AN ABSTRACT OF THE THESIS OF

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Title: Spatial and Temporal Effects on Large Truck-Involved Crash Injury Severities: A Mixed Logit Analysis.

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Salvador Hernandez

Large truck-involved crashes have a significant impact on both the economy and society. They are associated with high injury severities, high crash costs and contribute to congestion in urban areas. Past studies have investigated the contributing factors of large truck-involved crashes, however a study isolating the spatial and temporal effects is lacking. This thesis aims to bridge that gap as well as provide practical applications to improve safety from a large truck perspective through two new frameworks. This thesis contains two standalone documents, each detailing the spatial and temporal transferability framework, separately. These frameworks provide additional information that can be utilized in the development of planning tools to ultimately improve safety.

Random parameters logit models (i.e. mixed logit models) were utilized to help identify the contributing factors of large truck-involved crashes. One advantage of the mixed logit model is that it can account for the unobserved heterogeneity in the model which relaxes the independence of irrelevant alternatives (IIA) property. A series of log likelihood ratio tests were utilized to determine if transferability, spatial or temporal, was warranted.

The first document details the spatial transferability framework which is demonstrated through a case study on large truck-involved crashes in urban areas in Oregon and Texas. Strict regulations imposed on the trucking industry limits the variability of heavy-vehicle configurations and enhance the standards for truck drivers (as opposed to passenger vehicle drivers). Encouraging consistency between large trucks is one way to improve safety and has also lead to the investigation of commonalities between large truck-involved crashes in two spatially distributed regions. The results of the log-likelihood ratio tests indicate that spatial transferability is not warranted between Oregon and Texas. Key differences were non-driver or 'uncontrollable' characteristics (e.g. weather, light conditions and time of day) while driver related characteristics (e.g. gender, age and restraint use) had similar impacts. Since the major differences include non-driver characteristics, perhaps a regional model with similar 'uncontrollable' characteristics is warranted.

The second document illustrates the temporal transferability framework which is applied to large truck-involved crashes in urban areas in Texas. Traffic patterns, light conditions and driver behavior vary throughout the day and consequently can have a varied impact on large truck-involved crashes. The results of the log likelihood ratio tests indicate that temporal transferability is warranted and the database was divided into five time periods to be analyzed separately. Traffic flow, light conditions, surface conditions, month and percentage of trucks on the road were among the significant differences between the crash factors of each time period.

The two proposed transferability frameworks, spatial and temporal, provide new information that can be integrated into safety planning tools and more sharply guide

decision-makers. For example, the results of this thesis can help to pinpoint temporal or spatial-related countermeasures. In addition the results of this thesis can help in the allocation of limited resources (i.e. help prioritize projects), minimize economic loss and help decision makers improve safety from a large truck perspective (e.g. modify trucking regulations).

Finally, this thesis provides a foundation for future research. As indicated in Chapter 2, a future study to evaluate the feasibility of a regional large truck-involved crash model between neighboring regions and the development of a national crash data reporting standard are potential ideas for future research. Chapter 3 stressed the importance of time of day on large truck-involved crashes which can serve as the basis to study the safety and economic impacts of time of day shifts of truck freight movements to off-peak periods. In summary, this thesis involves original research that expands the literature and provides a new foundation to analyze large truck-involved crashes.

Spatial and Temporal Effects on Large Truck-Involved Crash Injury Severities: A Mixed Logit Analysis

by
Jasmine Pahukula

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APPROVED:

Major Professor, representing Civil Engineering

Head of the School of Civil and Construction Engineering

Dean of the Graduate School

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.

Jasmine Pahukula, Author

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CONTRIBUTIONS OF AUTHORS

Dr. Salvador Hernandez was involved in the overall concept and design of this research and provided extensive feedback on this thesis manuscript. Dr. Avinnash Unnikrishnan provided input and feedback on chapter three.

TABLE OF CONTENTS

LIST OF FIGURES

1.0 CHAPTER 1 - INTRODUCTION

1.1 Motivation

Needless to say, transportation is a key aspect of our daily lives. The economy is hugely dependent upon transportation infrastructure every day and large trucks contribute significantly to goods distribution across the United States. Large trucks rank at the top of freight transportation (i.e. rail, water, air and pipeline) for highest tonnage moved, highest value of tonnage moved, and number of vehicles (United States Department of Transportation, 2013). Unfortunately, large trucks also currently rank first for number of fatalities among freight transportation (United States Department of Transportation, 2013). This has raised many safety concerns regarding large trucks and the traveling public, especially in high density urban areas.

Past studies have developed severity models to identify contributing factors to these types of crashes. This research aims to address the transferability of these contributing factors both spatially and temporally by utilizing advanced econometric models. Spatial and temporal aspects of crash analyses have yet to be isolated in order to gain a clear understanding of the impacts of space and time on large truck-involved crashes. A framework detailing the methodology involving both spatial and temporal transferability is presented, separately, which provides a new outlook on crash analysis.

1.1.1 Large Truck-Involved Crashes in Urban Areas

As noted above large truck-involved crashes have a pronounced impact on the economy and society. The negative impacts include high injury severities, economic losses (i.e. loss of life and goods) and traffic congestion. In highly dense urban areas,

congestion can cause significant delays and cost thousands of dollars (Bureau of Transportation Statistics USDOT, 2013). This research focuses on large truck-involved crashes in urban areas.

The Insurance Institute for Highway Safety reports that differences between urban and rural roadways include density of road networks, land use and traffic patterns (Insurance Institute for Highway Safety, 2013). Consequently, there are different characteristics of motor vehicle crashes between rural and urban areas (Insurance Institute for Highway Safety, 2013). Khorashadi et al. (2005) also concluded that there were major differences between the factors of injury severities of large truck-involved crashes in rural and urban areas. In addition, Islam et al. (2014) assessed the impact of single and multi-vehicle crashes involving large trucks in rural and urban areas and also found major differences. Aggregating large truck-involved crashes into homogenous groups such as urban area crashes can produce more accurate results. These results can be used to help guide transportation safety plans to address significant issues regarding large truck-involved crashes in urban areas.

1.1.2 Econometric Models

Econometric models have been frequently used to identify and study the factors relating to highway crash severities which in return help to prioritize safety improvement projects and direct rule-making. Mannering and Bhat (2014) summarize the evolution of methodological approaches in crash research and acknowledge that over time these types of models have become increasingly sophisticated. They allow the researchers to address shortcomings of previous models as well as reveal new information about the variables included. This research utilizes an advanced econometric modeling approach, random

parameters logit model, to identify the contributing factors of large truck-involved crashes in urban areas.

Random parameters logit models have not only been proven to produce accurate results but they also account for the unobserved factors present in the model (Washington et al., 2010). For example, if the male indicator variable was found to be a significant contributing factor to a low injury severity there are varying characteristics between the male observations that are not explicitly included in the model. These characteristics could include height, weight, or pain tolerance. These unobserved factors (if not accounted for) could lead to bias estimates and incorrect inferences, which could ultimately lead to implementing ineffective mitigation measures. By acknowledging the presence of unobserved heterogeneity the independence of irrelevant alternatives (IIA) property violation is bypassed, however this approach does have drawbacks. The random parameters logit approach accounts for the unobserved factors by allowing the parameter estimates to vary across observations. The drawback is that an assumption must be made about the distribution of this variation which may not always hold true for each observation (Washington et al., 2010). There are other model approaches that can also account for the unobserved heterogeneity (e.g. latent class model), but the results of the various approaches are comparable. It should be noted that the econometric software utilized for the analysis is LIMDEP and NLOGIT, which provides a foundation to analyze data on multinomial choice (Greene, 2012).

1.1.3 Transferability

As mentioned above, the increasing sophistication of crash analysis methodologies have provided researchers with new insight. However, these advanced

models lack practical application which has increased the gap between researchers and practitioners regarding crash analysis (Mannering and Bhat, 2014). This research could bridge that gap. For example, temporal transferability can lend a hand to identify the best time to deploy licensed truck inspectors. In other words, this could help to allocate limited resources efficiently. State agencies could schedule the majority of their inspectors during high risk (i.e. higher severity) time periods as a preventative action aimed to reduce high severity crashes. Spatial transferability could prompt multiple states to work more closely when developing CDL training programs or when implementing countermeasures. Again, limited resources (i.e. time and money) could be saved. The random parameters logit severity models will serve as the basis for the evaluation of spatial and temporal transferability along with a series of log likelihood ratio tests.

The possibility of spatial transferability arises from the standardization within the trucking industry as compared to passenger vehicles. The federal government has strict standards for heavy vehicles and their operators. For instance, there are limited heavy vehicle configurations allowed on public roadways and heavy vehicle operators, specifically CDL carriers, must go through extensive and demanding training in order to obtain a CDL. Although the trucking industry is heavily regulated crashes still occur, thus is it still important to study large-truck involved crashes. However, with the persistent monitoring over the trucking industry it is anticipated that large truck-involved crash factors will be more similar and widespread (as opposed to passenger vehicles). Thus spatial transferability evaluates the commonalities of crash factors and injury severities between two spatially distributed regions. The spatial transferability framework, refer to

Figure 1, will be demonstrated with a case study comparing Texas and Oregon crashes which is detailed in Chapter 2.

In the case of temporal transferability, there are many factors that can vary throughout the day such as traffic patterns, light conditions and driver behavior. Therefore, the factors contributing to large truck-involved crashes at varying times of day can be hugely different. The complex relationships between the factors included in the models create a barrier to understand the true impact of time. The database was divided into five time periods in order to clearly understand the effects of time of day on the injury severity of large truck-involved crashes. To apply the temporal transferability framework, refer to Figure 2, large truck-involved crashes in Texas were utilized as a case study as depicted in Chapter 3.

The outcomes of this research can help to mold transportation policies and help to guide the efforts of NHTSA and FMCSA. The results could also benefit the trucking industry and state agencies to become more efficient.

