AN ABSTRACT OF THE THESIS OF

Joseph B. Claveria for the degree of Master of Science in Civil Engineering presented on May 10, 2018.

Title: Evaluating Distracted Driving Behavior Among Drivers of Large Trucks Through Econometric Modelling: A Pacific Northwest Case Study

Abstract approved:

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Distracted driving is an adverse driving behavior that is widely known to impair the safety of all roadway users and traffic flow. Despite the extensive research efforts on the prevalence and effects of distracted driving on roadway safety and performance, the number of vehicular crashes and fatalities resulting from distracted driving have continued to rise in recent years. This increasing trend may indicate that traditional distracted driving research efforts fail to yield effective solutions that reduce its presence on roadways. Alternatively, understanding the influential factors on the likelihood that drivers would engage in distracted driving behavior has the potential to develop effective distracted driving mitigation strategies. Recently, many studies have identified these factors that influence distracted driving behavior among passenger car drivers and few have focused on such factors affecting distracted driving behavior among drivers of large trucks. Because large truck involved crashes tend to result in more severe injury crashes and distracted driving among drivers of large trucks significantly increases crash risk, it is important to understand the factors that influence the likelihood that truck drivers would engage in distracted driving. Therefore, the objective of this thesis is to identify the factors that influence the likelihood that drivers of large trucks would engage in distracted driving behavior to aid interested

stakeholders mitigate distracted driving among drivers of large trucks. This thesis applies econometric methods on stated-preference survey data distributed to drivers of large trucks to determine the factors that affect the likelihood of self-reported distracted driving behavior. Results from this analysis indicate that policies tailored to improving trucking parking, certain fatigue management strategies, and encouraging short-haul deliveries have the potential to reduce distracted driving among drivers of large trucks.

This thesis is presented in two manuscripts that expands existing distracted driving literature by identifying influential factors of distracted driving behavior among drivers of large trucks. In Chapter 2, a random parameters binary logit model is used to determine the factors influencing cell phone use while driving among truck drivers. In Chapter 3, a random parameters bivariate binary probit model is applied to determine the factors that influence truck driver engagement with driver internal and driver external sources of distractions. With the continuous technological advancements and the inherent job responsibilities of truck drivers that require such devices, it is imperative to understand these factors so that effective distracted driving countermeasures can be developed.

Evaluating Distracted Driving Behavior Among Drivers of Large Trucks Through Econometric Modelling: A Pacific Northwest Case Study

by
Joseph B. Claveria

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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Joseph B. Claveria, Author

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CONTRIBUTION OF AUTHORS

Dr. Eric Jessup of Washington State University assisted with the collection of the survey data used in Manuscripts 1 and 2. Jason Anderson assisted with the writing and development of the methodology sections in Manuscripts 1 and 2.

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1 CHAPTER 1 - INTRODUCTION

1.1 Motivation

Since the inception of vehicles, drivers have engaged in behaviors that are detrimental for the safety of all road users. Whether intentional (speeding, ignoring traffic control devices, distracted driving, etc.) or unintentional (i.e., inattention, lapses in concentration, etc.), these adverse driver behaviors have been shown to contribute to traffic collisions (Cordazzo et al., 2014; Federal Motor Carrier Safety Administration, 2005; Gordon, 2009; National Center for Statistics and Analysis, 2017a; Treat, 1980). Treat (1980), in a multilevel analysis of more than 13,500 police-reported accidents, determined that human factors were a definite cause of 70.7% vehicular accidents. Of these human factors, Treat found that improper lookout (17.6%), inattention (9.8%), and internal distraction (5.7%) were among the top five most frequently implicated human errors. As evinced by Treat (1980), various forms of adverse driving behavior, particularly distracted driving, have been a major cause in vehicular accidents even before the technological advancements made to-date.

More recently, the National Highway Safety Administration (NHTSA) reports that distracted driving accounts for approximately 25% of all police reported crashes and is continuing to grow (Ranney et al., 2000; Wang et al., 1996). The National Center for Statistics and Analysis (NCSA) report that crashes involving distracted driving have increased by approximately 7% between 2011 (3,020) and 2015 (3,196) (NCSA, 2013, 2017). Over this period, fatalities resulting from distracted driving increased from 385 fatalities in 2011 to 476 fatalities in 2015, or 24% (NCSA, 2013, 2017). Further, NHTSA reports that fatalities due to distracted driving had the largest percent increase (8.8%) between 2014 and 2015 over other casual factors, such as alcohol-impaired or speed-related fatalities (NCSA, 2017). In terms of large trucks (GVWR greater than 10,000 pounds), the Large Truck Crash and Causation Study (LTCCS) reports that 35% of large truck-involved crashes in the US involved one form of driver recognition error, or inattention (Federal Motor Carrier Safety Administration, 2005). Additionally, the Federal Motor Carrier Safety Administration (FMCSA) reports that driver distraction/inattention was the second most common truck driver-related factor in single- and multiple-vehicle fatal crashes (FMCSA, 2016). These statistics ascertain that distracted driving is both a current and increasing issue in roadway safety and needs to be further investigated to reduce its presence on roadways.

To reduce the effects of distracted driving on roadway safety, extensive research has been conducted to further understand the prevalence of distracted driving and its effect on driver performance and crash risk (Beanland et al., 2013; Caird et al., 2008; Dingus et al., 2016; Fitch et al., 2013; Gliklich et al., 2016; Hickman and Hanowski, 2012; Klauer et al., 2006; McEvoy et al., 2005; McEvoy and Stevenson, 2007; Olson et al., 2009; Oviedo-Trespalacios et al., 2017b; Ranney, 2008; Schroeder et al., 2013; Strayer and Drew, 2004; Stutts et al., 2001; Violanti, 1997). However, according to Regan et al. (2011), distracted driving can arise from driver internal (e.g., daydreaming, mind wandering, lapses in concentration) and driver external (e.g., using a cell phone, adjusting radio, eating) sources. Majority of the existing distracted driving literature has primarily focused on distractions arising from driver external sources and do not investigate driver internal sources. Further, a significant portion of this literature has only assessed the impact of cell phone use among passenger car drivers and very few investigate its impact among drivers of large trucks. As such, there is a clear gap in driver inattention literature in that existing studies fail to consider drivers of large trucks and other sources of driver inattention.

Although understanding the safety implications of distracted driving on roadway safety is an important step in reducing crashes resulting from driver distraction, it is often difficult to derive effective strategies from such studies (Fitch et al., 2013; Klauer et al., 2006; McEvoy et al., 2005; Ranney, 2008). Until recently, few studies have emerged that investigate the factors influencing drivers' decisions to engage in distracted driving. Studies by Oviedo-Trespalacios et al. (2017), Marquez et al. (2015), Kidd et al. (2016), Hurwitz et al. (2016), and Jashami et al. (2017) have applied econometric modelling techniques on collected survey data to determine the factors that influence the likelihood that passenger car drivers would report using their cell phone (either texting or talking) while driving. While innovative, these studies only furthered the understanding of the relationship between cell phone use while driving and passenger car drivers, failing to account for drivers of large trucks and other sources of distraction.

To the author's knowledge, only one study has identified the factors that influence truck drivers' decision to use a cell phone while driving (Troglauer et al., 2006). The study by Troglauer et al. (2006) is limited, however, in that the analytical procedure used does not account for unobserved heterogeneity, which exists in most data sets, and results in inaccurate estimates and erroneous inferences (Mannering et al., 2016). Although this study fulfills a gap in literature by examining the factors influencing truck drivers' decision to use a cell phone while driving, it does not consider truck drivers' susceptibility to other forms of distracted driving, such as concentration lapsing (or inattention). Understanding the factors that directly influence drivers' decisions to engage in distractive tasks may be more beneficial to transportation officials in developing effective mitigation techniques.

1.2 Research Questions

To fill the gap in driver distraction literature, this thesis intends to understand the relationship between driver internal and driver external sources of driver distraction and drivers of large trucks. Specifically, this thesis identifies the factors that influence the likelihood that truck drivers would self-report using a cell phone and, as a proxy to driver internal sources, lapses in concentration while driving. These factors are determined through the application of advanced econometric modelling frameworks on data obtained from a stated-preference survey distributed to drivers of large trucks in the Pacific Northwest. This thesis expands on the well-known relationship between cell phone use and roadway safety by addressing the following research questions:

1) As measured by self-reported engagement, what are the factors that influence the likelihood of self-reported cell phone use while driving among Pacific Northwest truck drivers?

2) As measured by self-reported engagement, what are the factors that influence the likelihood that Pacific Northwest truck drivers experience lapses in concentration while driving?
3) Is there a statistical correlation between using a cell phone while driving and, simultaneously, experiencing lapses in concentration (or inattention) while driving?
   3a) If so, what are the factors that simultaneously impact the likelihood that truck drivers would self-report using a cell phone and experiencing lapses in concentration while driving?
4) What policies or initiatives can be derived from these findings to aid transportation agencies and CMV carriers alleviate the effects of distracted driving?

Because the term “loss of concentration” was not explicitly defined in the survey instrument, it is subjected to a variety of interpretations. This study follows the distracted driving definition developed by Regan et al. (2011), which considers lapses in concentration to include intentional or unintentional, internally triggered, task-unrelated thoughts (i.e., mind wandering, daydreaming).

The results of this thesis have the potential to aid transportation agencies and commercial motor vehicle (CMV) carriers develop effective countermeasures to reduce crashes resulting from driver distraction. For example, the factors that decrease the likelihood that truck drivers would experience lapses in concentration or use a cell phone while driving can be integrated into safety programs or policies to reduce its prevalence on roadways. If the factors influencing a truck drivers’ decision to engage in a distractive activity are understood, strategies can be implemented to potentially reduce the frequency of distracted driving and, subsequently, reduce distraction-affected crashes involving large trucks. The results of this work also provide a framework that can be used by stakeholders to conduct future distracted driving studies.

1.3 Methodological Approach

As discussed in detail in the ensuing chapters, the logistic (logit) and probit discrete choice modelling frameworks are utilized in this thesis to determine the factors that influence the likelihood of self-reported distracted driving behavior among drivers of large trucks. Further, the random parameter heterogeneity based extension is applied to both standard frameworks to account for unobserved heterogeneity (i.e., factors) that are not captured in the survey instrument and yield more accurate estimates and inferences (Mannering et al., 2016). In Chapter 3, the bivariate binary extension of the probit regression model is used to simultaneously determine influential factors that affect the likelihood of self-reported cell phone use and experiencing concentration lapses while driving.

In transportation literature, discrete choice modelling frameworks have been widely used for a variety of purposes, such as predicting injury severity levels and choice behaviors (i.e., route choice, seatbelt use, etc.) (Anderson and Hernandez, 2017; Haleem and Abdel-Aty, 2010; Jashami et al., 2017; Pahukula et al., 2015; Russo et al., 2014a, 2014b; Savolainen et al., 2011; Washington et al., 2011; Zhu and Srinivasan, 2011). Because the dependent variables of this thesis are binary in nature (i.e., a truck driver responds with either yes or no), the use of the binary logit and probit regression models are necessitated. This modeling framework is consistent with past studies that investigated the factors influencing drivers' decision to self-report distracted driving behavior (Jashami et al., 2017; Kidd et al., 2016; Márquez et al., 2015; Oviedo-Trespalacios et al., 2017b). Although these modelling frameworks have been used in previous studies, the work of this thesis, to the author's knowledge, would be one of the first to apply an advanced econometric technique (random parameters) to determine the factors that influence truck drivers' decision to report driver distraction – cell phone use and experiencing lapses in concentration while driving.

1.4 Thesis Organization

This thesis is presented in manuscript form to understand the factors that influence the likelihood that drivers of large trucks would self-report driver external or driver internal distractions.

Chapter 2 determines and assesses the factors that influence the likelihood that drivers of large trucks in the Pacific Northwest would self-report using their cell phone while driving by using a random parameter binary logit model. This chapter motivates the need for this research, reviews relevant literature, and provides solutions that have the potential to reduce the likelihood of truck drivers using their cell phone while driving.

In Chapter 3, factors that contribute to truck drivers engaging in driver internal distractions, as measured by self-reported lapses in concentration while driving, are determined. However, as discussed in Chapter 3, there is an inherent relationship between secondary task engagement while driving and increased cognitive load, which leads to driver internal distractions. This relationship creates a correlation between the error terms of experiencing lapses in concentration while driving, which is a proxy to understand driver internal distractions, and cell phone use. If this correlation is not accounted for, parameters estimates may be inconsistent and less asymptotically inefficient, resulting in erroneous inferences (Hensher et al., 2015; Wooldridge, 2010). As such, a random parameter bivariate binary probit model is utilized in this chapter to account for this correlation amongst error terms.

Chapter 4 concludes this thesis by summarizing the overall findings of this work and providing mitigation techniques that have the potential to resolve the current problem of distracted driving problem.

2 CHAPTER 2 – UNDERSTANDING TRUCK DRIVER BEHAVIOR WITH RESPECT TO CELL PHONE USE AND VEHICLE OPERATION

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2.1 Abstract

Distracted driving continues to pose threats to transportation safety as it impairs driver performance and increases crash risk. In recent years, cell phone use while driving has become the primary research interest regarding distracted driving. However, majority of this research has focused on the prevalence and risks of such behavior in passenger car drivers and few have investigated its effect on the performance of drivers of large trucks. Due to the inherent job responsibilities, truck drivers are more susceptible to use a cell phone, or other communication devices (e.g,, CB radio), while driving to coordinate delivery logistics. The purpose of this study is to further understand distracted driving in the context of large trucks by identifying the factors that contribute to large truck drivers' decision to report using a cell phone while operating a commercial motor vehicle. Through survey data collected in 2017 from drivers of large trucks who either pick-up or deliver goods in the Pacific Northwest (Oregon, Washington, Idaho, British Columbia), a random parameters binary logit model is used to identify these factors. Of the 515 respondents, 234 (45%) indicated that they use a cell phone while driving. Through the random parameters binary logit model, unobserved heterogeneity is captured, and certain driver behaviors, demographic, work, temporal, and management characteristics are found to affect the likelihood of truck drivers reporting to use their cell phone while driving. The findings of this study have the potential to aid government agencies and commercial motor vehicle carriers in understanding the factors influencing cell phone use while driving among truck drivers. Understanding these motives can aid in the development of

programs and policy initiatives that are intended to mitigate distracted driving among truck drivers.

Key Words: Distracted Driving, Cell Phone, Large Trucks, Random Parameters, Binary Logit, Driver Inattention

2.2 Introduction

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 (Farmer et al., 2010; Haigney et al., 2000; Klauer et al., 2006; Oviedo-Trespalacios et al., 2017b; Stavrinos et al., 2013). This interest stems from an increase in distracted driving related crashes. In 2015, fatalities involving cell phone use throughout the United States increased from 385 in 2011 to 476, or 23.6 percent (National Center for Statistics and Analysis, 2017b). These values are grossly underreported due to a lack of methods and/or procedures to assess the culpability of a crash due to cell phone use while driving. Furthermore, traffic fatalities that were attributed to distracted driving had the largest percentage increase (8.8 percent) from 2014 than alcohol-impaired or speed-related fatalities (National Center for Statistics and Analysis, 2017b). Of special interest are fatalities involving large trucks crashes (vehicle weighting greater than 10,000 pounds) which have continued to increase since 2009. In 2015, there were 4,067 killed in crashes involving large trucks compared to 3,380 in 2009; a 20% increase (National Center for Statistics and Analysis, 2017a).

