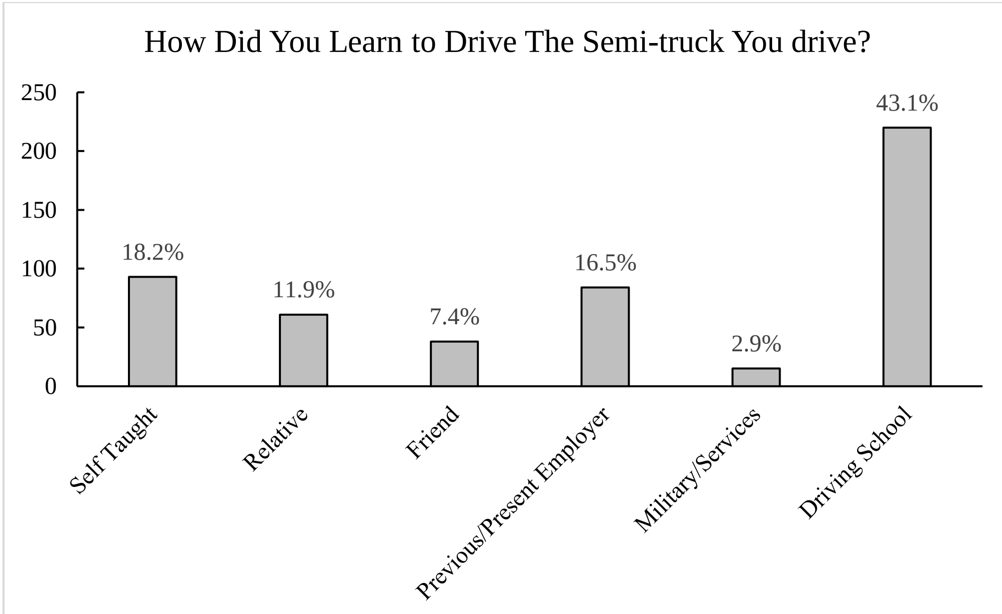

Figure 3.15 How did you learn to drive the semi-truck you drive?

3.1.19 What Kind of Road Do You Usually Drive on?

The surveyed drivers were asked to reveal the type of roadways they usually drove on. About 55 percent of drivers responded that they drove on highways, whereas nearly 36 percent of them drove on a mixture of roadways, as illustrated in figure 3.16. These two responses encompassed approximately 90 percent of all responses. The rest of drivers stated that they drove on rural roads (4.7 percent) and city roads (5.1 percent).

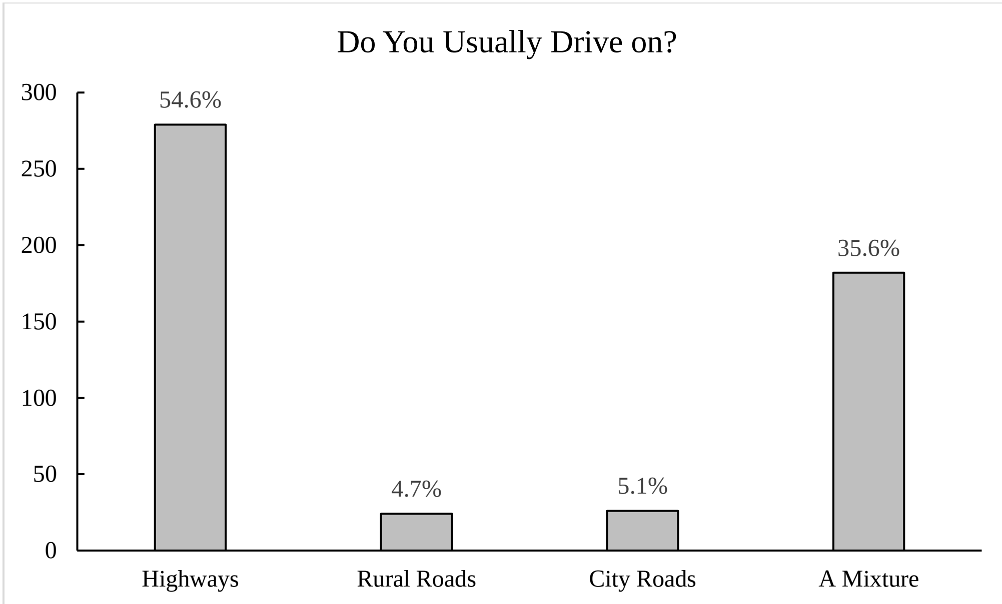

Figure 3.16 Do you usually drive on?

3.1.20 How Often Would You Check Your Truck over Each Week?

Regular maintenance of vehicles can extend the life of the vehicle itself and saves drivers costs that they would incur in road repairs. Given that, the drivers were asked how often they checked their trucks over each week, as shown in figure 3.17. Nearly, 46.4 percent of drivers checked their trucks before starting each trip, and 34.8 percent of them did that before starting and at every stop. Other responses showed that some drivers thought that it is not their job to check their trucks (4.7 percent,) while 12.7 percent did that occasionally (perhaps once every few days). A very small percentage of drivers (1.4 percent) checked their trucks when they felt there was something wrong with their vehicles.

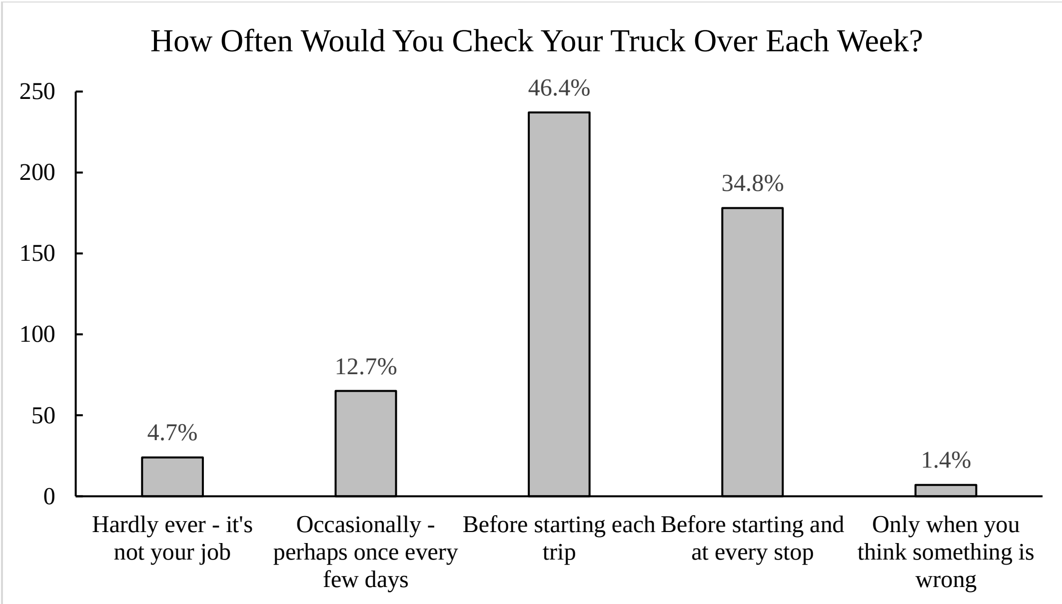

Figure 3.17 How often would you check your truck over each week?

3.1.21 Do You Participate in Team Driving?

Figure 3.18 shows the response distribution to a question that asked drivers whether they participated in team driving. Approximately, 23 percent of drivers responded that they never participated in team driving, while nearly 30 percent of them rarely participated. Figure 3.18 also shows that 31 percent of them participated sometimes, and drivers who often and always participated in team driving accounted for 9.4 percent and 7.4 percent, respectively.

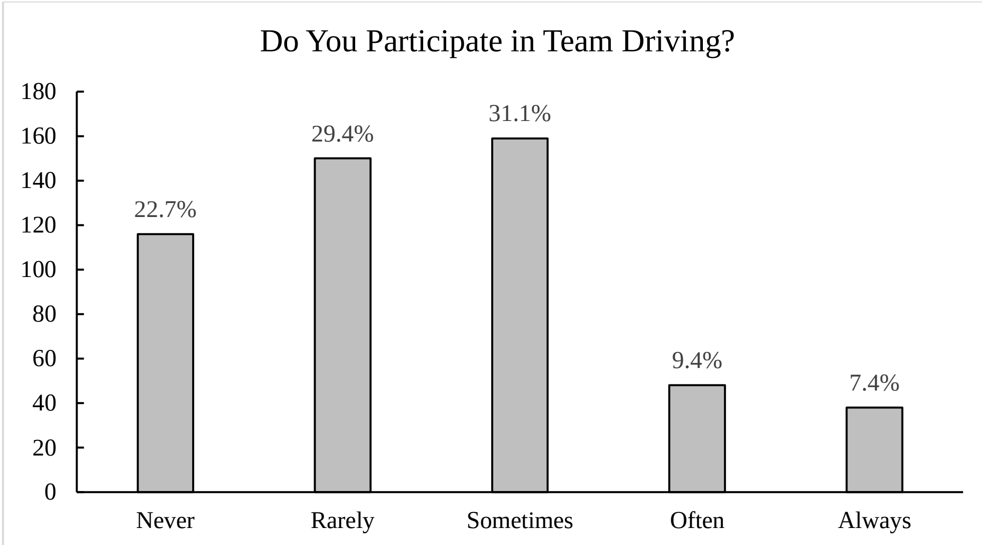

Figure 3.18 Do you participate in team driving?

3.1.22 When It Comes to Deciding Where to Stop to Park?

In deciding where to stop to park, figure 3.19 shows that about 78 percent of drivers were responsible for making that decision, and 21 percent of drivers indicated that the decision regarding where to stop to park was made by the company they worked for. Only 1 percent of drivers provided other answers to this question.

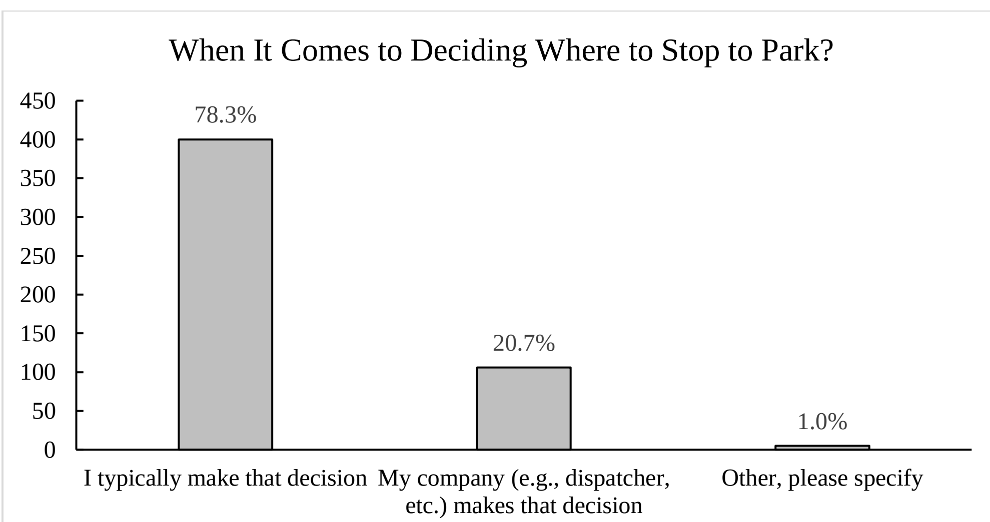

Figure 3.19 When it comes to deciding where to stop to park?

3.1.23 Have You Ever Had Any Specific Road Safety Training?

As a means of enhancing traffic safety, in particular, for drivers of large trucks, safety training programs are important. To figure out whether drivers had taken any road safety training program, this question was developed. Figure 3.20 clearly shows that 87 percent of drivers had taken a certain training program, whereas 13 percent of them had not enrolled in any safety training programs.

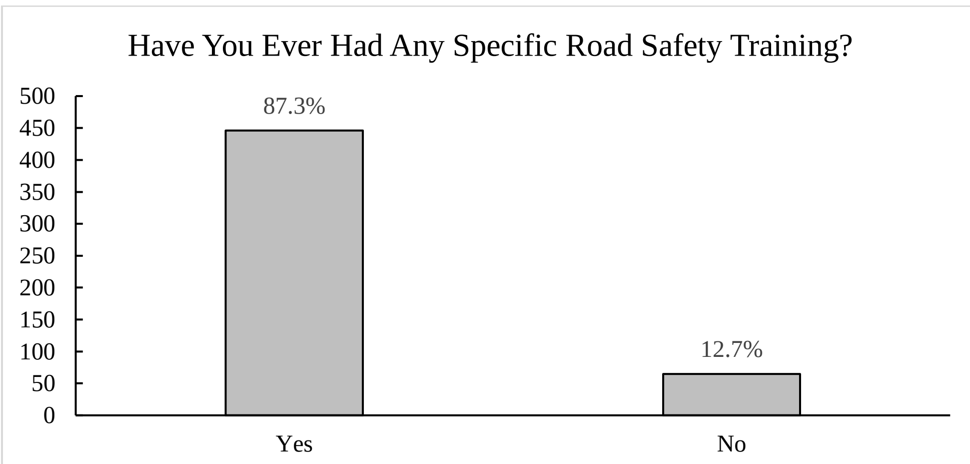

Figure 3.20 Have you ever had any specific road safety training?

3.1.24 How Confident Are You in Your Abilities to Professionally Drive a Semi-Truck?

The results of this question indicated that about 93 percent of drivers were extremely confident (52.6 percent) and very confident (40.1 percent) in their abilities to professionally drive a semi-truck, as figure 3.21 shows. Only 5.9 percent of surveyed drivers were moderately confident, while 0.8 percent of them were slightly confident and 0.6% were not at all confident in their abilities.

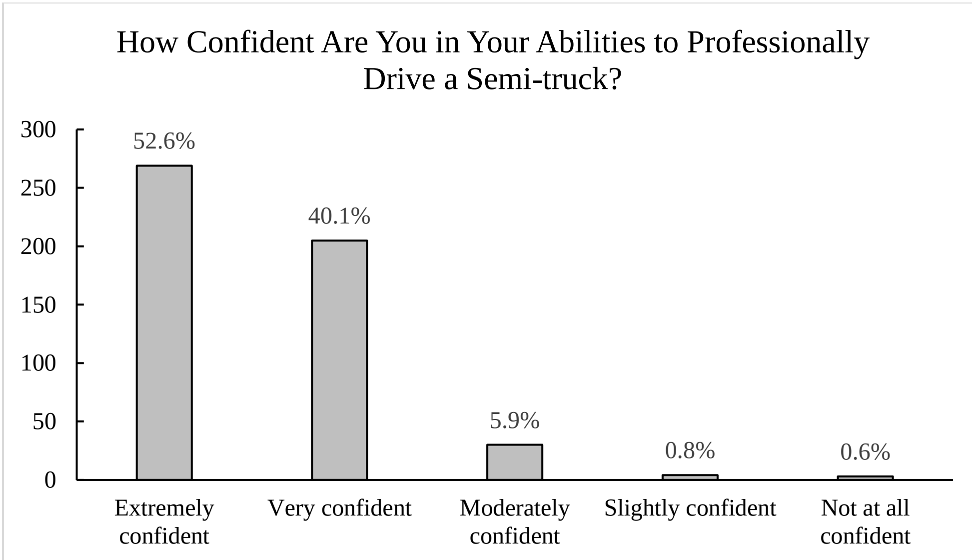

Figure 3.21 How confident are you in your abilities to professionally drive a semi-truck?

3.1.25 Which Situation Poses the Greatest Safety Hazard?

Figure 3.22 presents drivers' thoughts on the situation that thought posed the greatest safety hazard. In this question, three areas of the truck were presented as a risk for truck drivers: the front of the truck, back of the truck, and sides of the truck. These areas are called blind spots or no-zone areas on trucks. Clearly, about 40 percent of drivers thought that passenger vehicles on either side of their truck created the greatest safety concern, whereas passenger vehicles in front of and behind the truck accounted for 24 percent and 13.5 percent, respectively. Moreover, the presence of other trucks in the aforementioned blind spots also increased surveyed truck drivers concerns. Figure 3.22 shows that drivers perceived safety hazards when trucks were in front (10.8 percent), on either side (8.6 percent), and behind (3.5 percent) their vehicle.

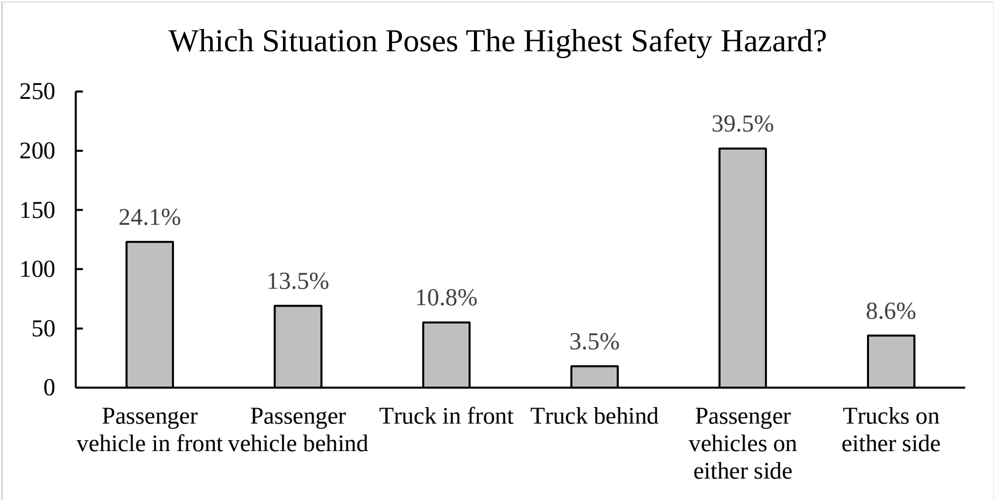

Figure 3.22 Which situation poses the highest safety hazard?

3.1.26 Do You Change Lanes to Avoid Traveling with Other Vehicles?

Figure 3.23 shows the distribution of drivers' responses to the question about whether they changed lanes to avoid travelling with other passenger vehicles and trucks in the aforementioned blind spot areas. As seen in figure 3.23, when passenger vehicles approached the blind spots of truck drivers, the hazard of passenger vehicles being invisible was perceived as higher than a situation in which other trucks approached a travelling truck.

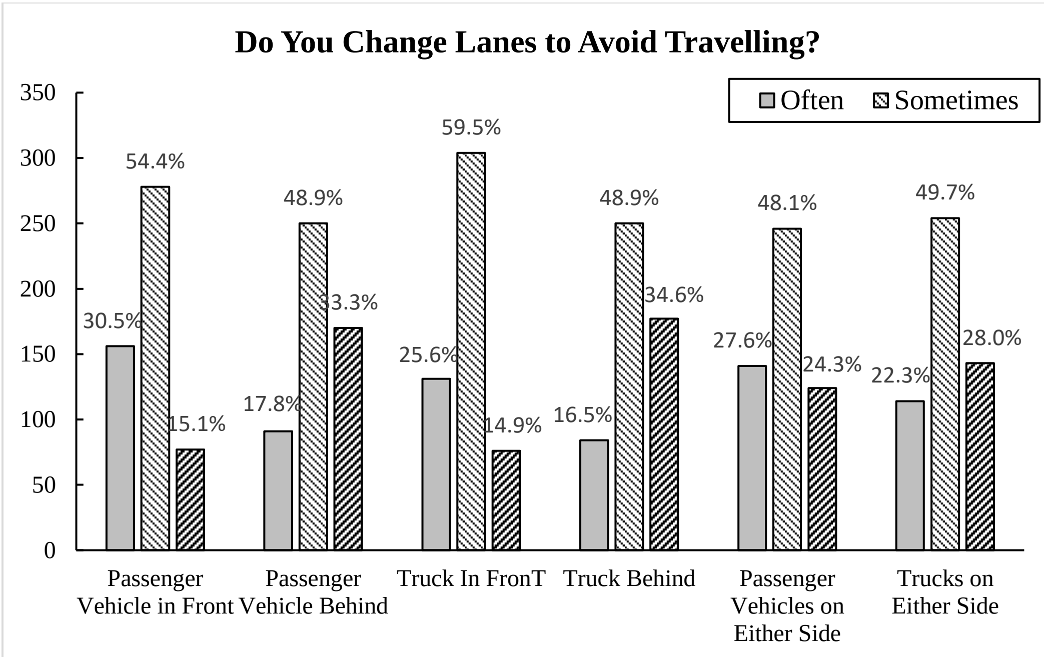

Figure 3.23 Do you change lanes to avoid traveling with?

3.1.27 How Often Do You Find Your Concentration Lapsing After Driving for a Long Time?

To highlight the impact of working hours on truck drivers, they were asked whether their concentration lapsed after having driven for a long time, as shown in figure 3.24. About 35 percent of them reported that this rarely happened, whereas 31 percent indicated that they their concentration sometimes lapsed. The rest of the drivers were distributed as 14.7 percent quite often, 11.7 percent very often, and 7.5 percent never having lapsed concentration after a long period of driving.

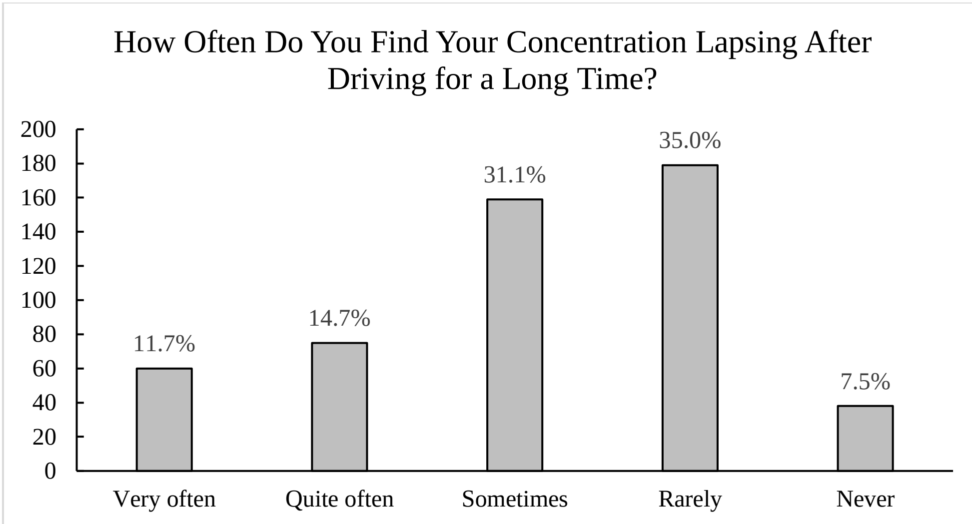

Figure 3.24 How often do you find your concentration lapsing after driving for a long time?

3.1.28 Do You Use a Cell Phone While Driving? (either handheld or hands-free)

As seen from figure 3.25, about 45 percent of surveyed drivers confirmed that they used their cell phones while driving, while 55 percent of them responded that they did not use it.

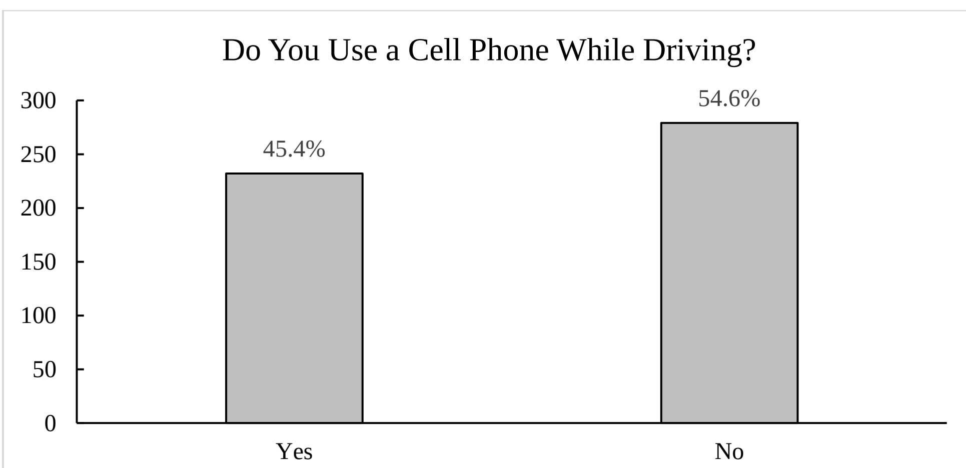

Figure 3.25 Do you use a cell phone while driving?