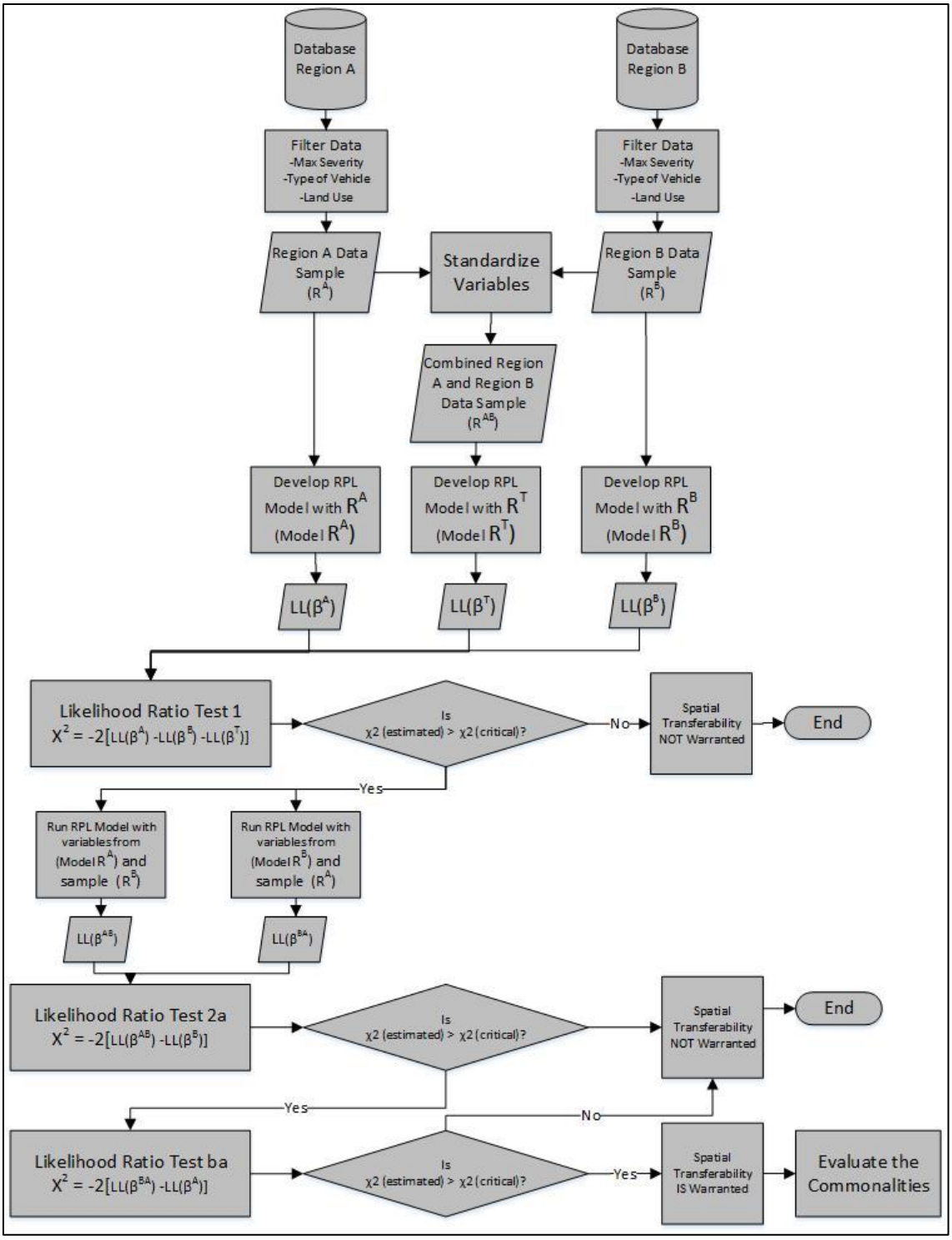

Figure 1.1: Spatial Transferability Framework

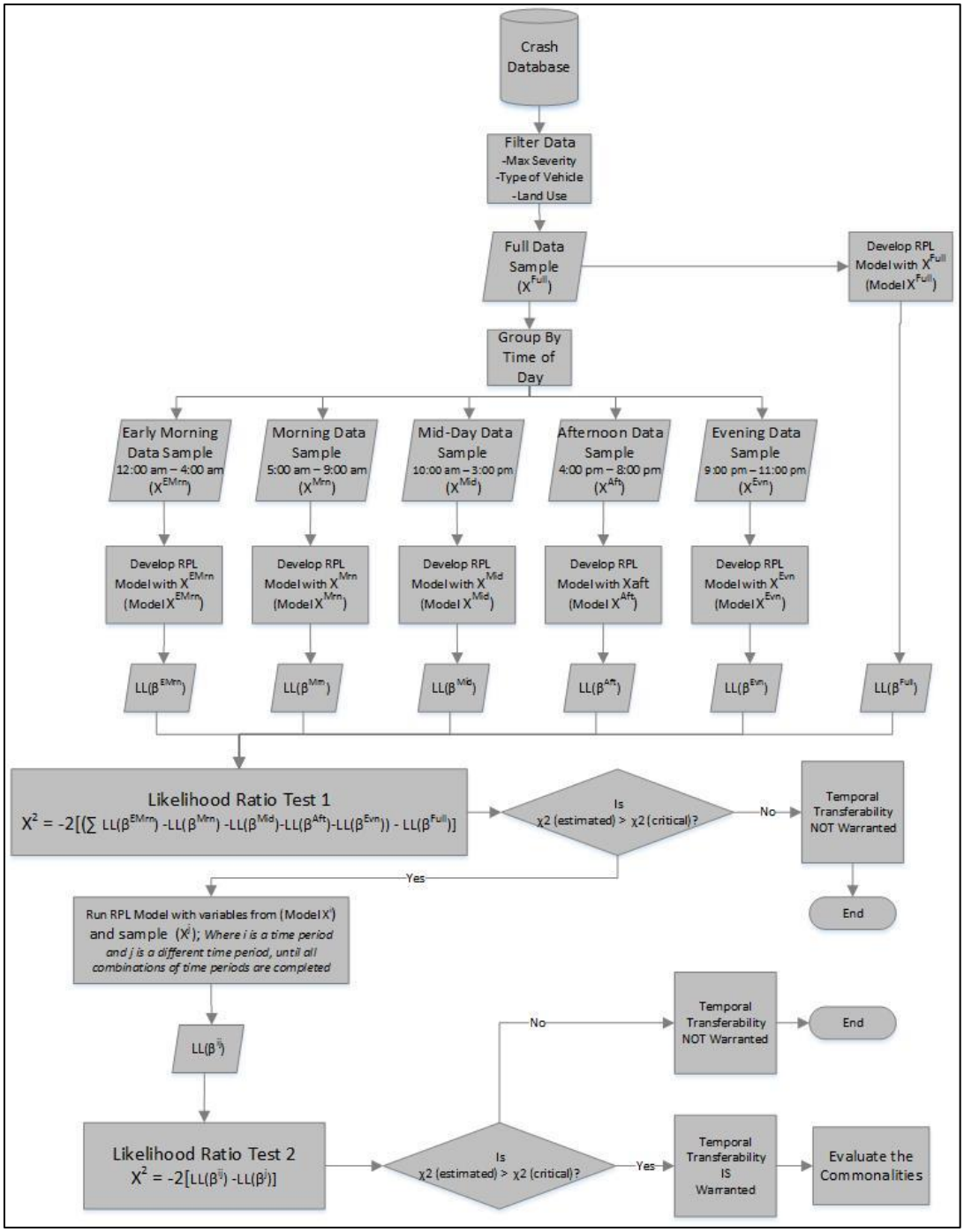

Figure 1.2: Temporal Transferability Framework

1.2 Organization of Document

This thesis contains two standalone documents that address the spatial and temporal transferability of large truck-involved crashes, separately.

The next chapter contains the first paper which demonstrates the spatial transferability framework. This study examines the commonalities between large-truck involved crashes in two spatially distributed urban regions. Crashes in Oregon and Texas are utilized as a case study to implement the spatial transferability framework. This article is currently under review by Accident Analysis and Prevention.

The third chapter contains the second paper which details the temporal transferability framework. This research aims to pinpoint the impact of time of day on large truck-involved crashes in urban areas. A case study involving large truck involved-crashes in Texas is presented. This article has been published in Accident Analysis and Prevention earlier this year (Pahukula et al., 2015).

The final chapter summarizes the major findings and contributions of the work. Practical applications of the results and implications for future research are also discussed.

2.0 CHAPTER 2 – SPATIAL TRANSFERABILITY OF LARGE-TRUCK INVOLVED CRASHES: AN EXPLORATORY RANDOM PARAMETER LOGIT ANALYSIS

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ABSTRACT

Recent studies have attempted to understand the contributing factors behind large-truck involved crashes; however these studies have primarily focused on state specific models using state specific datasets. In this study spatial transferability of large-truck crash models between two regions is evaluated. Random parameters (mixed) logit models for large-truck involved crashes in two urban areas are developed separately and together to study the spatial transferability of the models. A series of log likelihood ratio tests are used to compare the severity models. The results of the log likelihood ratio tests indicate that separate models for each region are necessary. Key differences include surface conditions, light conditions, speed and time of day. Also there were variables unique to each dataset such as median type or number of trailers that contributed to the differences between the severity models. There were also variables that were shared between the regions and more importantly the impacts of those variables were similar.

Keywords: Large Trucks, Injury Severity, Mixed Logit, Crash Analysis, Freight, Spatial Transferability

INTRODUCTION

Motivation

The trucking industry is heavily regulated and there are strict rules involving driver training, licensing, and registration as well as national standards on vehicle dimensions and cargo requirements. For instance, a Commercial Driver's License (CDL) is required in order to operate a heavy vehicle (26,000 pounds or more) and obtaining a CDL can be a lengthy process. Although each state has its own process to obtain a CDL, there are basic federal standards that must be met which require each driver to pass a written and skills test. For example, the written test is comprised of questions from the Federal Motor Carrier Safety Administration's (FMCSA) pre-approved pool of test questions to ensure consistency on the level of difficulty and topics covered across states. FMCSA also publishes and monitors vehicle standards, refer to Federal Motor Carrier Safety Administration (n.d.) for a detailed list of the vehicle regulations. The rigorous governance of the trucking industry promotes safe roadways by reducing the variability among heavy vehicles and their operators. These demanding safety precautions encourage consistency in the trucking industry, yet large-truck involved crashes still occur.

Recent studies have attempted to understand the contributing factors behind large-truck involved crashes (Dissanayake and Kotikalapudi, 2012; Dong et al., 2014; Hans and Gkritza, 2014; M. Bin Islam and Hernandez, 2013; Islam et al., 2014; Khattak et al., 2012; Pahukula et al., 2015), however these studies have primarily focused on state specific models using state specific datasets. Based on these previous studies, the objective of this paper is to study the spatial transferability of large truck crashes. A

unified model accounting for the factors that affect the injury severity of large truck-involved crashes across the US can help save valuable resources (i.e. time and money). Transportation safety professionals will be able to free-up resources for other issues while still improving safety of their highways from a large truck perspective. FMCSA continues to modify and develop regulations to improve highway safety. Analyzing the spatial transferability of large truck crashes can provide additional information by identifying the factors that contribute to these types of crashes which can help in the development of countermeasures or revised regulations. These types of tools have been previously developed with various databases and utilized to help identify area-specific safety countermeasures (Dissanayake and Kotikalapudi, 2012; Dong et al., 2014; Hans and Gkritza, 2014; M. Bin Islam and Hernandez, 2013; Islam et al., 2014; Khattak et al., 2012; Pahukula et al., 2015).

In order to demonstrate the spatial transferability framework between large-truck involved severity models in the US, two state databases and severity models were compared. Utilizing only two state databases provides a manageable dataset for this exploratory analysis. If spatial transferability is warranted, this framework can be applied to a larger area (i.e. include more state datasets). This analysis will serve as an initial step to comparing these types of crashes across the US. To the best of the authors' knowledge, this is the first attempt at evaluating the spatial transferability of large truck-involved severity models based on crashes in urban areas between two spatially distributed regions.

The remainder of the paper is organized as follows. First, a review of the current literature is presented followed by a discussion of the empirical settings. Next, the

methodological approach is explained and the case study results are summarized. Finally, implications of the findings and the conclusion are presented.

Background

Truck driver's go through an extensive training before they can obtain their commercial driver's license (CDL). All CDL drivers, in any state, are held to the same federal standards and constantly being monitored which make their driving behavior less random as compared to passenger vehicle drivers. For example, Kostyniuk and Blower (2008) conducted a study in Michigan comparing CDL and non-CDL (trucks less than 26,000 lbs.) driving records and found that non-CDL drivers were more likely to be assigned a hazardous action in the crash than CDL drivers. Non-CDL drivers generally had poorer driving records and were more likely to contribute to a crash than CDL drivers who undergo training, testing and licensing requirements (Kostyniuk and Blower, 2008). Although this study only included crashes in Michigan, it is evident that the training program enables safety driving strategies.

Spatial transferability of crash analysis results is a scarcely studied topic. Abdel-Aty (2003) conducted a spatial analysis of injury severity levels at multiple locations, roadway sections, signalized intersections and toll plazas utilizing an ordered probit model. Abdel-Aty (2003) considers multiple locations but does not perform a transferability test to determine if the three location-specific models are statistically similar, rather the author assesses crashes at each location separately. Porter and England (2000) studied red light running behavior at multiple signalized intersections in three urban settings. This work improved upon previous work by expanding the study area

from two to six locations. However, the locations still remain in only one state, furthermore in only three cities, the spatial transferability across a larger area is lacking. Previous studies involve a spatial analysis of traffic crashes by simply including multiple locations (but only one state) in the analysis, however spatial transferability across multiple location involving multiple datasets (i.e. multiple states) is lacking.

The United States Department of Transportation (USDOT) last reported in 2011 that the number of registered commercial drivers was roughly 4.8 million individuals (Federal Motor Carrier Safety Administration, 2011). As mentioned earlier each registered driver is involved in a lengthy training and licensing process. Commercial drivers also frequently cross state borders relative to passenger vehicle drivers, thus their exposure to highway mileage across multiple states in the US is greater. It is necessary to evaluate multiple state databases within the same context (e.g. large truck-involved crashes in urban areas) in order to address spatial transferability of severity models which could lead to routine improvement projects across the US. Taking this into consideration, random parameters logit (or mixed logit) models are used to understand the crash factors found in two state datasets and to account for the unobserved factors that may be influencing the model results.

It is important to note that a latent class approach may also be appropriate since it also accounts for possible unobserved heterogeneity. Cerwick et al. (2014) compares the two approaches (mixed logit and latent class) and found the latent class approach is slightly superior in terms of model fit. The latent class approach does not make assumptions about the parameter distribution, which may be inconsistent across all observations like the mixed logit approach; instead it assumes the observations come

from distinct classes based on common characteristics. Cerwick et al. (2014) also found the mixed logit predicted probabilities for the injury severities were closer to the observations. The authors further explain that there were only a few notable differences in between the models. Xiong and Mannering (2013) also concluded that it is difficult to determine the superior model approach which may vary by dataset. There are a few disadvantages regarding the latent class approach including a small number of classes encouraging a coarse approximation of the distribution of heterogeneity as well as not accounting for potential variation within a class (Behnood, 2014; Shaheed and Gkritza, 2014; Xiong and Mannering, 2013). The mixed logit approach will be utilized for this study.

Many other researchers have used the random parameters logit model in their crash analysis (Milton et al., 2008; Anastasopoulos and Mannering, 2009; Kim et al., 2010; Malyshkina and Mannering, 2010; Chen and Chen, 2011; Morgan and Mannering, 2011; Ye and Lord, 2011; Islam and Hernandez, 2013; Pahukula et al., 2015). Chen and Chen (2011) utilized a mixed logit model to analyze large truck crashes for single vehicle and multi-vehicle accidents on rural highways separately rather than combined. Islam et al. (2014) utilized 4 separate random parameters models to compare single and multi-vehicle crashes involving large trucks in rural and urban areas in Alabama.

The literature focusing on large truck-involved crash analysis has been evolving in the recent years however an exploration into the spatial transferability of these types of crashes has yet to be conducted. Previous studies typically utilize one database to analyze large truck-involved crashes and identify area specific contributing factors, but the results reveal similar causes. Table 1 summarizes previous studies across the US including the

state database and years utilized as well as a list of all the crash factors that were found to be significant. Although the years of analysis and locations differ there are many comparable contributing factors that impact the severity of these types of crashes which could identify collective safety issues potentially leading to routine countermeasures. For example light conditions and surface conditions were found to be significant in majority of the previous studies. These types of conditions themselves can't be controlled, but driver training can be geared to exploit these dynamic situations.