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 of (in 2005 USD) 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 where 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 (Al-Bdairi et al., 2018; Al-bdairi and Hernandez, 2017; Anderson and Hernandez, 2017; Pahukula et al., 2015), the relationship between cell phone use, distracted driving and large truck-involved crashes are not completely understood. This may be caused by the fact that in most distracted driving studies, data is derived from either naturalistic or simulator studies, which are both time and cost intensive, or crash data, which are retroactive in nature and typically results in significant amounts of unknown or missing information (Regan et al., 2008). Further, majority of the efforts in understanding distracted driving have only been applied to passenger vehicles (Dingus et al., 2016; Klauer et al., 2006). Few studies, however, 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 (Hickman and Hanowski, 2012; Olson et al., 2009). While studies conducted by Hickman & Hanowski (2012) and Olson et al. (2009) provide insight into the frequency and crash risk of distracted driving among commercial motor vehicle drivers, they do 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 is to seek and gain a better understanding of the factors that influence truck drivers' decisions to report using electronic mobile devices while driving. To accomplish this, a stated-preference survey distributed in 2017 to drivers of large trucks who originate, are destined to, or pass through the Pacific Northwest (Washington, Oregon, Idaho) is utilized. A random parameters binary logit modeling framework is then used and estimated to gain insights into the complex interactions between the factors captured through the survey and those unobserved factors (i.e., unobserved heterogeneity) that may be influencing cell phone use while driving. In doing so, this study seeks 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.

2.3 Literature Review

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 (Lee et al., 2009; Ranney et al., 2000; Regan et al., 2011; Young and Regan, 2007). Regan et al. (2011) developed a taxonomy of driver distraction that includes five sub-categories: restrictive, mis-prioritized, neglected, cursory, and diverted attention. These sub-categories consider 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 and driving have been widely studied in the context of passenger cars (Beanland et al., 2013; Caird et al., 2008; Dingus et al., 2016, 2006; Haigney et al., 2000; Hurwitz et al., 2013; McEvoy and Stevenson, 2007; Regan et al., 2008). In two naturalistic studies, cell phone use was present in about 23% of all crashes and near-crashes, and at least one form of driver inattention in as much as 78% 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 (Hickman and Hanowski, 2012; Klauer et al., 2006). Still, subtasks of cell phone use, such as texting, emailing, or operating the phone, increases crash risk odds by at least 3.5 times and as high as 164 times (Hickman and Hanowski, 2012; Klauer et al., 2006). 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 prove 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 had consistent findings with the results from passenger car studies in that 60% 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, is consistent with this finding and reports that 35% 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% of crashes where the large truck was assigned the critical reason for the crash was 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, increases the odds of being involved in a crash or near-crash by 164 times. Further, engaging in either a complex tertiary task (interacting with dispatch device, dialing cell phone) or moderate tertiary task (use other electronic device, talk/listen to 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 needed 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 their findings are limited. Data sources that derive from police crash reports are subjected to bias and significant amounts of unknown or missing information (Gordon, 2009). While naturalistic data observes drivers in real-time driving conditions, they are often time, cost, and data intensive. Additionally, the statistical measures used in these studies are limited and do not account for any unobserved heterogeneity in the data collection process or contributing factors to critical safety events. The results from these studies utilize simple statistical measures to determine either odds ratios of being involved in safety critical events or prevalence and frequency of driver distraction in vehicle crashes (Asbridge et al., 2012; Dingus et al., 2006; Hanowski et al., 2005; Olson et al., 2009).

To overcome these shortcomings, few studies have ventured away from traditional distracted driving study methods to assess personal and behavioral information that influence cell phone use while driving (Kidd et al., 2016; Márquez et al., 2015; 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 are instrumental for improving roadway safety as they 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. Despite providing useful information, these studies have been limited to passenger car drivers and statistical models that do not account for unobserved heterogeneity.

One study, however, investigated 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 that lead to a higher prevalence of phone use among heavy-vehicle drivers. Additionally, this study reports that 99% of the respondents indicated that they use 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 being that cell phone use while driving has been proven to significantly increase crash risk (Chang and Mannering, 1999; Klauer et al., 2006). Although this study identifies certain driver characteristics that are more likely to use a cell phone while operating a heavy-vehicle, the statistical procedure used does not account for unobserved heterogeneity that is inherent in any survey data, which in turn results in erroneous estimates and corresponding inferences (Mannering et al., 2016).

The present study will expand 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 originate, are destined to, or pass 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 will overcome the limitations of previous studies by accounting for unobserved heterogeneity (unobserved factors) present in the data collection process. By identifying 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 amongst large truck drivers. To the authors' knowledge, this study would be 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.

2.4 Data Description

To determine the factors that influence a truck driver's decision to use a cell phone while driving, a stated-preference survey was developed and distributed to drivers of large trucks in 2017. This survey included a total of 64 questions divided into eight parts: socioeconomic, business, driver, driving and accident characteristics, time of day operations, driving management, and truck configuration. To be considered for this study, truck drivers must have either originated in, or delivered goods, to the Pacific Northwest (Idaho, Oregon Washington). Drivers who passed through the Pacific Northwest were also considered for this study. The survey was administered through Oregon State University and utilized the Qualtrics survey platform, an online electronic survey program. The survey, prior to distribution, obtained approval from the Institutional Review Board (IRB).

All respondents voluntarily completed the survey, were at least 18 years of age, and held a Commercial Driver's license (CDL). A total of 1,919 individuals received the survey, but just 515 met the survey requirements and completed the survey; a response a rate of 26.8%. To determine the level of confidence that inferences can be made, the following equation is used (Smith, 2013):

$$n = \frac{z^2 \times p \times (1 - p)}{MoE^2} \qquad \text{Eq. (2-1)}$$

where n is the sample size needed for desired level of precision; p is an estimated value of proportion; MoE is the desired margin of sampling error; and z is the critical value for the desired level of confidence. As a conservative estimate, which assumes half of the population will answer positively and negatively to a posed question, a p value of 0.5 is used in this study (Dillman et al., 2014). Further, a value of 4.5 was assumed as the desired margin of error. In most studies, it is desired to achieve a 95% confidence level. The corresponding z value for this level of confidence is 1.96. Applying these values to Eqn. 1, it is determined that 475 responses are needed to ensure 95% confidence. With 515 valid and completed responses, this study exceeds this minimum requirement. In other words, parameter estimates and inferences can be made with well over 95% confidence.

The Internet Protocol addresses and geographical coordinates of respondents were recorded through Qualtrics, LLC. This data ensured that a single individual did not complete the survey twice and provide locational information to understand the geographical representation of respondents. Figure 1, using the geographical coordinates that were geocoded in ArcGIS, shows the relative location of survey respondents.

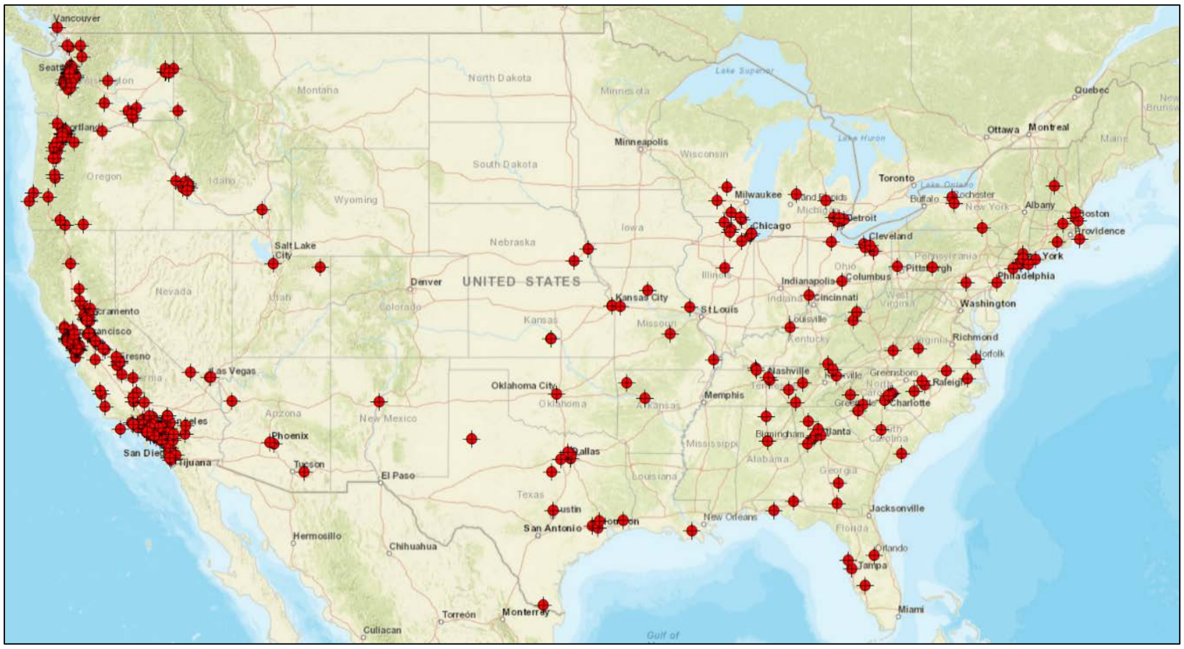

Figure 2-1: Origin of Truck Drivers that Deliver Goods in the Pacific Northwest

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 2 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 about 50% of surveyed respondents use a cell phone while driving (Nurullah et al., 2013; Schroeder et al., 2013).

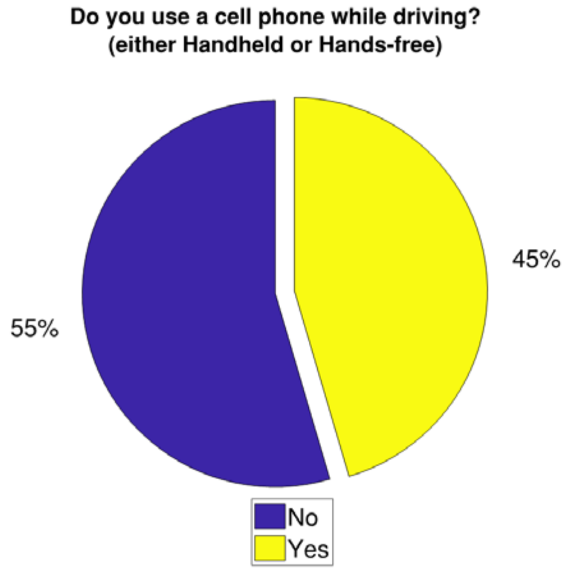

Figure 2-2: Percentage of respondents who indicate using a cell phone while driving

To corroborate on the increased crash risk associated with cell phone use while driving, self-reported crash history was disaggregated based on cell-phone use. In the survey, respondents were asked, *“During the last 5 years how many accidents have you had in which the police had to attend?”* Respondents had to respond with either one, two, three, four or more, or none. The initial survey analysis, as shown in Figure 3, revealed that 24% of respondents indicated that they were involved in at least one crash in the past five years in which the police had to attend. Of these respondents who indicated being involved in at least one crash in the past 5 years, 57% also reported that they use their cell phone while driving. As shown in Figure 4, the number of crashes reported by those who use their cell phone while driving is about 31% more than those who were involved in a crash and did not report cell phone use while driving. A t-test was conducted between these two groups and determined a statistically significant difference at the 99th percentile. Since the question was posed to the general use of cell phones while driving, this initial data comparison compliments the findings of Olson et al. (2009) and Klauer et al. (2006) that using a cell phone while driving leads to higher crash involvement.

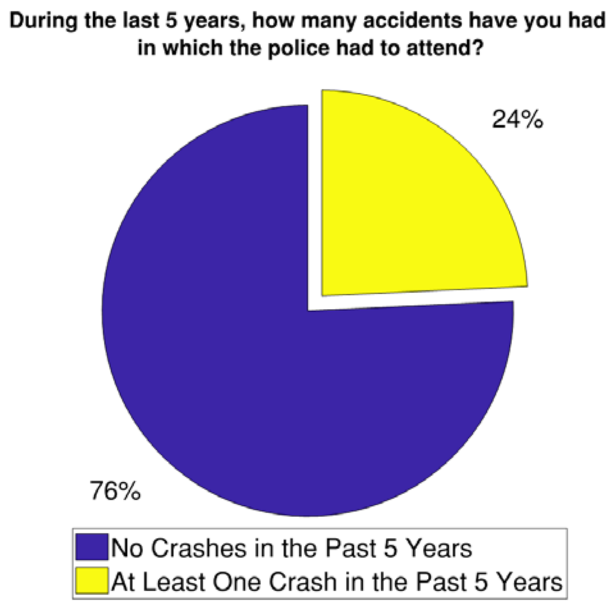

Figure 2-3: Self-Reported Crash History

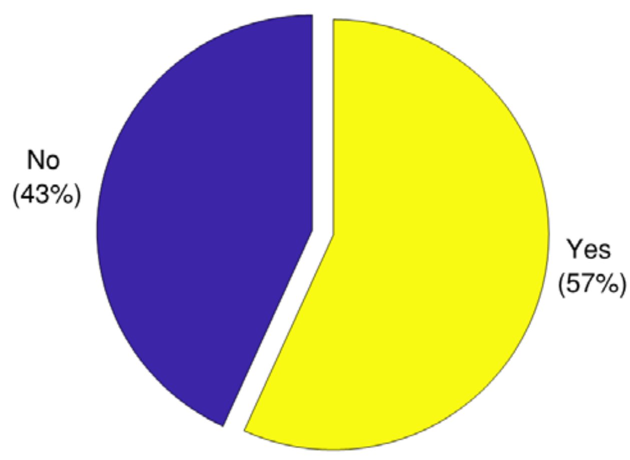

Figure 2-4: Respondents who indicate using their cell phone while driving and being involved in at least one crash in the past 5 years

Of the 288 indicator variables developed from the survey, 21 are found to be statistically significant. Descriptive statistics of these 21 significant variables, as well as the dependent variable, are shown in Table 1.

2.5 Methodology

As mentioned previously, the binary logit modelling framework has been applied in various areas of transportation engineering (Lee and Abdel-Aty, 2008; Moudon et al., 2011; Oviedo-Trespalacios et al., 2017b; Young and Liesman, 2007), 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 (Anderson and Hernandez, 2017; Islam et al., 2014; Milton et al., 2008; Morgan and Mannering, 2011; Pahukula et al., 2015). In this study, the reported use of a cell phone while driving is a binary choice; either the driver reports having used a cell phone while driving or the driver did not. Finally, since the survey data has inherent unobserved heterogeneity, a random parameters binary choice modelling framework is an appropriate technique for assessing drivers’ decisions on using a cell phone while driving.