3.1.29 How Long Are You Usually on the Phone While Driving (in minutes)?

Drivers who responded that they used their cell phones while driving were asked to provide the number of minutes they used their cell phones while driving. The responses were distributed from 1 to 200 minutes, with a mean of 18.1 minutes.

3.1.30 During the Last Five Years How Many Accidents Have You Had That the Police Had to Attend?

Roughly 76 percent of surveyed drivers had not been involved in any accidents during the last five years, as illustrated in figure 3.26. Other drivers indicated that they had been involved in one (12.9 percent), two (6.3 percent), three (3.1 percent), and four or more (1.6 percent) accidents.

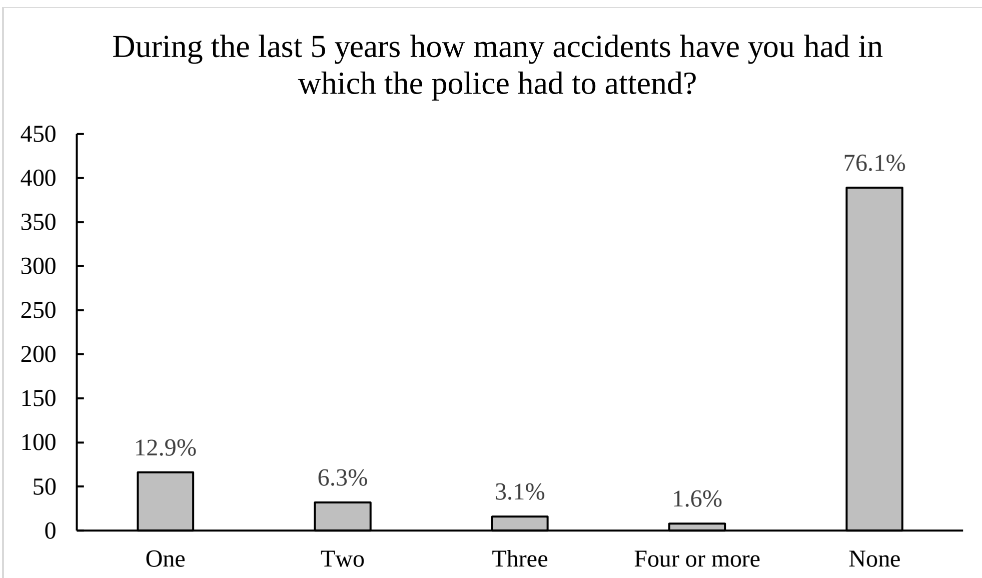

Figure 3.26 During the last 5 years how many accidents have you had in which the police had to attend?

3.1.31 Did This Accident/Any of These Accidents Not Involve Other?

This question was asked to figure out what types of crashes drivers had been involved with in the last five years. Figure 3.27 shows that roughly 57 percent of the accidents did not involve other vehicles, while 43 percent of crashes involved other vehicles. This finding may indicate that truck drivers are more prone to roadway departure crashes that stem from factors such as fatigue, falling asleep, and other driver-related factors.

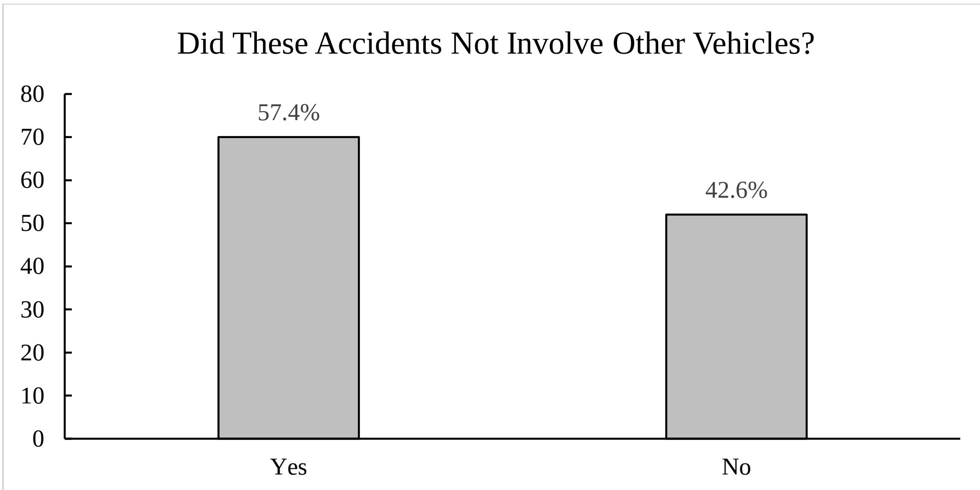

Figure 3.27 Did this accident/any of these accidents not involve other vehicles (e.g. you ran off the road/hit something on the road)?

3.1.32 Thinking About the Last Accident You Had - Was Your Truck Loaded or Unloaded at the Time?

The results of this question indicated that empty trucks (27 percent) are less likely to be involved in accidents, as illustrated in figure 3.28. In contrast, when trucks were partially loaded or fully loaded, the probability of being involved in accidents increased by 41 percent and 31 percent, respectively. A possible reason is that loaded trucks are less stable than empty trucks.

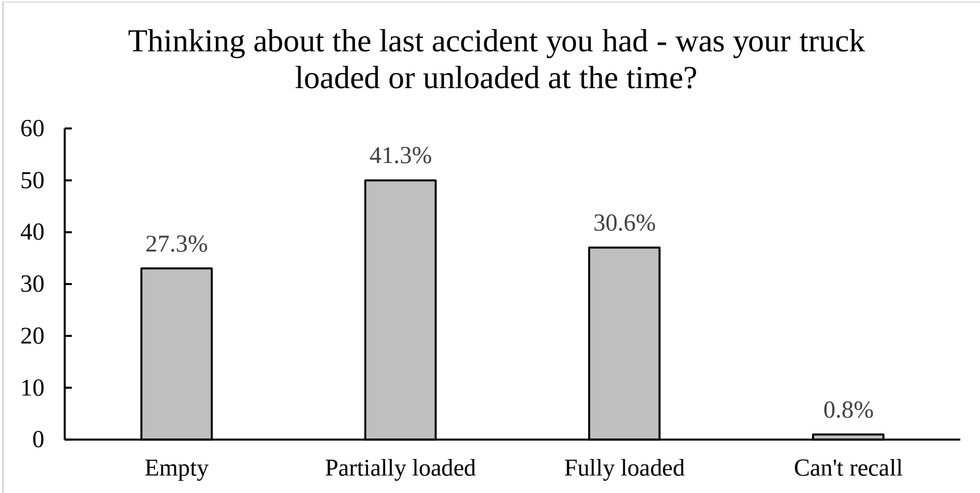

Figure 3.28 Thinking about the last accident you had - was your truck loaded or unloaded at the time?

3.1.33 Roughly, How Far Had You Driven before You Had That Accident?

Referring to figure 3.29, nearly 60 percent (73) of drivers responded to this question by providing the number of miles that they had driven before having the previously described accident. However, three responses were excluded because they provided unreasonable answers. Another 40 percent (49) of drivers claimed that they did not remember.

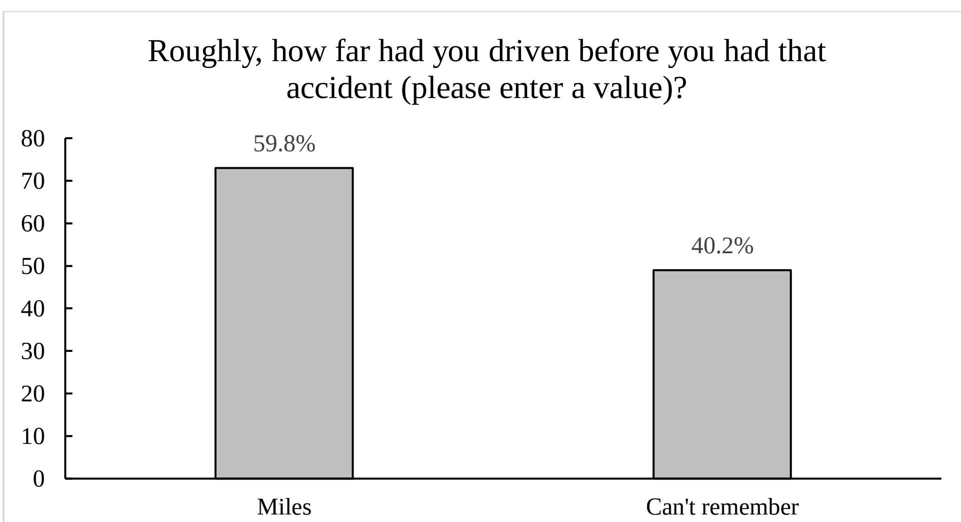

Figure 3.29 Roughly, how far had you driven before you had that accident (please enter a value)?

3.1.34 How Far Had You Driven before You Had That Accident?

Of the drivers who responded to the previous question by providing a number of miles, 68 drivers provided an estimate of how far they had driven before they had that accident. Their responses ranged from 2 to 350,000 miles, with a mean of 5,847 miles.

3.1.35 Which Road Type Were You Driving on During Your Last Crash?

Figure 3.30 shows the roadway types that drivers were driving on during their last crash. About 62 percent of crashes involving large trucks occurred on highways, and roughly 21 percent of the crashes took place on rural roadways. City roads experienced about 16.5 percent of the crashes involving large trucks.

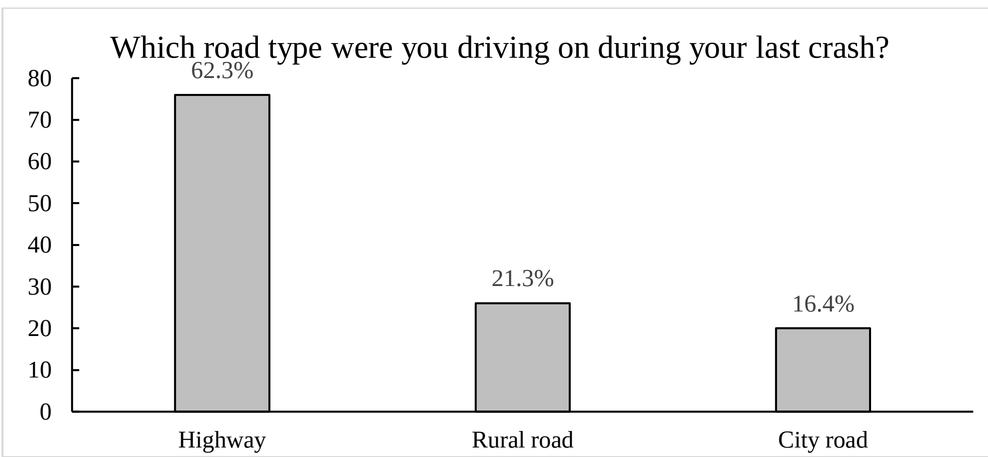

Figure 3.30 Which road type were you driving on during your last crash?

3.1.36 What Weather Conditions Were Present at the Time of the Crash?

The weather conditions in which the large truck crashes occurred are presented in figure 3.31.Weather conditions were clear for 32.8 percent of the crashes, cloudy for 32.8 percent, and rainy for 24.6 percent. Extreme weather conditions such as snow and fog accounted for 4.1 percent and 5.7 percent of the instances, respectively.

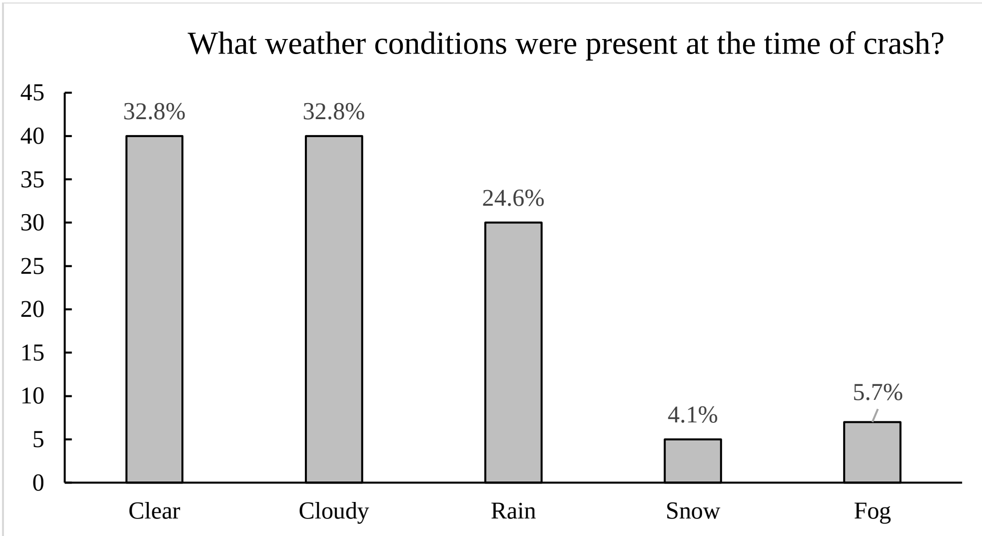

Figure 3.31 What weather conditions were present at the time of crash?

3.1.37 What Time of Day Did Your Crash Occur?

Figure 3.32 shows the times of day that the crashes occurred. The majority of crashes (47 percent) occurred near the middle of the shift, 31 percent of the crashes took place at the beginning of the shift, and 22 percent of crashes occurred near the end of the shift. These findings reflect the effects of hours of service and their impact on driver fatigue, which in turn, exacerbates driver performance.

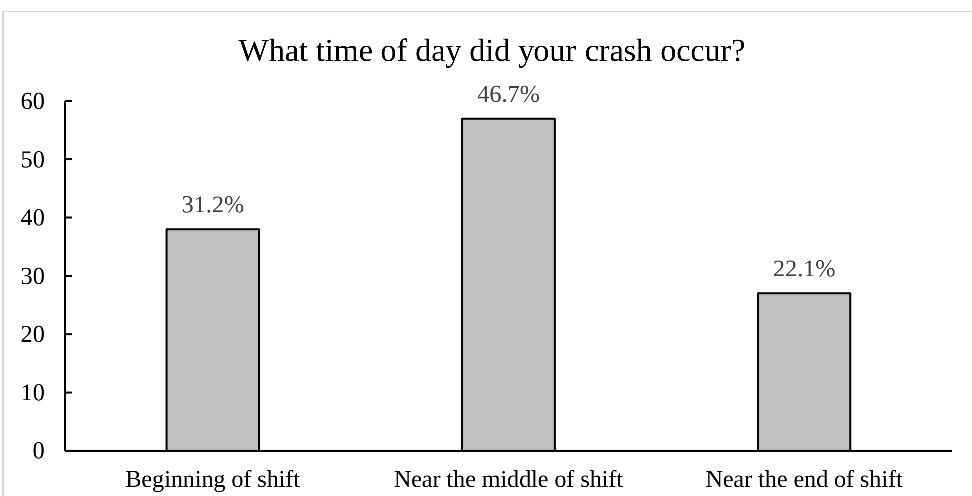

Figure 3.32 What time of day did your crash occur?

3.1.38 How Much Time Had Passed Since Your Last Break before the Crash Occurred?

As illustrated in figure 3.33, about 39 percent of drivers reported that 2 to 3 hours had passed since their last break before the crash occurred, and 23 percent of them indicated that 1 to 2 hours had passed since the last break. Of the other drivers responding to this question, 17.4 percent of them stated that 4 to 5 hours had passed, 12.4 percent of them said 5 hours, and 8.3 percent said less than an hour.

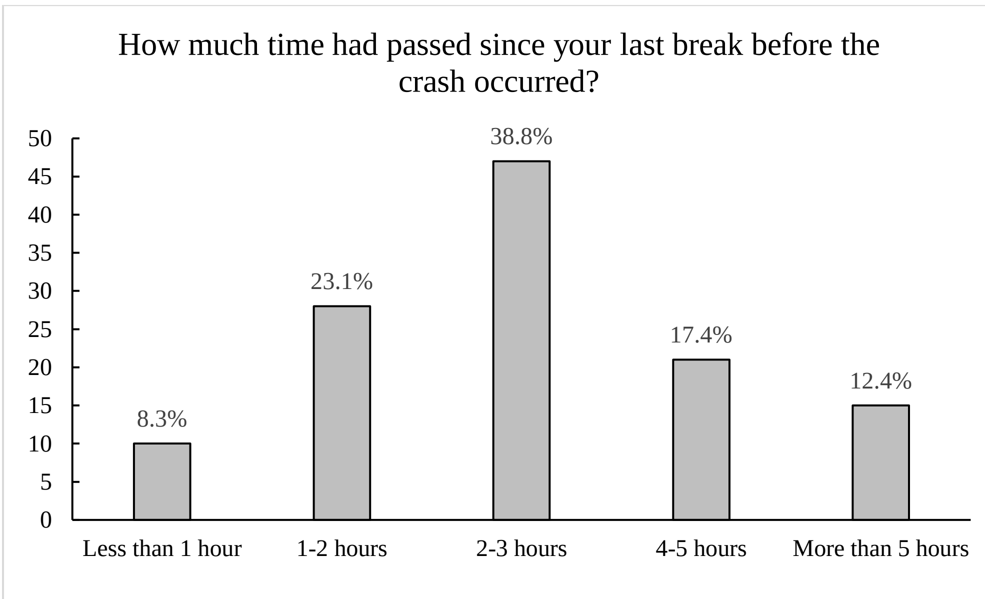

Figure 3.33 How much time had passed since your last break before the crash occurred?

3.1.39 Do You Feel Operating Trucks in Mixed Traffic Poses Any Safety Hazard to You?

Drivers' response to whether operating trucks in mixed traffic poses any safety hazard is shown in figure 3.34. About 57 percent of drivers thought that operating trucks in mixed traffic posed a safety hazard to them, whereas 33.3 percent said it did not pose any safety hazard. Other drivers (9.6 percent) were not sure whether it posed safety hazard.

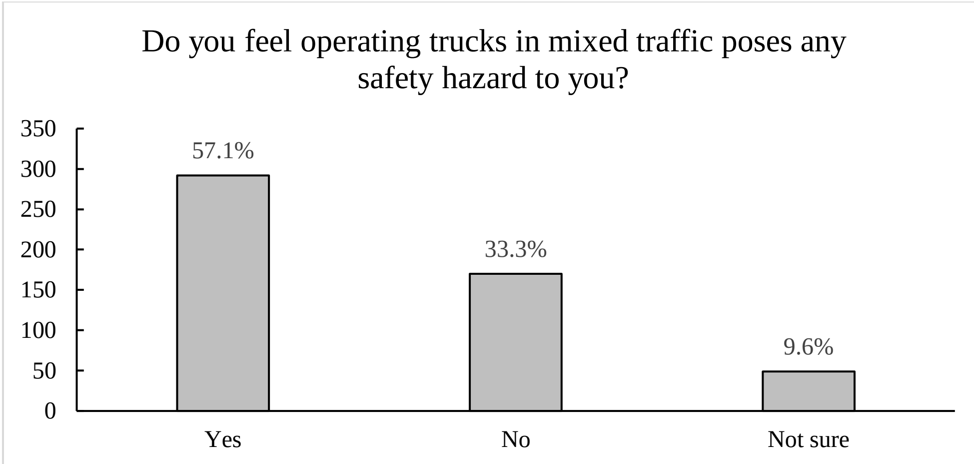

Figure 3.34 Do you feel operating trucks in mixed traffic poses any safety hazard to you?

3.1.40 When Do You Normally Start Your Work?

The times of day that drivers usually started their work are presented in figure 3.35. Drivers who stated that their work started by early morning (from midnight to 5:59 am) accounted for 37.4 percent, and morning starts (from 6:00 am to 9:59 am) constituted 41.5 percent of drivers. Drivers who reported that their work started by midday (10:00 am to 3:59 pm) encompassed 11.1 percent of responses, by afternoon (4:00 pm to 8:59 pm) were 5.3 percent, and by evening (9:00 pm to 11:59 pm) were 4.7 percent.

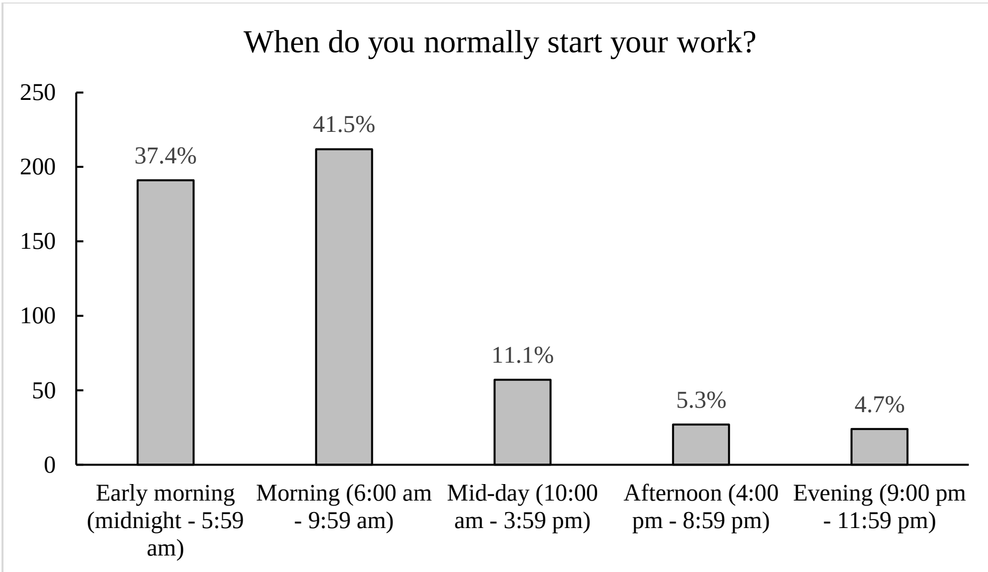

Figure 3.35 When do you normally start your work?

3.1.41 When Do You Normally Start Driving?

Similar to the trend revealed by the previous question, the majority of drivers started their driving in the early morning (25.8 percent) and morning (48.7 percent) , as illustrated in figure 3.36. Other drivers stated that their driving times started in the midday (14.5 percent), afternoon (6.5 percent), and evening (4.5 percent).

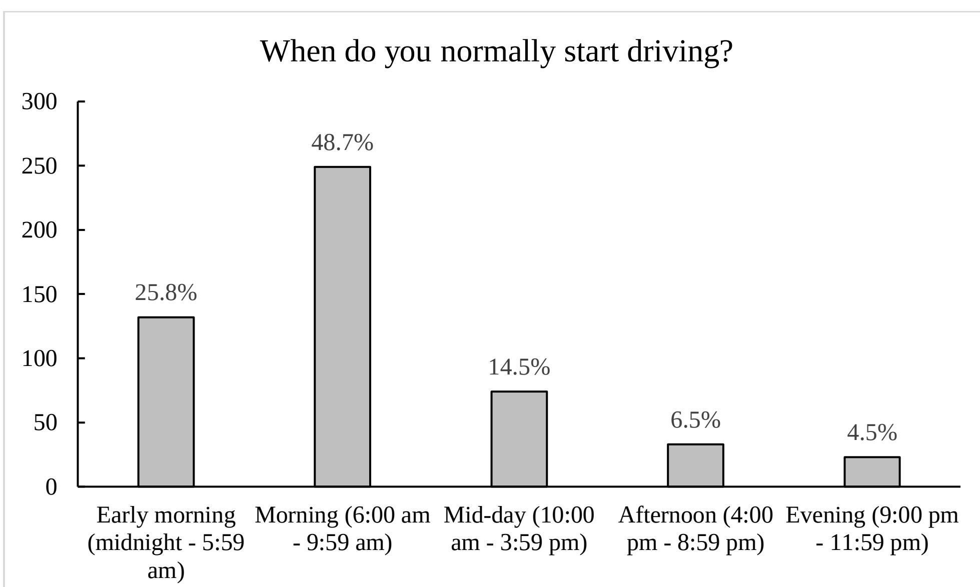

Figure 3.36 When do you normally start driving?

