Understanding How, Where and How much Freight Flows Using 2012 Commodity Flow Survey Data

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UNDERSTANDING HOW, WHERE AND HOW MUCH FREIGHT FLOWS USING 2012 COMMODITY FLOW SURVEY DATA

by

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ABSTRACT

In recent years, with increased economic globalization, growing e-commerce and internet based shopping, freight movement patterns are undergoing a transformative change. The shipment size distribution is moving towards a higher share of smaller size shipments affecting transportation mode and vehicle type requirements. In addition, freight transportation mode is closely affected by the destination location (and its attributes). In our dissertation, we contribute to freight research by developing a comprehensive framework to examine the how, where and how much freight flows in US. Specifically, we study the following dimensions of freight flow: (1) transportation mode, (2) mode and shipment weight choice and (3) mode and destination choice. For analyzing mode choice, an advanced discrete freight mode choice model- a hybrid utility-regret based model system has been estimated while accommodating for shipper level unobserved heterogeneity. To demonstrate the applicability of the proposed model system, detailed policy analyses examining the implementation of vehicle fleet automation and rerouting of freight movements away from a region were considered. While shipment weight could be considered as an explanatory variable in modeling mode choice (or vice-versa), it is more likely that the decision of mode and shipment choice is a simultaneous process. This joint decision is investigated both simultaneously employing a closed form copula structure and sequentially employing latent segmentation based sequence model. For destination choice, we investigated the connection between shipping mode and destination choice of shipment in a latent segmentation based sequential form. The analysis for the dissertation is conducted using 2012 Commodity Flow Survey (CFS) data.

To my parents, without whom I am nothing.

&

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CHAPTER ONE: INTRODUCTION

Background And Motivation

An efficient and cost-effective freight transportation system is a prerequisite for a region's economic growth and prosperity. About 122.5 million households, 7.5 million businesses and 90 thousand government units, daily depend on the efficient movement of about 55 million tons of freight valued at around $49 billion (Freight Facts and Figures, 2015). In the US, the demand for goods has grown steadily over the past half century and is expected to increase with the growth in population. The percentage share of freight transported in 2013 by weight and value by mode are as follows: truck (70 and 64), rail (9 and 3), water (4 and 1.5), air (0.1 and 6.5), and pipeline (7.7 and 6.0) (Freight Facts and Figures, 2015). The remainder of the freight is transported by multiple modes, mail and unknown modes. This percentage clearly indicates that, road based freight transportation is an important component of supply chain in the U.S and trucks are the preferred mode of shipping for most manufacturers and distributors in the country. Higher percentage of truck mode share is associated with negative externalities including, air pollution, traffic congestion, increase in accident severity and expeditious deterioration of road and bridge infrastructure. Though heavy trucks consist only 3 percent of the total registered vehicles in USA and comprise 7 percent of total vehicle miles driven, yet they are involved in 11 percent of total road fatalities (Bezwada, 2010). Usually multiple axle trucks produce rutting damage and single and tandem axles causes cracking on road surface (Salama et. al., 2006).

There is a growing recognition among transportation researchers that addressing the freight industry associated challenges needs us to examine several dimensions including freight mode choice, freight infrastructure, pricing strategies across modes, and wages. With the emerging advances in vehicle technology – connected and autonomous vehicles – there is likely to be a seismic shift in the freight industry in the near future. While level 4 adoption, which is a fully self-driving vehicle in all conditions, (as defined by NHTSA, 2013) is likely to take time, several intermediate levels of vehicle technologies are already being introduced by private and public companies. These vehicular advances offer significant advantages to the trucking industry in terms of fuel, time, and manpower cost savings. For instance, a platoon of connected trucks in a formation can reduce the impact of wind resistance by maintaining a shorter distance between them (15m instead of 50m) thus saving fuel and reducing CO2 emission by around 7 percent for a platoon of three trucks (https://www.daimler.com/innovation/digitalization/connectivity/connected-trucks.html). Further, adoption of fully autonomous vehicles will allow the trucking industry to circumvent the need for federally mandated driver breaks for long-haul trips. These are instances of how vehicle technology can offer environmental and financial benefits. While these changes are likely to improve the performance of the trucking industry, their impact on the overall freight mode choice is less straight forward and hence it is need to be investigated and understood deeply.