Table 2-1: Descriptive Statistics of Significant Variables

Variable	Mean	Standard Deviation
Dependent Variable		
Cell Phone Use (1 if driver reports using a cell phone - either handheld or hands-free - while driving, 0 otherwise)	0.45	0.50
Driver Characteristics		
Age (1 if between 18 and 25, 0 otherwise)	0.16	0.36
Marital Status (1 if single, 0 otherwise)	0.26	0.44
Income (1 if between $50,000 and $60,000, 0 otherwise)	0.28	0.45
Education (1 if completed trade school or technical certificate, 0 otherwise)	0.23	0.42
Crash History (1 if involved in at least one crash in the past 5 years, 0 otherwise)	0.24	0.43
Safety Training (1 if participated in road safety training, 0 otherwise)	0.87	0.33
Work Characteristics		
Private Carriage (1 if present employer is operated under private carriage, 0 otherwise)	0.35	0.48
Start Work (1 if work starts between midnight and 6 am, 0 otherwise)	0.11	0.32
Start Drive (1 if drive starts between 10am and 4pm, 0 otherwise)	0.26	0.44
Rural Roads (1 if routes are usually driven on rural roads, 0 otherwise)	0.05	0.22
City Roads (1 if routes are usually driven on city roads, 0 otherwise)	0.05	0.22
Truck Parking (1 if driver decides parking location, 0 otherwise)	0.78	0.41
Trailer (1 if truck is driven very often with two trailers, 0 otherwise)	0.10	0.31
Temporal Characteristics		
Most Difficult Day of the Week Finding Safe Parking (1 if Tuesday, 0 otherwise)	0.27	0.45
Most Difficult Hour Finding Safe Truck Parking (1 if afternoon, 0 otherwise)	0.15	0.36
Driving Behavior		
Driving while tired (1 if often, 0 otherwise)	0.47	0.50
Never change lanes to avoid travelling with passenger vehicle behind (1 if yes, 0 otherwise)	0.33	0.47
Driving Break (1 if a stop is made every 4-6 hours on a longer trip, 0 otherwise)	0.33	0.47
Truck Inspection (1 if driver inspects truck before starting each trip, 0 otherwise)	0.46	0.50
Management Characteristics		
Fatigue Management (1 if schedule imposed by CMV carrier makes it easier to take a break, 0 otherwise)	0.29	0.45
Driving Hours Management (1 if CMV carrier restricts the number of hours worked per week, 0 otherwise)	0.49	0.50

Due to the binary nature of the selected response variable, a binary logistic regression model is applied. The two possible outcomes for the response variable are represented by the following: 1 if a driver reports using a cell phone while driving, and 0 otherwise (driver does not report using their cell phone while driving). The following binary logit formulation 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):

$$P_n(i) = \frac{e^{(\hat{\beta})}}{1 + e^{(\hat{\beta})}} \quad \text{where} \quad \hat{\beta} = \beta_0 + \beta_1 X_{1,n} + \cdots + \beta_i X_{i,n} \qquad \text{Eqn. (2-2)}$$

where $P_n(i)$ is the probability that a truck driver uses their 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 the data, there exists a significant amount of information that affects the likelihood of using a cell phone while driving that is not measured for in the analysis. Information, such as type of driver behavior (i.e., aggressive vs. passive), forgetfulness, and reporting false information (i.e., indicate no cell phone use while driving to comply with laws and policies) are possible unobserved factors that can affect model results for cell phone use while driving. However, these unobserved factors are 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 is applied to allow estimated parameters to vary across observations. Eq. (1) can now be written as (Washington et al., 2011):

$$P_n(i|\varphi) = \int_X \frac{e^{(\hat{\beta})}}{1 + e^{(\hat{\beta})}} f(\hat{\beta}|\varphi) d\hat{\beta} \qquad \text{Eq. (2-3)}$$

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 was 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 are used, as they have been proven to be computationally efficient and preferred over purely random draws (Bhat, 2003; J. Halton, 1960; Train, 2000).

Lastly, marginal effects are used to measure variable impact on the use of 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 are found to be significant. As such, marginal effects are 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):

$$ME_{X_k}^{P_n(i)} = \text{Prob}[P_n(i) = 1 \mid X_k = 1] - \text{Prob}[P_n(i) = 1 \mid X_k = 0] \qquad \text{Eq. (2-4)}$$

2.5.1 Test for Model Significance

A log-likelihood ratio test (LRT) was utilized in this study to determine if the random parameter binary logit model is of more significance than the fixed parameter binary logit mode.. The LRT is defined as (Washington et al., 2011):

$$\chi^2 = -2[LL_{fix}(\beta^{fix}) - LL_{ran}(\beta^{ran})] \qquad \text{Eqn. (2-5)}$$

where:
χ^2: chi-square statistic with degrees of freedom equal to the number of random parameters
$LL_{fix}(\beta^{fix})$: log-likelihood at convergence of fixed parameter binary logit model
$LL_{ran}(\beta^{ran})$: log-likelihood at convergence for random parameter binary logit model

The LRT is used in this study to test the hypothesis that the random parameters logit model is statistically more significant than the fixed parameters logit model.

2.6 Results and Discussion

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 are homogeneous across drivers) and seven random parameters (i.e., the variables are heterogeneous across drivers). Results of this final model are shown in Table 2, which include model specifications and corresponding marginal effects

2.6.1 Model Significance

Results of the LRT, Eqn. (5), determined that the random parameters binary logit model is statistically superior over its fixed parameters counterpart with over 90% 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 is 12.12, with seven degrees of freedom, which is equal to the number of random parameters. The associated p-value for this statistic is 0.0967, which suggests that, with over 90% confidence, the null hypothesis can be rejected and the random parameters model is statistically preferred over the fixed parameters model. Further, this result indicates that there is indeed variation across drivers regarding specific characteristics that impact a driver reporting to use a cell phone (or not).

2.6.2 Variable Discussion

The best fitted random parameter binary logit model determined that driver, work, temporal, and management characteristics, as well as driver behavior, all influenced the probability of self-reported cell phone use while driving among drivers of large trucks. Understanding these factors can assist transportation agencies and

CMV carriers in identifying and developing policies and programs that aim to mitigate distracted driving among truck drivers.

Table 2-2: Random Parameters Binary Logit Model: 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)*		
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)*		

Table 2-2: Random Parameters Binary Logit Model: Predicting Cell Phone Use Among Truck Drivers

Variable	Coefficient	*t*-statistic	Marginal Effect	t-statistic
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
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			

2.6.2.1 Driver Characteristics

Younger truck drivers, 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%

of drivers within this age group have an estimated parameter mean greater than zero and 90.4% of respondents in this driver demographic have an estimated parameter mean less than zero. In regards to the 9.6% of drivers that are more likely to report using their cell phone while driving, this finding is consistent with passenger car research that finds younger passenger car drivers more likely to uses their cell phones while driving than other age groups (Farmer et al., 2010; Gliklich et al., 2016; Oviedo-Trespalacios et al., 2017b; Young and Lenné, 2010). On the other hand, 90.4% of drivers between 18 and 25 are less likely to report using their cell phone while operating a truck. The heterogeneous nature of this variable may be capturing differences in job experience among younger truck drivers. For instance, if a truck driver falls within this age demographic and has minimal truck driving experience, they might be less likely to use their cell phone while driving because they are 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 are more likely to report using their cell phone while driving.

Single marital status was another sociodemographic factors 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% of drivers and less than zero for 63.7% of the drivers. In other words, 36.4% of single truck drivers are more likely to report using their cell phone while driving and 63.7% behave differently (i.e., less likely to self-report). One possible explanation for this non-homogenous nature is that the random parameter might be capturing unobserved differences for the need to use a cell phone while driving. According to Sarksisian and Gerstel (2015), 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 be more socially active than others, which prompts 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 is 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 is less than zero for 45.3% of drivers and greater than zero for 54.7% of drivers. The latter finding is consistent with past studies, in which participants in higher income brackets were 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 due to using a cell phone while driving. Some drivers within this income range may not be affected by the financial impact of a fine, whereas others are attempting 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 is less than zero for 1.4% of drivers and greater than zero for 98.6% of drivers. That is to say, just 1.4% of drivers who received some form of safety training are 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 due to the training received may explain why almost all drivers (98.6%) have an increased outcome probability of self-reporting cell phone use while driving. For instance, in a driving safety course, a driver might be taught to improve their skills, which leads them to believe that they can handle driving situations better than expected (Gregersen, 1996). This is supported by past research that 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., source and consequences of distracted driving) as it may result in an overestimation of their driving abilities. The remaining proportion of drivers who have a decreased outcome probability of reporting cell phone use may not be affected by safety trainings and continue to limit their exposure to risky driving behaviors.

Regarding the driver, education level and crash history were the final factors found to be significant in the model, where both factors decrease 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. Further, marginal effects show that those who indicated being involved in at least one crash in the past 5 years have a 0.212 increase in self-reporting probability of using a cell phone while driving. This finding is consistent with past research that found drivers who have been involved in a crash are more likely to self-report texting while driving (Hurwitz et al., 2016; Jashami et al., 2017). Being involved in a crash may be considered as a form of reckless driving and explain why this parameter increases the self-reported likelihood of using a cell phone while driving.

2.6.2.2 Work Characteristics

Of the work characteristics found to be significant, the estimated parameters for truck parking decisions and drive start time are 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 make their own parking decisions is less than zero for 23.3% of drivers and greater than zero for 76.7% of drivers. In other words, 23.3% of drivers who make their own parking decisions are less likely to report using their cell phone while driving and 76.7% are more likely. A proportion of drivers (76.7%) who make their own parking decisions may not be familiar with safe and adequate parking locations along their route and must 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%) may be familiar with safe and adequate parking facilities along their route; therefore, these drivers are less likely to use their cell phone for such purposes.

In regards to starting a drive early in the morning (between midnight and 6:00 a.m.), the estimated parameter mean is less than zero for 39.4% of drivers and greater than zero for 60.6% of drivers and. That is to say, 39.4% of drivers who start driving in the early morning are less likely to report using their cell phone, but 60.4% are 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, the driver is 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 is consistent with past research that suggests 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 begin their work mid-day (between 10:00 a.m. and 4:00 p.m.) were found to be statistically significant and increase the self-reporting probability of using a cell phone while driving. Marginal effects suggest a 0.444 increase in probability in reporting using a cell phone while driving for those who start 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 a.m. to 9:00 a.m.) or afternoon peak hour times (5:00 p.m. to 7:00 p.m.). During these times, driving tasks are less demanding due to lower traffic volumes and fewer interactions between other vehicles. This result compliments past research on cell phone usage among passenger car drivers, where Kidd et al. (2016) showed that drivers are at increased odds of engaging in any secondary behavior during the afternoon.

Drivers who report primarily using city roads or rural roads for their routes are found to have an increased probability of reporting cell phone use while driving. For city and rural roads, marginal effects show 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 report driving a truck with two trailers often were found to have an increase in probability of self-reporting cell phone use. Marginal effects indicate that the probability of reporting cell phone use increases 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 are 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.

2.6.2.3 Temporal Characteristics

Drivers who report having difficulty finding safe and adequate truck parking on Tuesdays or in the afternoon have an increased probability of reporting using their cell phones while driving. Marginal effects for these variables show 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 find that receiving real-time information lowers the probability of encountering trouble when 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.

2.6.2.4 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 report using their cell phones while driving increases by 0.274, according to marginal effects, for those who often drive while tired. Driving while tired, or fatigued, has been proven 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 drive while tired are more likely to report using a cell phone while driving.

Similarly, drivers who take a break every four to six hours on a longer haul are more probable 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. (2017c) 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 take breaks every 4 to 6 hours are more likely to report using their cell phone while driving.

Further, drivers who never change lanes when a passenger vehicle is behind them were found to have an increased probability of reporting cell phone use while driving, as marginal effects show 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 (Oviedo-Trespalacios et al., 2017a; Young and Lenné, 2010; Zhou et al., 2016). 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 inspect 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 have 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.

2.6.2.5 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 restrict 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 is greater than zero for 34.9% of drivers and less than zero for 65.1% of drivers. This discrepancy among drivers may be capturing 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 only drive 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 work 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 operate under CMV carriers that manage fatigue by creating schedules that allow drivers to take breaks easily were found to have a decreased probability of reporting cell phone use while driving. Marginal effects show a 0.401 decrease in probability of reporting cell phone use. Because professional drivers perceive talking on a cell phone while driving mitigates the effects of driver fatigue, easily taking breaks when fatigued may explain why drivers are 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.

2.7 Conclusion and Future Work

Literature regarding the relationship between cell phone use and large truck crashes is sparse. As such, the current study is one of the first attempts at understanding this critical relationship. Unlike traditional studies that investigate the relationship between passenger car crashes and cell phone use, this study collected data through a stated-preference survey distributed to truck drivers who deliver goods in the Pacific Northwest (Oregon, Washington, Idaho, and British Columbia) to investigate the relationship of drivers of large trucks and cell phone use. The survey solicited information regarding driver socioeconomic characteristics, crash history, driver behavior, and management strategies. From this data, a random parameters binary logit model was utilized to determine contributing factors that influence a driver's decision on whether or not to report using a cell phone while driving. The influential factors that have been determined to either increase or decrease cell phone use probability among truck drivers can be leveraged to reduce the frequency of distracted driving and, as such, improve roadway safety for all users.

Contributing factors to truck drivers' decisions to report cell phone use while driving include: 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 vehicle. 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 shows 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 that a truck driver would use their cell phone while driving. As shown, CMV carriers that restrict the number of hours worked per work is an ineffective policy in mitigating cell phone use while driving. This finding can support other means of restricting driving hours, such as the amount 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.

Further, 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). Considering this shortage, Anderson et al. (2018) found that receiving real-time information, through GPS or other smartphone applications, would help truck drivers find safe and adequate parking. 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.

Although this study provides new insights into the relationship between cell phone use and truck driver behavior, there are some inherent limitations. Because this study assesses self-reported cell phone use while driving, it is subjected to the possibility of inaccurate responses by truck drivers. Respondents may not have truthfully reported if they use a cell phone and thus may lead to inaccurate responses. However, the results from this study provide significant insight into possible factors that influence cell phone use while driving among truck drivers and investigates the relationship between truck drivers and distracted driving. Additionally, the results from this study cannot be extrapolated beyond drivers who deliver or pick up freight in the Pacific Northwest. Future studies can use the same methodology but to a larger region via a random sampling process to generalize results. Additionally, there may be other driver and environmental factors that influence the probability of a truck driver using a cell phone while driving that were neither captured in this survey nor found to be significant in these results. Future studies should tailor survey questions around the idea of distracted driving among truck drivers that examines their interactions with all varieties of electronic mobile devices within the cab of a truck (ELD, CB Radio, GPS devices, etc.). These additional survey questions can further expand the understanding of distracted driving and large-truck drivers.

2.8 Acknowledgements

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810. The findings of this study do not necessarily reflect the views of PACTRANS or ODOT.

3 CHAPTER 3 – FACTORS CONTRIBUTING TO INTERNAL AND EXTERNAL DRIVER DISTRACTIONS AMONG DRIVERS OF LARGE TRUCKS: A RANDOM PARAMETERS BIVARIATE BINARY PROBIT APPROACH

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3.1 Abstract

Distracted driving is an adverse driving behavior that impairs driver performance and safety. Distracted driving can arise from either driver internal or driver external sources, yet majority of previous distracted driving research has primarily focused on the latter. Further, despite extensive research on distracted driving, particularly on using a cell phone while driving, crashes and fatalities resulting from distracted driving have continued to rise in recent years. This increase may indicate that results from existing research fail to assist in the development of effective countermeasures and understand other sources of driver distraction, such as mental inattention or lapses in concentration. To aid in the development of effective distracted driving countermeasures and understand all sources of driver distraction, this study, through stated preference survey data, determines the factors that influence the likelihood that drivers of large trucks would self-report engagement with driver internal (e.g., lapses in concentration) and driver external (e.g., using a cell phone) sources of distraction. Due to the inherent correlation between driver internal and driver external sources of distraction, a random parameters bivariate binary probit model (RPBBPM) was fitted to this data to determine such factors. Through the RPBBPM, unobserved heterogeneity was captured and 18 parameters related to certain driver behaviors, sociodemographic factors, and work, temporal, and management characteristics were found to be statistically significant. Among these parameters, factors related to truck parking decisions and fatigue management strategies have the potential to develop direct strategies that mitigate distracted driving among drivers of large trucks. Transportation

agencies and commercial motor vehicle carriers can use these results to tailor driver training programs and safety policies that can effectively prevent distracted driving among drivers of large trucks.

3.2 Motivation

Driver distraction is a complex concept in transportation engineering that poses threats to all roadway users. According to the National Highway Safety Administration (NHTSA), distracted driving accounts for approximately 25% of all police reported crashes and is continuing to grow (Ranney et al., 2000; Wang et al., 1996). The National Center for Statistics and Analysis (NCSA) reports that crashes involving distracted driving have increased by approximately 7% between 2011 and 2015 (NCSA, 2013, 2017). Over this period, fatalities resulting from distracted driving increased from 385 fatalities in 2011 to 476 fatalities in 2015, or 24% (NCSA, 2013, 2017). Further, NHTSA reports that fatalities due to distracted driving had the largest percent increase (8.8%) between 2014 and 2015 over other causal factors, such as alcohol-impaired or speed-related fatalities (NCSA, 2017). In terms of large trucks (GVWR greater than 10,000 pounds), the Federal Motor Carrier Safety Administration (FMCSA) reports that distraction and inattention was the second most frequent driver-related error in crashes large truck crashes (FMCSA, 2017). These statistics show an existing issue and growing trend regarding distracted driving data, and highlight the significant contribution in large-truck involved fatal crashes. However, these statistics are considerably underreported due to the inefficiencies of current methods and procedures to truly assess the culpability of a crash due to distracted driving (Gordon, 2009). As such, efforts must be made to reduce its presence on roadways and involvement in crashes, particularly in regard to large trucks.