3.1.42 What Time of Day Do You Think Is the Safest Time to Drive Your Truck?

Figure 3.37 illustrates the distribution of the times of day that drivers said it would be the safest to drive their trucks. Roughly 36 percent of drivers stated that early mornings (from midnight to 5:59 am) was the safest time. Other drivers believed that mornings (21.7 percent), midday (24.7 percent), afternoons (3.9 percent), and evenings (13.5 percent) were the safest times.

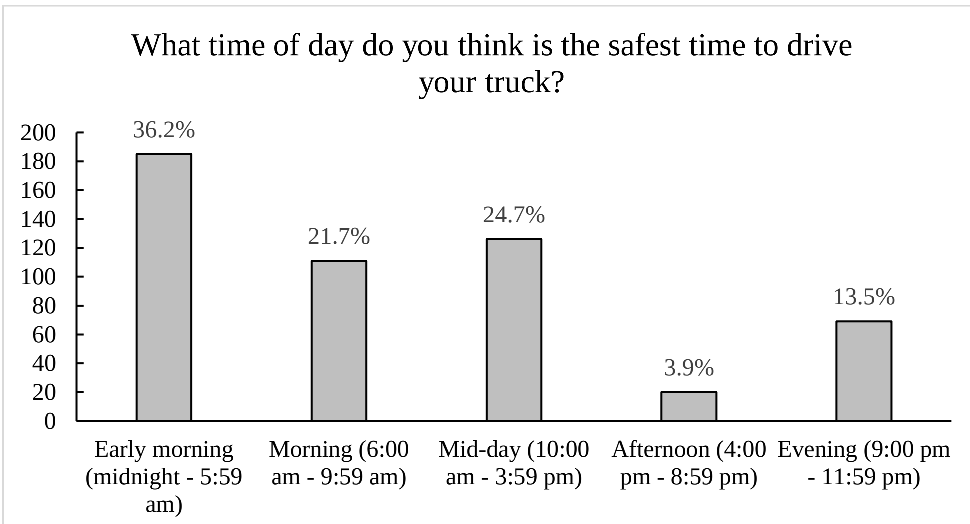

Figure 3.37 What time of day do you think is the safest time to drive your truck?

3.1.43 What Times of the Day Have You Found to Be the MOST Difficult for Finding Safe Truck Parking?

According to drivers' responses to this question, afternoon (from 4:00 pm to 8:59 pm) was the most difficult time to find truck parking, with nearly 33 percent of the responses. Interestingly, the demand on truck parking increases as the time of day progresses from early morning to evening. Therefore, the difficulty of finding truck parking increased as time progressed as well, as shown in figure 3.38. For example, 10.6 percent of drivers reported difficulty in finding parking in the early morning, 13.0 percent in the morning, 18.5 percent at midday, and 21.0 percent in the evening. Finally, 4.0 percent of drivers surveyed claimed that they did not have difficulty in finding safe truck parking.

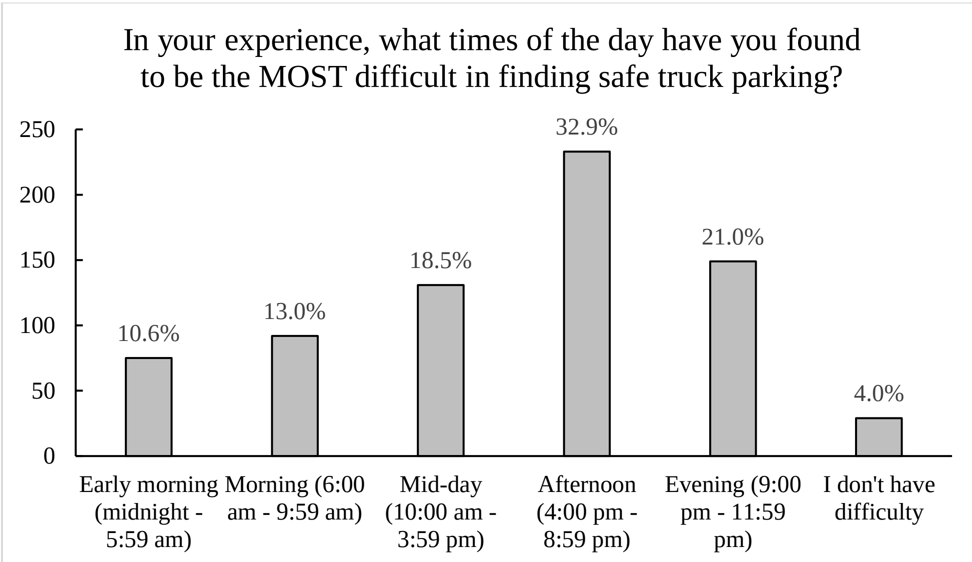

Figure 3.38 In your experience, what times of the day have you found to be the MOST difficult in finding safe truck parking?

3.1.44 In Your Experience, What Days of the Week Have You Found to Be the MOST Difficult for Finding Safe Truck Parking?

The days of week that were reported to be the most difficult for finding safe truck parking are presented in figure 3.39. Clearly, Friday (21.0 percent), Monday (16.1 percent), and Saturday (14.9 percent) were the most difficult days to find safe truck parking. Other days of week showed a similar trend, as shown in figure 3.39. For instance, 11.4 percent of drivers reported that they had difficulty in finding safe truck parking on Sunday and Tuesday, whereas 11.0 percent of drivers stated that Wednesday was the most difficult day to find safe truck parking, and 9.9 percent reported Thursdays. Another 4.4 percent of drivers indicated that they did not have difficulties.

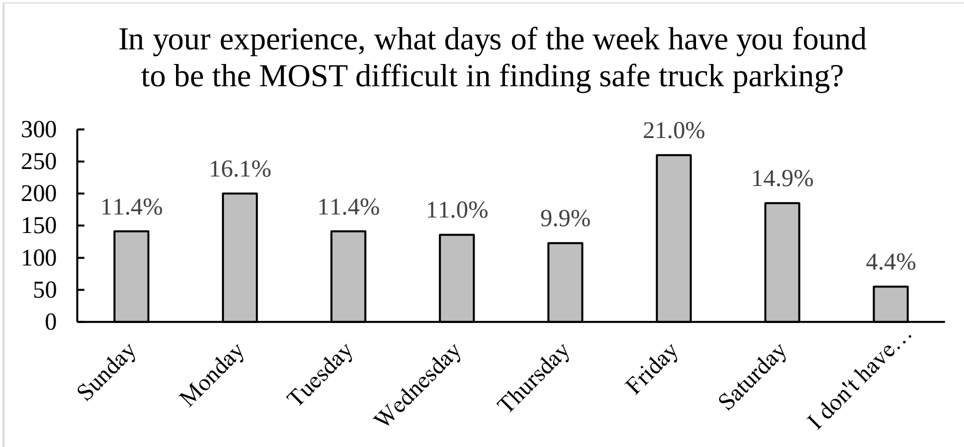

Figure 3.39 In your experience, what days of the week have you found to be the most difficult in finding safe truck parking?

3.1.45 Which Months of the Year Have You Found to Be the MOST Difficult for Finding Safe Truck Parking?

Roughly 17.4 percent of drivers stated that December is the most difficult month for finding safe truck parking, as illustrated in figure 3.40. January and July were selected to be difficult by 11.8 percent and 11.5 percent of drivers, respectively. Responses for other months were as follows: February 8.0 percent, March 4.7 percent, April 3.9 percent, May 5.7 percent, June 9.9 percent, August 7.8 percent, September 5.0 percent, October 4.8 percent, and November 9.5 percent.

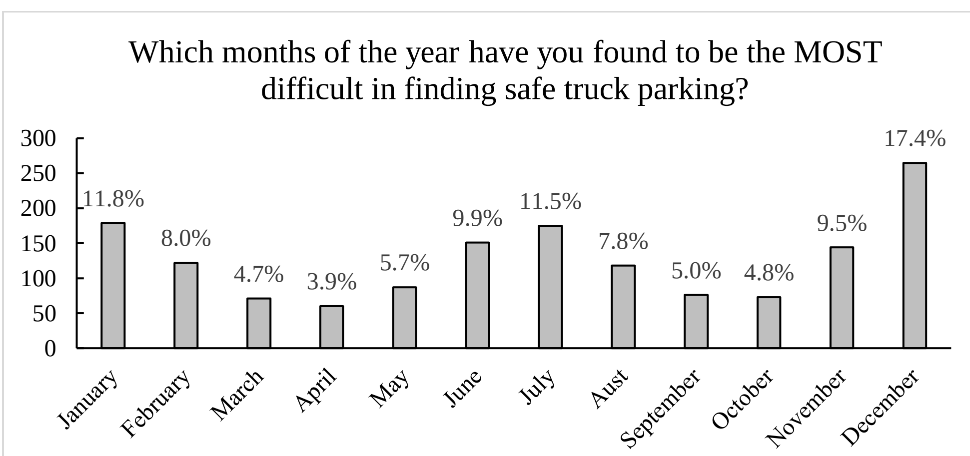

Figure 3.40 Which months of the year have you found to be the most difficult in finding safe truck parking?

3.1.46 How Often Does the Lack of Available Parking Cause Problems with Adhering to the Hours of Service Limitations?

This question was intended to determine whether the lack of available parking caused problems with adhering to the hours of service limitations. Drivers' responses indicated that for about 55.8 percent of respondents, failure to find truck parking sometimes affected the hours of service limitations, as depicted in figure 3.41. Nearly, 23.1 percent of drivers stated that it almost never affected HOS. On the other hand, 14.9 percent of drivers thought this issue frequently caused problem with HOS limitations, and 6.3% said it almost always did.

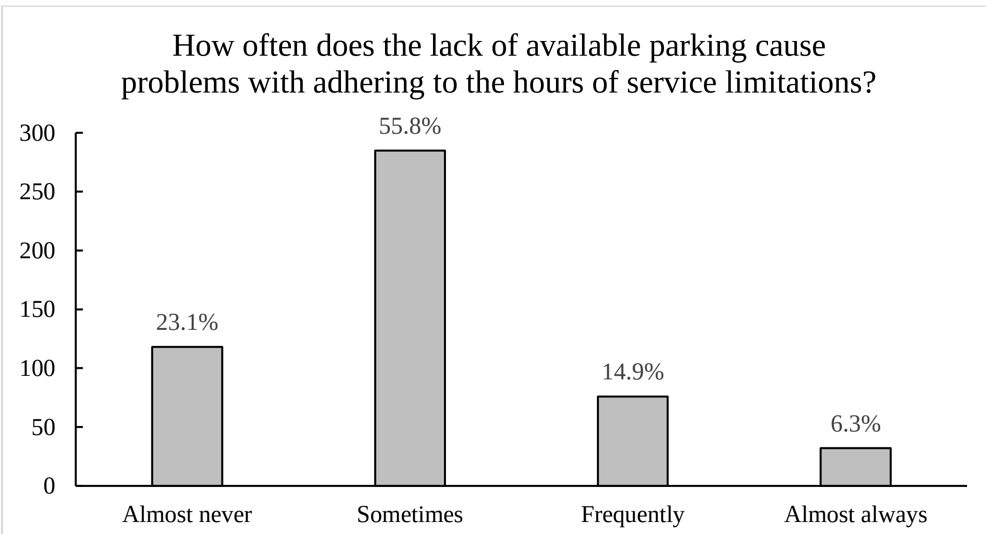

Figure 3.41 How often does the lack of available parking cause problems with adhering to the hours of service limitations?

3.1.47 Does Your Routing Software Accurately Provide You with the Location of Truck Parking onRroutes?

As shown in figure 3.42, 76 percent of drivers indicated that their routing software accurately provided them with the locations of truck parking on routes, whereas 24 percent of them did not think that their software was able to provide them with accurate locations of truck parking.

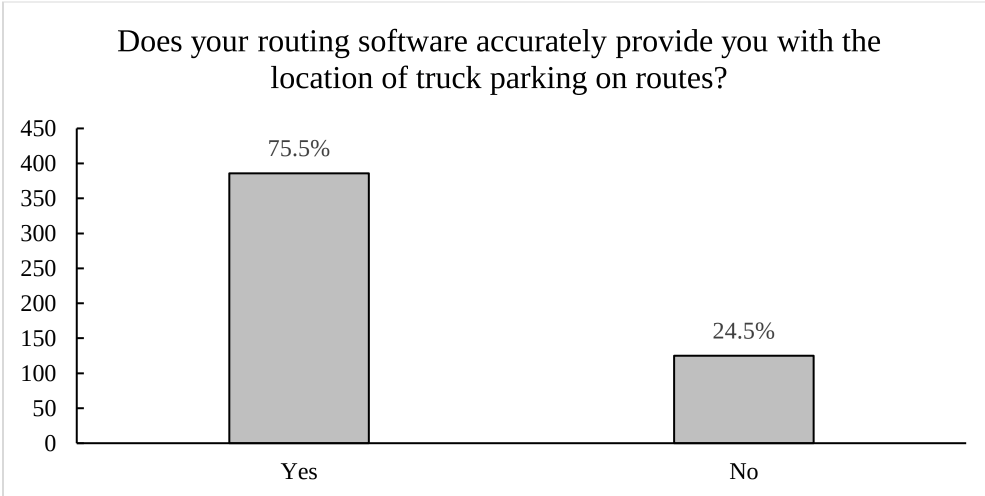

Figure 3.42 Does your routing software accurately provide you with the location of truck parking on routes?

3.1.48 Does Your Company Monitor Levels of Fatigue in Drivers?

Figure 3.43 presents answers to the question about whether the driver's company monitored levels of fatigue in drivers. The drivers' responses were distributed into three main categories: drivers who indicated that their companies monitored levels of fatigue (60.9 percent), drivers who stated that their companies did not monitor driver fatigue (38.5 percent), and a small percentage of drivers (0.6 percent) who provided other responses. For example, some drivers reported that they were told to be aware of fatigue, while others indicated that they were the owner of their trucks.

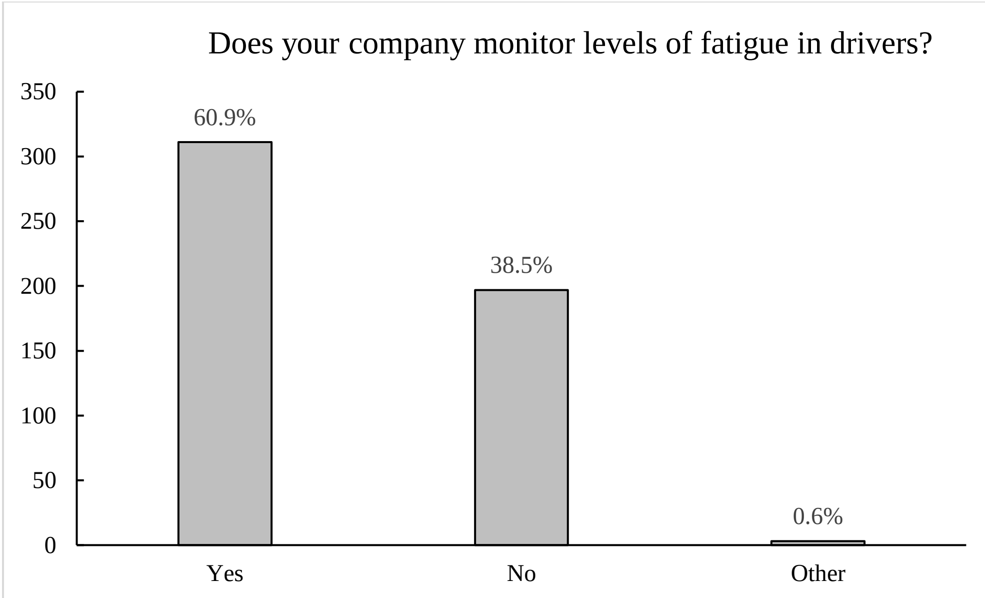

Figure 3.43 Does your company monitor levels of fatigue in drivers?

3.1.49 When Managing Drivers' Working Hours, Does Your Company Put a Restriction on Any of the Following?

The ways that companies would use for managing drivers' working hours are illustrated in figure 3.44. Putting restrictions on the number of hours worked per day (34.9 percent) and hours worked per week (31.4 percent) constituted the majority of drivers' responses. Other companies were reported to manage drivers' working hours by restricting the number of continuous days worked (23.7 percent) and/or imposing restrictions on the number of nights drivers could work in a week (10.0 percent).

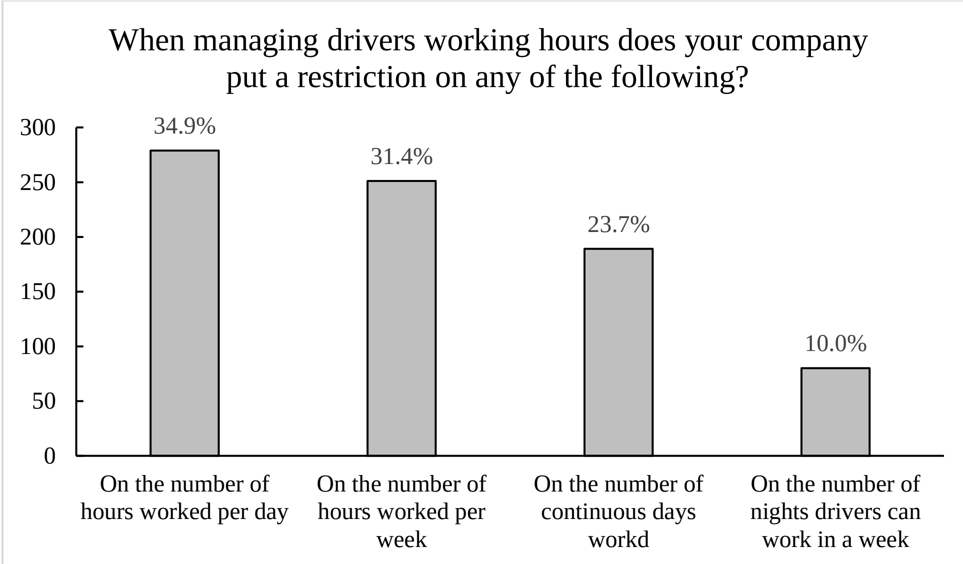

Figure 3.44 When managing drivers working hours does your company put a restriction on any of the following?

3.1.50 How Does Your Company Monitor Driver Fatigue?

Referring to figure 3.45, nearly 28.2 percent of drivers responded to this question by indicating that their companies reviewed their log book, and 21.3 percent said their companies asked drivers how they felt. Other companies had different approaches to monitor driver fatigue, such as using monitoring devices (16.7 percent), reviewing truck computer records (18.4 percent), and reviewing accidents and incidents (13.8 percent). Again, 1.7 percent of drivers either did not know or provided different answers, such as they monitored themselves or met frequently with their companies.

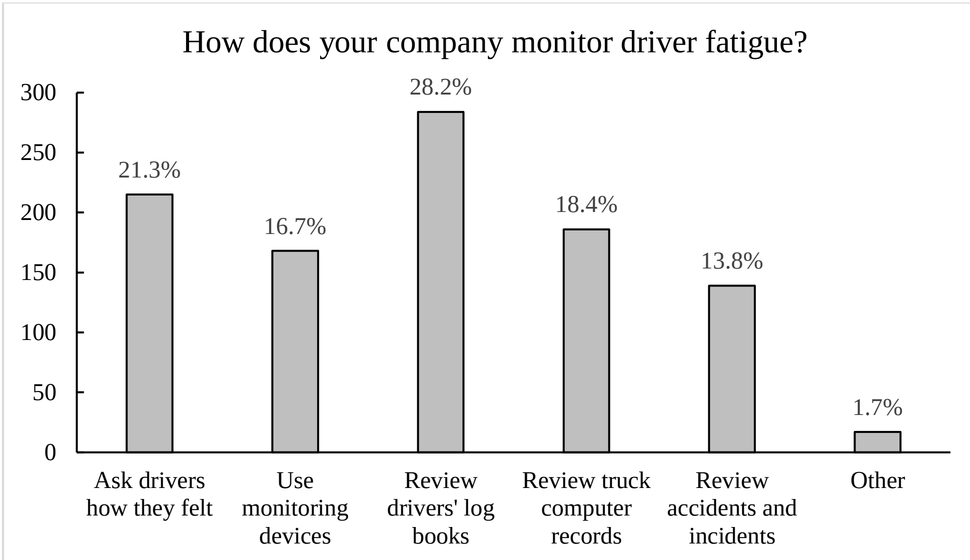

Figure 3.45 How does your company monitor driver fatigue?

3.1.51 How Is Fatigue Managed?

How fatigue is managed in companies from drivers' perspectives is presented in figure 3.46. In general, five approaches are available to drivers to choose from, and driver responses to these approaches were split into five categories: strongly agree, agree, neither, disagree, and strongly disagree. For drivers who responded strongly agree, 42.3 percent of them stated that management encouraged them to take breaks from driving whenever they needed, while 15.3 percent of them indicated that they preferred to carry on driving rather than stop to take breaks and rarely felt they needed to take breaks when driving long distances. About 23.5 percent of drivers strongly agreed that drivers should be allowed sufficient time to reach their destination, whereas 28.8 percent of drivers strongly agreed that the schedule imposed by their companies made it easy for them to take a break whenever they felt they needed to.

Regarding drivers who agreed to the available options of managing fatigue, their responses were distributed as follows: 38.4 percent thought that management encouraged them to take breaks from driving whenever they needed; 30.5 percent said they preferred to carry on driving rather than stop to take breaks; 31.0 percent said they rarely felt they needed to take breaks when driving long distances; 43.6 percent said that drivers were always allowed sufficient time to reach their destination; and 40.6 percent said the schedule imposed by their companies made it easy for them to take a break whenever they felt they needed to.

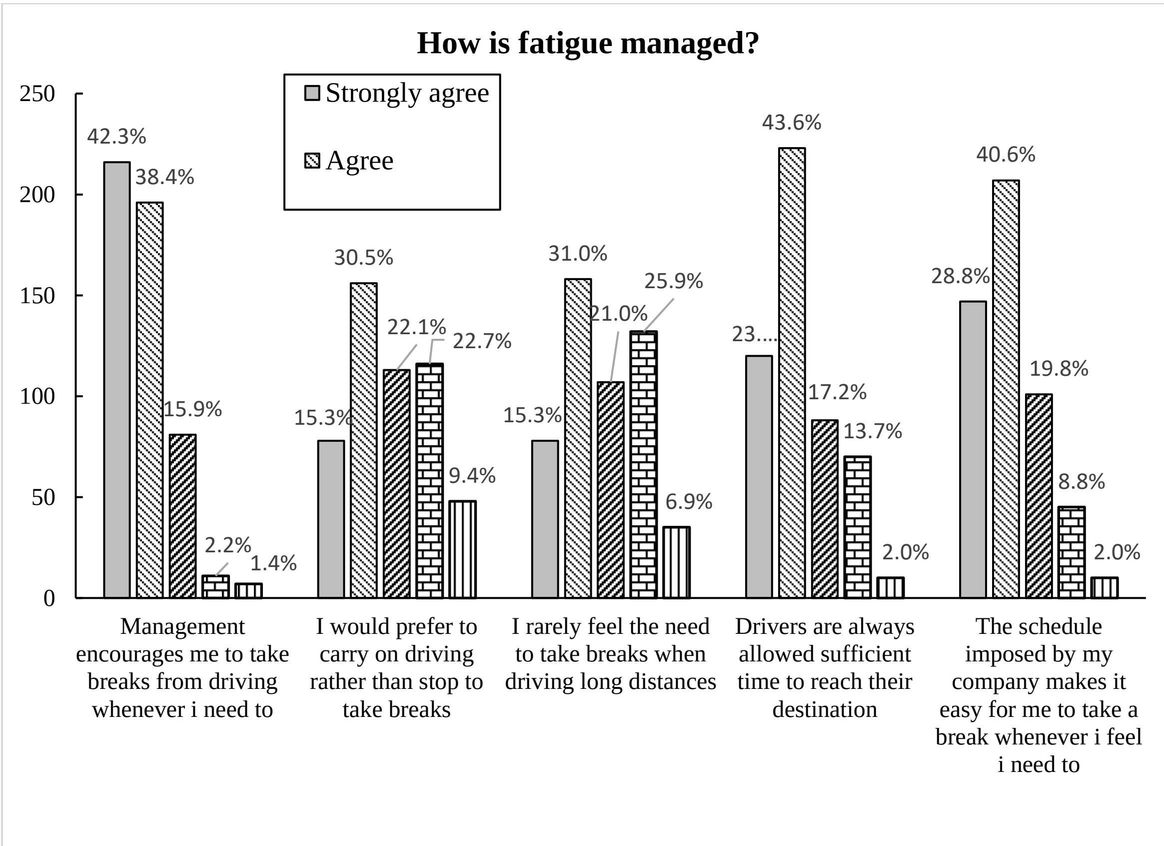

Figure 3.46 How is fatigue managed?