Also, in recent years, with increased economic globalization, growing e-commerce and internet based shopping, the traditional pattern of freight flows is rapidly changing; particularly the shipment size distribution is moving towards a higher share of smaller size shipments. The type of transportation mode in e-commerce industry is quite different from the conventional one In fact, with increasing online purchases (promoted by Amazon and other retailers), there is a reduction in personal travel that is offset by increased frequency of freight movements. According to Bureau of Transportation Statistics (BTS, 2004), smaller sized shipment (less than

500 pounds) increased by 56 percent by value from 1993 to 2002. This is further confirmed by analysis of 2012 Commodity Flow Survey (CFS) data. According to CFS data in 2012, almost 90 percent commodities were shipped with a weight less than 500 pounds and worth 25 percent by value. The proclivity toward smaller shipment sizes will result in increased truck and parcel mode usage. The growth in truck and parcel freight movements will result in increasing movement of large vehicles on residential streets impacting road surface, increasing emission, increasing establishment of intermodal hubs affecting infrastructure, increasing congestion and traffic safety concerns arising from collisions of trucks and other road users.

Making shipment size decision is very important in freight transportation, as it is directly related to logistical and technical requirements for both shippers and carriers. Also this shipment size choice is closely related to transportation mode as different shipment size demands different vehicle type. Different types of modes again have traffic safety and environmental issues. Therefore an efficient freight model is important for evaluating better policy and regulation in public sector. The aforementioned discussion clearly highlights the importance of freight transportation mode and shipment size on understanding the impact of freight on economy, transportation system, and environment. While shipment size could be considered as an explanatory variable in modeling mode choice (or vice-versa), it is more likely that the decision of mode and shipment choice is a simultaneous process. For instance, when there is a need to ship a commodity, the shipper might consider the available modes and then determine the exact shipment size in conjunction with the mode. For example, if the total commodity to be shipped is weighed 1000 tons, the shipper might consider a single shipment by rail (thus choosing mode as rail and shipment size as 1000 tons) or consider sending multiple shipments by truck.

Alternatively, this simultaneous decision of mode choice and shipment size decision can be analyzed based on a sequence approach. To elaborate, if the shipment size is already known then it is easier to choose the shipment mode and again when mode of transport is known first deciding on shipment size become easier too. In the sequence structure the two simultaneous choice decisions are considered in two segments. In first segment, shipment size is chosen first and then the mode; in the second segment mode is chosen first and then shipment size. Basically, this approach allows two discrete choice orders to be simultaneously considered in the analysis as two segments for individual shipments.

In freight transportation behavior choice of destination is also an important issue. Different types of areas have different types of demand. The spatial and economic attributes affect the freight demand of an area. Orientation of urban infrastructure, such as, distribution centers, number of warehouse and storage centers, shop location influences the freight demand. For instance, an industrial area might attract more raw materials and the urban areas or market places would have more demand for finished products. Suppliers or freight carriers always try to maximize their profit by minimizing the transportation cost. Therefore, to fulfill the demand of the destination and at the same time to make the most of profit the decision of mode and destination choice are more logical to be made simultaneously. But, all the modes cannot be chosen for all destination areas. For example, allowing ship or rail as a shipping mode where there is no port or rail yard is not appropriate. Also, roadway or parking pricing, loading/unloading area at destination would also have impact on mode choice decision. The above discussion surely emphasizes the importance of investigating the connection between shipping mode and destination choice. Following the same sequence approach as mentioned in the previous paragraph these two decision rules can also be explored. In the first segment the destination will be chosen first and knowing the attributes of the destination choice of mode will become less complicated. In the second segment mode will be chosen first and when we know the mode choice of destination will also become easier.

Objective Of The Dissertation

Reliable freight transportation planning is becoming a vital issue in urban transportation planning sector. The objective of the dissertation is to explore how, where and how much of freight flows in the US. The literature related to freight transportation is limited compared to passenger transportation and travel behaviour literature. Therefore, the primary aim of the current dissertation is to address the methodological and empirical gaps in existing body of freight transportation literature and hence, to employ advanced econometric frameworks to investigate important empirical issues, contributing to the current body of freight transportation and travel behavior literature.

The *first objective* is to examine the freight mode choice from alternative behavioral paradigms including classical random utility (RU) framework and newly emerging random regret (RR) framework. While comparison between RU maximization and RR minimization based approaches is beneficial, it is also possible that attribute impact on choice behavior could follow either approach. Towards accommodating such flexibility, a hybrid approach that allows attribute impacts to follow both RU and RR is employed in our analysis. While behavioral paradigm is quite important, the presence of unobserved heterogeneity is also likely to affect choice behavior. To accommodate for alternative behavioral paradigms and potential presence of unobserved heterogeneity, we develop the following models: (1) RU based mixed MNL (RUMMNL), (2) RR based mixed MNL (RRMMNL), (3) a hybrid utility-regret mixed MNL

(HUMMNL) model combining both RU and RR based attribute processing, and (4) latent class models with hybrid segments (LSRURR) – one segment following RU decision rule while the other following RR decision rule. Based on the variables effects several policy scenarios will be evaluated to examine the corresponding changes in freight mode share under future vehicle technology adoption.