There were studies that utilized dataset with multiple state crashes in the analysis such as McKnight and Bahouth (2009), Lemp et al. (2011) and Zhu and Srinivasan (2011) whom all used the Large Truck Crash Causation Study (LTCCS) data to develop severity models to study these types of crashes. The LTCCS represents a sample of large truck crashes between April 2011 and December 2003 from 24 locations in 17 states. One problem with the LTCCS dataset is the sampling of crashes was not purely random and oversampling of high severity crashes could skew the model results. There are other data sources such as the Highway Safety Information System (HSIS), National Automotive Sampling System (NASS) General Estimates System (GES) and Fatality Analysis Reporting System (FARS) which aggregate crash data across the country into a representative sample. These data sources are appropriate when a sample of the crashes is sufficient. This study aims to compare a complete record of two state databases in order to develop a collective severity model.

TABLE 2.1 Summary of Previous Studies and Key Variables by Injury Severity

Author (Year)	**Islam et al. (2014)**	**Hans and Gkritza (2014)**	**Dong et al. (2014)**	**M. Islam and Hernandez (2013)**	**Dissanayake and Kotikalapudi (2012)**	**Khattak et al. (2012)**	**Khorashadi et al. (2005)**
State (Years)/ Crash Factor	**Alabama (2010-2012)**	**Iowa (2007-2012)**	**Tennessee (2005-2009)**	**Texas (2006-2010)**	**Kansas (2004-2008)**	**Nebraska (2005-2006)**	**California (1997-2000)**
Age	x	x		x	x		x
Alcohol/Drug Involvement	x					x	x
Character of Roadway	x		x	x	x	x	x
Crash Location	x				x		x
Crash Type	x	x		x	x		x
Day of Week		x		x	x		
Fatigue	x						
Gender	x			x	x		x
Land Use	x						x
Light Conditions	x	x	x	x	x	x	x
Median Type			x			x	x
Month				x			
Number of Lanes	x		x		x		x
Number of Vehicles Involved				x			x
Number of Trailers							x
Posted Speed Limit		x	x		x		x
Restraint Use				x			
Speeding	x			x			x
Surface Conditions	x	x			x		
Time of Day	x	x			x		x
Traffic Control	x						
Traffic Volume			x		x		
Vehicle Maneuver	x			x	x		x
Vehicle Size (Configuration)	x	x			x		x
Weather Conditions	x				x	x	x

This study will extend the efforts initiated by Pahukula et al. (2015), in which the authors use large truck-involved crashes in urban areas in Texas considering three injury severity levels (i.e. serious injury, minor injury and property-damage-only). This study will incorporate Oregon crashes within the same context considering the same three injury severity groupings. Including large truck-involved crashes in urban areas in Oregon will help bring an understanding of the factors that contribute to these types of crashes across multiple states. It will help to identify similarities (if any) among truck crash characteristics involving truck drivers in different states who undergo similar sophisticated training programs.

METHOD

Data

To apply the spatial transferability methodology, a case study involving two individual state crash databases, Oregon and Texas, is presented. The state databases were selected purely based on immediate availability of data.

The Oregon dataset provided by the Oregon Department of Transportation (ODOT) included crashes between 2007 and 2013. ODOT requires drivers to file an Accident and Insurance Report Form with the Department of Motor Vehicles (DMV) within 72 hours of the crash if there is any injury suffered, if a vehicle is towed or the property damage exceeds $1,500 US dollars as of 2004. Since the driver is responsible for reporting the crash there are limitations regarding the accuracy of the reported information and uncertainty if all crashes that occurred are represented in the dataset. During this time period there were 6,197 crashes involving a large truck in urban areas and each observation represents the maximum level of injury sustained by the driver.

Large truck crashes under the same conditions in Texas were extracted from the Crash Records Information System (CRIS) database. The CRIS database compiles crashes in Texas based on Texas Peace Officer's Crash Reports which requires the reporting officer to record any injury suffered or if the damage exceeds $1,000 US dollars. In accordance with the Oregon sample of crashes, each observation represents the maximum level of injury sustained by the driver.

It is necessary to address the challenges encountered in this exploratory analysis while merging the two state databases. State DOT's have different reporting requirements and codes. Majority of the crash variables could be standardized between the two states but there were some variables that were excluded from the analysis due to irreconcilable definitions or lack of information. The inconsistent data reporting techniques among the states was evident in this exploratory analysis and may present major challenges expanding this study on a national level. Developing a national standard of data collection and reporting could greatly benefit crash analysis efforts across the US.

For this case study, there were low data observations for the higher injury severity outcomes within both state datasets. Injury severity for Oregon and Texas were recorded by five distinct injury severity levels based on the KABCO injury scale. This study condenses the five categories into three categories: serious injury (fatality and incapacitating injury), minor injury (non-incapacitating injury and possible injury) and no injury (property-damage-only). Descriptive statistics of the variables included in the individual state models are presented in Table 2.

TABLE 2.2 Descriptive Statistics of Key Variables by State

Meaning of Variable	Texas		Oregon	
	Mean	**SD**	**Mean**	**SD**
Age Group (1 if age less than 25, 0 otherwise)	0.093	0.290	-	-
Age Group (1 if age 35- 45, 0 otherwise)			0.186	0.389
Age (1 if age greater than 55, 0 otherwise)			0.228	0.419
Base Type (1 if flex base or stabilized earth, 0 otherwise)	0.583	0.493		
Collision Type (1 if sideswipe traveling in the same direction, 0 otherwise)	0.421	0.494	0.236	0.425
Collision Type (1 if struck a fixed object, 0 otherwise)	0.084	0.277		
Contribution Factor (1 if vehicle followed too closely, 0 otherwise)			0.237	0.425
Contributing Factor (1 if failed to control speed, 0 otherwise)	0.080	0.272		
Crash Type (1 if off-road, 0 otherwise)			0.071	0.257
Gender (1 if male, 0 otherwise)	0.936	0.245	0.900	.299
Intersection Related (1 if at or intersection related, 0 otherwise)	0.280	0.449	0.464	0.499
Light Condition (1 if dark including dawn and dusk, 0 otherwise)	0.233	0.423		
Median Width (1 if width between 51-75 ft., 0 otherwise)	0.135	0.342		
Number of Vehicles Involved (1 if two vehicles involved, 0 otherwise)			0.798	.402
Number of Trailers (1 if zero trailers, 0 otherwise)			0.305	0.460
Posted Speed Limit (1 if speed limit less than or equal to 30 mph, 0 otherwise)			0.523	0.499
Population Range (1 if population greater than 200,000 individuals, 0 otherwise)			0.341	0.474
Restraint Use (1 if used shoulder and lap belt, 0 otherwise)	0.909	0.287	0.588	0.492
Road Alignment (1 if level & straight, 0 otherwise)	0.777	0.416	0.416	0.493
Surface Condition (1 if wet at the time of the crash, 0 otherwise)	0.128	0.335		
Time of Day: Early Morning (1 if crash occurred between 12 AM – 4 AM)			0.038	0.191
Time of Day: Morning (1 if crash occurred between 5 AM – 9 AM)			0.227	0.419
Vehicle Movement Pre-crash (1 if changing lanes, 0 otherwise)	0.201	0.401		
Vehicle Movement Pre-Crash (1 if vehicle stopped, 0 otherwise)			0.086	0.280

Modeling Approach

In order to discover the relationship between large truck crashes in spatially distributed areas, a random parameters logit modeling approach was used to pinpoint contributing factors to each injury severity group. This approach accounts for the unobserved heterogeneity that may be present between the spatially dispersed crashes. First, a linear function is used to link the injury severity group (i.e. serious injury, minor injury and no injury) and the explanatory variables for the large truck-involved crashes in the two separated regions as follows:

$$\boldsymbol{S_{in} = \beta_i X_{in} + \varepsilon_{in}} \qquad \textbf{(1)}$$

where S_{in} is the different injury outcomes (i.e. serious injury, minor injury and no injury), X_{in} is the vector of explanatory variables (or the contributing factors to that injury outcome), β_i is the estimated parameter for each explanatory variable from each regions dataset and ε_{in} is the error term to capture the effects of the unobserved characteristics for the severity model (Washington et al., 2010). Then, McFadden (1981) proved the standard multinomial logit formulation as:

$$\boldsymbol{P_n(i) = \frac{EXP[\beta_i X_{in}]}{\sum_{\forall I} EXP(\beta_I X_{In})]}} \qquad \textbf{(2)}$$

where $P_n(i)$ is the probability of a large truck crash with an injury severity outcome (i) (i.e. serious injury, minor injury and no injury) and estimating the parameters (β_i) by maximum likelihood. The random parameters logit formulation, which relaxes the independence of irrelevant alternatives (IIA) property violations, is as follows,

$$\boldsymbol{P_n(i)} = \int \frac{\boldsymbol{EXP[\beta_i X_{in}]}}{\sum_{\forall I} \boldsymbol{EXP(\beta_I X_{In})]}} \; \boldsymbol{f(\beta_i \vdots \varphi) d\beta_i} \qquad \textbf{(3)}$$

Where, $f(\beta_i \vdots \varphi)$ is the density function of β and ϕ and the other variables are the same as before (Mcfadden and Train, 2000; Train, 2003). The density function $f(\beta_i \vdots \varphi)$ allows the each region's model to account for the variations in the parameter estimates by weighting the probabilities given an assumed distribution (Washington et al., 2010).

The maximum likelihood estimation is utilized to estimate the random parameters through a simulation based approach,

$$LL = \sum_{n=1}^{N} \sum_{i=1}^{I} \delta_{in} \, LN[P_n^m(i)]$$

Where N is the total number of crashes in each state database, *i* is the total number of injury outcomes (i.e. serious injury, minor injury and no injury), $\boldsymbol{\delta_{in}}$ determines the injury outcome for crash n. This simulation approach utilizes Halton draws which have been proven to produce accurate probability approximations efficiently with only 200 random draws (Bhat, 2003; Halton, 1960; Train, 1999). The marginal effects are also presented with the final model estimation results in Table 5 and 6. Marginal effects show the effect of a one unit change of variable x, on the injury outcome *i*, refer to Washington et al. (2010) for marginal effects computations.

CASE STUDY RESULTS

Estimation of parameters $\boldsymbol{\beta_i}$ was determined by maximum likelihood and simulation-based maximum likelihood methods. The normal distribution of random parameters was found to be statistically significant, but the lognormal, triangular and uniform distributions were also considered.

Log-likelihood ratio tests were conducted to determine if a unified model could accurately address large truck crash factors between crashes scattered across two areas following the procedures found in Washington et al. (2011). The severity models of the two partitioned regions were compared with two methods. The first log-likelihood ratio test for spatial transferability compares the variables (or parameters) used to explain the crash behavior and injury severity. It is as follows,

$$\boldsymbol{\chi^2 = -2[LL_T(\beta^T) - LL_{OR}(\beta^A) - LL_{TX}(\beta^B)]} \quad \textbf{(5)}$$

Where $LL_T(\beta^T)$ is the log likelihood at convergence of the model estimated with data from both regions, $LL_A(\beta^A)$ is the log likelihood at convergence of region A's data, $LL_B(\beta^B)$ is the log likelihood at convergence of region B's data, using the same variables for all three models. The χ^2 statistic, with degrees of freedom equal to the summation of the number of estimated parameters in the regional models (A and B) minus the number of estimated parameters in the combined model, provides the confidence level at which we can reject the null hypothesis. The null hypothesis states that there is no difference between the model parameters in the combined and regional models (i.e. the parameters are the same) (Washington et al., 2011). The results indicate that the models have statistically significantly different model parameters meaning a unified model is not justified. The results are summarized in Table 3 below.

TABLE 2.3 Summary of Transferability Test 1

$LL_T(\beta^T)$	$LL_A(\beta^A)$	$LL_B(\beta^B)$	**Degrees of Freedom**	χ^2
-5,033.251	-1,243.358	-3337.304	19	905.178

A second log likelihood test was conducted to test the spatial transferability of coefficients from the two individual region severity models. It is as follows:

$$\boldsymbol{\chi^2 = -2[LL_{j_1\, j_2}(\beta^{j_1\, j_2}) - LL_{j_1}(\beta^{j_1})]} \qquad \textbf{(6)}$$

Where $\boldsymbol{LL_{j_1\, j_2}(\beta^{j_1\, j_2})}$ is the log likelihood at convergence of a model using the converged parameters from the j_2's model (using j_2's data) on j_1's data and $\boldsymbol{LL_{j_1}(\beta^{j_1})}$ is the log likelihood at convergence of the model using j_1's data (without constraining the parameters). The χ^2 statistic with degrees of freedom equal to the number of estimated parameters in $\boldsymbol{\beta^{j_1\, j_2}}$ provides the probability that the individual severity models have different parameters. The second set of log likelihood ratio tests all yield chi square statistics greater than the 99.99% confidence limit based on specified degrees of freedom, further validating that each area should have its own severity model. The results of the second transferability test (Equation 6) can be found in Table 4 below.

TABLE 2.4 Summary of Transferability Test 2 Comparing the Oregon and Texas models (chi-square statistic and degrees of freedom)

j_1 \ j_2	**Oregon**	**Texas**
Oregon	0.00	9872.51 (d.f = 13)
Texas	5131.71 (d.f = 14)	0.00

The results of this exploratory analysis provide statistically significant evidence, at 99.95% confidence levels, that separate severity models for Oregon and Texas should be estimated. The individual state model estimation results were statistically significant within a 95% confidence level and are presenting in Tables 5 and 6.