3.1.52 When Required to Rest, Have You Experienced Any Problems Finding a Safe and Adequate Location to Park Your Truck?

Drivers' responses to whether they had experienced any problems finding a safe and adequate location to park their trucks are shown in figure 3.47. More than half of drivers (55.4 percent) stated that they had encountered difficulty in finding safe truck parking, whereas 44.6 percent of them indicated that they had not experienced such a problem.

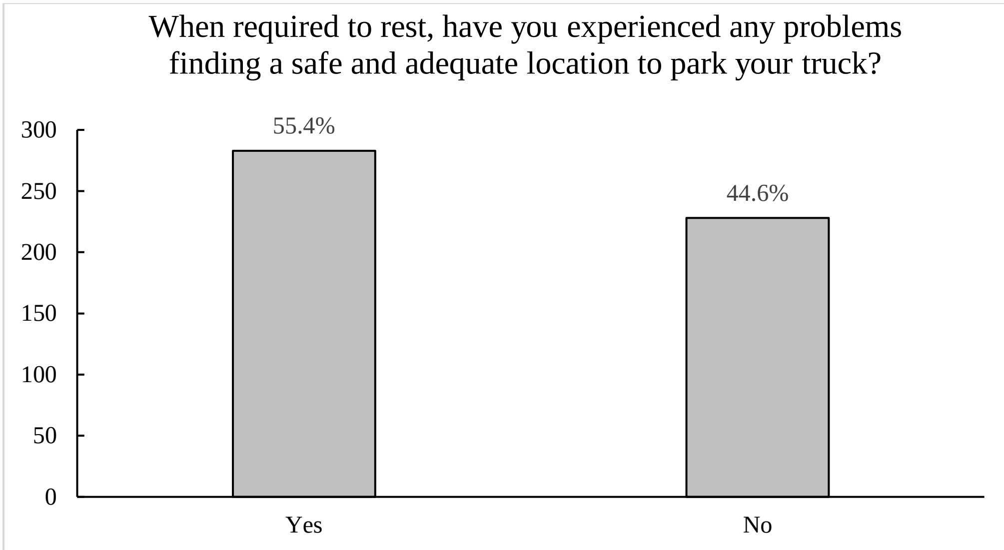

Figure 3.47 When required to rest, have you experienced any problems finding a safe and adequate location to park your truck?

3.1.53 How Well Do You Feel That Fatigue Is Managed in the Industry Now?

Drivers' opinions on how well fatigue was managed in the industry are presented in figure 3.48. Most drivers (38.4 percent) thought that it was managed quite well. Roughly, 25.0 percent of drivers surveyed thought fatigue in industry was managed quite badly, 20.2 percent said very well, and 8.4 percent said extremely badly. An additional 8.0 percent of drivers did not have an opinion.

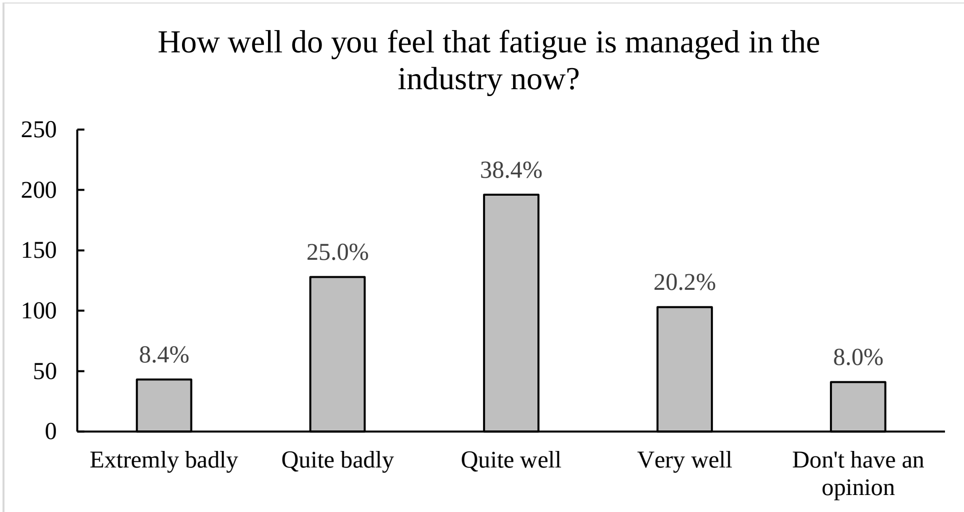

Figure 3.48 How well do you feel that fatigue is managed in the industry now?

3.1.54 How Often Do You Drive When Tired?

The drivers surveyed in this study were asked how often they drove when tired. Figure 3.49 shows the distribution of driver responses. In the figure, 38.4 percent of drivers indicated that they sometimes drove when they were tired, 30.5 percent reported that they rarely did that, 14.5 percent quite often drove when they were tired, 8.2 percent of them stated that did that very often, and 8.4 percent claimed that they never drove when they felt tired.

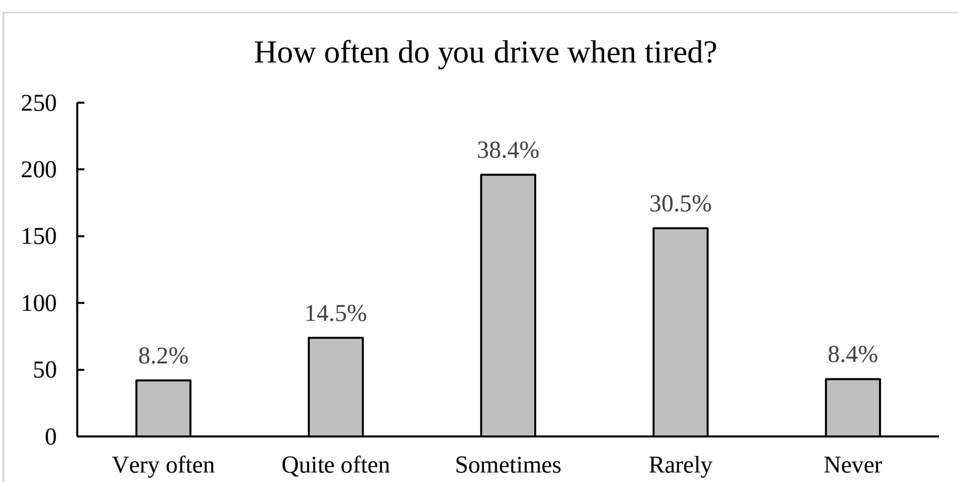

Figure 3.49 How often do you drive when tired?

3.1.55 Do You Feel You Get Enough Time to Stop to Rest When You Feel Tired?

Figure 3.50 shows the percentages of driver responses to the question about whether they got enough time to stop to rest when they felt tired. Approximately, 80 percent of drivers stated that they got enough time to stop to rest when they felt tired, whereas 20 percent said they did not get such time to rest.

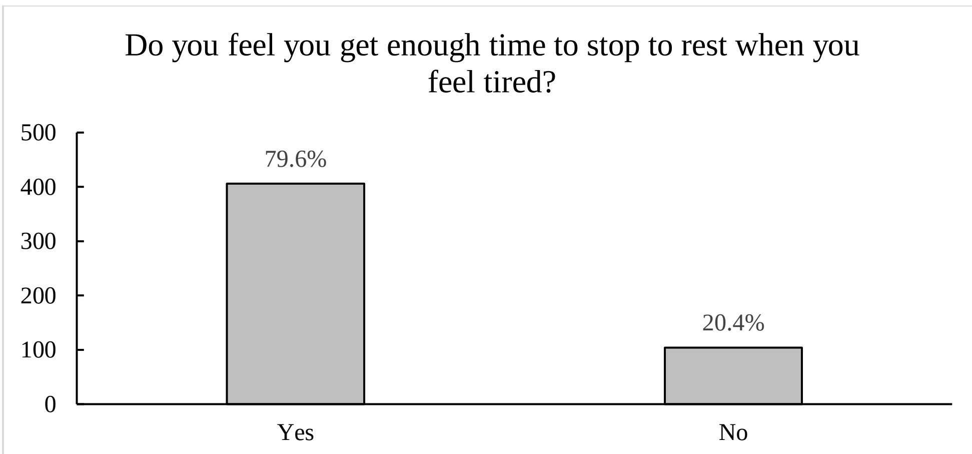

Figure 3.50 Do you feel you get enough time to stop to rest when you feel tired?

3.1.56 When You Are Making a Longer Trip, How Often Do You Stop?

To understand how drivers dealt with fatigue and tiredness, they were asked how often they stopped when making a long trip. Figure 3.51 clearly shows that 26.4 percent of drivers stopped to rest every three to four hours, 21.3 percent of them stopped every four to five hours, 19.6 percent stopped every two to three hours, and 12.5 percent stopped to rest whenever they felt tired. Stopping every five to six hours accounted for 11.7 percent, while 6.5 percent of drivers said that they stopped every six to eight hours. Interestingly, 2.0 percent of drivers claimed that they never stopped to rest at all.

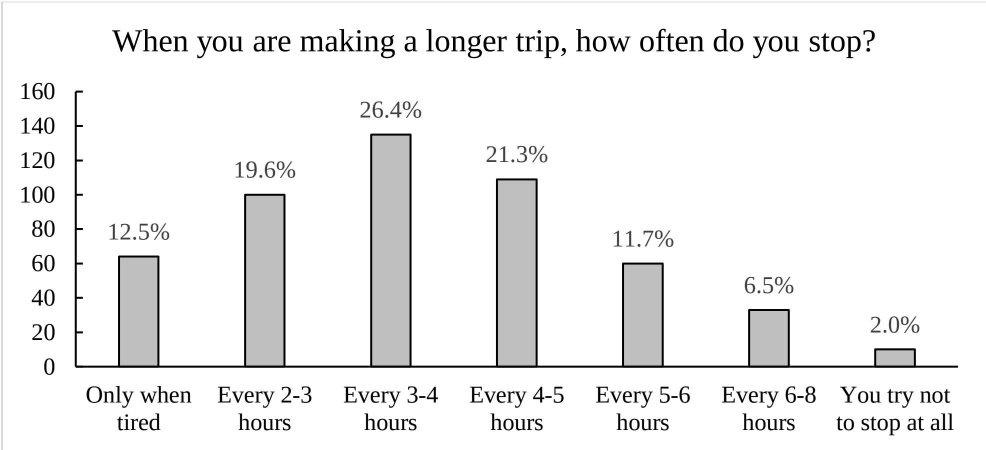

Figure 3.51 When you are making a longer trip, how often do you stop?

3.1.57 If Trucks Are Required to Have Electronic Logging Devices Installed That Have the Capability to Monitor Truck Operations and Movement, Will That Impact Your Driving/Operations Decisions?

Figure 3.52 shows the drivers' responses to a question about the effects of installing electronic devices that could monitor truck operations and movement on drivers' driving/operations decisions. Drivers' responses were split into three choices: drivers who indicated that would affect their driving/operations decisions (37.8 percent), drivers who were not sure whether that would influence their driving/operations decisions or not (38.0 percent), and drivers who did not think installing such devices would impact their driving/operations decisions (24.3 percent).

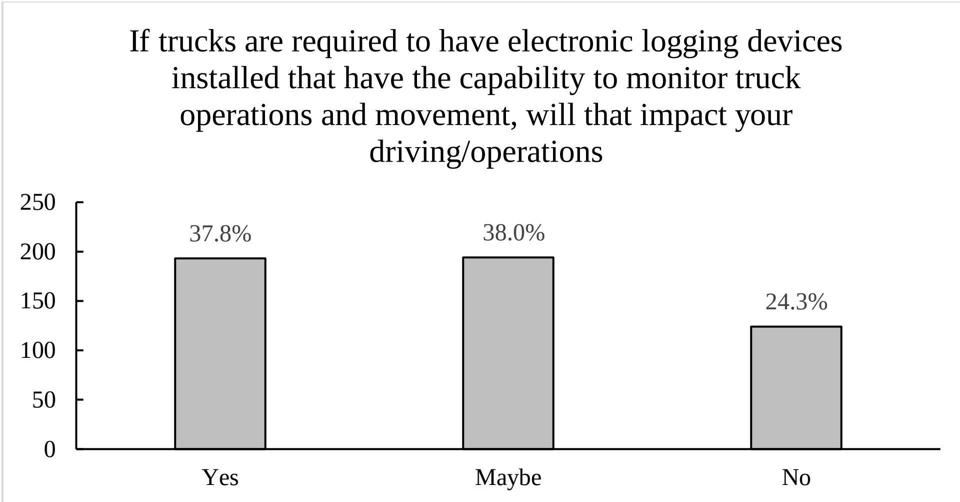

Figure 3.52 If trucks are required to have electronic logging devices installed that have the capability to monitor truck operations and movement, will that impact your driving/operations decisions?

3.1.58 If Trucks Are Required to Have Electronic Logging Devices Installed, Would the Amount of Time You Spend Driving Change?

Drivers had different opinions about the effects of installing electronic logging devices on the amount of time they would spend driving, as shown in figure 3.53. The majority of drivers (45.8 percent) did not think these devices would change their driving times. However, 28.2 percent of drivers stated that installing electronic logging devices would lead to a small decrease in the amount of time they spent driving, and 10 percent said it would lead to a large decrease. In addition, other drivers said such devices would exacerbate driving times, which in turn would result in a small increase in their driving times (10.8 percent) and a large increase (5.2 percent).

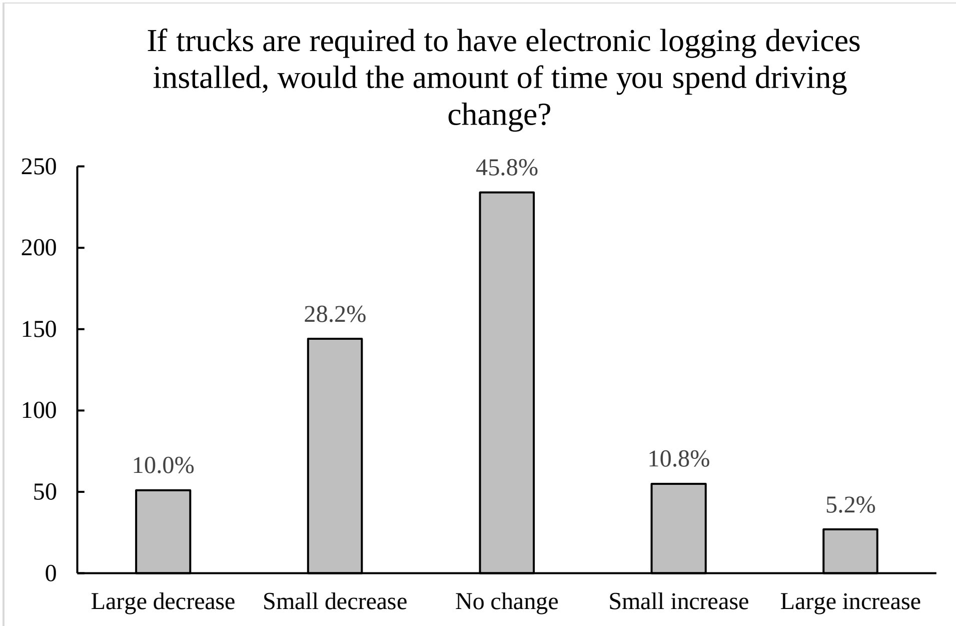

Figure 3.53 If trucks are required to have electronic logging devices installed, would the amount of time you spend driving change?

3.1.59 How Often Do You Drive a Tractor with Two Trailers?

Figure 3.54 shows the drivers' answers to the question about how often they drove a tractor with two trailers. Nearly 28.2 percent of drivers indicated that they almost never did that. About 27.2 percent stated that they sometimes drove a tractor with two trailers, and 21.1 percent of them rarely drove such trucks. Other drivers said that they drove a tractor with two trailers very often (10.2 percent) and quite often (13.3 percent).

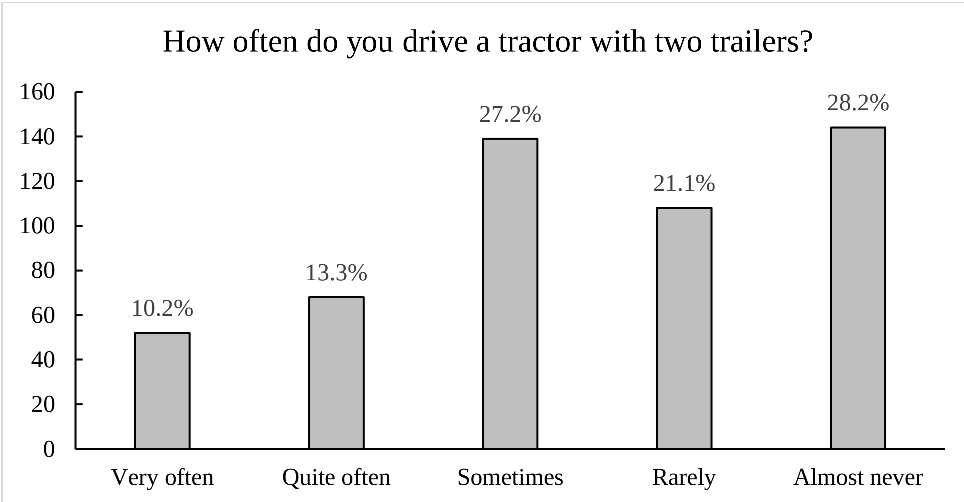

Figure 3.54 How often do you drive a tractor with two trailers?

3.1.60 Is Driving and Operating a Tractor with Two Trailers More Challenging Than a Tractor with One Trailer?

As shown in figure 3.55, roughly 68 percent of surveyed drivers said that driving and operating a tractor with two trailers was more challenging than a tractor with one trailer, while 20 percent did not have problems with driving and operating a tractor with two trailers. The rest of the drivers (12 percent) responded that driving such trucks might be associated with more challenges than driving and operating a one trailer.

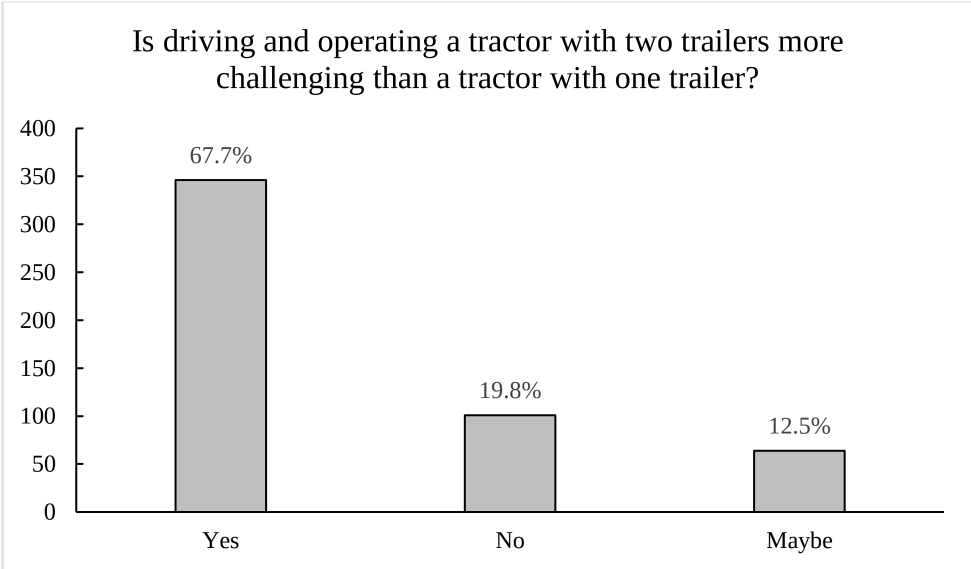

Figure 3.55 Is driving and operating a tractor with two trailers more challenging than a tractor with one trailer?

3.1.61 Would Driving a Tractor with Two 33-ft. Trailers Be More Challenging or Dangerous Than a Tractor with Two 28-ft. Trailers?

In terms of the potential safety hazards and challenges associated with driving a tractor with two 33-ft. trailers as opposed to a tractor with two 28-ft. trailers, 60.3 percent of drivers said they felt that driving a tractor with two 33-ft. trailers was more challenging, as presented in figure 3.56. Another 25.8 percent of drivers stated that there was not much difference in driving the two trucks, and 13.9 percent of drivers did not have any idea or they did not know.

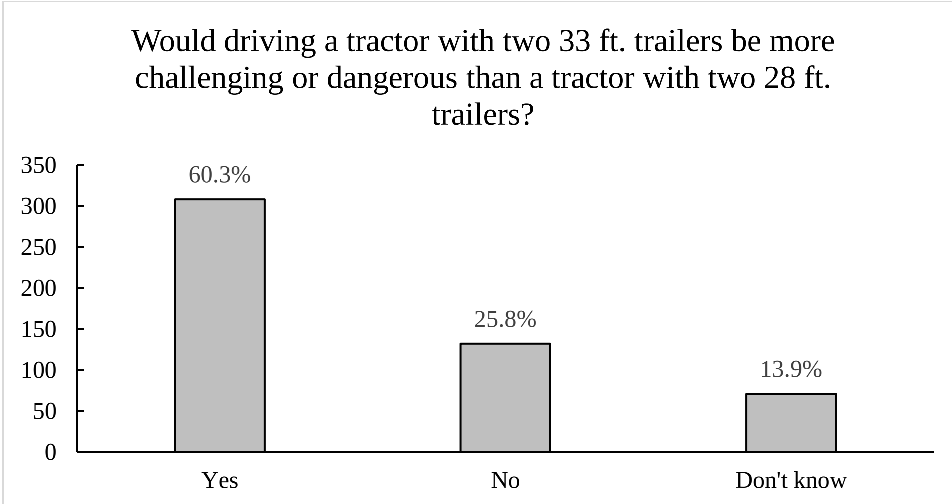

Figure 3.56 Would driving a tractor with two 33-ft. trailers be more challenging or dangerous than a tractor with two 28-ft. trailers?

3.2 Summary of the Survey Results

A representative stated-preference survey was designed and distributed to truck drivers who were destined for or who originated from the Pacific Northwest—namely, Washington state, Oregon, and Idaho. The stated-preference survey was administered through the Qualtrics platform of Oregon State University, and it was conducted over 16 consecutive days between August 17, 2017, and September 1, 2017. To eliminate the possibility of multiple entries from the same participant, IP addresses and user IDs were collected. The representative sample consisted of 515 participants (from a total of 1,919—a 26.8 percent response rate), all truck drivers. The survey was conducted to help us better understand the confounding factors of large trucks in SCEs. Drivers of large trucks in the Pacific Northwest were asked several questions to provide their opinions about factors that could help researchers in identifying the most important factors that influence drivers' choices related to SCEs and to help capture the confounding factors, as well.

In this study, participants were required to be truck drivers, to hold a commercial driver's license, to be at least 18 years old, and to be destined for or to originate from the Pacific Northwest. The survey was composed of several sections: (1) socioeconomic characteristics, (2) business characteristics, (3) driving characteristics, (4) accident characteristics, (5) time-of-day operations, (6) driving management (fatigue and hours of service), and (7) truck configuration characteristics. For socioeconomic characteristics, participants were asked to provide demographic information such as age, gender, income, marital status, education, payment method, driving experience, type of shipment carried, road safety training (whether they had received such training), and participation in team driving.