The *second objective* is to examine the joint choice of freight transportation mode and shipment size by developing an unordered choice model for mode and an ordered choice model for shipment size. We will adopt a closed form copula based model structure for capturing the impact of common unobserved factors affecting these two choices. Both random utility (RU) based multinomial logit (MNL) and the random regret (RR) minimization based multinomial logit (MNL) will be explored within a copula based model.

The *third objective* is to evaluate if the shipper is likely to process the decision of mode and shipment size choices as a joint decision or a sequential decision. For this purpose a latent segmentation based approach will be developed, where in Segment 1 an ordered logit model will be developed for shipment size and a multinomial logit (MNL) will be developed for shipment mode; and in Segment 2 freight mode first and shipment size second.

The *fourth objective* is to explore the joint decision of mode choice and destination of shipment in a sequential form. In the first segment destination will be chosen first and mode will be chosen second; and vice-versa in second segment.

Outline Of The Dissertation

The remainder of the dissertation is structured with seven additional chapters.

Chapter Two contains a comprehensive literature review of existing research on freight mode choice decision, some methodological overview of freight mode choice and joint decision of mode-shipment size choice and mode-destination choice. Different alternative modes, exogenous variables, such as, level of service variables, freight characteristics, origin-destination attributes, methodological framework used in these studies have been listed and described in a systematic format. Also the limitation and findings from these studies have also been discussed in this chapter.

Chapter Three describes the data processing steps involved in preparing the 2012 Commodity Flow Survey data for analysis. Further this data is augmented with several origin-destination, transportation network and level of service variables using different sources and methodology. A detailed description of all the exogenous variables along with the descriptive statistics of these variables has been provided in this chapter.

Chapter Four contributes to the first objective by evaluating the mode choice decision with an alternative behavioral paradigm- random regret (RR) based multinomial logit model. In this chapter a description of the econometric framework of the model has been provided. Also comparison of different model has been made. Finally, for various policy scenarios the modal shift of freight transportation is evaluated to examine the changes under adoption of connected and autonomous vehicle.

Chapter Five focuses on objective two and investigates the joint decision of mode choice and shipment size by developing a copula based structure. Both random utility based and random regret based MNL-OL copula is examined and the models are compared. The econometric framework of the model has been described in detail in this chapter. Also the empirical analysis and validation exercise are described in this chapter. The validation exercise includes the estimation and comparison of predictive log-likelihood for entire sample and at sub-sample level (sampling by freight characteristics) for different models.

Chapter Six presents an alternative approach to evaluate the joint decision of mode and shipment size choice. This chapters describes a latent segmentation based MNL-OL sequence model, where in one segment mode is chosen first and shipment size second and vice-versa in another segment. The empirical analysis results are then compared with the results from chapter five.

Chapter Seven investigate the joint decision of mode and destination choice. The methodology adopted for this study is latent segmentation based sequence model. Here both mode and destination choice are investigated in multinomial logit structure. The chapter also contains the empirical results obtained from the analysis.

Chapter Eight concludes the dissertations summarizing the findings and identifying scopes for futures research.

CHAPTER TWO: LITERATURE REVIEW

Transportation literature on freight mode choice and planning is relatively sparse compared to passenger mode choice and planning behavior. Also application of advanced models on freight transportation behavior is not so common in existing literature. The summary of the relevant earlier studies on freight mode choice, methodological applications on freight mode choice and joint decision of mode-shipment size and mode-destination choice are discussed in this chapter in both passenger and freight transportation realm.