TABLE 2.5 Random Parameters Logit Injury Severity Model for Large Truck-involved Crashes on Urban Interstate Roadways in Texas

Meaning of Variable	Coefficient	*t*-Statistic	Marginal Effects		
			Severe Injury	Minor Injury	No Injury
Severe Injury					
Constant	-3.493	-9.46	na	na	na
Base Type (1 if flex base or stabilized earth, 0 otherwise)	0.725	2.85	0.005	-0.001	-0.004
Vehicle Maneuver before the Crash (1 if changing lanes, 0 otherwise)	-1.333	-3.55	-0.001	0.000	0.001
Road Alignment (1 if level and straight, 0 otherwise)	-0.689	-2.75	-0.004	0.001	0.003
Collision Type (1 if struck a fixed object, 0 otherwise) (standard error of parameter distribution)	-2.159 (3.560)	-1.17 (2.88)	na	na	na
Minor Injury					
Restraint Use (1 if used shoulder and lap belt, 0 otherwise) (standard error of parameter distribution)	-5.635 (5.325)	-7.28 (7.63)	0.013	0.012	-0.013
Collision Type (1 if sideswipe, 0 otherwise)	-2.798	-9.24	0.002	-0.017	0.016
Contributing Factor (1 if failed to control speed, 0 otherwise)	0.967	2.67	0.000	0.002	-0.002
Surface Condition (1 if wet at the time of the crash, 0 otherwise)	0.876	2.99	0.000	0.003	-0.003
Gender (1 if male, 0 otherwise) (standard error of parameter distribution)	-1.598 (3.325)	-2.95 (5.87)	0.000	0.018	-0.018
No Injury					
Age Group (1 if age less than 25, 0 otherwise) (standard error of parameter distribution)	-2.420 (2.791)	-7.59 (6.36)	0.015	0.008	-0.023
Gender (1 if male, 0 otherwise) (standard error of parameter distribution)	2.614 (1.141)	5.41 (2.13)	-0.011	-0.040	0.052
Light Condition (1 if dark including dawn and dusk, 0 otherwise)	-0.773	-4.25	-0.002	-0.004	-0.006
Intersection Related (1 if at or intersection related including driveway access points, 0 otherwise)	1.491	6.52	-0.002	-0.008	0.010
Median Width including inside shoulder (1 if width between 51-75 ft., 0 otherwise)	-0.837	-3.67	0.001	0.003	-0.004
Model Statistics					
Number of Observations	11,560				
Restricted Log-likelihood	-12,699.958				
Log-likelihood at convergence	-3386.734				
McFadden pseudo-R-squared (ρ^2)	0.733				

TABLE 2.6 Random Parameters Logit Injury Severity Model for Large Truck-involved Crashes on Urban Interstate Roadways in Oregon

Meaning of Variable	Coefficient	*t*-Statistic	Marginal Effects: Severe Injury	Marginal Effects: Minor Injury	Marginal Effects: No Injury
Severe Injury					
Constant	-10.723	-4.38	na	na	Na
Restraint Use (1 if used shoulder and lap belt, 0 otherwise)	-6.861	-2.97	-0.005	0.002	0.003
Age Group (1 if age greater than 55, 0 otherwise)	3.511	2.65	0.002	-0.001	-0.002
Number of Vehicles Involved (1 if 2 vehicles involved, 0 otherwise) (standard error of parameter distribution)	-11.052 (6.418)	-2.38 (2.76)	-0.030	-0.077	0.107
Minor Injury					
Constant	-5.538	-3.66	na	na	na
Gender (1 if male, 0 otherwise) (standard error of parameter distribution)	-4.237 (4.172)	-2.90 (3.42)	0.002	-0.014	0.012
Time of Day: Morning (1 if crash occurred between 5 AM – 9 AM)	1.274	2.05	-0.0001	0.004	-0.003
Contribution Factor: Following Too Closely (1 if vehicle followed too closely, 0 otherwise)	-1.687	-2.25	0.0002	-0.004	0.004
Posted Speed Limit (1 if speed limit less than or equal to 30 mph, 0 otherwise)	-2.217	-3.10	0.0004	-0.009	0.009
Number of Vehicles Involved (1 if 2 vehicles involved, 0 otherwise)	-1.725	-2.36	-0.030	-0.077	0.107
Road Alignment (1 if level & straight, 0 otherwise)	-1.711	-2.19	0.0003	-0.008	0.007
Population Range (1 if population greater than 200,000 individuals, 0 otherwise) (standard error of parameter distribution)	-1.830 (5.635)	-1.64 (3.31)	0.0002	0.011	-0.012
No Injury					
Restraint Use (1 if used shoulder and lap belt, 0 otherwise) (standard error of parameter distribution)	0.482 (7.890)	0.43 (3.53)	0.005	0.063	-0.069
Age Group (1 if age 35-45, 0 otherwise)	-2.215	-2.89	0.001	0.007	-0.007
Collision Type (1 if sideswipe traveling in the same direction, 0 otherwise)	4.500	3.33	-0.0002	-0.005	0.005
Time of Day: Early Morning (1 if crash occurred between 12 AM – 4 AM)	-4.131	-3.49	0.001	0.004	-0.004
Intersection Related (1 if at or intersection related, 0 otherwise) (standard error of parameter distribution)	4.240 (3.931)	2.64 (2.71)	0.0001	-0.007	0.007
Number of Trailers (1 if zero trailers, 0 otherwise)	-2.210	-3.05	0.001	0.009	-0.010
Vehicle Movement Pre-Crash (1 if vehicle stopped, 0 otherwise)	-3.069	-2.89	0.001	0.005	-0.005
Crash Type (1 if off-road, 0 otherwise)	-3.082	-2.63	0.001	0.005	-0.006
Model Statistics					
Number of Observations	6,197				
Restricted Log-likelihood	-6,808.100				
Log-likelihood at convergence	-1,185.552				
McFadden pseudo-R-squared (ρ^2)	0.8255				

DISCUSSION

Five variables were found to be consistent between the two individual state severity models including restraint use, sideswipe collision, male driver, intersection related and a level and straight roadway. The sign of the coefficients also indicate that these variables had similar effects in each model. For example restraint use was found to decrease the likelihood of an injury in both state models. Similar results were found for male drivers, sideswipe collisions and level and straight roadways, where these conditions lessened the likelihood of a resulting injury, serious or minor.

Age was also found to be a significant factor in both state models, but the age group differed. In Oregon, if a driver's age was over 55 years they were found to be more likely to be involved in a serious injury crash and if the driver's age was between 35 and 45 they were found to be less likely to be involved in a no injury crash. In Texas, the age less than 25 years indicator was negative in the no injury severity group indicating that drivers under the age of 25 were less likely to be involved in a no injury crash. This parameter was also found to be random and normally distributed with a mean -2.420 and a standard deviation 2.791. This suggests that 5.83% of the observations have a mean greater than zero. Random variables account for the unobserved factors and suggest that a portion of the observations have an increased likelihood of a certain injury outcome while the other portions of the observations have a decreased likelihood of that injury outcome. With that being said, 5.83% of the observations were found to be more likely to be involved in a no injury crash and the remaining 94.17% of the observations were found to be less likely to be involved in a no injury crash. One possible explanation is typically young drivers have quick reaction times which could help them avoid a serious injury

crash. On the other hand, young drivers have less experience handling large trucks which could lead to higher severity crashes. Training programs and well as route selection based on driver experience could be some mitigations. For example, novice drivers can be placed on lower volume roads during their first year of service to gain handling experience.

Of the 24 variables included in the individual state severity models, five variables were unique to a specific state dataset. For example, roadway base type and median width were exclusive to the Texas dataset. The Oregon dataset did not record information about the roadway base type or any widths of any roadway features. The number of vehicles involved in the crash, posted speed limit and number of trailers were distinctive of the Oregon dataset.

Crash Characteristics

Changing lanes, failing to control speed, and hitting a fixed object were among the significant crash characteristics included in the Texas severity model. Following too closely, off-road collision, if the vehicle was stopped before the crash, if there were no trailers and if there were two vehicles involved in the crash were the crash characteristics found to explain large truck crashes in Oregon.

In the Texas model, the indicator representing crashes with a fixed object was found to be random and normally distributed with a mean -2.159 and standard deviation 3.560. Given these values, 87.6% of crashes with a fixed object were less likely to result in a serious injury with 12.4% of crashes with a fixed object were more likely to result in a serious injury. In the Oregon model, the indicator representing off-road collisions were found to decrease the likelihood of a no injury crash. These types of crashes are similar in

that there are different technological developments that could help to prevent these types of crashes. Jermakian (2012) investigated the use of a forward collision warning system and lane departure warning system which would alert the driver first that the truck is in danger of straying across lane markings and second that there was a fixed object ahead. However, it is uncertain how drivers would respond to such warning systems.

Failure to control speed was found to increase the likelihood of minor injury crashes in Texas. It is widely accepted and history has proven that higher speed crashes can lead to higher injury severities, thus it is not surprising that many previous studies found similar results. Islam et al. (2014) found speeding to be a contributing factor to a major injury in multi-vehicle large truck crashes in urban areas. Texas ranks among the highest speed limits in the US. According to the National Motorists Association Texas is one of the few states that set the speed limit for large trucks on urban interstate roadways at 75 mph (National Motorists Association, 2014). It is worth mentioning that large trucks can travel up to 85 mph on certain rural interstates which are among the highest in the world. Perhaps reconsideration of the approved speed limits is necessary to improve safety and reduce the number of fatalities especially for large trucks in urban areas.

Changing lanes and following too closely were found to decrease the likelihood of a crash resulting in an injury in Texas and Oregon, respectively. Both of these indicator variables reflect the level of knowledge the driver has with respect to safely operating a heavy vehicle. The CDL knowledge tests, described above, include topics such as basic controls, speed management, space management, emergency maneuvers as well as the relationship of cargo to vehicle control which all or some may have contributed to the

decreased likelihood of a resulting injury for crashes involving changing lanes and following too closely.

Time of Day Characteristics

Time of day was only found to be significant in the Oregon severity model. Crashes that occurred between 5:00 AM and 9:00 AM were found to increase the likelihood of a minor injury while crashes that occurred between 12:00 AM and 4:00 AM were found to decrease the likelihood of a no injury crash. This type of information could help local governments decide on the best time to deploy police officers or inspectors to ensure that large truck drivers are following the regulations such as the hours of service rules.

Environmental Characteristics

Environmental characteristics seemed to only affect large truck crashes in Texas. Both dark lighting conditions and wet roadway surface conditions were found to be statistically significant in the Texas severity model, while there were no environment-related characteristics in the Oregon model.

Dark lighting conditions decreases the likelihood of a no injury outcome while a wet roadway surface was found to increase the likelihood of a minor injury outcome. A wet roadway can create a slick surface, thus reducing the friction between the wheel and pavement; decreased friction reduces the control the driver has of the vehicle. With this in mind it makes sense that a wet roadway surface would increase the likelihood of a minor injury because quick maneuvers to avoid a collision will be more difficult to complete. Perhaps truck drivers in Oregon have grown accustom to driving in wet conditions due to the prevalent rainfall in the Pacific Northwest, which could explain why

wet surface conditions were not found to be a significant contributing factors to crashes in the Oregon severity model.

In summary, the results demonstrate that driver related characteristics including gender, restraint use and age had similar impacts for the different injury severity outcomes between the two states while external characteristics such as weather, light conditions, and time of day were among the major differences between the two states. These differences were a result of uncontrollable conditions. Analyzing crashes that are spatially distributed but clustered for example the Pacific Northwest region (i.e. Oregon, Washington and Idaho) with similar 'uncontrollable' conditions as opposed to crashes divided by a large distance and differing environmental conditions would produce a unified model.

CONCLUSIONS

Severity models were utilized to investigate the relationship between spatially distributed large truck crashes between two urban areas. Random parameters logit models along with log likelihood ratio tests were used to statistically evaluate the similarities between the crash factors between the two regions (i.e. evaluating spatial transferability). The strict regulations on the trucking industry on truck drivers and vehicles as well as frequent travel across state borders may present the opportunity for a unified model among large truck crashes.

The constant governance and high exposure may produce more similarities between large truck crash behaviors than passenger vehicle crash behavior, leading to one unified model that can account for large truck crash factors. Identifying key factors contributing to large truck-involved crashes in urban areas across the United States in a

single unified model can significantly mitigate conflicts and improve the overall safety for the traveling public. For government officials, transportation engineers and trucking industries, these types of models can direct trucking regulations, design policies and trucking operations to reduce the severity of these types of crashes.

Large truck-involved crashes in urban areas in Oregon and Texas were utilized as a case study to demonstrate the spatial transferability framework. Three injury severity outcomes were defined as follows serious injury (fatality and incapacitating injury), minor injury (non-incapacitating injury and possible injury) and no injury (property-damage-only). The statistical analysis concludes that separate models for each state should be estimated. Two individual random parameters logit models were developed for Oregon and Texas.

The model estimation results suggest that indicators including restraint use, sideswipe collision, male driver, intersection-related and a level and straight roadway were consistent in both state severity models and all had similar impacts on the injury outcomes. Similarities between the impacts of different crash characteristics (i.e. changing lanes and following too closely) regarding driver training were evident. These types of crashes were found to lessen the probability of an injury which could be attributed to the extensive training drivers undergo. Age was also found to impact both the severity models of Oregon and Texas, but the age group differed.