From an economic perspective, distracted driving and large truck crashes are detrimental to soceity. In 2010, Blincoe et al. (2015) estimates that the economic costs of all motor vehicle crashes accounted for $242 billion. In terms of distracted driving, distraction-affected crashes cost $40 billion in 2010, or 16% of the total economic impacts caused by traffic accidents. When considering the lost quality of life, Blincoe et al. (2015) estimates that distraction-affected crashes cost $123 billion in societal harm. Again, these estimates may be underestimating the true economic impacts caused by distracted driving because of the underreporting of distracted driving incidents. With regard to large trucks, Zaloshnja & Miller (2007) estimated the average cost of (in 2005 USD) 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). The economic impact of distraction-affected crashes and large truck-involved crashes highlight the importance of investigating the relationship between truck drivers and distracted driving.

According to Lee et al. (2009), distracted driving is defined as the diversion of attention away from critical driving activities toward a competing activity. Following this definition, Regan et al. (2011) asserts that distracted driving can arise from any competing activity, or task, that diverts drivers’ attention away from the driving task.

These activities can either be external (e.g., manipulating a cell phone, eating) or internal (e.g., daydreaming, mind wandering, lapses in concentration) to the driver. NHTSA corroborates this notion by categorizing the sources of driver distraction into three types: visual, manual, and cognitive (NHTSA, 2018a, 2018b). If driver distraction is understood to include both driver external and driver internal sources, the aforementioned crash and economic statistics are severely underestimated as they typically do not include incidents involving driver-internal distraction.

Furthermore, the primary focus of most distracted driving literature fail to consider driver internal distractions and have typically investigated the prevalence, crash risk, and impact of driver performance due to driver external tasks (Fitch et al., 2013; Horberry et al., 2006; Klauer et al., 2014, 2006; McEvoy et al., 2005; Olson et al., 2009; Regan et al., 2008; Schroeder et al., 2013; Strayer et al., 2013). While these studies provide insight into the associated safety risks of driver distraction, most focus on distractions involving passenger car drivers and fail to understand the factors that influence drivers' engagement with distracted driving. Therefore, research is needed to understand the relationship between distracted driving and drivers of large trucks, and the factors influencing drivers' engagement with distracted driving to develop practical solutions that may reduce its presence involvement in crashes.

Until recently, few studies have applied econometric modelling techniques on collected survey data to determine influential factors on passenger car drivers' engagement with distracted driving (Jashami et al., 2017; Márquez et al., 2015; Oviedo-Trespalacios et al., 2017b). These studies provide an innovative way to deepen the understanding of distracted driving and the results can be used to develop mitigation strategies. This current study expands existing distracted driving literature and continues this focus by investigating the relationship between distracted driving and large trucks, and identifying the factors that influence truck drivers' engagement with distracted driving. Specifically, through a stated-preference survey and application of a random parameters bivariate binary probit model (RPBBPM), this study determines the factors that influence the likelihood that truck drivers would report cell phone use while driving and, as measured by self-reported lapses in concentration while driving, engagement in internalized distractions.

3.3 Literature Review

As mentioned previously, current distracted driving literature has primarily investigated the crash risks associated with driver-external tasks. For instance, Klauer et al. (2006) and Fitch et al. (2013), through a naturalistic driving study, determined that cell-phone subtasks (e.g., texting, dialing, emailing) are associated with increased crash risk among passenger car drivers. These cell phone subtasks increase crash risk by at least 3.5 times and as high as 164 times (Fitch et al., 2013; Klauer et al., 2006). For commercial motor vehicle (CMV) operators, engaging in complex secondary tasks (i.e., texting, dialing, interacting with dispatching device) increases the likelihood of being at-fault in a safety critical event by at least 13.9 times (Olson et al., 2009). With increasing technological advancements, cell phones have more functionality (e.g., access to social media, GPS navigation, music streaming, etc.) that requires more visual and mental attention to perform and may further increase this crash risk. Further, due to their inherent job responsibilities, drivers of large trucks are more prone to engage in distracted driving to coordinate delivery logistics (e.g., use citizens band radio, navigation systems, etc.).

In addition to identifying the associated crash risk of distracted driving, studies have shown the prevalence of distraction-affected crashes. Naturalistic data on passenger car and CMV drivers found that at least one form of driver distraction (either driver internal or external) was present in 78% and 71% of all crashes, respectively (Klauer et al., 2006; Olson et al., 2009). Further, police report and crash analysis studies determine that distraction is a contributing factor in about 10% to 12% of all vehicular crashes (Gordon, 2009). In terms of large trucks, the Large Truck Crash and Causation Study (LTCCS) reports that 35% of large truck-involved crashes in the US involved one form of driver recognition error, or inattention (Federal Motor Carrier Safety Administration, 2005). These crash statistics, however, may be underestimating the actual relationship between distracted driving and crash involvement due to significant amount of unknown and missing information (Gordon, 2009). These studies prove that distractions internal and external to the driver are indeed significant factors in vehicular crashes, and efforts should be made to minimize its prevalence on roadways.

As mentioned previously, distracted driving includes driver-internal sources, such as daydreaming mind wandering, inattention, or lapses in concentration. These internal distractions (i.e., cognitive distractions) have been shown to result in degraded driving performance and increased likelihood of more severe single vehicle crashes

(Bunn et al., 2005; Peng and Boyle, 2012; Young and Regan, 2007). Most often, these cognitive distractions are induced by driver-external distractions, such as manipulating a cell phone or having a conversation, that require mental resources be diverted away from the driving task (Just et al., 2008; Strayer et al., 2013; Young and Regan, 2007). Other times, however, cognitive distractions can arise from internally triggered, unintentional thoughts, such as thinking about dinner plans or experiencing daydreams, and interfere with performance (Regan et al., 2011). These findings support the notion that distracted driving resulting from driver-internal sources pose threats to traffic safety and efforts should be made to understand and reduce the occurrence of such distractions.

Given the safety implications and prevalence of driver internal and driver external sources of driver distractions, it is imperative to understand the factors that affect these behaviors so mitigation techniques can be developed to reduce their occurrence. Recent studies by Jashami et al. (2017), Kidd et al. (2015), Márquez et al. (2015), and Oviedo-Trespalacios et al. (2017) have applied econometric modelling techniques on collected survey data to determine factors that influence passenger car drivers' engagement with distracted driving. These studies, however, partially address the nature of distracted driving such that they only account for driver engagement with driver-external sources of distracted driving (i.e., using a cell phone). Moreover, the identified factors only pertain to passenger car drivers and do not provide insight into the relationship between distracted driving and drivers of large trucks. Since distracted driving arises from driver internal and driver external sources, it is important to understand the factors leading to such engagement so that policies and programs can be enacted to more effectively reduce distracted driving on roadways.

In existing literature, much is known about the hazards of distracted driving, but there is a lack of research pertaining to the relationship between this adverse behavior and drivers of large trucks. Further, there is an incomplete understanding of the factors that influence distracted driving resulting from driver internal and driver external sources. Therefore, the purpose of this study is to determine factors that influence truck drivers' decision to use a cell phone and experience lapses in concentration while driving through a stated-preference survey distributed to drivers of large trucks. Through this study, government and transportation agencies, and CMV carriers may develop potential countermeasures that can potentially mitigate distracted driving among drivers of large trucks.

In this study, the factors that influence truck drivers' engagement with distracted driving are determined through a stated-preference survey that was distributed to large-truck drivers who deliver or receive goods in the Pacific Northwest. Specifically, factors that influence the likelihood that truck drivers would report using a cell phone while driving and experience unintentional, internally triggered cognitive distractions (e.g., lapses in concentration). As mentioned previously, engaging in driver external tasks while driving, such as using a cell phone, leads to driver internal distraction, or cognitive distraction (Just et al., 2008; Strayer et al., 2013; Young and Regan, 2007). This correlation needs to be accounted for in the analysis to yield more accurate estimates and inferences. As such, a RPBBPM is used to account for this correlation. If separate univariate probit models are developed for each of the dependent variables (e.g.: cell phone use and concentration lapsing), the correlation between disturbances would be ignored, leading to inefficient model estimation (Russo et al., 2014a). Further, the application of the random parameters framework investigates the complex interaction between the factors captured through the survey and any unobserved factors (i.e., unobserved heterogeneity) that may be influencing cell phone use and lapses in concentration while driving.

3.4 Data Description

To evaluate large truck drivers' decision to engage in driver internal or driver external driver distractions, a stated-preference survey was developed and distributed to truck drivers who either deliver or pick up goods in the Pacific Northwest. The intent of this survey was to understand truck driver opinions on truck at-fault safety critical events, which included questions related to distracted driving. The survey, which was conducted between August 17th and September 1st, 2017, was administered through Oregon State University and distributed to drivers of large trucks using Qualtrics, LLC, an online survey platform. This survey included questions that were divided into eight parts: socioeconomic, business, driver, driving, and accident characteristics, time of day operations, driving management, and truck configuration. Prior to distribution, the survey obtained approval from the Institutional Review Board (IRB).

All respondents voluntarily completed the survey and were required to be truck drivers, hold a commercial driver's license (CDL), be at least 18 years of age, and either pickup or deliver goods in the Pacific Northwest. In total, 1,919 individuals were reached, but only 515 individuals met the criteria and completed the survey; a 26.8% response rate. To ensure that an adequate sample size was achieved, the following equation is used (Smith, 2013):

$$n = \frac{z^2 \times p \times (1-p)}{MoE^2} \qquad \text{Eq. (3-1)}$$

where n is the sample size needed for the desired level of precision; p is an estimated value of proportion; MoE is the desired margin of sampling error; and z is the critical value for the desired level of confidence. In most studies, a 95% confidence level is desired. The corresponding z value for this level of confidence is 1.96. A 50/50 (0.5) proportion of p was used as a most conservative value since it assumes that half of the population will answer positively and negatively to a posed question (Dillman et al., 2014). For this study, a value of 4.5 was used as the margin of sampling error, MoE. By applying these values to Eqn. (3-1), 475 responses are needed to meet the 95% confidence level, which is exceed in this study with 515 valid and completed surveys.

Through Qualtrics, LLC, Internet Protocol (IP) addresses and geographical coordinates were recorded. The capturing of IP addresses ensured that the same respondent did not submit multiple responses. Using the geographical coordinates, locations of respondents are provided and are shown in Figure 3-1. As shown, there is an adequate geographical representation of respondents with majority of respondents from the West Coast.

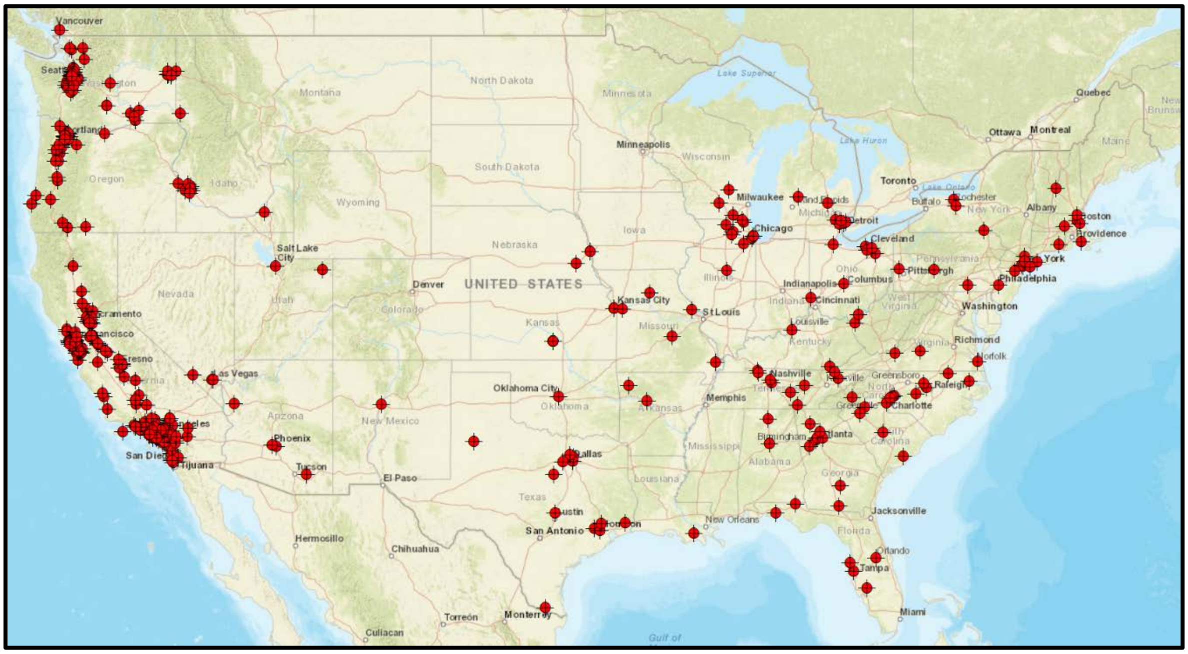

Figure 3-1: Origin of Truck Drivers that Deliver Goods in the Pacific Northwest

As mentioned, the purpose of this study is to identify the factors that influence the likelihood of truck drivers engaging in driver internal and driver external distractions. To assess the latter, truck driver respondents were specifically asked:

Do you use a cell phone while driving? (Either handheld or hands-free) [QNS. 1]

QNS. 1 presented a binary choice to respondents, as they had to choose either yes or no, and represents their decision to report using a cell phone while driving (distracted driving).

To assess driver internal distractions, the following question was presented to truck driver respondents:

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

[QNS. 2]

Truck drivers responded to QNS. 2 with either of the following five qualitative response options that closely resembles their driving characteristics: very often, quite often, sometimes, rarely, and never. Due to the complexities of accurately measuring driver internal distractions, QNS. 2 serves as a proxy to understand, and identify the factors that contribute to, this type of distracted driving among drivers of large trucks. Following the distracted driving definition developed by Regan et al. (2011), this study considers lapses in concentration to include intentional or unintentional, internally triggered, task-unrelated thoughts (i.e., mind wandering, daydreaming). To identify the factors that influence the likelihood of self-reported concentration lapses while driving, a binary response variable was created for QNS. 2. This variable was created by consolidating drivers who responded with either very often, quite often, or sometimes. Those who responded to QNS. 2 with either of these three responses are considered to have experienced their concentration lapsing while driving.

For this study, QNS. 1 and 2 are chosen as the dependent variables for analysis as these questions assess a drivers' engagement with driver internal (lapses in concentration) and driver external distractions (cell phone sue) based on self-reported information.

From the survey responses, 288 indicator variables were created, but only 18 variables were found to be statistically significant in explaining truck driver behavior regarding cell phone use and concentration lapsing. These 18 independent variables encompass factors that pertain to socioeconomic, business, driver, driving, and accident characteristics, time of day operations, and driving management. Table 3-1 shows the descriptive statistics of these 18 independent variables used in this study, respectively.