The second section, business characteristics, asked questions related to industry type, company operational characteristics, and average distances traveled. The driving characteristics section asked participants questions about their ability and confidence regarding driving a semi-truck, average speeds in various situations, roadway facility types, cell phone use while driving, frequency of lapses in concentration after driving for long periods, frequency of lane changing to avoid traveling with other vehicles, and situations that posed the greatest safety hazards to drivers. For the accident characteristics, drivers were asked about their involvement in accidents, the number of accidents over a 5-year period, the types of accidents, and the weather conditions at the time of the accident.

With regard to time-of-day operations, drivers were asked about the time of day they started working and driving, the safest time of day to drive trucks, and the most difficult time of- ay, day of the week, and month to find safe and adequate truck parking. Questions were asked about fatigue management, including the effects of fatigue on adhering to hours-of-service requirements. Lastly, questions were asked about truck configurations.

Male drivers constituted 77 percent of the participants, whereas 23 percent were female. Roughly, 60 percent of drivers were between 20 and 39 years. As for the type of shipment, nearly 82 percent of drivers' trips were truckload shipments. In terms of number of years the surveyed drivers had been driving large trucks, two-third (66 percent) of drivers had been driving a truck for 10 years or less. 43 percent of drivers revealed that they learned how to driver a semi-truck in a driving school. Further, a majority of drivers (87 percent) seemed to have a particular road safety training. In regard to team driving, the majority of drivers sometimes (31 percent), rarely (29 percent), and never (23 percent) participated in team driving. the drivers' history of accidents was been examined by asking them to reveal how many accidents they had been involved with in the last five years. Roughly, 76 percent of drivers reported that they had not had any accidents. Regarding actions that might distract drivers and alter their attention away from driving, 45 percent of drivers stated that they used a cell phone while driving.

4.0 Analytical Framework

This chapter discusses how some questions from the survey were used to estimate models to help us highlight the factors that impact drivers' behavior. These were use of cell phones while driving and the lane changing maneuvers of truck drivers, as well as their underlying factors. Each one of these is discussed in detail in the following sections.

4.1 Understanding Truck Driver Behavior with Respect to Cell Phone Use and Vehicle Operation

4.1.1 Background

As technology continues to penetrate and transform all aspects of society, there has been an increasing interest in understanding the effects of distracted driving, particularly due to cell phone use, on transportation safety (Haigney et al., 2000; Klauer et al., 2006; Farmer et al., 2010; Stavrinos et al., 2013; Oviedo-Trespalacios et al., 2017b). This interest stems from an increase in distracted driving related crashes. Fatalities involving cell phone use throughout the United States increased from 385 in 2011 to 476 in 2015, or 23.6 percent (National Center for Statistics and Analysis, 2017a). These values are grossly underreported because of a lack of methods and/or procedures to assess the culpability of cell phone use while driving. Furthermore, traffic fatalities that were attributed to distracted driving had a larger percentage increase (8.8 percent) from 2014 than alcohol-impaired or speed-related fatalities (National Center for Statistics and Analysis, 2017a). Of special interest are fatalities involving large truck crashes (vehicles weighting more than 10,000 pounds), which have continued to increase since 2009. In 2015, 4,067 were killed in crashes involving large trucks in comparison to 3,380 in 2009, a 20 percent increase (National Center for Statistics and Analysis, 2017b).

Regarding economic impacts, distracted driving related crashes are quite significant. In 2010, distracted driving fatalities accounted for roughly $40 billion in economic costs and $123 billion in societal costs, which equate to 16 and 15 percent, respectively, of the total economic impacts and societal harm caused by motor vehicle crashes in 2010 (Blincoe et al., 2015). With regard to large trucks, Zaloshnja & Miller (2007) estimated the average cost (in 2005 USD) of property damage only (PDO), non-fatal, and fatal crashes involving large trucks to be approximately $15,114, $195,258, and $3,604,518, respectively. In 2017 dollars, these values equate to about $19,500, $252,500, and $4,700,000, respectively (Bureau of Labor Statistics, 2017). These statistical and economic findings indicate a need for distracted driving research especially for cases in which cell phone use while driving could be a leading factor, particularly for crashes involving large trucks.

Although there have been several efforts to understand large truck-involved crashes (Pahukula et al., 2015; Al-Bdairi and Hernandez, 2017; Anderson and Hernandez, 2017; Al-Bdairi et al., 2018), the relationship among cell phone use, distracted driving, and large truck-involved crashes is not completely understood. This may be attributed to the fact that in most distracted driving studies, data are derived from either naturalistic or simulator studies, which are both time and cost intensive, or crash data, which are retroactive in nature and typically result in significant amounts of unknown or missing information (Regan et al., 2008). Furthermore, the majority of the efforts to understand distracted driving have only been applied to passenger vehicles (Klauer et al., 2006; Dingus et al., 2016). Few studies have examined the prevalence and associated crash risk of distracted driving among commercial motor vehicles by combining and assessing naturalistic observation data sets on large truck drivers (Olson et al., 2009; Hickman and Hanowski, 2012). While studies conducted by Hickman and Hanowski (2012) and Olson et al. (2009) provided insight into the frequency and crash risk of distracted driving among commercial motor vehicle drivers, they did not assess the contributing factors that influence truck drivers' decisions to use a cell phone, or participate in a secondary task, while driving.

Therefore, the main objective of this study was to seek and gain a better understanding of the factors that influence truck drivers' decisions to use electronic mobile devices while driving. To accomplish this, a stated-preference survey distributed in 2017 to drivers of large trucks who originated, were destined to, or passed through the Pacific Northwest (Washington, Oregon, Idaho) was utilized. A random parameters binary logit modeling framework is then used and estimated to gain insights into the complex interactions among the factors captured through the survey and those unobserved factors (i.e., unobserved heterogeneity) that might be influencing cell phone use while driving. In doing so, this study sought to provide additional insight into the prevalence of cell phone use by drivers of large trucks to aid government agencies and private carriers in identifying and/or developing potential countermeasures that can then be used to mitigate electronic device use while driving.

Previous research on distracted driving has concluded that a consistent definition of the term has yet to be achieved. Still, multiple authors have determined that distracted driving is a result of attention being diverted away from the driving task to a competing activity that is not related to safe driving (Ranney et al., 2000; Young and Regan, 2007; Lee et al., 2008; Regan et al., 2011). Regan et al. (2011) developed a taxonomy of driver distraction that included five sub-categories: restrictive, mis-prioritized, neglected, cursory, and diverted attention. These sub-categories considered driver inattention due to both driving and non-driving related activities, such as using a cell phone while driving, being consumed in internal thoughts, or reading a road information sign. Since driver distraction is a vast problem resulting from diverted attention, cell phone use while driving is a subset of a larger distraction problem; however, understanding its effects and the factors that lead individuals, or drivers of large trucks, to use cell phones while driving will significantly improve roadway safety.

While research on distracted driving by drivers of large trucks is scarce, the effects of cell phone use on driving have been widely studied in the context of passenger cars (Haigney et al., 2000; Dingus et al., 2006, 2016; McEvoy and Stevenson, 2007; Caird et al., 2008; Regan et al., 2008; Beanland et al., 2013). In two naturalistic studies, cell phone use was present in about 23 percent of all crashes and near-crashes, and at least one form of driver inattention in as much as 78 percent of all safety critical events for passenger vehicles (Klauer et al., 2006; Regan et al., 2008). Although there is an association between crash occurrence and cell phone use, some studies have shown that talking or listening on a cell phone, either handheld or hands free, does not significantly increase the odds of being involved in a safety critical event (Klauer et al., 2006; Hickman and Hanowski, 2012). Still, subtasks of cell phone use, such as texting, emailing, or operating the phone, increased crash risk odds by at least 3.5 times and as high as 164 times (Klauer et al., 2006; Hickman and Hanowski, 2012). The increased association with cell phone use and safety critical events may be due to increased cognitive load caused by cell phone use while driving. These studies have proved that driver distraction, particularly cell phone use, is a common occurrence on roadways and increases the chances of being involved in a safety critical event.

Turning to large trucks, naturalistic study data on drivers of large trucks have produced findings consistent with the results from passenger car studies in that 60 percent of all crashes and near-crashes in which the driver of the large truck was at-fault involved one secondary task (Olson et al., 2009). Data from the Large Truck Crash and Causation Study (LTCCS), which used police reports and interview information, were consistent with this finding, and it reported that 35 percent of truck-involved crashes involved some form of driver recognition error (this includes internal and external distractions) (Federal Motor Carrier Safety Administration, 2005). Specifically, 12 percent of crashes in which a large truck was assigned the critical reason for the crash were due to either internal or external distraction, or inattention (Federal Motor Carrier Safety Administration, 2005). As mentioned previously, talking or listening on a cell phone, either handheld or hands free, does not significantly increase the likelihood of being involved in a safety critical event. However, among drivers of large trucks, complex cell phone tasks, such as texting or emailing, increased the odds of being involved in a crash or near-crash by 164 times. Furthermore, engaging in either a complex tertiary task (interacting with a dispatch device, dialing a cell phone) or moderate tertiary task (use of another electronic device, talking/listening to a CB radio) increases the chances of being involved in a safety critical event by 10.34 and 1.30 times, respectively (Olson et al., 2009). The significant increase in crash risk for drivers of large trucks prompts the need for research to understand and reduce the effects of cell phone use on truck-involved crashes. Combined with the understanding that large truck-involved crashes are more severe than passenger car only crashes, and that truck drivers need to engage more frequently with electronic devices to perform their jobs, research in this area is needed to improve roadway safety.

Previous findings on distracted driving, for both passenger cars and truck drivers, are vital contributions to engineering safety, but they are limited. Data that derive from police crash reports are subject to bias and significant amounts of unknown or missing information (Gordon, 2009). While naturalistic data describe drivers in real-time driving conditions, they are often time, cost, and data intensive. Additionally, the statistical measures that have been used in these studies have been limited and have not accounted for any unobserved heterogeneity in the data collection process or contributing factors to critical safety events. The results from these studies have utilized simple statistical measures to determine either the odds ratios of being involved in safety critical events or prevalence and frequency of driver distraction in vehicle crashes (Hanowski et al., 2005; Dingus et al., 2006; Olson et al., 2009; Asbridge et al., 2012).

To overcome these shortcomings, a few studies have ventured away from traditional distracted driving study methods to assess the personal and behavioral information that influences cell phone use while driving (Márquez et al., 2015; Kidd et al., 2016; Oviedo-Trespalacios, et al., 2017b). Marquez et al. (2015) and Oveido-Trespalacios et al. (2017b) collected survey data regarding cell phone use while driving and used an integrated choice latent variable model, a mixed logit model, and a binary logit model to identify parameters influencing cell phone use while driving. Factors found in these studies, from the perspective of passenger car drivers' decisions to use a cell phone while driving, included age, driving experience, risk perception, and urgency of call (Márquez et al., 2015; Oviedo-Trespalacios, et al., 2017b). Additionally, Kidd et al. (2016) conducted roadside observations of motorists at different roadway characteristics, such as free-flow traffic, time-of-day, and at controlled intersections. The results of this study identified roadway and driver characteristics that affect the prevalence of any secondary behavior (Kidd et al., 2016). These studies were instrumental for improving roadway safety, as they helped identify the contributing factors influencing cell phone use while driving, and agencies can use this information to mitigate the occurrence of distracted driving by tailoring outreach initiatives to specific groups. However, despite providing useful information, these studies were limited to passenger car drivers and statistical models that did not account for unobserved heterogeneity.

One study did investigate the demographic and occupational characteristics of heavy-vehicle drivers that influence the likelihood of using a cell phone while driving. Troglauer et al. (2006) collected survey data from 1,153 professional truck drivers in Denmark to determine the extent of phone use among heavy-vehicle drivers through an ordinal logistic regression model.

Through this methodology, the study determined the odds of different demographic and occupational characteristics leading to a higher prevalence of phone use among heavy-vehicle drivers. Additionally, this study reported that 99 percent of the respondents indicated that they used their cell phone while driving (Troglauer et al., 2006). Coupled with the fact that large truck-involved crashes are more severe than passenger car only crashes, this finding is disturbing, since cell phone use while driving has been proved to significantly increase crash risk (Chang and Mannering, 1999; Klauer et al., 2006). Although this study identified certain driver characteristics that made use of a cell phone while operating a heavy-vehicle more likely, the statistical procedure used did not account for the unobserved heterogeneity that is inherent in any survey data, which in turn resulted in erroneous estimates and corresponding inferences (Mannering et al., 2016).

The present study expanded upon the work conducted by Oveideo-Trespalacios et al. (2017b), Marquez et al. (2015), and Toglauer et al. (2006) by collecting survey data distributed to drivers of large trucks who originated, were destined to, or passed through the Pacific Northwest (Washington, Oregon, Idaho). By using a random parameters binary logit model to identify the factors that influence the likelihood that truck drivers' would report using a cell phone while driving, the present study was intended to overcome the limitations of previous studies by accounting for unobserved heterogeneity (unobserved factors) present in the data collection process. By understanding the factors that lead to truck drivers using a cell phone while driving, commercial motor carriers and government entities can implement mitigation strategies tailored to specific groups that may reduce the occurrence of cell phone use while driving among large truck drivers. To the authors' knowledge, this study was one of the first to use a random parameters methodology to determine the contributing factors that influence cell phone use among drivers of large trucks.

4.1.2 Analysis Process

Of specific interest to this study was the following question: Do you use a cell phone while driving (either handheld or hands-free)? This question presented a binary choice to respondents, as they were required to respond with either yes or no. Figure 4.1 shows the frequency of respondents that responded yes or no to using a cell phone while driving. This finding is consistent with past studies that determined that about 50 percent of surveyed respondents used a cell phone while driving (Nurullah et al., 2013; Schroeder et al., 2013).

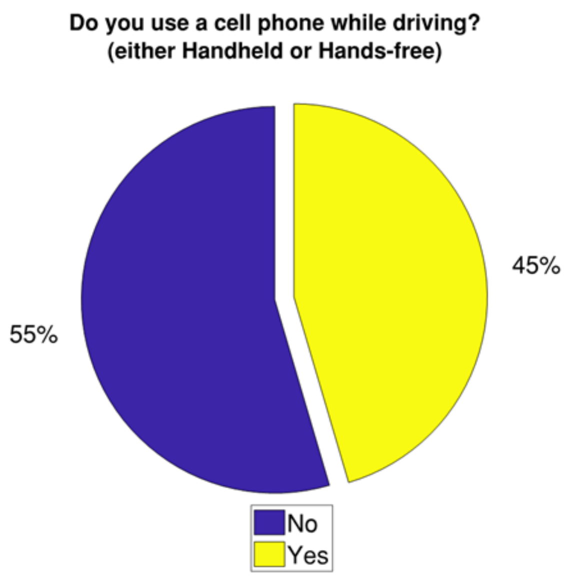

Figure 4.1 Percentage of respondents who indicated using a cell phone while driving

To corroborate the increased crash risk associated with cell phone use while driving, self-reported crash history was disaggregated on the basis of cell-phone use. In the survey, respondents were asked, "During the last 5 years how many accidents have you had which the police had to attend?" Respondents had to respond either one, two, three, four or more, or none. The initial survey analysis, as shown in figure 4.2, revealed that 24 percent of respondents indicated that they were involved in at least one crash in the past five years that the police had to attend. Of these respondents who indicated being involved in at least one crash in the past 5 years, 57 percent also reported that they used their cell phone while driving, as shown in figure 4.3. A t-test was conducted between these two groups and determined a statistically significant difference at the 99th percentile. Because the question was posed to the general use of cell phones while driving, this initial data comparison complements the findings of Olson et al. (2009) and Klauer et al. (2006) that using a cell phone while driving leads to higher crash involvement.

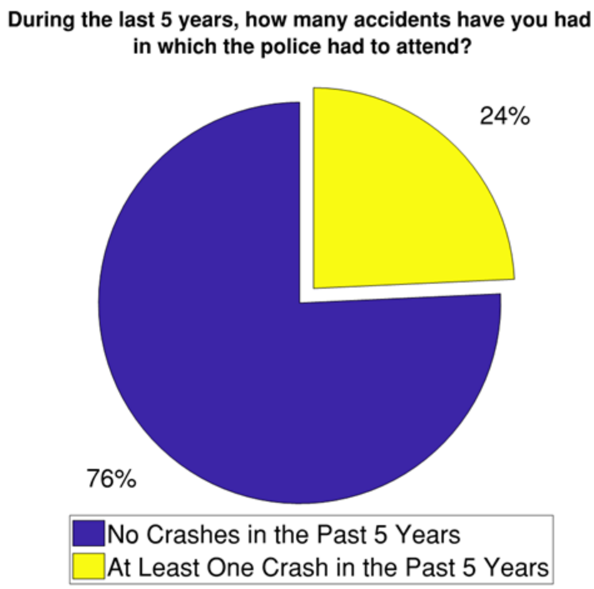

Figure 4.2 Self-reported crash history

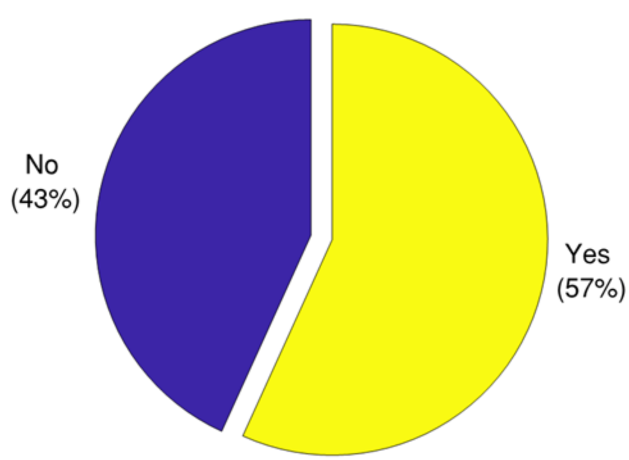

Figure 4.3 Respondents who indicated using their cell phone while driving and being involved in at least one crash in the past 5 years

4.1.3 Methodology

As mentioned previously, the binary logit modelling framework has been applied in various areas of transportation engineering (Young and Liesman, 2007; Lee and Abdel-Aty, 2008; Moudon et al., 2011; Oviedo-Trespalacios, et al., 2017b), in which Anderson et al. (2018) have recently and successfully applied this framework to truck driver survey data. Further, studies have expanded on the traditional logit modelling framework by utilizing a random parameters, or mixed logit, methodology to account for unobserved heterogeneity in the data (Milton et al., 2008; Morgan and Mannering, 2011; Islam et al., 2014; Pahukula et al., 2015; Anderson and Hernandez, 2017). In this study, the use of a cell phone while driving was a binary choice; either the driver used a cell phone while driving or the driver did not. Finally, because the survey data had inherent unobserved heterogeneity, a random parameters binary choice modelling framework was an appropriate technique for assessing drivers' decisions on using a cell phone while driving.

Because of the binary nature of the selected response variable, a binary logistic regression model was applied. The two possible outcomes for the response variable are represented by the following: 1 if a driver reported using a cell phone while driving, and 0 otherwise (driver did not report using a cell phone while driving). Equation 4.1 is used to estimate the probability that the outcome takes the value of 1 (using cell phone while driving) as a function of covariates (McFadden, 1973; Washington et al., 2011):

$$P_n(i) = \frac{e^{(\hat{\beta})}}{1+e^{(\hat{\beta})}} \quad \text{where} \quad \hat{\beta} = \beta_0 + \beta_1 X_{1,n} + \cdots + \beta_i X_{i,n} \tag{4.1}$$

where $P_n(i)$ is the probability that a truck driver uses a cell phone while driving (i.e., the outcome takes on the value 1); $\widehat{\beta}$ is a vector of estimated parameters; and X is a vector of explanatory variables (i.e., indicator variables coded from the survey data).

One shortfall of survey data is that responses can potentially have unobserved heterogeneity, or variation, across drivers. Within our data, there existed a significant amount of information that affects the likelihood of using a cell phone while driving that was not capable of being measured for analysis. Type of driver behavior (i.e., aggressive vs. passive), forgetfulness, and reporting false information (i.e., indicating no cell phone use while driving to comply with laws and policies) were possible unobserved factors that could affect model results for cell phone use while driving. However, these unobserved factors were not captured in the data through the survey responses. This inherent limitation of survey data will result in erroneous model estimates and, therefore, inferences if this unobserved heterogeneity is not accounted for in the model (Mannering et al., 2016). To account for potential heterogeneity within the data, a random parameters methodology was applied to allow estimated parameters to vary across observations, as illustrated in equation 4.2.

$$P_n(i|\varphi) = \int_X \frac{e^{(\hat{\beta})}}{1+e^{(\hat{\beta})}} f(\hat{\beta}|\varphi) d\hat{\beta} \tag{4.2}$$

where $P_n(i|\varphi)$ is the weighted average of $P_n(i)$ taking on the value of 1 determined by the density function, $f(\hat{\beta}|\varphi)$. The density function, $f(\hat{\beta}|\varphi)$, is a given distribution determined by the analyst (i.e., normal, uniform, triangular, etc.) that enables β to account for driver-specific variations of the effects of X on outcome probabilities, $P_n(i|\varphi)$ (Washington et al., 2011). Although the density function $f(\hat{\beta}|\varphi)$ can utilize different distributions, only the normal distribution is found to be statistically significant (based on significance of the standard deviations) and used in the current study. To simulate maximum likelihood estimation of the random parameters binary logit model, 200 Halton draws were used, as they have been proved to be computationally efficient and preferred over purely random draws (Halton, 1960; Train, 2000; Bhat, 2003).

Lastly, marginal effects were used to measure variable impact on the use of a cell phone while driving. Marginal effects measure the change in outcome probability due to a one-unit increase in an explanatory variable while holding all variables constant (equal to their means). This provides the analyst with an absolute change in probability on the outcome due to an explanatory variable. In this study, only indicator variables were found to be significant. Therefore, marginal effects were computed as the difference in probability as indicator variable X_k changes from zero to one while all other variables remain equal to their means (Greene, 2012):

$$ME_{X_k}^{P_n(i)} = \text{Prob}[P_n(i) = 1 \mid X_k = 1] - \text{Prob}[P_n(i) = 1 \mid X_k = 0] \quad (4.3)$$

4.1.4 Estimation Results

To estimate the random parameter binary logit model, only variables that were significant at the 95 confidence level were retained. Computed log-likelihood and Akaike information criteria (AIC) values were used to assess model improvement. With these criteria, the final model included 16 fixed parameters (i.e., the variables were homogeneous across drivers) and seven random parameters (i.e., the variables were heterogeneous across drivers). The results of this final model are shown in table 4.1, which include model specifications and corresponding marginal effects. The results of the likelihood ratio test determined that the random parameters binary logit model was statistically superior over its fixed parameters counterpart with over 90 percent confidence. The log-likelihood at convergence of the fixed and random parameters binary logit models were -304.53 and -298.47, respectively. The resulting chi-square statistic was 12.12, with seven degrees of freedom, which was equal to the number of random parameters. The associated p-value for this statistic was 0.0967, which suggests that, with over 90 percent confidence, the null hypothesis could be rejected and the random parameters model was statistically preferred over the fixed parameters model. Furthermore, this result indicated that there was indeed variation across drivers regarding specific characteristics that impact a driver reporting use of a cell phone (or not).