Some of the differences between the two state severity models were environmental conditions, speed, time of day and unique dataset specific variables. Environmental conditions, dark lighting conditions and wet roadway surface conditions, and speeding were only found to affect crashes in Texas. On the other hand, time of day

was only found to impact large truck crashes in Oregon. Currently, there are no national crash data reporting standards. In consequence, there were several variables that were unique to each dataset which contributed to the differences between the crash severity models. These variables include base types and median with in Texas and poster speed limit, number of vehicles involved and number of trailers in Oregon.

It is important to note several limitations regarding the empirical settings of this exploratory analysis. As mentioned above, there is inconsistent crash reporting between Oregon and Texas which lead to the exclusion of several variables from the analysis. Either one dataset was lacking the information or the variable definitions were incompatible. The number of observations between the two states greatly differed. Also, the years analyzed were slightly different, however majority of the years analyzed overlapped.

Although the results of this study indicate that large truck-involved severity models between Texas and Oregon should be analyzed separately suggesting that a unified severity model for the US is not feasible, a regional model might be warranted. Perhaps, studying crashes between states in closer proximity with similar characteristics such as weather conditions may be more appropriate. Future work will address regional spatial transferability utilizing large truck-involved crashes in urban areas in the Pacific Northwest (i.e. Oregon, Washington and Idaho). In addition, a framework for national crash data reporting procedures and standards will be explored.

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A TIME OF DAY ANALYSIS OF CRASHES INVOLVING LARGE TRUCKS IN URBAN AREAS

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3.0 CHAPTER 3 - A TIME OF DAY ANALYSIS OF CRASHES INVOLVING LARGE TRUCKS IN URBAN AREAS

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ABSTRACT

Previous studies have looked at different factors that contribute to large truck-involved crashes, however a detailed analysis considering the specific effects of time of day is lacking. Using the Crash Records Information System (CRIS) database in Texas, large truck-involved crashes occurring on urban freeways between 2006-2010 were separated into five time periods (i.e. early morning, morning, mid-day, afternoon and evening). A series of log likelihood ratio tests were conducted to validate that five separate random parameters logit models by time of day were warranted. The outcomes of each time of day model show major differences in both the combination of variables included in each model and the magnitude of impact of those variables. These differences show that the different time periods do in fact have different contributing factors to each injury severity further highlighting the importance of examining crashes based on time of day. Traffic flow, light conditions, surface conditions, time of year and percentage of trucks on the road were found as key differences between the time periods.

Keywords: Truck accidents, Injury Severity, Mixed Logit, Time-of-day, Interstate, Freight

INTRODUCTION

Motivation

Large truck crashes have a considerable impact on society and the economy. It has been estimated that the average cost of no injury crashes (i.e. property damage only), non-fatal injury crashes, and fatal crashes involving large trucks are $15,114, $195,258 and $3,604,518, respectively (Zaloshnja and Miller, 2006). These estimates include medical costs, emergency services costs, property damage costs, lost productivity and monetized value of the pain, suffering and quality of life lost due to death or injury. The estimated cost of large truck crashes between 1997-1999 exceeded US$ 19.6 billion (Zaloshnja and Miller, 2004). From the perspective of moving freight, in 2010 it was estimated that large trucks carried roughly 68% of freight tonnage in the U.S totaling approximately 12,500 millions of tons (Federal Highway Administration, 2013). The National Highway Traffic Safety Administration (NHTSA) reports that tonnage is expected to increase by 1.4% per year till 2040 (Federal Highway Administration, 2013). Currently this tonnage is being moved continuously day and night and as the tonnage grows so will the daily distribution of the freight movements required to haul this extra tonnage. This has raised concerns especially in large populated urban areas where congestion is only getting worse, where large truck crashes at various times of the day have created havoc to commutes. The added congestion to these urban commutes is the equivalent of 1.9% of the $14.96 trillion U.S. gross domestic product (GDP) in 2010 (Kilcarr, 2014). Evidently, efforts to improve our understanding of the factors that influence large truck-involved crashes are needed especially from a time of day perspective.

Although there have been several efforts to understand large truck-involved crashes, the relationships between crash related factors, crash severity and time of day effects are still not completely understood. A reason for this stems from the availability of sufficient data to capture the complex interactions of multiple factors under a single framework for various times of day scenarios. Recent studies conducted by (M. Bin Islam and Hernandez, 2013a; M. Islam and Hernandez, 2013b) developed random parameters models to predict injury severity of large truck- involved crashes with data from the Texas Crash Records Information System (CRIS), but considered time of day as a contributing factor. To better understand the relationships of crash related factors and crash severity by time of day separately, the CRIS database is utilized for this study.

In order to clearly identify injury related large truck crash factors, the data set will be divided by land use (i.e. rural and urban) and then further divided into time periods. Khorashadi et al. (2005) identified significant differences between urban and rural crashes due to differing driver, vehicle, environmental, road geometry and traffic characteristics. Additionally, time of day has been identified as a significant factor in previous studies (M. Bin Islam and Hernandez, 2013a; M. Islam and Hernandez, 2013b). Past works capture the impact of time of day by using indicator variables representing various times of day as independent variables in regression models. However there is a complex interaction between variables in these types of models. For example, traffic patterns, light conditions and driver behavior can vary throughout the day. The impact of traffic levels in urban areas during morning time period and afternoon time period on truck injury severity may potentially be different. With this in mind, this study aims to analyze injury crash severity of large truck-involved crashes under an urban land use

context and varying time of day scenarios through an econometric modeling approach by developing separate models for five time of days - early morning, morning, mid-day, afternoon and evening. Separate models for different time of day can help pinpoint specific issues.

The random parameters logit (or mixed logit) model is utilize here to gain a better understanding of the complex interactions between those factors found in the dataset and those unobserved factors that may be influencing (i.e., through unobserved heterogeneity). A latent class approach can also account for possible unobserved heterogeneity without having to make an assumption about the parameter distribution which may not always be consistent across all observations. Latent class models can account for possible unobserved heterogeneity by assuming that observations come from distinct classes based on common characteristics. However, one drawback of this approach is the number of classes is usually quite small so there is a coarse approximation of the distribution of heterogeneity (Behnood, 2014). Xiong and Mannering (2013) and Shaheed and Gkritza(2014) have identified another drawback that latent class models do not account for potential variation within a class. Xiong and Mannering (2013) further point out the difficulty in determining the statistically superior model which can vary by dataset. The random parameters approach will be utilized to this dataset to account for the unobserved heterogeneity. To the best of the authors' knowledge, this is the first attempt at modeling injury severity for large truck-involved crashes using a random parameters logit approach on urban freeways by separating crashes by time of day on three injury severity levels (serious injury, minor injury and no injury).

The remainder of the paper is organized as follows. First, a review of the current literature is presented followed by a discussion of the empirical settings and descriptive statistics. Next, the methodological approach is explained and the results are summarized. Finally, implications of the findings and the conclusion are presented.

Background

Although not the focus of this study, the following references provide valuable insights on time-of-day and its relation to crash rates and injuries sustained during crashes involving large trucks. According to the Fatality Facts provided by Insurance Institute for Highway Safety, highest incidence of deaths due to large truck crashes, nearly 19%, occur between the noon to 3 PM period ("FATALITY FACTS 2004 : LARGE TRUCKS," 2004). Blower and Campbell (1998) analyzed the Fatality Analysis Reporting System (FARS) data set from 1993 to 1995 and found that the higher fatalities occurred during daylight hours. However when fatality rates were calculated, a higher probability of fatality given the occurrence of a crash was observed during night time. An analysis of the General Estimates System (GES) data set for the same period revealed that while there were fewer crashes between midnight and 7 A.M., the chances of severe injuries were higher if a crash occurred during that period. It is important to note here that not all transportation facilities experience the same amounts of vehicular flows, thus exposure to higher traffic volumes may produce varying results with regards to maximum injury severity potential. Other possible exposure variables such as night-time hours of driving, truck-miles traveled, or ton-miles when considered could provide additional information on severity rates of large-truck involved crashes. In future work, the authors

are examining methods that take into account exposure based data and crash analysis techniques for large-truck crashes.

Curnow (2002) analyzed the Australian Truck Crash Database and found that articulated truck crash incidents were spread evenly throughout the 24 hour period whereas majority of the rigid truck crashes occurred during the day. Ghariani (2001) studied ten years of truck crash data from 1991 to 1999 obtained from Texas Department of Public Safety and found that a significant majority of the crashes occurred during day time. Similar trends were found in the rural freeways of Wyoming and Nebraska for the year 2000-2009 (Offei and Young, 2014). Knipling and Bocanegra (2008) analyzed the frequency of crash occurrence of combination unit trucks and single unit trucks from the truck crash causation study data (LTCCS) and found that the majority of the crashes occurred during the day and especially during rush hours. The percentage of crashes was found to be higher under dark conditions for combination unit trucks compared to single unit trucks. A majority of the above insights which focus on frequencies and distribution of crash occurrence based on time of day can be explained by the fact that most truck operations occur during the day.

Duncan et al. (1998) used an ordered probit model to understand the factors affecting truck- car rear end collisions based on highway safety information system data in North Carolina from 1993 to 1995. Injury severities were found to be higher during night time. Chang and Mannering (1999) analyzed the accidents in King County using a Nested Logit Model and found that for truck involved accidents there is a 50% higher chance of an injury or fatality if the accident occurred during night time and a 37% decrease in the probability of a possible injury if the accident occurred during night time.

Khorashadi et al. (2005) used a multinomial logit structure to understand the differences in factors affecting the severities of large-truck involved accidents in urban and rural areas using four years of crash data from 1997 to 2000 maintained by California Department of Transportation. The multinomial logit specifications were preferred to several nested logit specifications. Darker driving conditions were found to increase the probability of severe or fatal injury crashes. The probability of severe or fatal injury crashes decreased during rush hour with the decrease more prominent in the morning rush hour. Zhu and Srinivasan (2011) used an ordered probit model on the LTCCS data and found that crashes which occurred between 7:30 P.M. to 6:00 A.M lead to more severe crashes.

Lemp et al. (2011) used the heteroskedastic ordered probit model on the LTCCS dataset to study the impact of vehicle, environmental, and crash level variables on vehicle based and crash based maximum injury severity and found that non-bright conditions increased the probability of fatality. Chen and Chen (2011) studied the impact of driver, vehicle, environmental, roadway, temporal, and accident characteristics on single vehicle and multiple vehicle accidents involving large trucks using the highway safety information system data set for the state of Illinois from 1991 to 2000. Mixed logit specification was found to be better than the multinomial logit model. The probability of possible injury/non-incapacitating injury was found to increase during rush hour in single vehicle model. Non-bright conditions were found to significantly increase the probability of injury or fatality in multi-vehicle accident case.

M. Islam and Hernandez (2013b) used a random parameter ordered probit specification to study the impact of human, vehicle, and road environmental factors on

large truck crash injury severity using the National Automotive Sampling System General Estimated System (NASS-GES) database from 2005 to 2008. In contrast to the insight obtained from other literature, the likelihood of lower injury severity was higher when crashes occurred in darker conditions. In another research effort by M. Bin Islam and Hernandez (2013a), they developed mixed logit models for the truck crashes in Texas using data from the Texas Peace Officer's Crash Reports database for the year 2006 to 2010. The likelihood of fatal, incapacitating and possible injuries was found to reduce during the afternoon peak period due to congestion effects. The likelihood of fatal and incapacitating injuries increased during dark conditions.

The time of day dimension has been studied in automobile crashes using multivariate logistic regression (Martensen and Dupont, 2013), binary regression embedded in a hierarchical Bayesian framework (Qin et al., 2006), binomial regression and classification and regression tree based analysis (Chang and Chen, 2005) Almost all the models developed above use indicator variables to study the impact of time of day or lighting conditions on crash injury severity. However, such an approach is limited as different variables interact with each other and affect the injury severity outcomes in a complex and different manner depending on time of day. For example, driver behavior will be significantly different in the morning peak compared to the afternoon peak. The traffic flow obviously varies during the peak and off peak periods. A simple indicator variable based approach will not properly account for the complexities of the interactions during the different time periods. In order to account for these changes, it is critical to develop separate models so that the accurate impact of driver, environmental, and roadway related factors on injury severities and their variations with time of day can be

estimated accurately. This paper adopts the methodology of Morgan and Mannering (2011) by estimating separate models for time of day.

METHOD

Data

Large truck crashes between 2006 and 2010 reported by Texas Peace Officer's Crash Reports were utilized in this study. Only large truck-involved crashes on urban roadways were considered. A sample of 11,560 data observations were extracted from the CRIS database. Each observation represents the maximum level of injury sustained by the driver. Three different data components (crash, vehicle and person) were linked based on the 'Crash ID'.

Due to low data observations for the higher injury severity outcomes the five injury severity outcomes as defined by the KABCO injury scale were grouped into three categories (severe injury, minor injury and no injury). Serious injuries included fatalities and incapacitating injuries while minor injury included non-incapacitating injury and possible injury and property damage only crashes make up the no injury category. Overall, no injury crashes, minor injury crashes and serious injury crashes accounted for 90.8% (N= 10,499), 7.6% (N=878) and 1.6% (N=183), respectively. The individual data sets separated by time of day followed the same pattern where no injury crashes had the most observations and serious injury crashes accounted for the lowest percentage of crashes.

The effect of time of day on injury severity is the focus of this study. The analysis examined five different time periods, as shown in Table 1, which shows descriptive statistics of key variables included in the five models.