Table 3-1: Descriptive Statistics of Independent Variables

Variable	Mean	Std. Dev.
Socioeconomic Characteristics		
Driver Age (1 if 36 or older, 0 otherwise)	0.517	0.500
Marital Status (1 if Single, 0 otherwise)	0.256	0.437
Business Characteristics		
Type of Employer (1 if private carriage, 0 otherwise)	0.346	0.476
Driver Characteristics		
Type of road usually driven (1 if rural or city roads, 0 otherwise)	0.101	0.302
Shipment type (1 if less-than-truck load, 0 otherwise)	0.126	0.332
Truck Driving Education (1 if self-taught, 0 otherwise)	0.184	0.388
Parking Location decision (1 if driver makes decision, 0 otherwise)	0.783	0.413
Driving Characteristics		
Driver confidence in their ability to professionally drive a large truck (1 if extremely or very confident, 0 otherwise)	0.926	0.262
Situation that poses the highest safety hazard to drivers (1 if passenger car on either side or behind, 0 otherwise)	0.773	0.419
Lane-changing to avoid traveling with passenger vehicle behind (1 if never, 0 otherwise)	0.330	0.471
Lane-changing to avoid traveling with truck in front (1 if never, 0 otherwise)	0.148	0.355
Accident Characteristics		
Crash History (1 if at least one crash in past 5 years, 0 otherwise)	0.243	0.429
Time of Day Operations		
Day of week most difficult to find safe and adequate parking (1 if Tuesday, 0 otherwise)	0.274	0.446
Time of week most difficult finding safe truck parking (1 if weekend, 0 otherwise)	0.445	0.497
Start Drive (1 if between 10 am and 4 pm, 0 otherwise)	0.148	0.355
Driving Management		
Difficulty finding safe and adequate parking location when required to rest (1 if yes, 0 otherwise)	0.551	0.498
Frequency of making a stop on a longer trip (1 if every 4 to 6 hours, 0 otherwise)	0.330	0.471
Keep driving rather than stopping to take breaks to manage fatigue (1 if strongly agree or agree, 0 otherwise)	0.456	0.499

In terms of the dependent variables (QNS. 1 and QNS. 2), Figure 3-2 and Figure 3-3 show the percentage of respondents who reported using their cell phones while driving and experienced a lapse in concentration while driving, respectively. As shown, 45% of surveyed respondents (234) indicated that they use their cell phones while driving and 58% reported (298) that their concentration lapses while driving. In this study, the percentage of respondents who reported using their cell phone while driving is consistent with the findings of Schroeder et al. (2013) and Oviedo-Trespalacios et al. (2017), who found that nearly 50% of surveyed licensed drivers reported using their cell phone while driving at least some of the time.

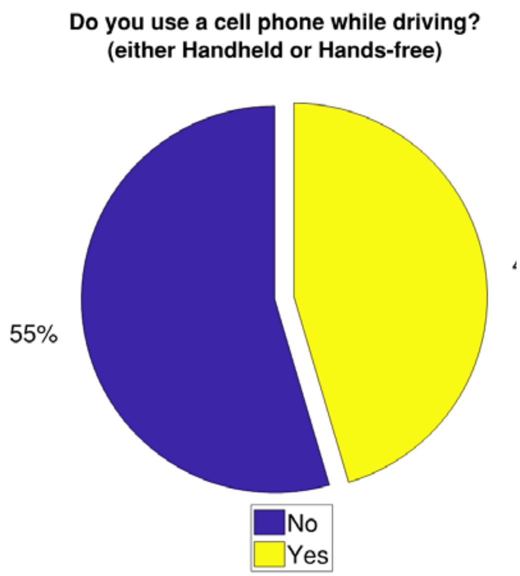

Figure 3-2: Self-Reported Cell Phone Use While Driving

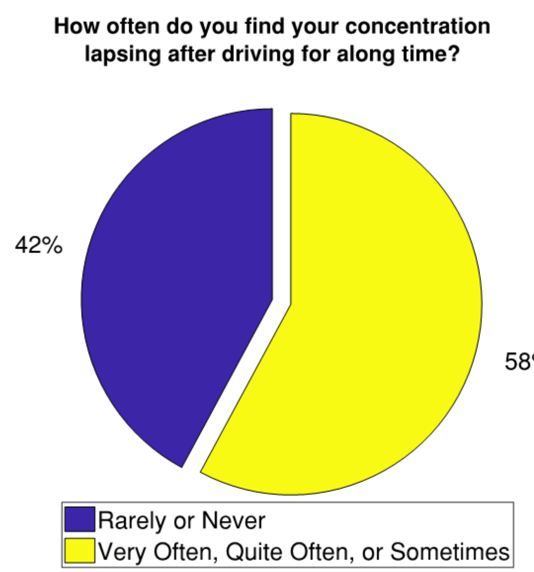

Figure 3-3: Self-Reported Concentration Lapses While Driving

To reinforce the fact that distracted driving leads to increased crash risk, self-reported crash history was disaggregated based on cell phone use and concentration lapsing while driving. In the survey, respondents were asked, *“During the last 5 years how many accidents have you had in which the police had to attend?”* Drivers had to choose among five choices: one, two, three, four or more, or none. Drivers who indicated either one, two, three, or four or more crashes were consolidated to identify those who were involved in at least one crash in the past 5 years. Figure 3-4 shows that 24% of survey respondents (125) were involved in at least one crash in the past 5 years. As shown by Figure 3-5, 57% of the surveyed truck drivers who stated they were involved in at least one crash reported using their cell phone while driving. Further, as shown in Figure 3-6, 81% of survey respondents who reported being involved in at least one crash indicated that their concentration lapses very often, quite often, or sometimes while driving. These findings support past research that distracted driving among truck drivers increases the likelihood of being involved in safety critical events or crashes (Hanowski et al., 2005; Hickman and Hanowski, 2012; Olson et al., 2009). These findings also support the fact that understanding the factors influencing driver’s decision to report being engaged in distracted driving is important to reduce the number of crashes on our roadways.

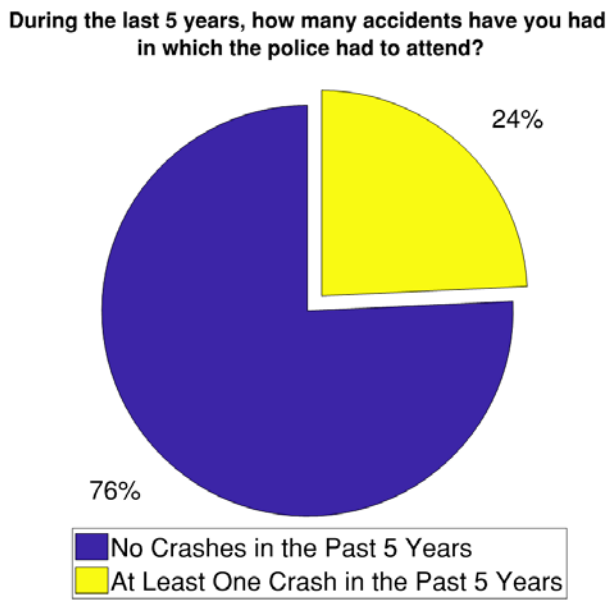

Figure 3-4: Self-Reported Crash History

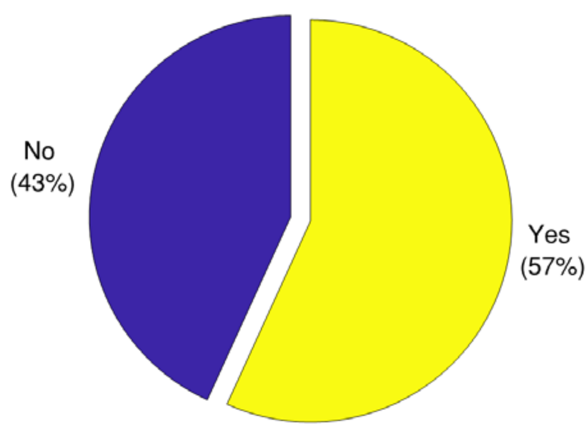

Figure 3-5: Respondents who indicate being involved in a crash and report using their cell phone while Driving

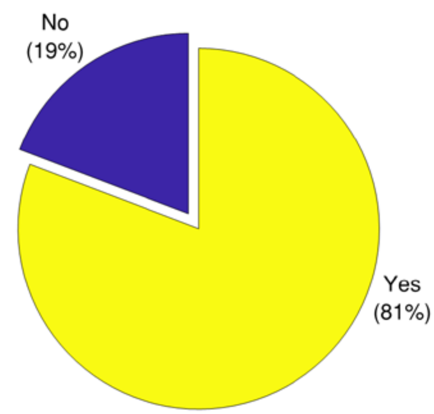

Figure 3-6: Respondents who indicate being involved in a crash and report experiencing lapses in concentration while driving

3.5 Methodology

Binary choice modelling has been extensively used in transportation injury severity analysis and distracted driving. Choice models, such as the logistic (i.e., logit) and probit based models, have been applied to large truck safety (Anderson and Hernandez, 2017; Anderson et al., 2018; Islam and Hernandez, 2013; Pahukula et al., 2015). Further, econometric analyses of distracted driving have used logit based models (Kidd et al., 2016; Márquez et al., 2015; Oviedo-Trespalacios et al., 2017b). Because the responses to QNS. 1 are binary in nature and the responses to QNS. 2 were dichotomized, a binary choice model is appropriate.

Univariate choice models are appropriate when there is only one dependent variable of interest, such as modelling whether or not drivers report talking on a cell phone while driving (Anderson et al., 2018; Oviedo-Trespalacios et al., 2017b). However, when two different but related binary dependent variables are of interest, a univariate analysis may not be the preferred method. In the case of this work, where the dependent variables are cell phone use and lapses in concentration, these decisions are intuitively correlated and potentially jointly determined (Greene, 2016). If these dependent variables are modeled separately using a univariate approach, the correlation among error (disturbance) terms may not be accounted for. If this correlation is not accounted for, parameters estimates may be inconsistent and less asymptotically inefficient (Hensher et al., 2015; Wooldridge, 2010). Therefore, for the current study, a special case of the bivariate binary probit model (BBPM) is adopted to identify and formulate the correlation between two binary dependent variables (drivers reporting cell phones use and lapses in concentration while driving) while yielding more consistent and efficient parameter estimates (Greene, 2016).[1]

However, since surveys cannot capture every possible factor that may contribute to a driver reporting cell phone use or lapses in concentration, unobserved heterogeneity (variation) is likely present in the data. For example, in terms of distracted driving, the ability to sustain substantial attention on the task-on hand may considerably vary across individuals, but cannot be measured through survey questions. If this unobserved heterogeneity is not accounted for in the analysis, model results will be biased and lead to erroneous inferences (see Mannering et al. (2016) for a full discussion on unobserved heterogeneity and the consequences of not accounting for it). As such, the BBPM alone is insufficient because the potential unobserved heterogeneity that derives from survey responses. To account for this heterogeneity and provide more accurate results, this study applies the previously discussed RPBBPM.

To begin, the fixed parameters BBPM is formulated by generalizing the index function model from a single latent variable to two potentially correlated latent variables (i.e., cell phone use and lapses in concentration while driving). The latent variables are estimated simultaneously as follows (Cameron and Trivedi, 2005; Christofides et al., 1997; Greene, 2012; Hensher et al., 2015; Russo et al., 2014a):

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[1] Although the logit model is also an appropriate modeling framework to analyze binary choice outcomes, a bivariate binary logit model has yet to be developed (Greene, 2016).

$$y_1^* = \boldsymbol{X_1\beta}_1 + \varepsilon_1,\ \ y_1 = 1 \text{ if } y_1^* > 0, 0 \text{ otherwise}$$
$$y_2^* = \boldsymbol{X_2\beta}_2 + \varepsilon_2,\ \ y_2 = 1 \text{ if } y_2^* > 0, 0 \text{ otherwise} \qquad \text{Eq. (3-2)}$$

where:
y_1^*, y_2^*: latent (unobserved) dependent variables of cell phone use and lapses in concentration while driving;
y_1, y_2: observed dependent variables of cell phone use and lapses in concentration while driving
$\boldsymbol{X_1}$, $\boldsymbol{X_2}$: vectors of explanatory variables with $1 \times K_1$ matrix and $1 \times K_2$ matrix for $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$, respectively;[2]
$\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$: vectors of estimable parameters;
ε_1, ε_2: error terms (assumed to be normally distributed with variance of 1) and assumed to be independent of $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$ with a bivariate normal distribution;
$E[\varepsilon_1] = E[\varepsilon_2] = 0$;
$\text{Var}[\varepsilon_1] = \text{Var}[\varepsilon_2] = 1$;
$\text{Cov}[\varepsilon_1, \varepsilon_2\ ] = \rho$ (the off-diagonal elements of the variance-covariance matrix, as seen in Eq. (3)).

As shown in Eq. (3-2), the dependent variables y_1 and y_2 are observed if latent variables y_1^* and y_2^* are greater than zero. Specifically, $y_1$is observed if a driver reports using their cell phone while driving (i.e., y_1^* takes on the value 1) and y_2 is observed if a driver reports that they have experienced lapses in concentration while driving (i.e., y_2^* takes on the value 1). Next, under the assumption that $\boldsymbol{\varepsilon} = \varepsilon_1, \varepsilon_2$ is independent of $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$, $\boldsymbol{\varepsilon} \mid \boldsymbol{X} = N(0, \Omega)$. This implies that all $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$ are exogenous, where Ω is a 2×2 matrix with an off-diagonal element ρ, the correlation coefficient for $\boldsymbol{\varepsilon}$ (i.e., $\rho = \text{Corr}(\varepsilon_1, \varepsilon_2)$) (Wooldridge, 2010). The correlation coefficient, as discussed below, determines the use of the BBPM.

[2] Matrix dimensions will change contingent on the number of explanatory variables. In Eq. (2), each equation has only one explanatory variable for formulation purposes; therefore, a $1 \times K_1$ matrix.

These assumptions are important, as they imply that y_1 and y_2 can be estimated via probit models conditional on $\boldsymbol{X}$ (Wooldridge, 2010). But, as discussed previously, if this assumption does not hold and ε_1 is correlated ε_2, the BBPM must be considered to account for this correlation. Again, if this potential correlation is not accounted for, parameter estimates may no longer be consistent and less asymptotically efficient (i.e., higher standard errors) (Hensher et al., 2015; Meng and Schmidt, 1985). Therefore, a test for correlation among the error terms in Eq. (3-2) must be conducted to determine if correlation is present. To test this correlation for binary variables, a tetrachoric correlation test is conducted on the error terms to determine the significance of the correlation coefficient ρ (Greene, 2016, 2012):[3]

$$\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} | \boldsymbol{X_1}, \boldsymbol{X_2} \Big) \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right] \qquad \text{Eq. (3-3)}$$

where ρ is the correlation coefficient of the error terms, as defined previously. As will be discussed later, for the BBPM to be justified, ρ needs to be statistically significant, which shows statistically significant correlation among the error terms ε_1 and ε_2.

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[3] The tetrachoric correlation for two binary variables is equivalent to the correlation of the two error terms in a bivariate probit model (Greene and Hensher, 2010; Hensher et al., 2015). In particular, it is computed by assuming the two binary variables are derived by censoring two observations from an underlying *continuous* bivariate normal population (i.e., bivariate probit model without covariates). As such, ρ can be easily determined by fitting such a model and measuring the correlation between underlying *continuous* variables if they were able to be observed (Greene and Hensher, 2010).

Using the bivariate normal CDF (Greene, 2012):

$$\text{Prob}[\boldsymbol{X_1} < x_1, \boldsymbol{X_2} < x_2\,] = \int_{-\infty}^{x_2}\int_{-\infty}^{x_1}\Phi_2(z_1, z_2, \rho)\, dz_1 dz_2 \quad \text{Eq. (3-4)}$$

the parameters of the BBPM can estimated by full information maximum likelihood with the log-likelihood function as follows (Greene, 2012; Hensher et al., 2015; Russo et al., 2014a):

$$\ln L = \sum \ln \Phi_2[q_{1i}\beta_1 X_{1i}, q_{2i}\beta_2 X_{2i}\,, q_{1i}q_{2i}, \rho] \quad \text{Eq. (3-5)}$$

where:
$\Phi_2(X_1, X_2, \rho)$: represents the bivariate normal cumulative density function with correlation parameter ρ;
q_{1i}: equal to $2y_{1i} - 1$;
q_{2i}: equal to $2y_{2i} - 1$.

Please note that $q_{1i} = 1$ if $y_{1i} = 1$ and $q_{1i} = -1$ if $y_{1i} = 0$, for $j = 1, 2$ (Greene, 2012; Greene and Hensher, 2010; Hensher et al., 2015).