Table 4.1 Random parameters binary logit model for predicting cell phone use among truck drivers

Variable	Coefficient	*t*-statistic	Marginal Effect	t-statistic
Constant	-4.18	-5.34		
Driver Characteristics				
Age (1 if between 18 and 25, 0 otherwise)	-1.84	-3.60	-0.357	-2.67
(Standard Deviation of Parameter, Normally Distributed)	*(1.41)*	*(2.41)*		
Marital Status (1 if single, 0 otherwise)	-3.79	-5.98	-0.735	-3.44
(Standard Deviation of Parameter, Normally Distributed)	(10.86)	(7.20)		
Income (1 if between $50,000 and $60,000, 0 otherwise)	0.69	1.97	0.133	1.77
(Standard Deviation of Parameter, Normally Distributed)	*(5.83)*	*(7.12)*		

Variable	Coefficient	*t*-statistic	Marginal Effect	t-statistic
Education (1 if completed trade school or technical certificate, 0 otherwise)	-0.68	-1.98	-0.133	-1.75
Crash History (1 if involved in at least one crashes in past 5 years, 0 otherwise)	1.10	3.15	0.212	-2.51
Safety Training (1 if participated in road safety training, 0 otherwise)	2.08	4.38	0.403	2.35
(Standard Deviation of Parameter, Normally Distributed)	*(0.94)*	*(4.16)*		
Work Characteristics				
Private Carriage (1 if present employer is operated under private carriage, 0 otherwise)	-0.69	-2.32	-0.134	-2.08
Start Work (1 if work starts between 10am and 4pm, 0 otherwise)	2.29	4.18	0.444	2.86
Start Drive (1 if drive starts between midnight and 6am, 0 otherwise)	0.74	2.18	0.144	1.96
(Standard Deviation of Parameter, Normally Distributed)	*(2.76)*	*(5.31)*		
Rural Roads (1 if routes are usually driven on rural roads, 0 otherwise)	3.99	4.94	0.773	3.17
City Roads (1 if routes are usually driven on city roads, 0 otherwise)	1.91	2.62	0.369	2.21
Truck Parking (1 if driver decides parking location, 0 otherwise)	2.06	4.93	0.398	3.10
(Standard Deviation of Parameter, Normally Distributed)	*(2.83)*	*(7.54)*		
Trailer (1 if truck is driven very often with two trailers, 0 otherwise)	2.45	4.38	0.475	2.97
Temporal Characteristics				
Most Difficult Day of the Week Finding Safe Parking (1 if Tuesday, 0 otherwise)	1.48	4.16	0.287	2.83
Most Difficult Hour Finding Safe Truck Parking (1 if afternoon, 0 otherwise)	1.52	3.27	0.294	2.59
Driving Behavior				
Driving while tired (1 if often, 0 otherwise)	1.41	4.50	0.274	2.96
Never change lanes to avoid travelling with passenger vehicle behind (1 if yes, 0 otherwise)	1.07	3.28	0.207	2.43
Driving Break (1 if a stop is made every 4-6 hours on a longer trip, 0 otherwise)	1.54	4.56	0.299	3.23
Truck Inspection (1 if driver inspects truck before starting each trip, 0 otherwise)	0.94	3.21	0.182	2.53
Management Characteristics				
Fatigue Management (1 if schedule imposed by CMV carrier makes it easier to take a break, 0 otherwise)	-2.07	-5.24	-0.401	-3.20

Variable	Coefficient	*t*-statistic	Marginal Effect	t-statistic
Driving Hours Management (1 if CMV carrier restricts the number of hours worked per week, 0 otherwise)	-1.98	-5.55	-0.384	-3.29
(Standard Deviation of Parameter, Normally Distributed)	*(5.10)*	*(7.78)*		
Model Summary				
Number of Observations	515			
Log-Likelihood at Zero	-354.82			
Log-Likelihood at Convergence	-298.47			
McFadden Pseudo R^2	0.16			

4.1.4.1 Driver Characteristics

Younger truck drivers, between the ages of 18 and 25, were found to have a random and normally distributed parameter based on the statistical significance of the standard deviation. With a mean of -1.84 and a standard deviation of 1.41, 9.6 percent of drivers in this age group had an estimated parameter mean of greater than zero, and 90.4 percent in this driver demographic had an estimated parameter mean of less than zero. In regard to the 9.6 percent of drivers that were more likely to report using their cell phone while driving, this finding was consistent with passenger car research that has found that younger passenger car drivers more likely to use their cell phones while driving than those in other age groups (Farmer et al., 2010; Young and Lenné, 2010; Gliklich et al., 2016; Oviedo-Trespalacios, et al., 2017b). On the other hand, 90.4 percent of drivers between 18 and 25 were less likely to report using their cell phone while operating a truck. The heterogeneous nature of this variable may have captured differences in job experience among younger truck drivers. For instance, truck drivers who fell within this age demographic and had minimal truck driving experience might be less likely to use their cell phone while driving because they were still learning to operate their truck. Contrarily, a small portion of drivers within this age group might have slightly more experience operating a truck and would be more likely to report using their cell phone while driving.

Single marital status was another variable found to have a random and normally distributed parameter at the 95th percentile. The mean for this parameter was -3.79 with a standard deviation of 10.86, resulting in the estimated parameter mean being greater than zero for 36.4 percent of drivers and less than zero for 63.7 percent of the drivers. In other words, 36.4 percent of single truck drivers were more likely to report using their cell phone while driving, and 63.7 percent behaved differently (i.e., less likely to self-report). One possible explanation for this non-homogenous nature is that the random parameter might have captured unobserved differences for the need to use a cell phone while driving. According to Sarksisian and Gerstel (2016), single individuals are more likely to socialize and exchange help with friends/neighbors and exchange more support with their parents than individuals that are married. In this study, a proportion of single respondents may have been more socially active than others, prompting the need, or desire, to use a cell phone while driving a large truck, despite the inherent risks and associated fines if caught.

The next driver characteristic found to be significant was driver income, particularly those who reported earning between $50,000 and $59,999. This estimated parameter was found to be random and normally distributed, with a mean and standard deviation of 0.69 and 5.83, respectively. This finding suggests that the estimated parameter mean was less than zero for 45.3 percent of drivers and greater than zero for 54.7 percent of drivers. The latter finding was consistent with past studies, in which participants in higher income brackets were found to be more likely to use their cell phone while driving (Nurullah et al., 2013). The heterogeneity in this variable might be explained by the difference in perception of possible fines from using a cell phone while driving. Some drivers within this income range might not be affected by the financial impact of a fine, whereas others would attempt to minimize any unnecessary costs.

The last driver characteristic found to be significant, also with a significant random and normally distributed parameter, was safety training. With a mean of 2.08 and a standard deviation of 0.94, the estimated parameter mean for drivers who previously had some form of safety training was less than zero for 1.4 percent of drivers and greater than zero for 98.6 percent of drivers. That is to say, just 1.4 percent of drivers who received some form of safety training were less likely to report using their cell phones while driving. As studied by Gregersen (1996), there is a relationship between training strategies and overestimation of driving skill among young drivers. This notion of overestimating one's driving ability because of the training received may explain why almost all drivers (98.6 percent) had an increased outcome probability of self-reporting cell phone use while driving. For instance, in a driving safety course, drivers might be taught to improve their skills, leading them to believe that they can handle driving situations better than expected (Gregersen, 1996). This is supported by past research that found that the self-efficacy of driving is a significant predictor of distracted driving (Hill et al., 2015). If the goal is to eliminate cell phone use among truck drivers, this finding suggests that training programs should focus on more than just developing driver skills (i.e., the sources and consequences of distracted driving) as it may result in an overestimation of their driving abilities. The remaining proportion of drivers who had a decreased outcome probability of reporting cell phone use may not have been affected by safety training and may have continued to limit their exposure to risky driving behaviors.

Regarding the drivers, education level and crash history were the final factors found to be significant in the model, and both factors decreased the likelihood of self-reporting cell phone usage while driving. As measured by marginal effects, those who reported that their highest completed level of education was either trade school or a technical certificate were found to have a 0.133 lower probability of reporting using a cell phone while driving. This may be explained by the fact that trade school programs for truck operators educate drivers on the inherent complexities of operating a heavy truck; therefore, these drivers do not want to complicate the matter by using a cell phone while driving. Furthermore, marginal effects showed that those who indicated being involved in at least one crash in the past 5 years had a 0.212 increase in self-reporting probability of using a cell phone while driving. This finding is consistent with past research that found that drivers who have been involved in a crash are more likely to self-report texting while driving (Jashami et al., 2017). Being involved in a crash may be considered a form of reckless driving and may explain why this parameter increased the self-reported likelihood of using a cell phone while driving.

4.1.4.2 Work Characteristics

Of the work characteristics found to be significant, the estimated parameters for truck parking decisions and drive start time were found to be random and normally distributed. With a mean of 2.06 and a standard deviation of 2.83, the estimated parameter mean for drivers who made their own parking decisions was less than zero for 23.3 percent of drivers and greater than zero for 76.7 percent of drivers. In other words, 23.3 percent of drivers who made their own parking decisions were less likely to report using their cell phone while driving and 76.7 percent were more likely. A proportion of drivers (76.7 percent) who made their own parking decisions may not have been familiar with safe and adequate parking locations along their route and may have had to use their cell phone to identify possible locations (e.g., call employer, call information services, check truck parking applications/websites). In opposition, a proportion of drivers (23.3 percent) may have been familiar with safe and adequate parking facilities along their route; therefore, these drivers were less likely to use their cell phone for such purposes.

In regard to starting a drive early in the morning (between midnight and 6:00 AM), the estimated parameter mean was less than zero for 39.4 percent of drivers and greater than zero for

60.6 percent of drivers and. That is to say, 39.4 percent of drivers who started driving in the early morning were less likely to report using their cell phone, but 60.4 percent were more likely to report engagement in the secondary task. This variation among drivers may be attributed to the variation in traffic flow and density at various times and locations during the morning that defer cell phone use while driving. For example, if traffic volumes are high and require full driver attention, drivers may be less likely to use their cell phone. However, if traffic volumes are low, this may lead to cell phone usage for some drivers. This finding was consistent with past research that suggested that engagement in secondary tasks while driving is influenced by low driving hazards, such as traffic volume (Oviedo-Trespalacios, et al., 2017a).

Although not found to be random, drivers who began their work mid-day (between 10:00 AM and 4:00 PM) were found to be statistically significant and to have an increased self-reporting probability of using a cell phone while driving. Marginal effects suggested a 0.444 increase in probability in reporting using a cell phone while driving for those who started their work mid-day. This finding is plausible, as traffic during mid-day is typically less congested than morning commute times (i.e., 7:00 AM to 9:00 AM) or afternoon peak hour times (5:00 PM to 7:00 PM). During these times, driving tasks are less demanding because of lower traffic volumes and fewer interactions with other vehicles. This result complements past research on cell phone usage among passenger car drivers, was Kidd et al. (2016) showed that drivers are at increased odds of engaging in any secondary behavior during the afternoon.

Drivers who reported primarily using city roads or rural roads for their routes were found to have an increased probability of reporting cell phone use while driving. For city and rural roads, marginal effects showed a 0.369 and 0.773 increase in probability, respectively. City roads and rural roads, compared to highways or interstates, experience lower traffic volumes, and drivers may feel more comfortable using their cell phones in these roadway environments. As mentioned previously, engagement with secondary tasks are influenced by the roadway environment (Oviedo-Trespalacios, et al., 2017a). In addition, drivers who primarily use city roads or rural roads are likely to be near their destination (e.g., retail business or warehouse distribution center) and may need to communicate with the recipient of the delivered goods.

Regarding truck configuration, drivers who reported driving a truck with two trailers often were found to have an increase in probability of self-reporting cell phone use. Marginal effects indicated that the probability of reporting cell phone use increased by 0.475. One possible explanation for this finding is that two-trailer trucks are intended to carry a higher volume of goods, and this increased amount may require drivers to coordinate the delivery with one or more recipients.

Lastly, drivers working for a private carriage were found to have a 0.134 probability decrease in self-reporting cell phone use according to marginal effects. Private carriers may impose strict safety policies that discourage risky driving behaviors among their operators so that they can maintain a high safety rating. A high safety rating would expand these carriers' client base.

4.1.4.3 Temporal Characteristics

Drivers who reported having difficulty finding safe and adequate truck parking on Tuesdays or in the afternoon had an increased probability of reporting using their cell phones while driving. Marginal effects for these variables showed a 0.287 and 0.294 increase in probability for difficulty finding parking in the afternoon and on Tuesdays, respectively. This finding is plausible, as parking difficulties, especially when nearing hours of service limitations, may force drivers to use their phones to communicate with their employer or access an application/website to identify other safe parking locations along their route. This notion is supported by Anderson et al. (2018), who found that receiving real-time information lowered the probability of encountering trouble when drivers were locating safe and adequate truck parking. Using a cell phone while driving may be a way to receive such information and counteract truck parking difficulties.

4.1.4.4 Driving Behavior

Regarding truck driver behavior and its influence on cell phone use while driving, several characteristics were found to be significant and increase the outcome probability of a driver reporting using a cell phone while driving. The probability of drivers who reported using their cell phones while driving increased by 0.274, according to marginal effects, for those who often drive while tired. Driving while tired, or fatigued, has been proved to increase crash risk and result in higher levels of injury severities (Bunn et al., 2005). Because of these safety risks, truck drivers may adopt strategies to combat the effects of fatigue, such as using a cell phone. According to Gershon et al. (2011), professional drivers perceive talking on a cell phone while driving as an effective countermeasure to driver fatigue. This may explain why the surveyed respondents who often drove while tired were more likely to report using a cell phone while driving.

Similarly, drivers who took a break every four to six hours on a longer haul were more likely to report using their cell phones while driving. Marginal effects for this variable indicate a 0.299 increase in probability of reporting cell phone use. This finding is consistent with Oviedo-Trespalacios et al. (2017b), who determined that, among passenger car drivers, every additional hour driven per day increases the likelihood of reporting using a cell phone while driving. Truck drivers may exhibit similar driving behavior, and this might explain why those who took breaks every 4 to 6 hours were more likely to report using their cell phone while driving.

Furthermore, drivers who never changed lanes when a passenger vehicle was behind them were found to have an increased probability of reporting cell phone use while driving, as marginal effects showed a 0.207 increase in probability. Studies have shown that when drivers use their cell phones while driving, they adopt compensatory driving behaviors, such as decreased speed or increased headway, to account for the added cognitive demand from the cell phone (Young and Lenné, 2010; Zhou et al., 2016; Oviedo-Trespalacios, et al., 2017a). With passenger cars behind the truck, truck drivers are more capable of dictating their speed and headway than when following other vehicles. This driving situation can allow drivers to use their cell phones and perform compensatory driving behaviors.

Lastly, those who inspected their trucks before starting each trip were found to have a higher probability of reporting using their cell phone while driving. As measured by marginal effects, these drivers had a 0.182 increase in probability of reporting cell phone use. Drivers who inspect their trucks before every trip may feel that their vehicle is safe and mechanically sound and overestimate their ability to avoid being involved in safety critical events even when using a cell phone while driving.

4.1.4.5 Management Characteristics

Two CMV carrier management characteristics, particularly those aimed at fatigue and hours of service, were found to be significant and decrease the probability of reporting cell phone usage while driving. One variable, CMV carriers who restricted the number of hours worked per week, was found to have a random and normally distributed parameter. With a mean of -1.98 and standard deviation of 5.10, the estimated parameter mean was greater than zero for 34.9 percent of drivers and less than zero for 65.1 percent of drivers. This discrepancy among drivers may have captured the ineffectiveness of such policies in mitigating fatigue. For instance, because weekly hours are restricted, some drivers may elect to drive for 8 consecutive hours before taking a break, which is allowed under the FHWA's HOS regulations; but, this may increase the likelihood of feeling fatigue effects. As mentioned previously, professional drivers perceive that talking on a cell phone is an effective countermeasure to driver fatigue (Gershon et al., 2011). On the other hand, some drivers may drive only for a short period before taking a break, which minimizes the likelihood of feeling fatigued. This may explain the heterogeneity in reporting cell phone usage while driving among drivers who worked under weekly hour restrictions. This may suggest that more specific regulations, such as restricting the number of consecutive hours driven, may be more effective in reducing distracted driving among truck drivers.

Similarly, drivers who operated under CMV carriers that managed fatigue by creating schedules that allowed drivers to take breaks easily were found to have a decreased probability of reporting cell phone use while driving. Marginal effects showed a 0.401 decrease in probability of reporting cell phone use. Because professional drivers think that talking on a cell phone while driving mitigates the effects of driver fatigue, easily taking breaks when fatigued may explain why drivers were less likely to report using their cell phones while driving (Gershon et al., 2011). If drivers can easily take breaks when fatigued, they do not have to rely on using their cell phones while driving to combat the effects of driver fatigue. Additionally, being able to take breaks easily allows drivers to pull over at a rest stop or other safe location (e.g., private truck stop) when they need to use their cell phone.

4.2 Lane-Changing Behavior and the Opinions of Drivers of Large Trucks in the Pacific Northwest

4.2.1 Background

Lane changing is a pervasive maneuver in which drivers seek an adequate gap to move safely to an adjacent lane. This maneuver entails drivers paying attention to the traffic in the adjacent lanes and, at the same time, being aware of the traffic in their current lane (Lee et al., 2004; Henning et al., 2008). Lane-changing maneuvers occur frequently, particularly around merging and diverging areas near interchanges. These maneuvers can be somewhat difficult at times and may require increased driver engagement, thus increasing a driver’s stress level (Hill and Boyle, 2007). According to Chovan et al. (1994), lane changing is a deliberate and substantial shift in the lateral position of a vehicle. In general, lane changing can be categorized into two main maneuvers: mandatory lane changing (MLC), in which drivers need to change their lanes because of a lane drop, lane closure, or the need to maintain a route; and discretionary lane changing (DLC), which is executed to avoid slower leading vehicles (Keyvan-Ekbatani et al., 2016). In 2015, lane changing was the leading cause of crashes—451,000 or 4.6 percent of all reported crashes. In terms of injury severity, roughly 678 were fatal crashes (1.6 percent of all fatalities), 72,000 were injury-related crashes (2.9 percent of injury-related crashes), and 378,000 were property-damage-only crashes (5.2 percent of crashes resulting in property damage only) (NHTSA, 2015). Traffic safety is considerably affected by such maneuvers, making lane changing behavior an area of concern for many transportation safety professionals and researchers.

While a number of studies have examined lane-changing behavior, the factors influencing driver lane changing, especially from the perspective of drivers of large trucks, are not completely understood. This could be attributed to a lack of reliable data that reveal driver behavior under various lane-changing scenarios (Keyvan-Ekbatani et al., 2016). Some studies have used microscopic traffic simulation software to assess driver behavior with regard to lane changing (Van Winsum et al., 1999; Salvucci and Liu, 2002; Lv et al., 2011, 2013; Xiaorui and Hongxu, 2013; Li and Sun, 2017). However, these studies have not accounted for the behavioral factors that influence a driver's decision to change or not to change lanes; they also have not considered the point of view of the drivers of passenger vehicles. Other studies have simulated driver behavior or used univariate analyses to identify the factors that influence driver lane changing (Van Winsum et al., 1999; Salvucci and Liu, 2002; Lv et al., 2011, 2013; Xiaorui and Hongxu, 2013; Li and Sun, 2017). Simulating driver behavior has the advantages of allowing for controllability andreproducibility, ease of data collection, and standardization of driver behavior. However, simulating driver behavior suffers from limited physical, perceptual, and behavior fidelity; in addition, validation is difficult (Winter et al., 2012). Univariate analyses have been used to explain lane-changing behavior, but these methods have failed to capture the inherent correlation among various lane-changing scenarios. For instance, drivers are faced with an array of different lane-changing scenarios, each one affecting the other. Using univariate analysis to estimate driver lane-changing behavior can lead to biased and erroneous inferences. The reason is that the choice to change lanes varies according to the situation (e.g., if another vehicle is in front of, behind, or at the side of a vehicle) faced by drivers. Developing separate univariate models for each situation ignores the correlations between the disturbances in these situations, and this in turn leads to inefficiencies in model estimation (Russo et al., 2014).

Given the above considerations, this study used an econometric modeling framework to address lane changing from the perspective of drivers of large trucks. Specifically, a multivariate probit modeling framework was used to address the shortcomings of univariate analyses by accounting for multiple binary choice outcomes (i.e., lane-changing scenarios) while accounting for correlations in the error terms between the individual scenario outcomes (Greene, 2012). In this study, the binary choice outcomes refer to six lane-changing scenarios derived from a stated preference survey distributed to truck drivers who were destined for or who originated from the Pacific Northwest—namely, Washington state, Oregon, and Idaho. These scenarios were used to uncover the factors affecting driver lane changing behavior. In the scenarios, drivers of large trucks were asked about six conditions under which would they change lanes:

1. Would they consider changing lanes if a passenger vehicle were in front of their truck?
2. Would they consider changing lanes if another truck were in front of their truck?
3. Would they consider changing lanes if a passenger vehicle were behind their truck?

4. Would they consider changing lanes if another truck were in behind their truck?
5. Would they consider changing lanes if a passenger vehicle were on either side of their truck?
6. Would they consider changing lanes if another truck were on either side of their truck?

Identifying lane-changing behavioral factors can shed light on crashes related to these types of maneuvers, particularly those involving large trucks. Given the increased interest in the effects of driver behavior on traffic safety and the societal and economic impacts of lane-changing-related crashes, identifying the factors that influence truck driver lane-changing behavior is vital. This study contributes to the body of knowledge on transportation safety in two ways. First, this study attempted to highlight all the factors that may affect the lane-changing decisions of drivers of large trucks, and it also looked at the risky driving behavior of these drivers. Second, the developed multivariate probit model can be used to estimate the factors influencing lane changing, overcoming the potential deficiencies of previous univariate modeling approaches. To the best of the authors' knowledge, this is the first attempt to apply a multivariate probit modeling approach to model the lane-changing behavior of drivers of large trucks.

4.2.2 Analysis Process

To evaluate the effects of six different car-following scenarios on truck driver behavior with regard to lane changing, a representative stated-preference survey was designed and distributed to truck drivers who were destined for or who originated from the Pacific Northwest—namely, Washington state, Oregon, and Idaho. The representative sample consisted of 515 (from a total of 1,919—a 26.8 percent response rate) participants, all truck drivers. As previously mentioned, the objective of this study was to gain a better understanding of the factors influencing truck drivers' lane-changing behaviors. Accordingly, the dependent variables were six questions that represented all of the possible scenarios of the lane-changing behavior of truck drivers to avoid travelling where a passenger vehicle was in front, a passenger vehicle was behind, another truck was in front, another truck was behind, passenger vehicles were on either side, or other trucks were on either side. A total of 250 indicator variables were created from the survey. Only 27 of these variables were found to be statistically significant.

4.2.3 Methodology

Truck drivers may be exposed to situations in which they may opt to change lanes to avoid traveling with other vehicles (trucks or passenger vehicles)—whether these vehicles are in front, behind, or on either side of their trucks. The reasons for each of these scenarios may be the result of several factors, but the decision itself to change lanes is binary (i.e., yes they change lanes or no they do not change lanes). These dependent variables may be correlated; therefore, a univariate modeling approach may not appropriate. For example, the decision to change lanes to avoid traveling with another truck in front of their truck may affect the decision to change lanes to avoid traveling with another truck on either side. As described, these decisions are intuitively correlated and are potentially jointly determined (Greene, 2016a). If, in fact, these decisions are correlated and are modeled using a traditional univariate approach, the correlation between these variables (and the error terms between equations, as will be discussed later in this section) may not be accounted for. In the context of parameter estimates, if this potential correlation is not accounted for, parameter estimates may be inconsistent and inefficient (Wooldridge, 2010). Therefore, to account for the binary nature of the dependent variables and the potential correlation of these dependent variables, the current study proposed a multivariate probit modeling framework. Multivariate probit models are commonly used in behavioral, medical, and psychological studies because the nature of the dependent variables and the questions of interest are usually binary and correlated in nature (Lu and Song, 2006). The application of this modeling framework for better understanding driver behavior is rare in the literature. Although their study was not directly related to lane-changing behavior, Golob and Regan (2002) used a multivariate modeling framework to identify the influences of 20 operational characteristics on the propensity of trucking firms in California to adopt seven different information technologies.