The driver demographics including gender, age and restraint use remain consistent throughout the different time periods. Only 13.6% of the crashes occurred during dark lighting conditions. Male drivers accounted for about 93% of the total observations for each of the five datasets. Drivers under the age of 25 and between 35 and 45 accounted for about 10% and 29% of the total observations, respectively. Drivers using both a lap and shoulder belt grossed about 90% of the total observations.

The crash characteristics specifically a sideswipe collision varied across the five time periods. The evening data set had a high of 48.9% while the early morning data set had a low of 37.2% of the total observations resulting in a sideswipe crash. Sideswipe crashes in the Morning, midday and afternoon data set accounted for 42.4%, 40.5%, and 44.1% of the total observations, respectively.

TABLE 3.1 Descriptive Statistics of Key Variables by Time of Day

	Early Morning (12:00 a.m.- 4:00 a.m.)		Morning (5:00 a.m. – 9:00 a.m.)		Mid-day (10:00 a.m. – 3:00 p.m.)		Afternoon (4:00 p.m. - 8:00 p.m.)		Evening (9:00 p.m. – 11:00 p.m.)	
Meaning of Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Age (1 if age <25, 0 otherwise)	0.12	0.32	0.09	0.29	0.09	0.29	0.09	0.28	0.09	0.29
Age (1 if age 35- 45, 0 otherwise)	-	-	-	-	0.29	0.45	0.30	0.46	-	-
Base Type (1 if granular base: flex or stabilized earth, 0 otherwise)	-	-	-	-	0.56	0.50	-	-	0.60	0.90
Collision Type (1 if going straight & sideswipe, 0 otherwise)	0.37	0.48	0.42	0.49	0.41	0.49	0.44	0.50	0.49	0.50
Contributing Factor (1 if failed to control speed, 0 otherwise)	-	-	-	-	0.08	0.27	-	-	-	-
Contributing Factor (1 if unsafe to change lanes, 0 otherwise)	-	-	-	-	0.09	0.28	-	-	-	-
Gender (1 if male, 0 otherwise)	0.93	0.26	0.94	0.23	0.94	0.24	0.93	0.26	0.92	0.27
Intersection Related (1 if at intersection, 0 otherwise)	-	-	0.28	0.45	0.32	0.47	0.26	0.44	0.24	0.42
Light Condition (1 if dark including dawn and dusk, 0 otherwise)	0.93	0.26	-	-	-	-	-	-	-	-
Median Width (1 if width between 51-75 ft., 0 otherwise)	-	-	-	-	0.14	0.35	-	-	-	-
Month (1 if crash occurred between June and August, 0 otherwise)	-	-	-	-	-	-	0.27	0.44	-	-
Object Struck (1 if another vehicle, 0 otherwise)	-	-	-	-	0.86	0.35	0.90	0.31	-	-
Percentage of Trucks (1 if percent trucks between 12-16%, 0 otherwise)	-	-	0.20	0.40	-	-	-	-	-	-
Percentage of Trucks (1 if more than 16% trucks, 0 otherwise)	-	-	-	-	-	-	-	-	0.12	0.33
Restraint Use (1 if used shoulder and lap belt, 0 otherwise)	0.87	0.34	0.91	0.28	0.91	0.28	0.91	0.28	0.90	0.30
Right Shoulder Width (1 if width 20 feet, 0 otherwise)	0.60	0.49	-	-	-	-	-	-	-	-
Right Shoulder Width (1 if width greater than 20 feet, 0 otherwise)	-	-	-	-	-	-	-	-	0.23	0.42
Road Alignment (1 if level and straight, 0 otherwise)	0.73	0.45			0.78	0.42	-	-	-	-
Surface Condition (1 if dry at the time of the crash, 0 otherwise)	-	-	-	-	-	-	0.86	0.35	-	-
Vehicle Maneuver before the Crash (1 if changing lanes, 0 otherwise)	-	-	-	-	0.09	0.28	-	-	-	-

TABLE 3.1 cont'd

	Early Morning (12:00 a.m.-4:00 a.m.)		Morning (5:00 a.m. – 9:00 a.m.)		Mid-day (10:00 a.m. – 3:00 p.m.)		Afternoon (4:00 p.m. - 8:00 p.m.)		Evening (9:00 p.m. – 11:00 p.m.)	
Meaning of Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Vehicle Maneuver before the Crash (1 if going straight, 0 otherwise)	-	-	0.12	0.33	-	-	-	-	-	-
Weather Condition (1 if clear at the time of the crash, 0 otherwise)	-	-	-	-	-	-	-	-	0.85	0.36
Weather Condition (1 if raining at the time of the crash, 0 otherwise)	-	-	-	-	-	-	0.09	0.29	-	-

Modeling Approach

As previously mentioned (2.1), each large truck-involved crash (observation) used in this study represents the maximum level of injury sustained by the driver. The injury severity levels are serious injury (fatalities and incapacitating injuries), minor injury (non-incapacitating injury and possible injury) and no injury (property damage only). It has been shown in previous studies that the random parameters logit model is an appropriate method of modeling the ordered nature of injury severity data (Gkritza and Mannering, 2008; Morgan and Mannering, 2011; M. Bin Islam and Hernandez, 2013a; Islam et al., 2014). The advantage of utilizing this approach is that it overcomes the limitations of previous models(e.g., multinomial logit, nested logit, ordered probit, Bayesian ordered, etc.) by allowing the parameter estimates to be random (Savolainen et al., 2011; M. Bin Islam and Hernandez, 2013a; M. Islam and Hernandez, 2013b). In allowing the parameter estimates to vary across observations, in contrast to fixed parameter models, one can account for some of the unobserved heterogeneity (unobserved factors) and avoid the independence of irrelevant alternatives (IIA) property

violations (Savolainen et al., 2011; Washington et al., 2011). As a result, any heterogeneous effects and correlation in unobserved factors are addressed. Thus, in this study a random parameters logit modeling approach is used to model injury severity for large truck-involved crashes in urban areas for various time of day scenarios.

To start, a linear function is used to model the relationship between the latent continuous variable for injury severity and the explanatory variables as follows: estimate the injury severity (i.e., serious injury, minor injury and no injury) for the large truck-involved crashes:

$$\mathbf{S_{in}} = \boldsymbol{\beta}_\mathbf{i}\mathbf{X_{in}} + \boldsymbol{\varepsilon}_\mathbf{in} \tag{1}$$

where S_{in} is the latent continuous variable for injury severity i (where $i \in I$ denotes serious injury, minor injury and no injury) of an individual n (driver), $\boldsymbol{X_{in}}$ is the vector of explanatory variables (or the contributing factors to that injury severity), $\boldsymbol{\beta_i}$ is the vector of estimated parameters for each injury severity, and ε_{in} is the error term to capture the effects of the unobserved characteristics for each time of day model (Washington et al., 2011). Furthermore, if the ε_{in} values in equation (1) are assumed to be generalized extreme distributed, McFadden has shown that the following multinomial logit formulation results are as follows (McFadden, 1981):

$$P_n(i) = \frac{EXP[\boldsymbol{\beta_i X_{in}}]}{\sum_{\forall I} EXP(\boldsymbol{\beta_I X_{In}})]} \tag{2}$$

where $P_n(i)$ is the probability of an individual n (driver) suffering injury severity i (where $i \in I$ denotes serious injury, minor injury and no injury).

To account for the possibility of unobserved heterogeneity due to under reporting of crashes and to capture the randomness associated to some of factors necessary to understand injury severity sustained by the drivers, equation (2) is extended and the following is the resulting random parameters logit model (Mcfadden and Train, 2000; Train, 2003):

$$P_n(i) = \int \frac{EXP[\boldsymbol{\beta_i X_{in}}]}{\sum_{\forall I} EXP(\boldsymbol{\beta_I X_{In}})]} \; f(\boldsymbol{\beta_i} \,|\boldsymbol{\varphi}) d\boldsymbol{\beta_i} \qquad \textbf{(3)}$$

where, $f(\boldsymbol{\beta_i}|\boldsymbol{\varphi})$ is the density function of $\boldsymbol{\beta_i}$ and $\boldsymbol{\varphi}$ and is the vector of parameters of the density function (mean and variance). Equation (3) can now account for injury severity outcome specific variations of the effect of the factors $\boldsymbol{X_{in}}$ on large truck-involved crash probabilities for each time of day model developed, with the density function $f(\boldsymbol{\beta_i}|\boldsymbol{\varphi})$used to determine $\boldsymbol{\beta_i}$. The random parameters logit probabilities are then a weighted average for different values of $\boldsymbol{\beta_i}$ across the observations where some elements of the vector $\boldsymbol{\beta_i}$ could be fixed and some randomly distributed. If the parameters are found to be random, the random parameter logit weights can be determined by the density function $f(\boldsymbol{\beta_i}|\boldsymbol{\varphi})$ (Washington et al., 2011).

To estimate the random parameters logit model as illustrated by equation (3), maximum likelihood estimation is performed through a simulation based approach to address the computational complexity of computing the outcome probabilities. The chosen simulation approach utilizes Halton draws which have been shown to provide a more efficient distribution of the draws for numerical integration than purely random draws (Halton, 1960; Train, 1999; Bhat, 2003). The marginal effects are computed for the variable included in the models. The marginal effect shows the effect of a one unit

change of variable, x, on the injury outcome i. For marginal effects computations the readers are referred to (Washington et al., 2011)

EMPIRICAL RESULTS

Maximum likelihood and simulation-based maximum likelihood methods are utilized to estimate parameter vector $\boldsymbol{\beta_i}$ for the full urban and urban time of day random parameters logit models. We considered normal, lognormal, triangular, and uniform distributions for the distribution of the random parameters in our analysis. However, the normal distribution was found to be statistically significant. In addition, to estimate the random parameters, 200 Halton draws were used. This number has been empirically shown to produce accurate parameter estimates under the simulation-based maximum likelihood estimation procedure (Bhat, 2003).

Once the models were developed, log likelihood ratio tests were conducted to determine if separate models based on time of day were justified following the procedures found in (Washington et al., 2011). The full urban model was compared to the individual time of day models with two methods. The first test compared the full model against all of the time of day models while the second test compared the models individually. The first log likelihood ratio test for transferability is as follows,

$$\boldsymbol{\chi^2 = -2[LL_{Full}(\beta^{Full}) - \sum_{j=1}^{J} LL_j(\beta^j)]} \quad \textbf{(4)}$$

Where $LL_{Full}(\beta^{Full})$ is the log likelihood at convergence of the full model (-3386.73), $LL_j(\beta^j)$ is the log likelihood at convergence of subgroup j (i.e., the set of time of day periods of early morning, morning, midday, afternoon and evening) using the same

variables included in the full model, and J is the total number of subgroups ($\sum_{j=1}^{J} LL_j(\beta^j) = -3321.16$). The χ^2 statistic ($\chi^2 = -131.1431$), with degrees of freedom equal to the summation of the number of estimated parameters in all time of day models minus the number of estimated parameters in the overall model, provides the confidence level at which we can reject the null hypothesis. The null hypothesis states that there is no difference between the model parameters in the full and separate models (i.e. the parameters are the same) (Washington et al., 2011). The chi square statistics with 60 degrees of freedom resulted in a value greater than then 99.99% confidence limit ($\chi^2 = 99.16$), indicating that the models have statistically significantly different model parameters.

For further validation a second log likelihood test was conducted to test the transferability of coefficients from the full model to each time of day model. The second log likelihood ratio test for transferability is as follows:

$$\boldsymbol{\chi^2 = -2[LL_{j_1 j_2}(\beta^{j_1 j_2}) - LL_{j_1}(\beta^{j_1})]} \quad \textbf{(5)}$$

Where $\boldsymbol{LL_{j_1 j_2}(\beta^{j_1 j_2})}$ is the log likelihood at convergence of a model using the converged parameters from the j_2's model (using j_2's data) on time period j_1's data and $\boldsymbol{LL_{j_1}(\beta^{j_1})}$ is the log likelihood at convergence of the model using time period j_1's data (without constraining the parameters). The χ^2 statistic with degrees of freedom equal to the number of estimated parameters in $\boldsymbol{\beta^{j_1 j_2}}$ provides the probability that the models have different parameters. The second set of log likelihood ratio tests all yield chi square statistics greater than the 99.99% confidence limit based on specified degrees of freedom,

further validating that separate models by time of day is justified. The results of the second transferability test (Equation 5) can be found in Table 2 below.

TABLE 3.2: Summary of Transferability Test Comparing the Individual Time of Day Models (chi-square statistic and degrees of freedom)

j_1 \ j_2	**Early Morning**	**Morning**	**Mid-day**	**Afternoon**	**Evening**
Early Morning	0.00	800.27 (d.f = 9)	621.24 (d.f = 16)	975.42 (d.f = 11)	796.39 (d.f = 10)
Morning	735.83 (d.f = 9)	0.00	924.02 (d.f = 16)	1394.64 (d.f = 11)	1,169.25 (d.f = 10)
Mid-day	1570.69 (d.f = 9)	2,354.19 (d.f = 9)	0.00	2811.63 (d.f = 11)	2,336.08 (d.f = 10)
Afternoon	644.16 (d.f = 9)	1,017.51 (d.f = 9)	865.66 (d.f = 16)	0.00	1,106.83 (d.f = 10)
Evening	180.04 (d.f = 9)	417.24 (d.f = 9)	366.07 (d.f = 16)	557.09 (d.f = 11)	0.00

The results of the log likelihood tests provide statistically significant evidence, at 99.99% confidence levels, that separate severity models by time of day should be estimated. The individual time of day model estimation results were statistically significant within a 95% confidence level and are presented in Tables 3 through 7.