As discussed previously, this study overcomes the inherent limitation of unobserved heterogeneity by using a RPBBPM. The random parameters method accounts for unobserved heterogeneity by allowing estimable parameters to vary across observations (i.e., drivers) according to a user-defined distribution (e.g., normal, triangular, uniform, lognormal, etc.) (Greene, 2016). In this study, the random parameters are assumed to vary across drivers based on a normal distribution. To allow parameters to vary across drivers, in an attempt to account for driver-specific variation, the random parameters method is incorporated into the BBPM by estimating $\boldsymbol{\beta}$ as (Anastasopoulos et al., 2012; Greene, 2016):

$$\boldsymbol{\beta_i} = \beta + \mu_i \qquad \text{Eq. (3-6)}$$

where:
$\boldsymbol{\beta_i}$: vector of driver-specific parameters;
μ_i: randomly distributed term (normally distributed with mean zero and constant variance σ^2)

The RPBBPM is estimated through simulated maximum likelihood estimation. In this analysis, 200 Halton draws are used to simulate this estimation, as past studies have shown this approach to be computationally efficient and preferred over purely random draws (Bhat, 2003; J. H. Halton, 1960; Train, 2000).

Lastly, to interpret model results for the RPBBPM, both the sign and marginal effects of the estimable parameters are used. The positive or negative sign of the estimable parameters determines if the probability of a response taking on the value 1 increases or decreases. However, the magnitude of effect on the probability cannot be determined by the estimated parameters $\boldsymbol{\beta}$ alone. Therefore, in the case of a two-equation modeling framework, evaluating marginal effects that assess the change in the conditional expected value of the dependent variables, $E[y_1 \mid y_2 = 1, X]$, are of additional interest to the analyst (Christofides et al., 1997; Gkritza, 2009; Greene, 2016):

$$E[y_1 \mid y_2 = 1, X_1, X_1] = \frac{\text{Prob}[y_1 = 1, y_2 = 1 \mid X_1, X_1, \rho]}{\text{Prob}[y_2 = 1 \mid X_1]} \qquad \text{Eq. (3-7)}$$

Then, in the case of indicator variables, marginal effects are computed using the differences in expected values of the dependent variables when indicator X changes from zero to one and all other variables remain equal to their means (i.e., they remain constant) (Greene, 2016):

$$ME_X = E[y_1 \mid y_2 = 1, X = 1] - E[y_1 \mid y_2 = 1, X = 0] \qquad \text{Eq. (3-8)}$$

where X is the variable of interest. In the case of indicator variables, the effect accounts for all appearances of the variable in the model, rather than having a "direct" and "indirect" effect (i.e., there is no distinction for indicator variables and the marginal effect is the same for both equations) (Greene, 2016; Hensher et al., 2015).[4]

3.5.1 Model Significance

A likelihood ratio test (LRT) is conducted to determine if the log-likelihood of the RPBBPM is more significant than the log-likelihood of the fixed parameters BBPM. The LRT is conducted by performing (Washington et al., 2011):

$$\chi^2 = -2\left[LL_{fix}(\beta^{fix}) - LL_{ran}(\beta^{ran})\right] \qquad \text{Eq. (3-9)}$$

where:
χ^2: chi-square statistic with degrees of freedom equal to the number of random parameters
$LL_{fix}(\beta^{fix})$: log-likelihood at convergence for fixed parameter BBPM
$LL_{ran}(\beta^{ran})$: log-likelihood at convergence for random parameter BBPM

[4] The marginal effects are computed as the joint probability that $y_1 \mid y_2 = 1$. In other words, a one-unit increase (changes from zero to one) in an indicator variable provides the absolute change in probability that both y_1 and y_2 will take on the value 1.

The LRT is used to test the null hypothesis that there is no difference in model significance against the alternative hypothesis, which is that the RPBBPM is more significant than the fixed parameter BBPM.

3.6 Results and Discussion

3.6.1 Model Significance

To justify the use of the BBPM, the correlation coefficient ρ must be statistically significant. As shown in Eqn. 3-3, this coefficient is a measure of any correlation amongst the error terms of the models in the BBPM. When a BBPM is fitted with the constant only, this correlation coefficient is defined as the tetrachoric correlation (Greene, 2016). The tetrachoric correlation between two binary dependent variables (y_1 and y_2), as discussed previously, is equivalent to the correlation of the two error terms in a bivariate probit model (Greene and Hensher, 2010; Hensher et al., 2015). In particular, it is computed by assuming the two binary variables are derived by censoring two observations from an underlying *continuous* bivariate normal population (i.e., bivariate probit model without covariates). Therefore, to estimate this correlation and determine significance, a BBPM with y_1 and y_2 was fitted with constants only. As shown in Table 3-2, the tetrachoric correlation between cell phone use and concentration lapsing while driving is statistically significant at the 99th percentile. This finding indicates that there is correlation across error terms, or correlation among the two binary dependent variables (cell phone use and concentration lapsing while driving) as the tetrachoric correlation coefficient is defined

(Greene and Hensher, 2010; Hensher et al., 2015). This correlation is further corroborated by the estimated correlation coefficient, ρ, of the full random parameters BBPM, which is also significant at the 99th percentile. As shown by the tetrachoric correlation and ρ values, two separate binary probit models are not appropriate for this study, as they will ignore the correlation between the error terms and result in inefficient and incomplete model estimates (Greene, 2016). Therefore, the BBPM is the accurate model to be estimated.

The findings of the tetrachoric correlation and ρ values provide clear evidence that there is a correlation between driver external and driver internal distractions. As mentioned previously, studies have shown that drivers are more susceptible to internal distractions when engaged in secondary tasks while driving due to increases in mental workload (Just et al., 2008; Strayer et al., 2013; Young and Regan, 2007). The increased cognitive load results in mental attention being diverted away from the driving task, which leads to degraded performance (Just et al., 2008). This association between cognitive load and engagement with secondary tasks while driving may explain why, as measured by the tetrachoric correlation and ρ value, there is correlation between the two dependent variables in this study.

To conclude that there is indeed unobserved heterogeneity in this data and justify the use of the RPBBPM, the LRT (Eq. 3-9) is conducted. The log-likelihood at convergence for the random and fixed parameters BBPM were determined to be -602.25 and -612.16, respectively. Using this information, the χ^2 statistic calculated from Eq. (3-9) is 19.82 with nine degrees of freedom (the number of estimated random parameters). The associated p-value for this statistic is 0.0191, which indicates that, with over 95% confidence, the RPBBPM statistically outperformed the fixed parameters BBPM. This finding provides evidence that factors influencing cell phone use or lapses in concentration while driving varies across drivers.

3.6.2 Variable Significance

Table 3-2 shows, in detail, the model estimates for the RPBBPM, which determined 18 statistically significant variables that influence the likelihood of truck drivers reporting using their cell phone or experiencing lapses in concentration while driving. As shown in Table 3-2, there are three variables (crash history, type of employer, and type of road usually driven) that affect the likelihood of drivers engaging in both sources of distracted driving (i.e., they are significant in both equations). Further, five statistically significant variables explicitly influenced a driver's likelihood of self-reporting using a cell phone while driving whereas ten statistically significant variables specifically influenced the likelihood of a driver reporting lapses in concentration while driving. Lastly, of the 18 significant variables, nine were found to have normally distributed random parameters based on the significance of the standard deviation, indicating variation across drivers. The distribution of these random parameters under the normal distribution curve are shown in Table 3-2, where the columns "Above 0" and "Below 0" indicate the percentage of drivers who are either more or less likely to report engagement in a distracting task, respectively.

Joint probability marginal effects for the statistically significant variables are provided in Table 3-2. As previously mentioned, these values indicate the magnitude of effect each variable has on the joint probability that a truck driver would report both types of driver distraction. Understanding the influential factors and their effect on distracted driving are important if transportation agencies and commercial motor vehicle (CMV) carriers intend to reduce the occurrence of large truck crashes that result from driver distraction among truck drivers. The following discussion is organized by influential factors related to socioeconomic characteristics, business characteristics, driver characteristics, driving characteristics, accident characteristics, time of day operations, and driving management.

Table 3-2: Random Parameter Bivariate Binary Probit Model Results

Variable	Parameter Estimate	t-statistic	Marginal Effects‡	Percent Observations Above 0	Percent Observations Below 0
Y_1 = Likelihood of reporting using a cell phone (either handheld or hands-free) while driving					
Constant	-0.976	-5.42			
Socioeconomic Characteristics					
Marital Status (1 if Single, 0 otherwise)	-0.613	-3.89	-0.216	7.80%	92.2%
(Standard Deviation of Parameter)	0.432	3.1			
Business Characteristics					
Type of Employer (1 if private carriage, 0 otherwise)	-0.322	-2.21	-0.0888	30.8%	69.2%
(Standard Deviation of Parameter,)	0.641	5.04			
Driver Characteristics					
Type of road usually driven (1 if rural or city roads, 0 otherwise)	0.741	3.09	0.203		
Parking Location decision (1 if driver makes decision, 0 otherwise)	0.613	3.63	0.213		
Driving Characteristics					
Lane-changing to avoid traveling with passenger vehicle behind (1 if never, 0 otherwise)	0.463	3.31	0.160	77.1%	22.9%
(Standard Deviation of Parameter)	0.623	5.04			
Accident Characteristics					
Crash History (1 if at least one crash in past 5 years, 0 otherwise)	0.711	3.72	0.193	63.2%	36.8%
(Standard Deviation of Parameter)	2.10	6.61			

Table 3-2: Random Parameter Bivariate Binary Probit Model Results

Variable	Parameter Estimate	t-statistic	Marginal Effects[ǂ]	Percent Observations Above 0	Percent Observations Below 0
Time of Day Operations					
Day of week most difficult to find safe and adequate parking (1 if Tuesday, 0 otherwise)	0.421	2.80	0.145		
Driving Management					
Frequency of making a stop on a longer trip (1 if every 4 to 6 hours, 0 otherwise)	0.464	3.36	0.160		
Y_2 = Likelihood of reporting concentration lapsing while driving over a long period of time					
Constant	1.47	3.93			
Socioeconomic Characteristics					
Driver Age (1 if 36 or older, 0 otherwise)	-0.560	-3.78	0.0295	2.21%	97.79%
(Standard Deviation of Parameter)	0.280	2.88			
Business Characteristics					
Type of Employer (1 if private carriage, 0 otherwise)	-0.410	-2.64	-0.0888		
Driver Characteristics					
Type of road usually driven (1 if rural or city roads, 0 otherwise)	0.940	2.99	0.203		
Truck Driving Education (1 if self-taught, 0 otherwise)	0.45	2.35	-0.0221		
Shipment type (1 if less-than-truck load, 0 otherwise)	-0.53	-2.28	0.0303	18.09%	81.91%
(Standard Deviation of Parameter)	0.59	2.7			
Driving Characteristics					

Table 3-2: Random Parameter Bivariate Binary Probit Model Results

Variable	Parameter Estimate	t-statistic	Marginal Effects[ǂ]	Percent Observations Above 0	Percent Observations Below 0
Driver confidence in their ability to professionally drive a large truck (1 if extremely or very confident, 0 otherwise)	-1.10	-3.43	0.0461		
Situation that poses the highest safety hazard to drivers (1 if passenger car on either side or behind, 0 otherwise)	-0.47	-2.69	0.0237		
Lane-changing to avoid traveling with truck in front (1 if never, 0 otherwise)	-0.56	-2.93	0.0319		
Accident Characteristics					
Crash History (1 if at least one crash in past 5 years, 0 otherwise)	1.10	5.15	0.193	92.64%	7.36%
(Standard Deviation of Parameter)	0.76	3.82			
Time of Day Operations					
Start Drive (1 if between 10 am and 4 pm, 0 otherwise)	0.72	3.14	-0.0339		
Time of week most difficult finding safe truck parking (1 if weekend, 0 otherwise)	-0.37	-2.58	0.0199	23.15%	76.85%
(Standard Deviation of Parameter)	0.51	4.6			
Driving Management					
Difficulty finding safe and adequate parking location when required to rest (1 if yes, 0 otherwise)	0.50	3.36	-0.0265		

Table 3-2: Random Parameter Bivariate Binary Probit Model Results

Variable	Parameter Estimate	t-statistic	Marginal Effects[ǂ]	Percent Observations Above 0	Percent Observations Below 0
Keep driving rather than stopping to take breaks to manage fatigue (1 if strongly agree or agree, 0 otherwise)	0.73	4.58	-0.0385	71.43%	28.57%
(Standard Deviation of Parameter)	1.29	7.86			
Model Summary					
Number of Observations	515				
Correlation Coefficient, ρ (Constants Only)	0.145	2.10			
Correlation Coefficient, ρ (Full Model)	0.300	3.14			
Log-Likelihood at Zero	-703.23				
Log-Likelihood at Convergence	-602.25				
AIC	1270.5				
McFadden Pseudo R^2	0.144				

*: Standard Deviation of random parameters are normally distributed

ǂ: Marginal effects represent change in joint probability $y_1 \mid y_2 = 1$

3.6.2.1 Socioeconomic Characteristics

According to model results, single marital status significantly influences the likelihood that drivers of large trucks would report using their cell phone while driving. Further, this parameter was found to be random and normally distributed. Specifically, about 8% of truck drivers who indicate being single are more likely to report using their cell phone while driving whereas 92% of these same drivers are less likely (Table 3-2). One possible explanation for this non-homogenous nature is that the random parameter might be capturing unobserved differences for the need to use a cell phone while driving. A study by Sarksisian and Gerstel (2015) find that single individuals are more likely to socialize and exchange help with friends/neighbors and offer more support with their parents than individuals who are married. Following Sarksisian and Gerstel (2015), a proportion of single respondents in the current study may be more socially active than others, which prompts the need, or desire, to use a cell phone while driving a large truck, despite the inherent risks and associated fines if caught.

The parameter referring to respondents who are 36 years of age or older was the only significant socioeconomic characteristic that affected the likelihood of drivers reporting that their concentration lapses while driving (Table 3-2). Like marital status, the parameter for this variable was found to be random and normally distributed. Interestingly, about 2% of respondents who are older than 36 years of age are more likely to report having lapses in concentration while driving. The finding that almost all older drivers are less likely to experience their concentration lapsing while driving is somewhat counterintuitive; however, this finding may be explained by the correlation between driving experience and age. Older drivers typically have more experience operating a large truck and, over this time, may have developed strategies to maintain their attention on the driving-task and prevent themselves from being distracted. The heterogeneous nature of this variable may be capturing some individuals who may be of an older age, but have few years of truck driving experience. Moreover, according to Emory University (2017), simple mental attention is preserved in older age, but may be complicated when divided attention is required. This may also explain the heterogeneous nature of this variable and why majority of older respondents are less likely to report having lapses in concentration while driving, though some are more likely.

3.6.2.2 *Business Characteristics*

Questions in the survey that solicited information on the business characteristics for whom respondents work for were assessed for significance to understand if they have an influence on distracted driving among truck drivers. Working or contracting for a private carriage employer was the only statistically significant business characteristic in the BBPM. This parameter affects the likelihood that truck drivers would report both sources of driver distractions (i.e., report using their cell phone and experiencing lapses in concentration while driving).

When explaining the likelihood of self-reported cell phone use while driving, the estimated parameter for private carriage drivers was found to be random and normally distributed. Specifically, 31% of drivers who indicate that they work for or contract for a private carriage are more likely to report using a cell phone while driving and 69% are less likely. This heterogeneity may be explained by inconsistent cell phone use policies imposed upon drivers from their private carrier employers. Some private carriers may have specific policies against distracted driving and strictly enforce such policies, resulting in reduced likelihood of using a cell phone while driving. Other carriers, however, may neither enforce nor advocate such policies to the same extent, resulting in increased likelihood of using a cell phone while driving.