To begin, a multivariate probit model for six dependent variables was formulated by generalizing the index function model from a single latent variable to six potentially correlated latent variables, in which the six latent variables were defined and estimated simultaneously as follows (Christofides et al., 1997; Cameron and Trivedi, 2005; Greene, 2012; Hensher et al., 2015):

$$y_m^* = \boldsymbol{\beta_m X_m} + \varepsilon_m, y_m = 1 \text{ if } y_m^* > 0, 0 \text{ Otherwise}, m = 1, 2, \dots, 6 \qquad (4.4)$$

where y_m^* is an unobserved (latent) variable representing the latent utility of lane-changing scenario m, $\boldsymbol{X_m}$ is a vector of observed characteristics determining lane-changing scenario m, $\boldsymbol{\beta_m}$ is a vector of the estimated parameters, ε_m represents an error term that is M-variate normally distributed with a mean of zero and constant variance (i.e., $(\varepsilon_1, \dots, \varepsilon_6) \sim N_M[0, \boldsymbol{\Omega}]$) and independent of $\boldsymbol{X_m}$, $E[\varepsilon_m \mid \boldsymbol{X_1}, \dots, \boldsymbol{X_6}] = 0$, $\text{Var}[\varepsilon_m \mid \boldsymbol{X_1}, \dots, \boldsymbol{X_6}] = 0$, and $\text{Cov}[\varepsilon_m \mid \boldsymbol{X_1}, \dots, \boldsymbol{X_6}] = \rho_{jm}$. Under these assumptions, $\boldsymbol{X_m}$ is exogenous and $\boldsymbol{\Omega}$ is a 6×6 matrix with off-diagonal element ρ (the correlation coefficient for ε_m), such that $\rho = \text{Corr}(\varepsilon_1, \varepsilon_2, \dots, \varepsilon_6)$ (Wooldridge, 2010). As discussed below, correlation coefficient ρ determines the use of a multivariate probit analysis.

The above assumptions are discussed because of their importance, as they imply that $y_1, y_2, \dots, y_6$ can be estimated by a probit modeling framework conditional on $\boldsymbol{X_m}$ (Wooldridge, 2010). However, as discussed previously, if these assumptions did not hold true and ε_m was correlated across equations, a univariate approach would no longer be adequate, and a multivariate probit framework would have to be considered to account for the correlation between ε_m. Once more, not accounting for this potential correlation would result in parameter estimates that wer no longer consistent and less asymptotically efficient (i.e., larger standard errors) (Hensher et al., 2015; Meng and Schmidt, 1985). Therefore, a test for correlation among the error terms was conducted to determine whether correlation was present. Being that the current study had dependent variables that were binary, a tetrachoric correlation test was conducted on the error terms to determine the significance of the correlation coefficient ρ (Greene, 2016a, 2012):

$$\begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_6 \end{pmatrix} \Big| \, \boldsymbol{X_1}, \ldots, \boldsymbol{X_6} \sim N_M[0, \boldsymbol{\Omega}] \tag{4.5}$$

where $\boldsymbol{\Omega}$ is the variance-covariance matrix:

$$\boldsymbol{\Omega} = \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \rho_{14} & \rho_{15} & \rho_{16} \\ \rho_{21} & 1 & \rho_{23} & \rho_{24} & \rho_{25} & \rho_{26} \\ \rho_{31} & \rho_{32} & 1 & \rho_{34} & \rho_{35} & \rho_{36} \\ \rho_{41} & \rho_{42} & \rho_{43} & 1 & \rho_{45} & \rho_{46} \\ \rho_{51} & \rho_{52} & \rho_{53} & \rho_{54} & 1 & \rho_{56} \\ \rho_{61} & \rho_{62} & \rho_{63} & \rho_{64} & \rho_{65} & 1 \end{pmatrix} \tag{4.6}$$

where ρ represents the tetrachoric correlation coefficient of the error terms, as defined previously. The tetrachoric correlation between the six binary dependent variables was equivalent to the correlation of the six error terms in a multivariate probit model (Greene and Hensher, 2010; Hensher et al., 2015). To be exact, the tetrachoric correlation between the six binary dependent variables was computed by assuming the six binary variables were derived by censoring six observations from an underlying continuous multivariate normal population (a multivariate probit model with no estimated covariates). In doing so, the correlation coefficient ρ was easily calculated by fitting a multivariate model with no covariates and measuring the correlation between underlying continuous variables if they were able to be observed (Greene and Hensher, 2010; Hensher et al., 2015).

Continuing, the joint estimation of the lane-changing behavior of truck drivers under different potentially correlated scenarios was the primary objective of this study. To do so, the joint probabilities of all observed lane-changing scenarios, m, were then computed as follows (Chib and Greenberg, 1998; Young et al., 2009):

$$\Pr(y_m = 1, \dots, y_6 = 1) = \Phi_M(\cdot) \tag{4.7}$$

where y_m represents the observed binary response corresponding to lane-changing scenario m, where $y_m = 1$ if $y_m^* > 0$ (0 otherwise), and Φ_M is the cumulative density function of a multivariate normal distribution (Greene, 2016b, 2012):

$$P = \int_{A(M)}^{B(M)} \cdots \int_{A(1)}^{B(1)} f(x_1, \dots, x_m)\, dx_1, \dots, dx_M \tag{4.8}$$

where $f(\cdot)$ is the M-variate normal density function of $\boldsymbol{X}$ with mean vector zero and positive definite covariance $M \times M$ matrix $\boldsymbol{\Omega}$. Because of the complexity of the integral in equation 4.8, it is solved via approximation by averaging a set of R replications obtained by draws produced from a random number generator, in which accurate and efficient evaluation can be attained for model estimation of moderate to relatively large models, as in the case in the current study (Greene, 2016b, 2012; Greene and Hensher, 2010; Hensher et al., 2015).

For the multivariate probit model, maximum likelihood estimation was used to estimate the parameters and tetrachoric correlation. In the case of the multivariate probit model, the joint probability of observed lane-changing behaviors ($[y_{i1}, \dots, y_{iM=6} \mid \boldsymbol{X}_{i1}, \dots, \boldsymbol{X}_{iM=6}]$) is used to formulate the log-likelihood function for M-variate normal probabilities (Greene, 2012; Greene and Hensher, 2010; Hensher et al., 2015):

$$\log(L_i) = \sum_{i=1}^{N} \log\Phi_M[q_{i1}\boldsymbol{\beta}_1\boldsymbol{X}_{i1}, q_{i2}\boldsymbol{\beta}_2\boldsymbol{X}_{i2}, \dots, q_{iM}\boldsymbol{\beta}_M\boldsymbol{X}_{iM} \mid \boldsymbol{\Omega}^*] \tag{4.9}$$

where $q_{iM} = 2y_{1m} - 1$, and $\boldsymbol{\Omega}^* = 1$ if $m = n$ or $\boldsymbol{\Omega}^* = q_{im}q_{im}\rho_{mn}$ if $m \neq n$.

Lastly, to interpret model estimates, marginal effects are computed to evaluate the effect of explanatory variable $\boldsymbol{X}_{iM}$ on the outcome probability of the dependent variables. Marginal effects represent the change in the expected value of y_m, given all other y are equal to one. Therefore, the marginal effects of y_m for the current study were computed as follows: (Greene, 2016a):

$$\begin{aligned} &E[y_1 \mid y_2 = 1, \dots, y_M = 1] = \frac{\Pr(y_1 = 1, \dots, y_M = 1)}{\Pr(y_2 = 1, \dots, y_M = 1)} = \frac{P_{1\dots M}}{P_{2\dots M}} = E_1 \\ &\vdots \\ &E[y_6 \mid y_1 = 1, \dots, y_{M-1} = 1] = \frac{\Pr(y_1 = 1, \dots, y_M = 1)}{\Pr(y_1 = 1, \dots, y_{M-1} = 1)} = \frac{P_{1\dots M}}{P_{1\dots M-1}} = E_6 \end{aligned} \tag{4.10}$$

4.2.4 Estimation Results

It is widely accepted that the statistical assessment of the multivariate probit model is elusive because there is no universally reported measure of goodness of fit for such models. However, as was done in the work of Choo and Mokhtarian (2008) and Golob and Regan (2002), a chi-square goodness-of-fit test and pseudo R^2 were used. The chi-square test is used for deciding between competing models (in this study, comparisons between the null model with only constants and the full model). The estimated results of the multivariate probit model are summarized in table

4.2. The chi-square statistic representing the difference between the values of the log-likelihood for the full and null models was equal to 233.21. Therefore, this value with the corresponding degrees of freedom (31, the number of estimated parameters in the multivariate probit model) could be used to assess statistical significance. The chi-square test implied that the fit (i.e., log-likelihood value) of the final multivariate probit model was significantly superior to the null model at the 99.99 percent confidence level. Moreover, the pseudo R^2 value was 0.09, which is consistent with Choo and Mokhtarian (2008).

Table 4.3 clearly shows that all correlation coefficients were positive and statistically significant at the 99.99 percent confidence level. This means that the unobservable (i.e., error terms) in each equation were highly correlated, and the six lane-changing scenarios needed to be modeled using a multivariate approach rather than a univariate analysis. Regarding the explanatory variables, table 4.2 includes variables that affect drivers' decisions in a lane-changing maneuver, in addition to their marginal effects. Notably, these variables had a greater than 90 percent significance level with the exception of two variables included in the multivariate probit model because of their conceptual relevance. Because the explanatory variables were grouped into four main categories (driver characteristics, temporal characteristics, driving characteristics, and driver fatigue management factors), the discussion for each group will be presented separately.

Table 4.2 Parameter estimates of the multivariate probit model

Variable	**Parameter estimate**	***t*-stat.**	**Marginal effects**
Y_1: Lane changing to avoid traveling with passenger vehicle in front			
Constant	-0.833^{***}	-7.32	-
Driver income (1 if between 40,000 and 50,000, 0 otherwise)	0.312^{*}	1.84	0.165
The situation that poses the highest safety hazard to drivers (1 if passenger vehicle in front, 0 otherwise)	0.961^{***}	3.31	0.510
Early morning (1 if drivers start their work between midnight and 5:59 am, 0 otherwise)	0.272^{**}	2.13	0.145
The safest time to drive truck (1 if between 10:00 am - 3:59 pm, 0 otherwise)	-0.375^{*}	-1.90	-0.199
Keep driving rather than stopping to take breaks to manage fatigue (1 if disagree, 0 otherwise)	-0.435^{**}	-2.47	-0.231
Fatigue management does not require to take breaks when driving long distances (1 if strongly agree, 0 otherwise)	-0.678^{**}	-2.11	-0.360
Y_2: Lane changing to avoid traveling with passenger vehicle behind			
Constant	-0.270	-1.53	-
Participating in team driving (1 if never, 0 otherwise)	0.310^{**}	2.27	-0.176
Driving when tired (1 if quite often drive when tired, 0 otherwise)	-0.550^{***}	-2.99	-0.627
Driver gender (1 if male, 0 otherwise)	0.312^{**}	2.15	0.302
Driver age (1 if between 26 and 35 years, 0 otherwise)	-0.396^{***}	-3.45	-0.040
Shipment type (1 if truckload, 0 otherwise)	-0.331^{**}	-2.57	-0.033
Frequency of checking your truck over each week (1 if hardly ever, 0 otherwise)	-0.978^{***}	-3.49	-0.243
Frequency of driving a tractor with two trailers (1 if almost never, 0 otherwise)	-0.752^{**}	-2.09	-0.076
Y_3: Lane changing to avoid traveling with truck in front			
Constant	-1.337^{***}	-6.15	-
The situation that poses the highest safety hazard to drivers (1 if passenger vehicles on either side, 0 otherwise)	0.313^{*}	1.87	0.169
Driving when tired (1 if quite often drive when tired, 0 otherwise)	-0.645^{**}	-2.34	-0.214
Driver gender (1 if male, 0 otherwise)	0.451^{**}	2.23	0.096
The most difficult time of the day to find safe and adequate parking (1 if no difficulty, 0 otherwise)	-0.887^{*}	-1.75	-0.479
The type of company restrictions to manage drivers working hours (1 if putting restriction on the number of continuous days worked, 0 otherwise)	-0.328^{**}	-2.21	-0.177
Fatigue management encourages drivers to take breaks from driving whenever they need to (1 if agree, 0 otherwise)	-0.352^{**}	-2.17	-0.190
Frequency of stopping in a longer trip (1 if only when tired, 0 otherwise)	0.603^{***}	3.43	0.326
Y_4: Lane changing to avoid traveling with truck in behind			
Constant	-0.886^{***}	-5.53	-
Driver gender (1 if male, 0 otherwise)	0.339^{**}	2.36	0.048
Lapsing concentration after driving for a long time (1 if quite often, 0 otherwise)	-0.222^{*}	-1.70	-0.013
Participating in team driving (1 if never, 0 otherwise)	0.546^{***}	4.34	-0.033
The safest time to drive truck (1 if between midnight and 5:59 am, 0 otherwise)	0.255^{**}	2.45	0.015

Variable	**Parameter estimate**	***t*-stat.**	**Marginal effects**
Keep driving rather than stopping to take breaks to manage fatigue (1 if agree, 0 otherwise)	-0.220**	-1.97	-0.013
Fatigue management in the industry (1 if quite badly, 0 otherwise)	0.235*	1.87	0.014
Y_5: Lane changing to avoid traveling with passenger vehicles on either side			
Constant	-0.875***	-10.65	-
Type of company that drivers work or contract for (1 if private carriage, 0 otherwise)	0.293***	2.73	0.113
Driving when tired (1 if rarely drive when tired, 0 otherwise)	0.193*	1.96	0.075
Frequency of checking your truck over each week (1 if hardly ever, 0 otherwise)	-0.332*	-1.69	0.055
Y_6: Lane changing to avoid traveling with trucks on either side			
Constant	-0.600***	-9.48	-
Lapsing concentration after driving for a long time (1 if very often, 0 otherwise)	-0.296*	-1.74	-0.020
Frequency of problems of adhering to the hours of service limitations due to the lack of available parking (1 if almost always, 0 otherwise)	-0.364	-1.59	-0.025
Fatigue management in the industry (1 if extremely badly, 0 otherwise)	0.264	1.53	0.018
Number of observations	515		
Log-likelihood at convergence (LL_β)	-1177.38		
Log-likelihood at zero (LL_C)	-1293.98		
$\chi^2 = -2[LL_C - LL_\beta]$	233.21		
Pseudo R^2	0.09		

*, **, *** denote significance at the 10, 5 and 1% level respectively.

Table 4.3 Correlations (ρ) in the error terms of the individual equations of the multivariate probit model (t-statistics in parentheses)

Dependent variables	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6
Y_1*	-	0.767 (12.81)	0.668 (8.04)	0.694 (9.93)	0.527 (6.21)	0.607 (8.03)
Y_2*		-	0.549 (6.65)	0.838 (21.68)	0.696 (12.85)	0.656 (11.77)
Y_3*			-	0.710 (10.93)	0.367 (3.57)	0.544 (6.68)
Y_4*				-	0.557 (8.35)	0.665 (12.31)
Y_5*					-	0.905 (34.91)
Y_6*						-

* Y1: Lane changing to avoid traveling with passenger vehicle in front (1 if yes, 0 otherwise), Y2: Lane changing to avoid traveling with passenger vehicle behind (1 if yes, 0 otherwise), Y3: Lane changing to avoid traveling with truck in front (1 if yes, 0 otherwise), Y4: Lane changing to avoid traveling with truck in behind (1 if yes, 0 otherwise), Y5: Lane changing to avoid traveling with passenger vehicles on either side (1 if yes, 0 otherwise), Y6: Lane changing to avoid traveling with trucks on either side (1 if yes, 0 otherwise)

4.2.4.1 Driver Characteristics

Three factors were found to be statistically significant and to have direct effects on truck driver behavior in lane-changing maneuvers. These factors were driver gender (male), age (between 26 and 35), and income (between $40,000 and $50,000). For male drivers, table 4.2 shows that they were found to affect three of the six lane-changing scenarios. In each of the three scenarios, when traveling with a passenger vehicle behind them, another truck in front, or another truck behind, male drivers were more likely to report changing lanes. Looking more closely at the values of the marginal effects corresponding to male drivers' behaviors in the three lane-changing scenarios, male drivers had the highest probability of reporting lane changing if a passenger vehicle was traveling behind them. The value of marginal effects for traveling with a passenger vehicle behind was 0.302, whereas the values of marginal effects for male truck drivers traveling with other trucks in front and behind were 0.096 and 0.048, respectively.

More specifically, on the basis of the marginal effects discussed above, male drivers likely feel that traveling with a passenger vehicle behind poses high risks (i.e., a higher increase in probability of changing lanes). This finding is intuitive because large trucks have specific operating limitations, one of which is blind spots or "no-zone areas" (Federal Motor Carrier Safety Administration, 2017). These blind spots are very large compared to those of passenger vehicles. Thus, due to limited visibility in these four "no zone" locations (i.e., front, back, and both sides of the vehicle), other drivers and roadway users should attempt to stay out of these locations (Federal Motor Carrier Safety Administration, 2017). In addition, the Federal Motor Carrier Safety Administration recommends that passenger vehicle drivers be able to see the driver of the large truck in their side mirrors (i.e., side mirrors of the trucks), as this means the driver of the large truck can see you (Federal Motor Carrier Safety Administration, 2017a). Therefore, passenger vehicles following a truck very closely can increase the risk of being involved in crash because of a lane-changing maneuver, which will likely result in a driver of a large truck reporting lane changing with a higher probability. Therefore, this finding further suggests that drivers of passenger vehicles maintain an adequate distance behind trucks to safely share lanes and to avoid being in “no zone areas” of trucks.

As for the other lane-changing scenarios, although marginal effects were substantially lower, males were still more likely to report changing lanes when another truck is traveling in front of or behind them. In general (regardless of vehicle type and/or location), a potential reason for males being more likely to change lanes could be attributed to driver aggressiveness, as driver aggressiveness has been shown to impact driving patterns and behaviors (e.g., different sizes of acceptable gaps, different levels of acceleration/deceleration, different speeds, etc.) (Moridpour et al., 2007). For example, Royal (2003) showed that 58 percent of surveyed drivers had felt threatened by unsafe driving behaviors, and males (17 percent) were found to most likely report having felt threatened weekly or more often. If a proportion of male drivers feel threatened by the unsafe driving behavior of others, then it is likely they will report changing lanes when other vehicles are traveling around them; this would be especially true for drivers of large trucks who are traveling around passenger vehicles. One more possible reason for this finding might be due to the fact that male drivers were overrepresented in the data. This was also seen in the general trends of drivers of large trucks. To illustrate, in 2015, there were approximately 3.5 million drivers of large trucks, and female drivers accounted for roughly 177,000 of these drivers (about 5.1 percent) (Hsu, 2016; American Trucking Associations, 2018). This was also shown in a recent truck parking study, in which Hernández and Anderson (2017) found that the majority of truck drivers they surveyed were male.

Truck drivers between 26 and 35 years old were less likely to change lanes if a passenger vehicle was traveling behind their trucks. Table 4.2 also illustrates this finding, where the value of the marginal effects was −0.04. The significance of this factor was anticipated, as previous works have found that socio-demographic characteristics (e.g., age) are essential characteristics in assessing driving performance and behavior (Li et al., 2015; Nauert, 2015). However, in the context of lane changing or passing other vehicles, younger drivers have stated that they tend to change lanes to pass other vehicles more often than they are passed (Tasca, 2000; Royal, 2003). This was the opposite of what the current study found. A possible explanation could be related to less experience driving a large truck; therefore, this age group of drivers may prefer to change lanes only when necessary. Hernández and Anderson (2017) showed that the majority of drivers who deliver or pick up goods in the Pacific Northwest (the same region of the current study) fit this age group and had been driving a truck for fewer years than older age groups.

Drivers of large trucks with incomes of between $40,000 and $50,000 were more likely to report changing lanes to avoid traveling with a passenger vehicle in front of their truck; the value of the marginal effects was 0.165. This implies that those drivers tended to change lanes to avoid traveling with the leading passenger vehicle. Drivers' sensitivity to the economic burden of truck-related crashes could be a potential reason for this finding, in the sense that drivers with such income would be more cautious in their driving and lane-changing decisions; this may be especially true if there was a passenger vehicle in front of their truck (bearing in mind the "no zone" areas). In addition, if the driver was for-hire and responsible for any damages sustained, they would be more likely to be cautious in terms of traveling with or around passenger vehicles. For example, in 2015, 524,058 registered trucks delivered goods across states or hazardous materials within states, where for-hire carriers accounted for greater than half (272,928 for-hire carriers) (Federal Motor Carrier Safety Administration, 2017b). Considering that the average cost per large truck crash (in 2015) was $148,279, it would take additional revenue of $7,413,950 to pay the costs of the crash (assuming the profit margin was 2 percent) (Ross, 2015). Therefore, such drivers would be more likely to change lanes to avoid traveling with a passenger vehicle in front of their truck.

4.2.4.2 Temporal Characteristics

Four temporal characteristics were found to affect the decisions of drivers of large trucks to report lane-changing maneuvers: drivers starting their shift in the early morning (midnight to 5:59 AM), the safest time to drive a truck (10:00 AM to 3:59 PM), the most difficult time of the day to find safe and adequate parking (no difficulty), and the safest time to drive a truck (midnight to 5:59 AM). In terms of work start time for truck drivers, table 4.2 reveals that drivers starting their work between midnight and 5:59 AM were more likely to report changing lanes if a passenger vehicle was directly in front of their trucks. Table 4.2 illustrates that those drivers had a 0.145 higher probability of reporting lane changing when the leading vehicle was a passenger vehicle. Drivers having a higher probability of reporting lane changing during this time period may be directly linked to the volume of traffic on the highway. That is, during this time period, traffic volumes are substantially lower than in the afternoon/evening peak hours. Using hourly traffic count data obtained from the U.S. Department of Transportation (via a Freedom of Information request), Galka (2016) illustrated this through an interactive traffic map. In such conditions, drivers who do not want to travel near passenger vehicles are free to change lanes with less concern of vehicles being present in the “no zone” areas.

The second factor, drivers’ perceptions about the safest time of day to drive a truck (10:00 AM to 3:59 PM) was found to affect a driver’s decision to report lane-changing maneuvers. Table 4.2 illustrates that at that time of day, drivers had a 0.199 lower probability to report changing lanes when a passenger vehicle was in front. This particular finding is intuitive, as this time of day is characterized by higher traffic volumes (see Galka (2016) for an illustration of traffic volumes by time of day). In addition, visibility conditions are typically good during these daylight hours; therefore, drivers can easily detect passenger vehicles in front of their trucks. That is, if a driver is able to clearly see a passenger vehicle in front and maintain a safe following distance (for operating speeds on highways, this would be at least 5 seconds) (Federal Motor Carrier Safety Administration, 2015), drivers may feel that changing lanes is unnecessary to ensure safe following conditions. However, this finding disagrees with that of Pahukula et al. (2015), who found that 10:00 AM to 3:00 PM was highly associated with lane changing and speeding for truck drivers in the context of injury severity. Furthermore, this could be attributed to increased workload and adaptations in driver behavior due to higher visual complexity (i.e., higher traffic volumes) (Rudin-Brown et al., 2014). That is, drivers of large trucks may adapt to the higher traffic volumes by electing not to change lanes.

In contrast, the indicator variable for the safest time to drive a truck (midnight to 5:59 AM) was found to more likely influence drivers' decisions to report lane changing when another truck was directly behind their truck, but the value of marginal effects was lower at -0.015. This finding, too, is likely attributed to the low traffic volumes during this time period, as drivers may feel that lane changing does not need to occur to ensure safe traveling conditions.

The last factor was the indicator representing drivers' opinions about the most difficult time of day to find safe and adequate parking. Truck drivers who did not have any difficulty finding safe and adequate parking had a 0.479 lower probability of reporting changing lanes to avoid travelling with another truck in front of their truck. This finding is likely linked to parking availability and HOS. For instance, if drivers near their HOS and have difficulty finding parking, they may be inclined to change lanes to avoid traveling behind slower vehicles to arrive at a parking facility before their legal drive time has been reached. Therefore, if no parking difficulty is experienced, drivers may not need to change and may be less likely to report lane changing.