TABLE 3.3 Random Parameters Logit Injury Severity Model for Early Morning Large Truck-involved Crashes.

Meaning of Variable	Coefficient	*t*-Statistic	Marginal Effects		
			Severe Injury	Minor Injury	No Injury
Severe Injury					
Constant (standard error of parameter distribution)	-3.091 (1.826)	-3.28 (2.07)			
Restraint Use (1 if used shoulder and lap belt, 0 otherwise)	-2.237	-3.3	-0.033	0.0027	0.030
Minor Injury					
Restraint Use (1 if used shoulder and lap belt, 0 otherwise) (standard error of parameter distribution)	-3.046 (3.378)	-3.00 (3.29)	0.0003	0.011	-0.011
Collision Type (1 if sideswipe, 0 otherwise)	-2.618	-4.09	0.002	-0.024	0.022
Road Alignment (1 if level and straight, 0 otherwise)	-1.262	-3.12	0.004	-0.046	0.041
No Injury					
Age Group (1 if age less than 25, 0 otherwise)	-1.946	-3.98	0.01	0.017	-0.026
Gender (1 if male, 0 otherwise)	1.526	3.24	-0.025	-0.071	0.096
Light Condition (1 if dark including dawn and dusk, 0 otherwise)	-1.745	-3.06	0.033	0.086	-0.119
Right Shoulder Width (1 if width 20 feet, 0 otherwise)	0.747	2.39	-0.008	-0.022	0.03
Model Statistics					
Number of Observations	866				
Restricted Log-likelihood	-951.398				
Log-likelihood at convergence	-390.055				
McFadden pseudo-R-squared (ρ^2)	0.590				

TABLE 3.4 Random Parameters Logit Injury Severity Model for Morning Large Truck-involved Crashes

Meaning of Variable	Coefficient	*t*-Statistic	Marginal Effects		
			Severe Injury	Minor Injury	No Injury
Severe Injury					
Constant	-3.456	-5.86			
Minor Injury					
Restraint Use (1 if used shoulder and lap belt, 0 otherwise) (standard error of parameter distribution)	-3.230 (2.577)	-3.29 (2.48)	0.004	-0.024	0.02
Collision Type (1 if sideswipe, 0 otherwise)	-1.311	-2.9	0.001	-0.01	0.009
Gender (1 if male, 0 otherwise) (standard error of parameter distribution)	-1.117 (4.215)	-0.97 (4.05)	0.0001	0.071	-0.071
No Injury					
Age Group (1 if age less than 25, 0 otherwise) (standard error of parameter distribution)	-1.657 (4.009)	-2.14 (3.45)	0.01	0.008	-0.018
Gender (1 if male, 0 otherwise)	4.171	4.04	-0.015	-0.074	0.089
Intersection Related (1 if at or intersection related including driveway access points, 0 otherwise)	0.961	2.19	-0.001	-0.005	0.006
Vehicle Maneuver before the Crash (1 if going straight & sideswipe, 0 otherwise) (standard error of parameter distribution)	-2.353 (2.819)	-2.37 (2.17)	0.013	0.014	-0.027
Percentage of Trucks (1 if percent trucks between 12-16%, 0 otherwise)	0.976	2.05	-0.001	-0.004	0.004
Model Statistics					
Number of Observations	2,659				
Restricted Log-likelihood	-2,921.21				
Log-likelihood at convergence	-682.709				
McFadden pseudo-R-squared (ρ^2)	0.766				

TABLE 3.5 Random Parameters Logit Injury Severity Model for Mid-day Large Truck-involved crashes

Meaning of Variable	Coefficient	*t*-Statistic	Marginal Effects		
			Severe Injury	Minor Injury	No Injury
Severe Injury					
Constant	-2.302	-4.79			
Base Type (1 if flex base or stabilized earth, 0 otherwise)	0.804	2.22	0.007	-0.001	-0.006
Vehicle Maneuver before the Crash (1 if changing lanes, 0 otherwise)	-1.934	-2.62	-0.001	0.0002	0.001
Road Alignment (1 if level and straight, 0 otherwise)	-0.942	-2.79	-0.012	-0.04	0.052
Median Width including inside shoulder (1 if width between 51-75 ft., 0 otherwise)	1.07	2.98	0.003	-0.0004	0.003
Minor Injury					
Restraint Use (1 if used shoulder and lap belt, 0 otherwise) (standard error of parameter distribution)	-3.388 (3.721)	-4.55 (5.89)	0.001	0.019	-0.021
Road Alignment (1 if level and straight, 0 otherwise)	-0.707	-2.75	-0.012	-0.040	0.052
Gender (1 if male, 0 otherwise) (standard error of parameter distribution)	-0.53 (2.377)	-0.8 (4.03)	-0.0002	0.03	-0.03
Age Group (1 if age between 35 and 45, 0 otherwise)	0.635	2.22	0.014	0.036	-0.050
Collision Type (1 if sideswipe, 0 otherwise)	-1.504	-4.55	0.001	-0.011	0.011
Contributing Factor (1 if failed to control speed, 0 otherwise)	1.04	2.29	-0.0002	0.004	-0.003
No Injury					
Age Group (1 if age less than 25, 0 otherwise) (standard error of parameter distribution)	-2.347 (2.749)	-5.41 (3.57)	0.017	0.01	-0.027
Gender (1 if male, 0 otherwise)	1.849	5.24	-0.014	-0.042	0.056
Intersection Related (1 if at or intersection related including driveway access points, 0 otherwise)	1.208	4.38	-0.003	-0.009	0.011
Object Struck (1 if another vehicle, 0 otherwise)	0.945	3.8	-0.006	-0.019	0.025
Vehicle Maneuver before the Crash (1 if changing lanes, 0 otherwise)	1.5	2.52	-0.0003	-0.002	0.002
Model Statistics					
Number of Observations	4,571				
Restricted Log-likelihood	-5,021.767				
Log-likelihood at convergence	-1,324.138				
McFadden pseudo-R-squared (ρ^2)	0.736				

TABLE 3.6 Random Parameters Logit Injury Severity Model for Afternoon Large Truck-involved Crashes

Meaning of Variable	Coefficient	*t*-Statistic	Marginal Effects		
			Severe Injury	Minor Injury	No Injury
Severe Injury					
Age Group (1 if age between 35 and 45, 0 otherwise)	-1.853	-2.47	-0.001	0.0004	0.001
Month (1 if crash occurred between June and August, 0 otherwise)	-1.451	-2.32	-0.002	0.001	0.001
Minor Injury					
Constant	3.158	8.06			
Restraint Use (1 if used shoulder and lap belt, 0 otherwise)	-1.665	-4.9	-0.013	-0.079	0.092
Collision Type (1 if sideswipe, 0 otherwise)	-1.115	-3.96	0.0014	-0.011	0.01
Weather Condition (1 if raining at the time of the crash, 0 otherwise)	-1.267	-2.92	0.001	-0.005	0.004
No Injury					
Age Group (1 if age less than 25, 0 otherwise)	-1.771	-5.04	0.003	0.011	-0.014
Gender (1 if male, 0 otherwise) (standard error of parameter distribution) (standard error of parameter distribution)	3.978 (2.858)	5.22 (4.51)	-0.001	-0.011	0.013
Intersection Related (1 if at or intersection related including driveway access points, 0 otherwise)	0.739	2.5	-0.001	-0.006	0.006
Object Struck (1 if another vehicle, 0 otherwise)	2.38	6.88	-0.013	-0.058	0.07
Surface Condition (1 if dry at the time of the crash, 0 otherwise)	0.827	2.58	-0.004	-0.022	0.026
Model Statistics					
Number of Observations	2,763				
Restricted Log-likelihood	-3,035.466				
Log-likelihood at convergence	-669.006				
McFadden pseudo-R-squared (ρ^2)	0.780				

TABLE 3.7 Random Parameters Logit Injury Severity Model for Evening Large Truck-involved Crashes

Meaning of Variable	Coefficient	*t*-Statistic	Marginal Effects		
			Severe Injury	Minor Injury	No Injury
Severe Injury					
Constant	-3.482	-4.47			
Base Type (1 if flex base or stabilized earth, 0 otherwise)	-1.612	-2.16	-0.008	0.001	0.007
Gender (1 if male, 0 otherwise)	-1.806	-2.54	-0.016	0.001	0.015
Right Shoulder Width (1 if width greater than 20 feet, 0 otherwise)	2.083	2.77	0.013	-0.002	-0.011
Percentage of Trucks (1 if more than 16% trucks, 0 otherwise)	1.864	2.18	0.006	-0.0004	-0.005
Minor Injury					
Restraint Use (1 if used shoulder and lap belt, 0 otherwise) (standard error of parameter distribution)	6.152 (5.242)	2.33 (2.61)	0.041	-0.450	0.408
Collision Type (1 if sideswipe, 0 otherwise)	-2.276	-3.31	0.001	-0.024	0.023
Weather Condition (1 if clear at the time of the crash, 0 otherwise)	-1.044	-2.63	0.002	-0.029	0.028
No Injury					
Age Group (1 if age less than 25, 0 otherwise)	-2.874	-5.11	0.016	0.017	-0.033
Intersection Related (1 if at or intersection related including driveway access points, 0 otherwise)	1.578	2.77	-0.002	-0.011	0.013
Model Statistics					
Number of Observations	701				
Restricted Log-likelihood	-770.127				
Log-likelihood at convergence	-223.83				
McFadden pseudo-R-squared (ρ^2)	0.709				

DISCUSSION

Of the 22 variables included in the time of day models, only four variables were consistent in each time period. Restraint use, sideswipe collision, age less than 25 and male drivers were found to affect the injury severity regardless of the time, still the sign and magnitude of the estimated coefficients vary across the time of day models. For example, the restraint use indicator is positive in the early morning model indicating that

using a lap and shoulder restraint will increase the likelihood of a minor injury. This parameter was also found to be random and normally distributed with a mean 3.046 and a standard deviation 3.378. This suggests that 37.4% of the observations have a mean less than zero, or that 37.4% of the observations are less likely to be involved in a minor injury crash. The restraint use indicator included in the afternoon model was found to be negative indicating that using a lap and shoulder restraint will decrease the likelihood of a minor injury. One possible explanation for the difference could be the light conditions and traffic patterns. The early morning time period can be characterized by dark lighting conditions and lower traffic volumes whereas typically the afternoon period is lighted with high traffic volumes. Thus, the combination of reduced travel speeds and increased sight distance could explain the decreased likelihood of being involved in a minor injury crash.

Of the 22 variables included in the time of day models, 11 variables were found to be random and normally distributed. These random variables account for unobserved heterogeneity and indicate that the effect of a particular variable is varied across the observations. In other words, a portion of the observations may have an increased probability of a certain injury severity and the other portion of the observations will have a decreased probability of that injury severity due to that variable. For example, in the morning model the male indicator was found to be significant and random with a normal distribution. The mean is 1.117 and the standard deviation of 4.215 specifying that for 57.9% of the observations the mean is below zero. In other words, 57.9% of the observations have a decreased probability of being involved in a minor injury crash while

42.1% of the observations have an increased probability of being involved in a minor injury crash.

The results of each time of day model show major differences in both the combination of variables included in each model and the magnitude of those variables. These differences show that the different time periods do in fact have different contributing factors to each injury severity further highlighting the importance of examining crashes based on time of day.

As presented in Table 5, three variables were found to be significant in only the mid-day model: changing lanes, median width between 51-75 feet and speeding. Changing lanes and speeding could be capturing the uncongested conditions of the transportation facility. As a reminder, the mid-day dataset includes crashes between 10:00 am to 3:00 pm that is in between the typical morning and afternoon traffic peak volume periods. Since there are lower traffic volumes during this time period truck drivers are able to travel at higher speeds and perhaps even change lanes to pass slower moving trucks. A large median can also increase a driver's comfort level which could result in increased speed.

Variables found to be exclusive to the afternoon model (4:00 pm to 8:00 pm) consist of crashes occurring between June and August, during raining conditions and on a dry surface. Crashes occurring during the summer between June and August were found to decrease the likelihood of a severe injury which may be explained by the types of trips made during this time period. Normally this time frame would be considered the 'after school' period, but during the summer there may be fewer students (i.e. young drivers) on the road.

Weather also had an increased impact during the afternoon time frame. Both rain and dry conditions were found to affect the injury severity. Rain at the time of the crash lead to a decreased likelihood of a minor injury crash while a dry surface at the time of the crash lead to an increased likelihood of a no injury crash. One factor that could be influencing injury outcomes that is not included in the model is light condition. This time frame is tricky because depending on the season the light condition can change dramatically between 4:00 pm and 8:00 pm. The elasticity estimates suggest that rain at the time of the crash increases the likelihood of a serious injury or no injury. One possible explanation could be the combination of the light condition as well as the weather conditions. For example, rain and dark lighting conditions can significantly reduce the sight distance as well as the friction between the tire and the roadway surface thus increased the possibility of a crash and a potentially higher injury severity.