In addition, drivers who work for a private carriage were found to be statistically significant in regards to self-reporting concentration lapses while driving (the parameter for this variable, however, was not found to be random in this equation). Pertaining to self-reporting lapses in concentration while driving, drivers who work for a private carriage are less likely to report such an experience. This finding could be explained by the possible training courses offered to drivers or current policies that mitigate driver inattention. Private carriage employers typically establish strict safety policies and require drivers to attend safety training courses to reduce safety critical events and be marketable as a safety-oriented company, both of which help gain more clients. These strategies may explain why private carriage drivers are less likely to report being manually or cognitively distracted while driving.

3.6.2.3 Driver Characteristics

Of the driver characteristic questions included in the survey, four were found to be significant in the BBPM. These driver characteristics include: type of road usually driven, parking location, shipment type, and truck driving education. Understanding these factors can aid in the development of tactical-level (i.e., driver level) strategies that can mitigate driver inattention.

When truck drivers report primarily driving on either rural or city roads, the likelihood of self-reported cell phone use and lapses in concentration while driving increases. Specifically, the joint probability marginal effect shows that drivers who typically drive on rural or city roads have a 0.203 higher probability of reporting both sources of driver distraction. Typically, when drivers utilize city or rural roads, they are likely to be near their delivery location. Being near their destination may explain why truck drivers are more likely to use their cell phones while driving so that they can coordinate final delivery logistics with the arrival destination. Similarly, drivers may be unfamiliar with the final routes and may rely on navigation devices or other mechanisms (i.e., communicating with dispatch center) to guide them to their destination, which may divert their attention away from the driving task. As mentioned, past studies have shown a correlation between driver external and driver internal distractions (Just et al., 2008; Strayer et al., 2013; Young and Regan, 2007). This finding may explain why driving on rural or city roads affects the likelihood of reporting both types of driver distraction.

Further, drivers who personally decide their parking location have an increased likelihood of self-reporting cell phone use while driving. According to the Federal Highway Administration (2012) there is a severe and widespread truck parking shortage throughout the United States. Considering this finding, Anderson et al. (2018b) determined that receiving real-time information, such as the number of available truck parking spaces at upcoming facilities, would reduce the probability of truck drivers encountering problems finding safe and adequate parking. This may explain why drivers are more likely to use their cell phones while driving, and consequently self-reporting such an engagement, to receive real-time information and minimize the possibility of experiencing parking issues. Although not significant in explaining the likelihood of concentration lapses while driving, the joint probability shows that drivers who personally select their parking location have a 0.215 higher probability of reporting both forms of driver inattention. This relatively high marginal effect suggests that cell phone use results in diverted mental attention and increases the likelihood of using a cell phone while driving, confirming past studies that showed such relationship (Just et al., 2008; Strayer et al., 2013). As such, eliminating cell phone use can simultaneously help reduce the occurrence of concentration lapses while driving.

Drivers who taught themselves how to drive large trucks are more likely to report having experienced lapses in concentration while driving. The lack of structured curriculum and omission of certified training courses in self-taught truck driver education programs may cause this increased probability of drivers self-reporting lapses in concentration while driving.

Lastly, the parameter representing drivers who indicated that they typically drive, on average, LTL shipments was found to be random and normally distributed. About 18% of respondents who deliver LTL shipments are more likely to report that their concentration lapses while driving whereas 82% are less likely. LTL shipments are typically associated with shorter hauls (between 200 and 600 miles) and this association may explain the heterogeneous nature of this parameter (Anderson et al., 2018). For instance, if a driver is delivering a LTL shipment where the destination is on the lower end of that range, the likelihood that their concentration lapses while driving may decrease because they can finish their delivery before becoming mentally exhausted or fatigued. On the other hand, a driver could be delivering a LTL shipment that is much farther and the extended driving time may increase the likelihood of experiencing lapses in concentration while driving due to the increased time-on-task needed to finish a delivery.

3.6.2.4 Driving Characteristics

Of the driving characteristics questions asked in the survey, four were found to influence the likelihood of drivers reporting either cell phone use or lapses in concentration while driving. Combined with the understanding of significant driver characteristic parameters, driving characteristic factors can lead to the development of operational-level strategies to mitigate driver inattention among truck drivers.

Lane-changing behavior was the only driving characteristic that influenced the likelihood of truck drivers reporting using a cell phone while driving. Specifically, never changing lanes to avoid traveling with passenger vehicle behind affects the likelihood that a driver would report using a cell phone while driving. The parameter for this driving characteristic was found to be random and normally distributed. As shown in Table 2, 23% of drivers who exhibit this lane-changing behavior are less likely to report using a cell phone while driving whereas 77% are more likely. Past studies have shown that drivers adopt compensatory behaviors when engaged in a secondary task, such as increased headway or reduced speeds, to account for the increased crash risk (Oviedo-Trespalacios et al., 2017b; Young and Lenné, 2010). The adoption of such compensatory behaviors may explain why drivers who never change lanes to avoid travelling with a passenger car behind are more likely to report using a cell phone while driving. Without vehicles in front of them, truck drivers can dictate their headway and travel speed so that they can use their cell phone while driving and compensate for the adverse behavior.

Three driving characteristics were found to decrease the likelihood of drivers reporting that their concentration lapses while driving: driver confidence, dangerous driving situation, and lane-changing behavior. If a driver reports that they are extremely or very confident in their abilities to professionally operate a large truck, they are less likely to report that their concentration lapses while driving. This finding may be an example of confirmation bias where drivers accept information that confirms a belief (Heshmat, 2015). In this context, drivers who confidently believe in their abilities to professionally drive a large truck confirm this belief by reporting that they do not experience lapses in concentration while driving, which may be contradictory to confidence. Further, drivers who are confident in their abilities to professionally drive a large truck may in fact have developed skills that enable them to stay focused on the driving task and prevent their concentration from lapsing while driving. Contrarily, in terms of joint probability, confident truck drivers have a 0.0461 higher probability of reporting both forms of distracted driving. Confident drivers may have developed a sense of self-efficacy in their ability to drive while multi-tasking and may tend to use their cell phone while driving, which, in turn, results in driver internal distraction (i.e., lapses in concentration) (Hill et al., 2015; Just et al., 2008; Strayer et al., 2013)

In addition to confidence operating a large truck, drivers who report that passenger cars traveling on either side or behind their truck poses the highest safety hazard have a decreased likelihood of self-reporting lapses in concentration while driving. If drivers perceive this driving situation to be pose the highest safety hazard, they may need to be more alert to reduce the risk of being involved in a safety critical event. For instance, if a truck driver is unaware of an approaching passenger car that enters their blind spot, the truck driver may change lanes with the potential of being involved in an accident. Being more alert in hazardous driving situations leads to drivers concentrating more on the roadway and its environment.

Similarly, drivers who report never changing lanes to avoid traveling with another truck in front are less likely to report that their concentration lapses while driving. This decreased likelihood may be influenced by the same reasoning for the decreased likelihood of truck drivers who perceive being surrounded by passenger cars pose the highest safety hazard. That is, truck drivers need to be more alert when near other vehicles to account for unanticipated events. This vigilance decreases the opportunity for drivers to experience a lapse of concentration.

3.6.2.5 *Accident Characteristics*

Truck drivers who were involved in at least one crash in the past five years are more likely to report that they use their cell phone and experience concentration lapses while driving. In terms of joint probability, drivers who were involved in at least one crash have a 0.193 increased probability of reporting both types of distracted driving. In both models, this parameter was random and normally distributed. Specifically, 36.8% and 7.36% of truck drivers who reported being involved in at least one crash in the past five years are less likely to report using a cell phone and experience a lapse of concentration while driving, respectively. The heterogeneity in this parameter may be explained by individual perceptions of distracted driving and crash risk. As mentioned previously, distracted driving leads to increased crash risk (Fitch et al., 2013; Klauer et al., 2006; Olson et al., 2009). The proportion of truck drivers who have been involved in a crash and are less likely to report being distracted while driving may now be more cognizant of the associated crash risks and oppose engaging in such tasks. For instance, a driver who has been involved in a crash might be more aware of, or pay closer attention to, the driving environment and choose to refrain from using their cell phone while driving, which would hinder their ability to sustain focus on the driving task. On the other hand, the proportion of drivers who have been involved in a crash and are more likely to report being distracted may not have been at-fault and their decision to use a cell phone or prevent lapses in concentration while driving may not have changed. Further, because distracted driving increases crash risk, it is possible that cell phone use or driver inattention was a factor in these self-reported crashes.

3.6.2.6 Time of Day Operations

Truck drivers who indicate that Tuesdays are the most difficult day of the week to find safe and adequate truck parking are more likely to report using their cell phone while driving. As previously mentioned, there is a widespread truck parking shortage through the United States and using a cell phone while driving to access real-time information may allow drivers to find the nearest available parking location (Anderson et al., 2018; Federal Highway Administration, 2012). Accordingly, joint probability effects indicate that drivers who encounter difficulties finding parking have a 0.145 increased probability of reporting both types of driver inattention.

Regarding self-reported lapses in concentration while driving, the estimated parameter for those who indicate weekends as the most difficult time of the week to find safe and adequate truck parking is randomly and normally distributed. About 23%

of respondents are more likely to report that their concentration lapses while driving whereas 77% are less likely. This heterogeneity may be capturing the differences in how truck drivers perceive safe and adequate parking. For instance, some drivers may perceive that parking on freeway ramps or shoulders are safe and adequate while others may believe designated parking areas are the only safe and adequate locations. If a driver perceives the latter, they might be more likely to report lapses in concentration while driving because they are thinking of potential places to park. Drivers who may perceive that parking on freeway ramps and shoulders is acceptable may be less likely to report lapses in concentration because they would not experience any problems finding a parking location.

Lastly, starting a drive mid-day (10:00 am to 4:00 pm) was determined to increase the likelihood that a truck driver would report experiencing lapses in concentration while driving. This finding is plausible as starting a drive mid-day avoids travel during morning or afternoon peak periods, especially near larger cities. During these times, the driving task is less demanding because of lower traffic volumes and fewer interactions with other vehicles. This may explain why drivers who start their drives mid-day are more likely to report that their concentration lapses while driving.

3.6.2.7 Driving management

Turning to driving management characteristics that affect the likelihood of self-reporting cell phone use and concentration lapsing while driving, three parameters were found to be statistically significant. These parameters include the frequency of making stops when making a longer trip, difficulty finding parking when required to rest, and fatigue management strategies. Understanding these factors can further help develop operational-level strategies that reduce truck driver engagement in distracting activities.

Truck drivers who make a stop every 4 to 6 hours are more likely to report using their cell phones while driving. According to a Zendrive study, which analyzed data from 3.1 million anonymized passenger car drivers through smartphone sensors, the average phone use while driving is 3.5 minutes per hour of driving (Zendrive, 2017). Large truck drivers might exhibit this similar driving behavior and may explain why those who stop every four to six hours during a longer drive are more likely to report using their cell phone while driving. Driving for four to six hours without stopping is a considerable amount of time and drivers may report using their cell phones while driving to stay updated with personal or business matters. Accordingly, joint probability effects show that truck drivers who stop every 4 to 6 hours have a 0.160 increased probability of reporting both types of driver inattention.

Truck drivers who indicated experiencing difficulty finding safe and adequate parking when required to rest are more likely to report that their concentration lapses while driving. The requirement to rest arises from the FMCSA’s Hours-of-Service (HOS) regulation, which is in place to ensure drivers are rested and improve the safety of all road users. As drivers near the end of their HOS limitations, they are often fatigued, or sleepy, from driving a long period of time. When drivers have difficulty finding safe and adequate parking to rest, they do not immediately find a place to rest and continue to drive while fatigued until they identify a safe location to park. According to Eoh et al. (2005), Lal and Craig (2001), and Lyznicki et al. (1998), driver fatigue affects the ability to sustain adequate attention on the driving task and leads to degraded driving performance. The lack of attention on the driving task may reason why drivers who have difficulty finding safe and adequate parking are more likely to experience lapses in concentration while driving.

The variable referring to truck drivers who indicate that they rather keep driving than take breaks to manage fatigue was found to affect the likelihood that drivers would report lapses in concentration while driving. This parameter was found to be random and normally distributed with approximately 29% and 71% of respondents being less and more likely to report lapses in concentration while driving, respectively. As mentioned previously, fatigued driving leads to reduced impaired mental performance, alertness, and loss of attention to the driving task (Lal and Craig, 2001; Lyznicki et al., 1998). However, because every individual is biologically different, the heterogeneity of this variable might be capturing the differences in how driver fatigue affects certain drivers. In this study, majority of truck drivers who continue to drive rather than stop to manage fatigue might be experiencing the negative effects of driver fatigue and report that their concentration lapses while driving. On the other hand, other truck drivers may not feel the effects of driver fatigue and are less likely to report experiencing lapses in concentration while driving. CMV carriers can use this information to establish policies that prohibit their drivers from continuing to drive when fatigued so that it minimizes the likelihood that truck drivers would drive while mentally inattentive.

3.7 Summary

Through a stated preference survey that was distributed to drivers of large trucks who deliver or receive goods in the Pacific Northwest, this study assessed the factors that affect the likelihood of self-reported cell phone use or lapses in concentration while driving. Because past studies have shown a connection between cell phone use and driver internal distractions, a RPBBPM was fitted to this survey data to determine such factors(Just et al., 2008; Strayer et al., 2013; Young and Regan, 2007). As measured by the tetrachoric correlation and disturbance term correlation coefficient (ρ), this study determines that there is a statistical correlation among cell phone use while driving and, through self-reported lapses in concentration, driver internal distractions experiencing lapses in concentration, which compliments the known relationship. This study, to the authors' knowledge, is the first to simultaneously determine the factors that influence the likelihood that truck drivers would engaging in driver external (i.e., using a cell phone while driving) and driver internal (i.e., lapses in concentration) distractions.

Because distracted driving impairs the safety of all roadway users, understanding the factors that influence such behavior is important to develop successful mitigation strategies at the tactical and operational level that minimize distracted driving among truck drivers. As shown in Table 2, model results determined 18 statistically significant parameters, nine of which were random and normally distributed (indicating heterogeneity within the dataset). Among these parameters, factors that are related to truck parking or HOS regulations, such as difficulty finding safe and adequate truck parking or continuing to drive to manage fatigue, were found to increase the likelihood that drivers would report either using their cell phone or experiencing lapses in concentration while driving (Table 2). This increase in likelihood may be a result of the effects of the widespread truck parking shortage throughout the U.S. (Federal Highway Administration, 2012). This shortage may cause truck drivers to use their cell phone to identify available truck parking locations and exceed HOS regulations, which affects the ability to sustain adequate attention on the driving task and leads to degraded driving performance (Eoh et al., 2005; Lal and Craig, 2001; Lyznicki et al., 1998). CMV carriers and associations can use this information to urge government agencies or encourage public-private partnerships to fund and implement projects that improve the quality and quantity of truck parking. By addressing the truck parking shortage, government agencies can simultaneously reduce the occurrence of distracted driving among truck drivers and improve roadway safety for all users.

Further, as shown in Table 2, LTL shipments were found to decrease the likelihood that drivers would report experiencing lapses in concentration while driving. As mentioned, LTL shipments are typically associated with shorter hauls and, because of the resulting shorter time on task, may explain why drivers are less likely to report experiencing lapses in concentration (Anderson et al., 2018). By developing delivery strategies that focus on decreasing the length of hauls, CMV carriers can reduce the occurrence of cognitive distraction among truck drivers. Lastly, majority of drivers who reported being involved in at least one crash in the past five years are more likely to report using their cell phone and experiencing lapses in concentration. Establishing mandatory safety training courses or requiring periodic safety assessments that include driver inattention and distraction topics can be a mechanism to reduce driver inattention among truck drivers.