4.2.4.3 Driving Characteristics

Modeling results revealed ten factors that significantly affect a driver's decision to report lane-changing maneuvers. However, only the six factors with the largest effects (higher marginal effects) will be discussed. For drivers who seldom conducted weekly checks on their trucks, the indicator variable showed that they had a 0.243 lower probability to report changing lanes to avoid traveling with passenger vehicles behind their trucks, whereas they had a 0.055 higher probability to change lanes when passenger vehicles were on either side of their truck. This finding may have captured inattentiveness and irresponsible behavior of truck drivers. Rule 49 CFR § 396.13 states that "*before driving a motor vehicle, the driver shall be satisfied that the motor vehicle is in safe operating condition.*" To some, this is interpreted specifically for drivers of large trucks to inspect their trucks prior to each trip to ensure the truck is in safe operating conditions (Schultz, 2018). Therefore, failure to check their trucks regularly to ensure their safety could lead to the conclusion that such drivers fail to ensure safety while driving and tend not to be aware of the vehicles around them. Furthermore, mirrors play a major role in being able to detect and see passenger vehicles driving behind their truck (Green, 2018). But if mirrors are not properly cleaned or placed (for example) as part of a check before trips, drivers may be unable to detect and see passenger vehicles traveling behind them.

Drivers on longer trips who stop only when tired have a 0.326 higher probability of reporting changing lanes to avoid traveling with another truck in front of their truck. This outcome could be attributed to the effect of the HOS regulations on driver performance, as HOS are generally associated with several factors—namely, hours off duty, hours driving, hours working, breaks, and recovery. If HOS regulations are not strictly adhered to, these factors can lead to driver fatigue, which, in turn, can lead to a deterioration in driving performance (Jovanis et al., 2011). Therefore, if drivers are on a long trip, tired, and looking for a location to park, they may be inclined to change lanes to pass slower vehicles to get to a parking facility.

Drivers who did not participate in team driving were less likely to report changing lanes when other trucks or passenger vehicles were traveling behind their trucks. Table 4.2 shows that the values of the marginal effects were −0.176 and −0.033, respectively, when a passenger vehicle or a truck was behind the driver's truck. This finding might be linked to driver fatigue. For example, when drivers near the end of their allowable driving time, they tend to be fatigued. However, they participate in team driving, one can switch when the other is fatigued. If drivers are fatigued, they may spend most of their driving workload tasks on looking ahead and less time on other tasks (i.e., checking mirrors often to be aware of the vehicles surrounding them) (Herman, 2016). In addition, if this is linked to fatigue, drivers may not want to make any unnecessary lane changes; therefore, they will be less likely to change lanes if vehicles are traveling behind them.

Next, the drivers who stated that the presence of a passenger vehicle in front of their trucks posed the highest safety hazard were found to have a 0.510 higher probability of reporting changing lanes to avoid traveling with a passenger vehicle in front. This finding is intuitive, as drivers who feel passenger vehicles in front pose the highest safety hazard are likely to change lanes to avoid traveling behind them. Being that crashes in which a large truck crashes into the back of another vehicle are most common (Blower and Campbell, 2002), drivers are likely to change lanes to avoid traveling behind a passenger vehicle. Drivers reporting changing lanes was also true when a passenger vehicle was on either side of the truck, but with lower marginal effects (table 4.2 shows that the value of the marginal effects was 0.169). This means that these truck drivers had a 0.169 higher probability of reporting changing lanes when passenger vehicles were on either side of their truck. This finding, as discussed previously, may be attributed to the considerable blind spots of large trucks due to the differences in height and size (i.e., "no zone" areas) (Federal Motor Carrier Safety Administration, 2017a). Detecting a passenger vehicle on either side of the truck is quite difficult for drivers of large trucks. Therefore, they are likely to change lanes to avoid traveling with passenger vehicles in their "no zone" areas.

Lastly, drivers who often drove when they were tired were less likely to change lanes when a passenger vehicle and a truck were traveling behind and in front of them, respectively. Table 4.2 shows that the values of the marginal effects of lane changing to avoid traveling with a passenger vehicle behind and another truck in front were −0.627 and −0.214, respectively. When another truck was in front of a large truck, the driver had a 0.214 lower probability of changing lanes. Although the majority of large truck crashes occur when a large truck is following another vehicle (Blower and Campbell, 2002), drivers may not change lanes because they are able to easily detect the leading truck (this would also allow them to provide adequate following distance to avoid a rear-end crash). Likewise, when a passenger vehicle followed a large truck, the driver had a 0.627 lower probability of reporting changing lanes. Drivers who often drive when tired are likely to minimize risks, such as minimizing lane changes. Moreover, if drivers are driving while tired, they may not be as alert to their surroundings (e.g., passenger vehicles behind the truck) and therefore, less likely to change lanes.

4.2.4.4 Driver Fatigue Management Factors

Drivers of large trucks, in general, encounter higher levels of stress than other drivers because of their irregular schedules, long working hours, night work, and economic pressures. These factors are the main sources of stress. This, in turn, leads to insufficient sleep and the development of short- and long-term health problems (National Academies of Sciences, Engineering, and Medicine, 2016; Saltzman and Belzer, 2007). The aforementioned factors increase the risk of driver fatigue. Drivers of large trucks, in particular, are required to have essential driving skills, such as excellent judgment, vigilance, and quick reactions. And, in some cases, drivers require specialized training to be able to operate their equipment (Saltzman and Belzer, 2007). Unfortunately, fatigue diminishes alertness, reduces vigilance and driving performance, decreases motivation, impairs judgment, and increases drowsiness (Knipling, 2015). Moreover, it has been shown that high levels of fatigue are tantamount to a blood alcohol concentration over the legal limit (i.e., greater than 0.07 percent) (Dawson and Reid, 1997; Saltzman and Belzer, 2007).

Therefore, to assess the drivers' perspectives on the issue of driver fatigue, the survey contained several questions that aimed to highlight the most important factors related to driver fatigue and its effects on driver decisions to report lane-changing maneuvers. The results of the analysis, shown in table 4.2, show that ten fatigue-related factors were found to be statistically significant and to have direct implications on drivers reporting lane-changing behavior. However, only four of these factors will be discussed because of their greater effects (higher marginal effects).

These factors were the following: drivers who did not stop to take breaks to manage fatigue; drivers who strongly agreed that fatigue management does not require taking breaks when driving long distances; drivers who worked or contracted for companies that restricted the number of continuous days worked to manage drivers' working hours and fatigue; and drivers who agreed that fatigue management could be achieved by encouraging drivers to take breaks when necessary. Interestingly, these factors all had a negative impact on the probability of drivers reporting lane changing. For the first two factors (drivers who did not stop to take breaks to manage fatigue and drivers who strongly agreed that fatigue management does not require taking breaks when driving long distances), drivers had a 0.231 and 0.360 lower probability, respectively, of reporting changing lanes to avoid traveling with a passenger vehicle in front of them. This finding might be attributed to driver behavior in that these truck drivers did not believe that taking breaks on long trips could alleviate their fatigue. Instead, they may continue to drive for several reasons, including family pressures, the need for on-time delivery, the work compensation structure, and commuting patterns (National Academies of Sciences, Engineering, and Medicine, 2016). Furthermore, drivers may adopt other measures to address their fatigue while driving. For example, Gershon et al. (2011) found that professional drivers often perceive that talking on a cell phone is an effective countermeasure to fatigue. Therefore, in combination with fatigue, if drivers are talking on the phone, they may be less aware of surrounding traffic, which would affect their decision to change lanes. In addition, previous work has shown that fatigued drivers have an improvement in visual distance estimation (Liu and Wu, 2009). This might explain why fatigued drivers are less likely to change lanes, as they are able to detect inadequate gaps for lane changing.

The last two factors were drivers who worked or contracted for companies that restricted the number of continuous days worked to manage drivers' working hours and fatigue, and drivers who agreed that fatigue management could be achieved by encouraging drivers to take breaks when necessary. Table 4.2 shows that both of these factors were associated with the lane changing scenario of another truck traveling in front of a large truck. The values of the marginal effects of these factors were −0.177 and −0.190, respectively. This finding illustrates truck drivers' behaviors when the leading vehicle is another truck. Size and weight disparities between trucks are minimal, and this, in turn, decreases the risk of blind spots for truck drivers who follow another truck. Therefore, drivers may be less inclined to change lanes.

5.0 Summary

The current study utilized a survey issued to large truck drivers that deliver goods in the Pacific Northwest to uncover existing relationships between observed HOS on the likelihood of safety critical events (SCE) and a set of potential confounding factors related to time of day (TOD), from the viewpoint of the drivers. Because of data heterogeneity, random parameters binary logit approaches and the multivariate probit approach were applied to produce the most accurate estimates and to make appropriate inferences. In this study, some questions of interests were used to better understand the effects of HOS on large truck drivers' safety. Of particular interest were questions related to using a cell phone while driving and lane-changing behavior. The summary of each question is presented separately below.

5.1 Using a Cell Phone While Driving

The influential factors that that were determined to either increase or decrease cell phone use probability among truck drivers can be leveraged to reduce the frequency of distracted driving and, thus, improve roadway safety for all users. Factors contributing to truck drivers' decisions to report cell phone use while driving included driver, work, temporal, and management characteristics, as well as driving behaviors. More specifically, age, single marital status, education, crash history, fatigue management, and driving hours management were all found to decrease the probability of truck drivers' decisions on reporting cell phone use while operating their large vehicles. From a policy standpoint, policies can be enacted at the strategic operating level of private carriers to address factors that influence cell phone use among truck drivers. For instance, this study showed that factors related to fatigue and driving hours management, such as restricting the number of hours worked or schedules that enable drivers to easily take breaks when fatigued, are effective methods to reduce the likelihood of truck drivers using a cell phone while driving. As shown, CMV carriers that restrict the number of hours worked per shift is an ineffective policy for mitigating cell phone use while driving. This finding can support other means of restricting driving hours, such as the number of consecutive hours driven before taking a break. CMV carriers can develop and enforce similar policies within their company to reduce the occurrence of distracted driving among their truck drivers.

Furthermore, income level, safety training, difficulty finding safe parking, and various driving behaviors (driving while tired, frequency of breaks) were found to increase the probability of truck drivers reporting cell phone use while driving. As mentioned, safety training programs may cause an overestimation of drivers' ability to operate a large truck and lead to increased self-efficacy of driving (Gregersen, 1996; Hill et al., 2015). In addition to developing driving skills, future safety training programs can include topics that highlight the sources and safety implications of distracted driving. Additionally, government agencies can reduce the likelihood that truck drivers would use their cell phone while driving by addressing truck parking shortages. In 2012, the Federal Highway Administration determined that there is a severe and widespread truck parking shortage in the U.S. (Federal Highway Administration, 2012). If truck drivers can find truck parking locations without difficulty, they may be less inclined to use their cell phone while driving and reduce their crash risk.

5.2 Lane-Changing Movements

Lane changing is necessary on multilane highways, and it is deemed to be a primary cause of two-vehicle crashes involving at least one large truck. Therefore, a better understanding of the effects of driving behavior and the driving environment on drivers' decision making when changing lanes is crucial for developing appropriate countermeasures to reduce such crashes. The current study, therefore, utilized a multivariate probit model to identify the factors that influence lane-changing decisions for drivers of large trucks. The multivariate probit model was used because of the correlation between the dependent variables and the error terms across equations, as the multivariate probit model attempts to account for this correlation. In this study, the dependent variables were the drivers' perspectives on six lane-changing scenarios. These scenarios were selected to represent all possible lane-changing situations in which passenger vehicles and/or other trucks may be in the "no-zone" areas of large trucks. These include a passenger vehicle in front of the truck, another truck in front, a passenger vehicle behind the truck, another truck behind, a passenger vehicle on either side of the truck, and another truck on either side.

The analysis assessed all the possible factors affecting truck drivers' decisions to report lane-changing maneuvers on multilane highways. These included driver characteristics, temporal characteristics, roadway characteristics, built environment variables, driver and occupant characteristics, driving characteristics, and driver fatigue management factors. The results demonstrated that all tetrachoric correlations between each pair of lane-changing scenarios were positive and highly significant. In particular, the correlations between y_5 and y_6, and between y_2 and y_4 were very high. This reveals that these dependent variables and the error terms were highly correlated, in that situations in which another truck and a passenger vehicle were following them very closely were likely to influence one another. Likewise, drivers indicated that the situation in which passenger vehicles and other trucks were on either side of their trucks posed a high risk. As a result, the probability of drivers reporting lane changing in these situations was substantially higher.

Regarding the drivers' perspectives on the factors that greatly influence drivers' behaviors in lane-changing maneuvers, the empirical results revealed that four factors (with higher marginal effects) were highly significant. These factors were the indicator variable representing truck drivers who did not find any difficulty finding safe and adequate parking (-0.479), drivers who often drove when tired (-0.627), drivers who strongly agreed that fatigue management did not require taking breaks when driving long distances (-0.360), and drivers who stated that the presence of a passenger vehicle in front of their trucks posed the greatest safety hazard (0.510). Except for the first factor (truck drivers who did not find any difficulty finding safe and adequate parking), the other factors emphasize the drivers' perception that the presence of passenger vehicles in the large trucks' blind spots is problematic.

In particular, the findings of this study can prompt transportation agencies and the trucking industry to further cooperate toward exploiting advanced technology to mitigate lane changing related to crashes involving large trucks. This could be achieved by increasing the deployment of integrated in-vehicle crash avoidance warning systems for passenger vehicles and large trucks. Specifically, they could support the installation of lane change assistance (LCA) systems to enable trucks and passenger vehicles to perform some kind of communication with surrounding traffic and to alert drivers when changing lanes to avoid colliding with another vehicle in an adjacent lane. Similarly, a recent study showed that smartphone collision warning applications can be used to generate safer driving behavior (Botzer et al., 2017). With smartphone market penetration, this may be a viable option to give drivers of large trucks warning when they change lanes. Moreover, Mangones et al. (2017) found that the implementation of crash avoidance systems on transit buses in New York was economically justifiable, which could also be the case for large trucks.

Another option, and more economically viable for trucking firms, would be to post warning signs on their trucks to encourage drivers to stay out of their blind spots (Green, 2018). In addition, drivers can reduce their blind spots by adding more mirrors to their truck and having mirrors located in several different positions. Specifically, Green (2018) recommended that simply mounting two mirrors on both the right- and left-hand side of the hood can significantly narrow the size of blind spots. Similarly, drivers can install accessories to help with lane-changing behavior, such as audible tones, wide-angle cameras, and fish-eye mirrors (Green, 2018).

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APPENDIX

Front Matter

Do you drive a commercial grade truck for your profession?

- Yes
- No

Do you pickup or deliver goods in the Pacific Northwest (California, Idaho, Oregon, Washington, or British Columbia)?

- Yes
- No

EXPLANATION OF RESEARCH
Project Title: Confounding Factors of Commercial Motor Vehicles in Safety Critical Events
Principal Investigator: Salvador Hernandez, PhD
Student Researcher: Jason Anderson, Nabeel Al-Bdairi, and Aleah Olsen
Sponsor: PACTRANS
Version Date: July 10, 2017

Purpose: You are being asked to take part in a research study. The purpose of this research study is to give guidance and to assist the Pacific Northwest in important policy decisions with regards to improved roadway safety and truck parking issues in the region. The results of the study will be used for the graduate student's dissertation.

Activities: The study activities include the administration of a survey designed to understand driving behaviors.

Time: Your participation in this study will last about 15 minutes.

Confidentiality: It is possible that others could learn that you participated in this study but the information you provide will be kept confidential to the extent permitted by law. The data will be shared between Oregon State University and collaborating institutions.

Risks: The security and confidentiality of the information collected from participants online cannot be guaranteed. Confidentially will be kept to the extent permitted by the technology being used. Information collected online can be intercepted, corrupted, lost, destroyed, arrive late or incomplete, or contain viruses.

Benefits: There are not direct benefits to participants, however the research has the potential to influence improved roadway safety for commercial motor vehicle drivers.

Voluntary: Participation in this study is voluntary. If you choose to participate, you can choose to skip questions, however for your results to be included in the research all question must be answered.

Study contacts: If you have any questions about this research project, please contact: Dr. Salvador Hernandez at sal.hernandez@oregonstate.edu. If you have questions about your rights or welfare as a participant, please contact the Oregon State University Institutional Review Board (IRB) Office, at (541) 737-8008 or by email at IRB@oregonstate.edu

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Socioeconomic Characteristics (individual)

We care about the quality of our data. In order for us to get the most accurate measures of your opinions, it is important that you thoughtfully provide your best answers to each question in this survey.

Do you commit to thoughtfully provide your best answers to each question in this survey?

- ○ I will provide my best answers
- ○ I will not provide my best answers
- ○ I can't promise either way

Are you male or female?

- ○ Male
- ○ Female

Age: How old are you (please enter a value)?

Which of the following annual income categories best describes you?

- less than $19,999
- $20,000 - $29,999
- $30,000 - $39,999
- $40,000 - $49,999
- $50,000 - $59,999
- $60,000 or more

How are you normally paid?

- hourly rate
- flat day rate
- day rate with overtime
- flat weekly rate
- weekly rate with overtime
- flat rate for every contained or truck load carried
- for each pallet carried
- trip was part of a long term contract

Which of the following categories best describes your marital status?

single	married or defacto relationship	divorced or separated	widowed

What is your highest completed level of education?

- primary, elementery/middle school only
- some high school/technical school
- completed high school/technical school
- trade or technical certificate
- some secondary education
- completed secondary diploma/degree

What type of company do you work or contract for?

For-hire	Private carriage	Both for-hire and private	Don't know/refuse
○	○	○	○

Business Characteristics

What type of company do you work or contract for?

For-hire	Private carriage	Both for-hire and private	Don't know/refuse
○	○	○	○

To the best of your knowledge, what is the total number of trucks operating in your company?

To the best of your knowledge, what is the total number of drivers operating in your company?

On average, how many freight related trips do you make weekly (please enter a value)?

On average, how many miles do you drive trucks each week (please enter a value)?

miles

About what percentage of your total freight related trips (e.g. trips loaded or empty) are within the following ranges (must add up to 100%)?

Less than 50 miles	0 %
50 to 99 miles	0 %
100 to 249 miles	0 %
250 to 500 miles	0 %
greater than 500 miles	0 %
Total	0 %

Driver Characteristics

On average, what type of shipments do your trips consist of?

less-than-truckload	truckload	parcel	don't know/refuse
○	○	○	○

How many years have you been driving commercial motor vehicles (please enter a value)?

Years ______

How did you learn to drive the semi-truck you drive?

- ○ self taught
- ○ relative
- ○ friend
- ○ previous/present employer
- ○ military/services
- ○ driving school

Do you usually drive on:

- ○ highways
- ○ rural roads
- ○ city roads
- ○ a mixture

How often would you check your truck over each week?

- ○ hardly ever - it's not your job
- ○ occasionally - perhaps once every few days
- ○ before starting each trip
- ○ before starting and at every stop
- ○ only when you think something is wrong

Do you participate in team driving?

- never
- rarely
- sometimes
- often
- always

When it comes to deciding where to stop to park...

- I typically make that decision
- my company (e.g., dispatcher, etc.) makes that decision
- other, please specify

Have you ever had any specific road safety training?

- yes
- no

Driving Characteristics

How confident are you in your abilities to professionally drive a semi-truck

- extremely confident
- very confident
- moderately confident
- slightly confident
- not at all confident

What is the average speed that you drive on main roads in miles per hour (MPH) on non-freeways?

What is the average speed that you drive on freeways/interstates in miles per hour (MPH) ?

Which situation poses the highest safety hazard?

- passenger vehicle in front
- passenger vehicle behind
- truck in front
- truck behind
- passenger vehicles on either side
- trucks on either side

Do you change lanes to avoid traveling with...

	Often	Sometimes	Never
passenger vehicle in front	○	○	○
passenger vehicle behind	○	○	○
truck in front	○	○	○
truck behind	○	○	○
passenger vehicles on either side	○	○	○
trucks on either side	○	○	○

How often do you find your concentration lapsing after driving for a long time?

very often	quite often	sometimes	rarely	never
○	○	○	○	○

Do you use a cell phone while driving? (either handheld or hands-free)

- yes
- no

If so, on average how long are you usually on the phone while driving (in minutes)?

Accident Characteristics

During the last 5 years how many accidents have you had in which the police had to attend?

one	two	three	four or more	none
○	○	○	○	○

Did this accident/any of these accidents not involve other vehicles (e.g. you ran off the road/hit something on the road)?

○ yes

○ no

Thinking about the last accident you had - was your truck loaded or unloaded at the time?

empty	partially loaded	fully loaded	can't recall
○	○	○	○

Roughly, how far had you driven before you had that accident (please enter a value)?

○ miles

○ can't remember

Which road type were you driving on during your last crash

○ highway

○ rural road

○ city road

What weather conditions were present at the time of crash?

Clear	Cloudy	Rain	Snow	Fog
○	○	○	○	○

What time of day did your crash occur?

○ Beginning of shift

○ Near the middle of shift

○ Near the end of shift

early morning (midnight - 5:59 am)

morning (6:00 am - 9:59 am)

mid-day (10:00 am - 3:59 pm)

afternoon (4:00 pm - 8:59 pm)

evening (9:00 pm - 11:59 pm)

In your experience, what times of the day have you found to be the MOST difficult in finding safe truck parking? (Please select all that apply)

- early morning (midnight - 5:59 am)
- morning (6:00 am - 9:59 am)
- mid-day (10:00 am - 3:59 pm)
- afternoon (4:00 pm - 8:59 pm)
- evening (9:00 pm - 11:59 pm)
- I don't have difficulty

In your experience, what days of the week have you found to be the MOST difficult in finding safe truck parking? (Please select all that apply)

- Sunday
- Monday
- Tuesday
- Wednesday
- Thursday
- Friday
- Saturday
- I don't have difficulty

Which months of the year have you found to be the MOST difficult in finding safe truck parking? (Please select all that apply)

- January
- February
- March

- April
- May
- June
- July
- Aust
- September
- October
- November
- December

How often does the lack of available parking cause problems with adhering to the hours of service limitations?

- Almost never
- Sometimes
- Frequently
- Almost always

Does your routing software accurately provide you with the location of truck parking on routes?

- Yes
- No

Driving Management (Fatigue, HOS)

Does your company monitor levels of fatigue in drivers?

- yes
- no
- other

When managing drivers working hours does your company put a restriction on any of the following:

- on the number of hours worked per day
- on the number of hours worked per week
- on the number of continuous days workd
- on the number of nights drivers can work in a week

How does your company monitor driver fatigue? (select all that apply)

- ask drivers how they felt
- use monitoring devices
- review drivers' log books
- review truck computer records
- review accidents and incidents
- other, please specify

How is fatigue managed?

	strongly agree	Agree	neither	Disagree	Strongly disagree
management encourages me to take breaks from driving whenever i need to	○	○	○	○	○
I would prefer to carry on driving rather than stop to take breaks	○	○	○	○	○
I rarely feel the need to take breaks when driving long distances	○	○	○	○	○
drivers are always allowed sufficient time to reach their destination	○	○	○	○	○

	strongly agree	Agree	neither	Disagree	Strongly disagree
the schedule imposed by my company makes it easy for me to take a break whenever i feel i need to	○	○	○	○	○

When required to rest, have you experienced any problems finding a safe and adequate location to park your truck?

- ○ yes
- ○ no

How well do you feel that fatigue is managed in the industry now?

- ○ extremly badly
- ○ quite badly
- ○ quite well
- ○ very well
- ○ don't have an opinion

How often do you drive when tired?

- ○ very often
- ○ quite often
- ○ sometimes
- ○ rarely
- ○ never

Do you feel you get enough time to stop to rest when you feel tired?

- ○ Yes
- ○ No

When you are making a longer trip, how often do you stop?

- only when tired
- every 2-3 hours
- every 3-4 hours
- every 4-5 hours
- every 5-6 hours
- every 6-8 hours
- you try not to stop at all

If trucks are required to have electronic logging devices installed that have the capability to monitor truck operations and movement, will that impact your driving/operations decisions?

- Yes
- Maybe
- No

If trucks are required to have electronic logging devices installed, would the amount of time you spend driving change?

- Large decrease
- Small decrease
- No change
- Small increase
- Large increase

Truck Configuration

How often do you drive a tractor with two trailers?

- Very often
- Quite often
- Sometimes
- Rarely

Almost never

Is driving and operating a tractor with two trailers more challenging than a tractor with one trailer?

- ○ Yes
- ○ No
- ○ Maybe

Would driving a tractor with two 33 ft. trailers be more challenging or dangerous than a tractor with two 28 ft. trailers?

- ○ Yes
- ○ No
- ○ Don't know