Clear weather conditions, a large right shoulder (greater than 20 feet), and a high percentage of large trucks (greater than 16%) were the variables unique to the evening model (9:00 pm to 11:00 pm). The evening time period is characterized by dark lighting conditions resulting in lower sight distance, usually lower traffic volumes potentially yielding lower speeds, and possibly sleepy drivers that may lead to inattentive driving. The model results reveal that clear weather conditions increase the likelihood of a severe or no injury and decrease the likelihood of a minor injury crash. One possible explanation could be that clear weather conditions maximized the sight distance available during the evening providing drivers with more time to react to an incidence, hence no injury crashes; however increased sight distance can also provide additional confidence for the driver and promote higher speeds leading to severe injury crashes.

A wide shoulder width was found to increase the likelihood of a severe injury. Excessively wide shoulders may promote improper use of the additional space. Instead of providing positive separation from roadside obstacles, vehicles including large trucks could use that space to pull off the roadway briefly to complete a task such as reading a map. Vehicles located in the right shoulder could create obstacles and distractions for drivers.

A high percentage of large trucks on the roadway were found to increase the likelihood of a crash in both the morning and evening period. The morning model found that if the percentage of large trucks falls between 12-16% the likelihood of a no injury crash is increased. Driver fatigue due to inadequate sleep while on the road could be a contributing factor to the crash occurrence while congested morning peak conditions could explain the lower injury severity. The evening model found that if the percentage of large trucks exceeds 16% the likelihood of a serious injury increases. Driver fatigue along with reduced sight distance and lower traffic volumes (i.e. increased speed) could contribute to the high injury severity. McCartt et al. (2000) surveyed 593 long-distance truck drivers randomly on the road at select truck stops. The questions were designed to address typical predictors of driver fatigue. The results show that grueling schedules and poor sleep on road were some factors causing long-distance truck drivers to fall asleep on the road. The survey also revealed that some truck drivers exceeded the 10 consecutive driving hour limit and falsified their log books in order to make the delivery on time.

In summary, the results provide insights related to the impact of crash factors and the complex interactions of these factors on crash severity by time of day in urban areas. Additionally, various factors were found to be random and accounting for the presence of

unobserved heterogeneity validating the methodological approach of the random parameters logit model.

CONCLUSIONS

Random parameters logit models are utilized to examine the effect of time of day on the injury severity of large truck-involved crashes. Using crashes on urban freeways between 2006 and 2010 in Texas, it was determined that separate random parameters logit models are warranted. There were three injury severity outcomes: serious injury (fatality and incapacitating injury), minor injury (non-incapacitating and possible injury) and no injury (property damage only) and there were five time periods: early morning (12:00 am- 4:00 am), morning (5:00 am – 9:00 am), mid-day (10:00 am – 3:00 pm), afternoon (4:00 pm – 8:00 pm) and evening (9:00 pm – 11:00 pm).

The results of the individual models demonstrate considerable differences among the five time periods. Key differences include traffic flow, light conditions, surface conditions, time of year, and percentage of trucks on the road. Ever-changing traffic flow patterns throughout the day were evident in the mid-day model. Free-flow like characteristics such as speeding and changing lanes contributed to large truck-involved crashes between 10:00 am and 3:00 pm (i.e. typically uncongested time period). The summer indicator variable in the afternoon model may also suggest that traffic volume may impact injury severity. Crashes between June and August were found to decrease the likelihood of a severe injury which may be explained by less young drivers on the road due to summer vacation.

The evening model suggests that clear weather conditions, but dark light conditions results in either a serious injury or no injury crash. The clear weather

conditions may promote speeding for some drivers, while other drivers may take more precaution under dark lighting conditions. Finally, a high percentage of large trucks on the roadway increased the likelihood of a crash in the morning and evening. This could be explained by lack of sleep either from the previous night or failing to pull into a rest stop when the driver is fatigued.

Although the results of this study are exploratory, the results themselves provide evidence of the effect of time of day on large truck-involved crashes. In future work, the authors are working on utilizing these results to develop planning tools to help mitigate the impact of these types of crashes. In addition, we are addressing the spatial transferability of the models to other state specific datasets.

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4.0 CHAPTER 4 – CONCLUSION

The preceding chapters contain individual articles that advance the literature on large truck-involved crash analysis by exploring two new transferability frameworks. First, the spatial transferability of large truck-involved crash factors is evaluated and the second paper documents the temporal transferability of large truck-involved crashes. This chapter will summarize the major findings of this work and discuss the practical applications and implications for future research.

4.1 Summary of Findings

In the second chapter, the spatial transferability framework for large truck-involved crashes in two spatially distributed regions is presented. The stringent and heavy regulations on the trucking industry (Federal Motor Carrier Safety Administration, n.d.) prompted the investigation of commonalities of large truck-involved crash factors in two distinct regions. Large truck-involved crashes in Oregon and Texas were utilized as a case study to demonstrate the spatial transferability framework. The case study results reveal that spatial transferability is not warranted. In other words, there weren't many significant commonalities between the crash factors and injury severities for the large truck-involved crashes in Oregon and Texas.

Many of the differences involved were not related to the driver or the truck itself but rather 'uncontrollable' external factors such as light conditions and weather conditions. Khorashadi et al. (2005), Dissanayake & Kotikalapudi (2012) and Islam et al. (2014) found similar results, but these studies focused on only one area. The Oregon and Texas crash databases also varied both in the types of crash-related variables recorded as well as the intermittent categories for each crash variable (Oregon Department of

Transportation, n.d.; Texas Department of Transportation, n.d.). For example, Texas recorded the median width of the roadway where the crash occurred while Oregon did not. Since the median width variable was not consistent in both databases, it was excluded from the analysis. The limitations due to the structure of the databases could be addressed by implementing a standardized national crash data reporting framework. Lastly, although the case study concluded that spatial transferability was not warranted, a regional model of crashes between clustered states with more similar characteristics might be warranted. Perhaps, if crash databases were consistent and the 'uncontrollable' external factors were more similar spatial transferability could be warranted.

The third chapter addresses the impact of time of day on large truck-involved crashes. Many factors such as traffic patterns and driver behavior vary throughout the day which could have a mixed effect on large truck-involved crashes. In an attempt to predict individual behavior for agent-based modeling simulations, Bonabeau (2002) also agrees that individual behavior is affected by time of day (e.g. stress, sleepiness). Bonabeau (2002) further describes the complex relationship between individual decision-making and various traffic conditions such as how a driver responds to congestion (e.g. will a driver select a different route?).

To understand the impact of time of day on large truck-involved crashes, the temporal transferability framework is demonstrated through a case study with Texas crash data. The case study results verify the mixed impact of time of day on large truck-involved crashes and indicate that separate models by time of day are warranted.

Five separate random parameters logit models including early morning, morning, mid-day, afternoon and evening corresponding to five time periods 12:00 a.m.-4:00 a.m.,

5:00 a.m.-9:00 a.m., 10:00 a.m.-3:00 p.m., 4:00 p.m.-8:00 p.m. and 9:00 p.m.-11:00 p.m., respectively, were developed. There were major differences in the combination of variables included in each of the models as well as the magnitude of impact for each variable. As anticipated, traffic flow was among one of the key differences between the models. For example, free-flow like characteristics such as speeding and changing lanes were found to be significant in only the mid-day model where typically the traffic volumes are lower (i.e. off-peak volumes). Although this article is an exploratory analysis, these results highlight the importance of time of day on large truck-involved crashes for future safety studies and improvement projects.

In summary, the proposed spatial and temporal transferability frameworks for large truck-involved crashes provide an unexplored approach to analyzing crash data. This new approach attempts to exploit the unobserved factors of these types of crashes. For example, the spatial transferability framework attempts to capture the training experience of large truck drivers which is not explicit in the data. The temporal transferability framework attempts to group crashes with similar unobserved, uncontrollable characteristics such as traffic patterns or driver behavior which also is not always explicit in the data. Ultimately, this innovative methodology for crash analysis will reveal new information that can enhance safety planning tools.

4.2 Practical Applications

The results of most crash analyses can lend a hand in the development of safety planning tools to help mitigate the impacts of those crashes. This thesis provides a new outlook on large truck-involved crash analysis and reveals additional information that can be used when identifying mitigation measures. The results of this thesis can more sharply

guide the development of safety planning tools and identify spatial or temporal-related mitigation measures to maximize the benefits. More specifically, the results of this thesis can help to identify effective countermeasures, aid in the allocation of limited resources (i.e. labor, time, money), minimize economic losses, support the implementation of trucking regulations and ultimately increase the safety of urban roadways from a large-truck perspective.

The proposed frameworks provide new information that can be applied directly to reduce the impact and severity of large truck-involved crashes. One practical application of this research is the identification of countermeasures. The new information from the frameworks could identify low-cost countermeasures such as increasing the median width or removing off-road obstructions from high severity off-road crash locations.

The Oregon Department of Transportation (ODOT) has developed a data driven safety program, All Roads Transportation Safety (ARTS) Program (Oregon Department of Transportation, n.d.). The program utilizes crash data to identify the most cost-effective countermeasure. The results of this thesis can directly feed into this program. The ODOT ARTS Program developed a list of countermeasures based on crash factors such as vehicle type, injury severity, urban or rural roadway, and crash type. The ODOT ARTS Program can filter the countermeasure list by the different crash factors to identify the applicable countermeasures. For example, the countermeasure corresponding to a roadway segment with frequent crashes at nighttime is improving the lighting at that roadway segment whereas the countermeasure corresponding to frequent road departures along a straight segment at nighttime is to install raised pavement markers. The temporal transferability framework can offer additional information regarding crashes at various

times of day. It could allow ODOT or any state Department of Transportation to add another layer of information into their analysis.

Another practical application of this research is the allocation of limited resources (i.e. time, money) by helping to prioritize improvement projects or utilizing labor most effectively. First, the results can help to identify the vulnerable areas within the transportation system, which may be too great for the resources available. Transportation planners, the trucking industry and state and local governments can focus on higher severity crashes factors and prioritize projects to reduce high severity crashes.

Secondly, the two proposed frameworks can aid in the distribution of limited man-power. The spatial transferability framework can encourage multiple regions to conduct a joint large truck-involved crash analysis which could save time and labor costs. For instance, instead of having two engineers conduct a large truck safety study of two regions separately, one engineer could conduct a large truck safety study for both regions combined. Considering both regions together could highlight common issues with large truck-involved crashes that could be prevented through engineering or education. For example, if two regions exhibit curved segments as a highly problematic then perhaps the CDL training programs (Federal Motor Carrier Safety Administration, 2010) should improve that portion of the training courses or the design speed of the curve should be lowered. The temporal transferability framework can help to pinpoint the ‘best’ time to deploy trucking inspectors. Trucking inspectors or police enforcement could be scheduled to monitor the roadways during higher severity time periods. Allocating resources and prioritizing projects to focus on high severity crashes can improve overall safety for the traveling public.

The trucking industry could also use these results during an economic analysis. They could assess the safety or economic impacts of large truck-involved crashes by time of day. Trucking operations are typically shifted to off-peak periods, but some believe that there are higher accident risks during off peak periods (United States Department of Transportation, 2003). Since the early morning and nighttime coincides with the natural sleep cycle it is believed to make a driver less alert (United States Department of Transportation, 2003). This study provides a foundation for further analysis of the safety or economic impacts of shifted trucking operations.

The results could also identify a collective problem potentially due to the driver or vehicle. If there is a persistent issue among truck drivers or heavy vehicles, decision makers could implement a policy change to resolve these 'collective' issues. Finally, these results could aid in the development of trucking regulations. Trucking regulations are designed to improve roadway safety however there may be some unintentional or unavoidable consequences. For example, Hours of Service regulations restrict a driver to a specified number of continuous hours of service (Federal Motor Carrier Safety Administration, n.d.). This ruling was intended to reduce the number of fatigued drivers yet it could have negative unintentional consequences such as speeding in order for the delivery to be on-time. The results of this thesis can help during the development of new or revised regulations.

In summary, there are several practical implications of this research that could be applied directly to improve roadway safety. These results could benefit transportation planners, the trucking industry and state and local governments throughout the decision-

making process. These results provide new spatial and temporally-related information for large truck-involved crashes.

4.3 Implications for Future Research

This thesis presents several avenues for future research. First, this thesis builds a foundation for future temporal and spatial crash analysis research. Secondly, it prompts future research efforts regarding a national standard for crash data reporting.

The spatial transferability framework demonstrates the analysis of crashes in two spatially distributed regions. This methodology could be applied to a larger area with any number of sub-regions. Future research should continue to investigate the feasibility of spatial transferability of large-truck involved crash severity models between multiple regions with some commonalities. In this thesis, the commonalities include the truck driver training and experience as well as the heavy vehicle configurations. External factors including weather, light conditions, and time of day were among the key differences which may have outweighed the commonalities. A future study accounting for these external factors such as a regional large truck-involved crash model between neighboring regions with similar weather conditions may warrant spatial transferability.

The temporal transferability framework has highlighted the importance of time of day on large truck-involved crashes. This research encourages future studies to consider the safety and economic impacts of these types of crashes at various times of day and well as the impact of shifting trucking operations to off-peak periods.

Lastly, the inconsistencies between the databases were a major limiting factor of this work. The subtitle differences between the data reporting techniques led to the exclusion of certain crash variables in the analysis. Consequently, potentially significant

variables containing useful information could be excluded from the analysis. A national standard for crash data reporting would support spatial transferability analysis and the obstacles encounter in this thesis could be avoided.

Overall, this thesis explored original research to extend the literature regarding large truck-involved crash analysis. The results were based on exploratory studies, but highlight the importance of time and space on large truck-involved crashes. This work provides a foundation to analyze large truck-involved crashes in a new light.

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