Since most distracted driving research has focused on the prevalence and associated crash risk of cell phone use among passenger car drivers, this study contributes to the body of knowledge by examining the relationship between drivers of large trucks and driver distraction. Particularly, this study identified the factors that influence the likelihood that a truck driver would report engaging in both driver external and internal sources of distraction (cell phone use and concentration lapsing while driving). The findings of this study present an opportunity for public-private partnerships between state-level Departments of Transportation and CMV carriers to collaborate on strategies that help minimize driver inattention among truck drivers. Because the results of this study cannot be extrapolated beyond drivers who deliver or pick up goods in the Pacific Northwest, future studies should consider sampling from a larger population. Future studies should also assess additional factors that may affect distracted driving engagement, such as various roadway environments or environmental characteristics, to further enhance the understanding of what prompts driver distraction and develop additional countermeasures. Continuing to understand the factors that either influence drivers' decision to use a cell phone or likelihood of experiencing lapses in concentration will result in safer roads for all users.

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4 CHAPTER 4 – CONCLUSIONS

The preceding two chapters are individual manuscripts that compliment and advance existing distracted driving literature by understanding truck driver behavior with respect to driver internal and driver external sources of distraction. In Chapter 2, factors that influence the likelihood of truck drivers self-reporting cell phone use while driving were determined. This chapter overcomes the limitations of existing literature, as it is one of the first to identify these factors with respect to drivers of large trucks. Chapter 3 expanded this work and contributes to literature by determining the factors that influence the likelihood that truck drivers, as measured by self-reported lapses in concentration while driving, would engage in driver internal distractions,. Prior to this work, existing literature has primarily investigated distracted driving arising from driver external sources and only a small portion have looked into driver internal sources (i.e., daydreaming, inattention, lapses in concentration).

The results of this thesis have a practical and theoretical application that may assist in improving transportation safety. First, the significant factors identified in this thesis can aid transportation agencies and commercial motor vehicle carriers develop strategies that reduce the likelihood of truck drivers engaging with, or experiencing, different sources of distracted driving (i.e., driver internal and external). Secondly, the methods used in this thesis provides a framework for future academic research to investigate additional factors, or motives, that entice truck or passenger car drivers to engage in distracted driving.

This chapter addresses the limitations of this thesis, summarizes key findings, and discusses the practical and theoretical applications of this study.

4.1 Significant Findings

This section highlights the significant findings of Chapters 2 and 3. The reported results in this section have the potential to develop tangible countermeasures that may reduce the occurrence of distracted driving among truck drivers. The reader is referred to Chapters 2 and 3 for further details.

4.1.1 Chapter 2 Findings

In Chapter 2, a stated-preference survey was administered to drivers of large trucks who either deliver or receive goods in the Pacific Northwest. From this survey, respondents were explicitly asked, *"Do you use a cell phone while driving (Either handheld or hands-free)?"* and had to respond with either "*Yes*" or "*No.*" The binary nature of this response necessitated a binary discrete choice model. As such, a random-parameter binary logit model was fitted using the responses of this question as the dependent variable. Through a step-wise modelling procedure, 21 parameters were found to be statistically significant, seven of which are random and normally distributed, in explaining the probability that truck drivers would report using their cell phone while driving.

With over 90% confidence, the Log-Likelihood ratio test determined that the random parameters binary logit model outperformed the fixed binary logit model, indicating heterogeneity among respondents. Further, the McFadden Psuedo-R^2, which is a measure of fit between calculated probabilities and observed response frequencies, was determined to be 0.16 (McFadden and Domencich, 1975). According to Louviere et al. (2000), McFadden Psuedo-R^2 values between 0.2 and 0.4 are considered to be indicative of exceptionally good fits, which means a Mc Fadden Psuedo-R^2 value of 0.16 can be considered as a good fit.

Of the 21 significant parameters in this model, variables referring to age, truck parking, fatigue management, and safety training provided interesting results. Past studies have shown that younger passenger car drivers are more likely to use their cell phone while driving, but results from this thesis indicate that younger truck drivers (18-25) are less likely to use their cell phone while driving (Gliklich et al., 2016; Oviedo-Trespalacios et al., 2017b; Schroeder et al., 2013). This finding supports the fact that there are inherent differences between drivers who are either operating a large truck or passenger car and the results of passenger car distracted driving studies do not necessarily reflect the outcomes of truck drivers.

Parameters related to truck parking decisions and difficulty all increase the probability that drivers of large trucks would report using their cell phones while driving. As mentioned by Anderson et al. (2018), there is a severe and widespread truck parking shortage throughout the U.S. that leads to truck drivers encountering problems finding safe and adequate parking. Anderson et al. (2018) further finds that receiving real-time information, such as through cell phone applications, lowers the probability of truck drivers encountering problems finding safe and adequate parking. This finding may explain why the parameters related to truck parking decisions and difficulty increase the probability that truck drivers would report using their cell phone while driving.

Parameters related to driver fatigue management decrease the probability that drivers of large trucks would self-report using a cell phone while driving. Specifically, CMV carriers who either restrict the number of hours worked per week or impose a schedule that enables drivers to easily take breaks decrease this likelihood. This finding complements the work conducted by Gershon et al. (2011) who find that professional drivers perceive talking on a cell phone is an effective countermeasure to driver fatigue. If a truck driver can easily take breaks on a route to manage fatigue, they would not need to use their cell phone to combat the effects of driver fatigue.

Lastly, truck drivers who indicated that they have participated in road safety training course are more likely to report using a cell phone while driving. This finding is counterintuitive, but it highlights the ineffectiveness of such programs in developing safe driving behaviors among truck drivers. As studied by Gregersen (1996), there is a relationship between training strategies and overestimation of driving skill among young drivers. This overestimation can lead to self-efficacy of the driving task, which Hill et al. (2015) finds to be a significant predictor of distracted driving.

4.1.2 Chapter 3 Findings

In Chapter 3, efforts were made to understand the relationship between driver internal sources of driver distraction (i.e., lapses in concentration, daydreaming, misprioritised information) and drivers of large trucks. As a proxy to understand this relationship, a random parameters binary probit model was fitted to the responses of the question, "*How often do you find your concentration lapsing after driving for a long time?*" As mentioned in Chapter 3, this study considers lapses in concentration to include intentional or unintentional, internally triggered, task-unrelated thoughts (i.e., mind wandering, daydreaming) (Regan et al., 2011). Truck driver respondents selected either very often, quite often, sometimes, rarely, or never. Those who indicated that their concentration lapses either very often, quite often, or sometimes while driving were considered in this work to have experienced their concentration lapsing while driving. As such, a binary variable was created for those who responded with any of these responses to discern who has reported experiencing lapses in concertation while driving or not.

As discussed in descriptive detail in Chapter 3, there is an inherent correlation between using a cell phone while driving and experiencing internal driver distractions (e.g.,lapses in concentration). This correlation is confirmed by a highly significant tetrachoric correlation and error term correlation coefficient (ρ). This statistical finding compliments existing research which have determined that using a cell phone while driving increases cognitive workload and results in internal distractions (Just et al., 2008; Strayer et al., 2013; Young and Regan, 2007). Because of this correlation, a random parameter bivariate binary probit model was fitted with self-reported cell phone use and lapses in concentration while driving as the dependent variables.

A total of 18 statistically significant variables, nine of which are random and normally distributed, were included in the final model following a step-wise procedure. Of these, three variables (crash history, type of employer, and type of road usually driver) were found to affect the likelihood of a truck driver reporting both using a cell phone and experiencing lapses in concentration while driving. Further, there were five significant variables that specifically influenced a driver's likelihood of using a cell phone while driving and ten significant variables that only influenced the likelihood of a driver's concentration lapsing while driving.

Interestingly, drivers who indicated being involved in at least one crash in the past 5 years have an increased likelihood of reporting using a cell phone and experiencing lapses in concentration while driving. In both models, this parameter is random and normally distributed. The heterogeneity in this parameter may be explained by individual perceptions of distracted driving and crash risk. In other words, some drivers may be more cognizant of the associated crash risks with distracted driving and oppose engaging in such behavior while others may not have altered their existing behavior or perceptions. This finding is consistent with Jashami et al. (2017) who finds that crash history increases the likelihood of self-reported texting while driving.

Similarly, truck drivers who work for private carriage have a decreased likelihood of reporting using a cell phone and experiencing lapses in concentration while driving. In explaining the likelihood of self-reported cell phone use while driving, this parameter was random and normally distributed. This finding may indicate that private carriage employers have developed sufficient strategies that reduce the occurrence of their drivers experiencing lapses in concentration, but are inefficient for some drivers in reducing cell phone use while driving.

Consistent with the findings of Chapter 2, variables pertaining to truck parking decisions and difficulty were found to increase the likelihood that truck drivers self-report using a cell phone and experience lapses in concentration while driving. This finding, in combination with Chapter 2, highlights the cascading effect of the truck parking shortage on roadway safety (Anderson et al., 2018).

Lastly, parameters related to adverse fatigue management strategies, such as continuing to drive rather than take breaks to manage fatigue, increase the likelihood that truck drivers would self-report lapses in concentration while driving. According to Lyznicki et al. (1998) and Lal and Craig (2001), fatigued driving leads to impaired mental performance, alertness, and loss of attention to the driving task. This result may explain why drivers who choose adverse fatigue management strategies (i.e., fewer breaks, continuing to drive when fatigued) are more likely to experience lapses in concentration while driving.

4.1.3 Summary

Influential factors on the likelihood that truck drivers would self-report engagement with one source of driver distraction (i.e., using a cell phone or experiencing lapses in concentration while driving) were determined in this thesis. Influential factors included variables related to: socioeconomic, business, driver, driving, and accident characteristics, time of day operations, and driving management strategies. These influential factors were determined using a random parameters binary logit and bivariate binary probit models. The methods used in this analysis can be used as a framework for future studies that intend to further investigate factors that prompt driver internal and external sources of distraction.

While some of these factors simply provide insight into what influences driver inattention (i.e., age, lane-changing behavior) certain parameters have the potential to aid transportation agencies and CMV carriers. Agencies and CMV carriers can use the results of this thesis to justify the need for certain programs or strategies that may potentially reduce the presence of driver inattention on roadways. For instance, parameters related to truck parking issues, fatigue management strategies, and current safety training programs have an effect on driver inattention and this information can be used to create effective driver inattention countermeasures. The following subsection will discuss practical applications of these results in mitigating driver inattention among drivers of large trucks.

4.2 Practical Applications

As mentioned previously, certain factors identified in this thesis can be used to create tangible solutions that may mitigate driver inattention among drivers of large trucks. For instance, parameters referring to truck parking difficulty or decisions were found to increase the likelihood that truck drivers would self-report using a cell phone and experiencing lapses in concentration while driving. The FHWA, in a 2012 analysis, determined that there is a severe and widespread truck parking shortage throughout the U.S. (Federal Highway Administration, 2012). Because of this shortage, truck drivers may rely on their cell phone to find the nearest safe and adequate parking spot and continue to drive while fatigued, which can cause lapses in concentration. The results of this thesis supports the notion of a cascading effect of this shortage on roadway safety (Anderson et al., 2018; Federal Highway Administration, 2012). Because truck parking difficulty and decisions have been shown in this work to increase the likelihood of self-reported driver inattention, agencies can use this information to justify and advance current efforts to improve truck parking throughout the U.S. By addressing the current truck parking shortage, government agencies can simultaneously reduce the occurrence of distracted driving among truck drivers and improve roadway safety for all users.

Drivers who engage in adverse fatigue management strategies, such as continuing to drive when fatigued rather than take breaks or often driving while tired, have an increased likelihood of being inattentive while driving (i.e., using a cell phone or experiencing lapses in concentration while driving). Policies should be enacted at the organizational level to prevent truck drivers from participating in these adverse driving behaviors. For instance, as determined by the results of this work, organizational policies that manage driver fatigue by restricting the number of hours worked per week or imposing schedules that make taking breaks easier were found to decrease the likelihood that drivers report using a cell phone while driving. CMV carriers can adopt similar, or identical, fatigue management strategies to reduce the likelihood that truck drivers would use their cell phone while driving. In doing so, CMV carriers can reduce the presence of both fatigued driving and driver inattention on roadways and mitigate the associated safety implications.

Lastly, drivers who have participated in a road safety training course are more likely to report using a cell phone while driving. This finding highlights the ineffectiveness of such programs in developing safe driving behaviors. If the purpose of current safety training programs are to enhance a driver's ability to safely operate a truck, drivers may develop a sense of self-efficacy (i.e., confidence), which has been shown to be a predictor of distracted driving (Hill et al., 2015). Due to the severity, prevalence, and increased crash risk of distracted driving, specific training programs that are tailored to target driver inattention should be developed (Federal Motor Carrier Safety Administration, 2005; Gordon, 2009; Klauer et al., 2006; Treat, 1980). Such programs may be an effective intervention against driver inattention

4.3 Limitations

The use of self-reported measurements in this study is an inherent limitation as respondents are susceptible to inaccurate memories and providing false information. Despite this susceptibility, there was a high proportion (45%) of truck drivers who reported that they use their cell phone while driving. This proportion is consistent with past telephone-based survey studies that determined about 50% of respondents report using a cell phone while driving (Nurullah et al., 2013; Schroeder et al., 2013). This high proportion and consistency with past studies suggest that truck drivers responded honestly to the questions.

Additionally, this thesis assumes that self-reported cell phone use and lapses in concentration while driving reflects the true behavior exhibited by truck drivers. Without this assumption, strategies cannot be developed from the study's results to reduce the presence of distracted driving the pre on roadways. It should also be noted that there are other environmental factors, such as traffic flow and roadway geometry, and occupational factors that influence driver inattention (Kidd et al., 2016; Oviedo-Trespalacios et al., 2017a) among truck drivers and should be considered in developing mitigation strategies.

Lastly, there are perception issues regarding the interpretation of the question: "*How often do you find your concentration lapsing after driving for a long time?*" Because concentration lapsing was not explicitly defined in the survey, there may be different interpretations of what defines and constitutes lapses in concentration among truck driver respondents. For instance, some may interpret lapses in concentration simply as daydreaming while others may perceive it to be instances where they miss an exit. In this study, lapses in concentration is considered to include intentional or unintentional, internally triggered, task-unrelated thoughts (i.e., mind wandering, daydreaming).. However, an explicit definition of the term should be provided to respondents to eliminate this ambiguity and ensure accurate parameter estimates and inferences.

4.4 Future Work

The work of this thesis presents several opportunities for future research. First, this thesis builds on the applicability of using econometric modelling techniques and survey data in developing potential countermeasures for driver inattention. Second, it prompts further investigation of the factors that induce driver distraction among passenger car and truck drivers.

The prevalence of distracted driving and its effect on roadway safety has been widely investigated in existing literature. Because of this profound understanding, future distracted driving studies should focus on investigating the factors that compel drivers to engage in different sources of distracted driving. Due to the abundant amount of factors that influence distracted driving, not all influential factors were identified in this work. Future studies can employ the methodologies used in this study to identify additional factors that affect the likelihood of distracted driving. Finding additional influential factors, such as roadway environment, time-of-day, and effectiveness of current distracted driving policies and enforcement strategies, can be solicited through survey instruments and tested for statistical influence using the modelling techniques. Identifying additional factors that affect driver inattention can help create and develop practical solutions that reduce driver inattention and improve roadway safety for all users.

In this thesis, certain parameters that affect the use of cell phones and experiencing lapses in concentration while driving can be used to construct policies and programs that can potentially reduce driver inattention among truck drivers. Future work can use these and future findings to develop such solutions and measure their effectiveness in reducing driver distraction by conducting a pre- and post-implementation analysis. For example, this thesis has shown that difficulty finding safe and adequate truck parking increases the likelihood that truck drivers would use their cell phone while driving. If the existing truck parking shortage is addressed and truck drivers have less difficulty finding a safe parking location, future studies can determine whether there was a corresponding decrease in distracted driving among truck drivers.

To fill the notable gap in distracted driving literature, this thesis investigated the factors that influence the likelihood that driver of large trucks would engage in distracted driving. This thesis also demonstrates the applicability of such factors in developing programs and policies that have the potential to reduce the occurrence of distracted driving and improve roadway safety for all users. This study also provides a framework to further examine the relationship between distracted driving and all motor vehicle drivers.

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