Earlier Research On Freight Mode Choice

Table 2.1 presents a summary of earlier research on freight mode choice. The information provided in table include study area, data source and type, model framework, dependent variable of interest, modes considered, and independent variables considered. The independent variables are categorized into the following variable groups: (i) LOS measures (such as shipping travel time, shipping cost, speed, delay, service frequency, service reliability, fuel cost); (ii) freight characteristics (such as commodity group, commodity size, commodity density, commodity value, commodity weight, product state, temperature controlled or not, perishability, trade type, quantity); (iii) transportation network and O-D attributes (such as shipment O-D, distance, ratio of highway and railway miles in origin and in destination); and (iv) others (loss and damage, shipper's characteristics etc.). The important observation made from Table 2.1 includes: *First*, majority of the studies considered either two or three alternative modes, mostly truck and rail. *Second*, alternative availability was no considered by any of the studies. The choices available to the shipper might be different based several factor, such as, freight characteristics and O-D attribute. *Third*, shipping cost and shipping time are not always considered together in all the studies. Most common influencing factors found in the literature were shipping time, shipping cost, commodity type, weight, value, service frequency, distance and reliability. *Finally*, the most commonly utilized model framework for mode choice is the multinomial logit (MNL) model and its several extensions, such as, nested logit model and mixed logit model, or heteroscedastic extreme value model, latent class multinomial logit model and a copula based joint model embedded with a multinomial logit (MNL) model. Alternative approaches such as artificial neural network, neuro-fuzzy model have also been developed. More recently random regret based MNL has also been employed. Earlier researches have also developed Value of Time (VOT) measures that provide guidance on the premium placed on reducing travel time. For example, Samimi et al. (2011) concluded that a 50 percent increase in fuel price affects the modal shift from truck to rail minimally; an increase ranging between 150 to 200 percent, shifts about 7 percent of truck share to rail mode.

Methodological Overview Of Freight Mode Choice

From Table 2.1 it can be observed that, on the methodological front, the majority of earlier studies have employed traditional random utility based multinomial logit (RUMNL) model and its variances, such as, nested logit model, mixed logit model, latent class multinomial logit model and a copula based joint model embedded with a multinomial logit (MNL) model. The most commonly employed approach, the random utility framework is mainly a compensatory behavioral framework that might not be optimal in determining choice behavior with alternative specific attributes. An alternative random regret framework that allows for pairwise alternative attribute comparison has been successfully applied in several fields including transportation (for travel mode choice (Chorus, 2010) or route choice (Chorus, 2014), road pricing (Chorus et. al, 2011), departure time (Chorus and Jong, 2011), automobile fuel choice (Hensher Et. al., 2013), online dating (Choris and Rose, 2013), healthcare (de Bekker-Grob and Chorus, 2013), and recreational site choice (Boeri et. al., 2012). Recently, Boeri and Masiero (2014) used random regret based multinomial logit (RRMNL) model to study freight mode choice and road alternatives based on a stated preference survey conducted on some Swiss medium to large industries. In their study, the authors found that the RRMNL model performed slightly better than its utility counterpart.

Methodological Overview of Joint Decision of Mode Choice and Other decision in Transportation Research

The investigation of joint or simultaneous choice behavior is not new in the field of transportation research. To portray the objective of our research in the context of existing literature, we will provide a brief review from the point of different methodologies employed to analyze the joint decision of mode choice along with some other decision variables in both passenger and freight transportation realm. Table 2.2 illustrates the list of such studies in two groups (passenger and freight). This table provides information on study area, joint decision variables, level of analysis (trip/tour/activity), mode considered and methodologies employed.

There are immense studies exploring joint decision of passenger mode choice along with some other decision variables compared to joint decision of freight mode choice. From the table for the studies of passenger travel *first*, the joint decision variables considered are mainly mode choice and departure time choice (Bhat, 1998(a); Bhat, 1998(b); Tringides et. al., 2004; Hess et. al., 2007; Bajwa et. al., 2008; Habib et. al. (2009); Habib, 2013; Ding et. al., 2014; Zou et. al., 2016; Shabanpour et. al.; 2017). Some studies also considered auto ownership (Train, 1980;

Dissanayake and Morikawa, 2003; Pinjari et. al., 2011), residential location choice (Vega and Reynolds-Feighan, 2009; Yang et. al., 2013), station choice (Debrezion et. al., 2009; Chakour and Eluru, 2014), route choice (Shakeel et. al., 2016) and destination choice (Seyedehsan and Shafahi, 2013) in association with mode choice. Very few studies have been found which considered more than two simultaneous decision variables. For example, Dissiyanake and Morikawa (2003) discussed joint decision of mode choice, car ownership and trip chaining, Pinjari et. al. (2011) investigated joint decision of mode choice, residential location and auto or bicycle ownership, Habib (2012) considered simultaneous decision of mode choice, work start time and work duration and Yang et. al. (2013) considered mode, residential location and departure time choice decision jointly. Almost all the studies considered mainly car and transit mode in their analysis. *Second*, we can observe that analysis has been performed at both trip and tour level. *Third*, from the table we can notice that many studies used traditional Multinomial Logit (MNL) model and Nested Logit (NL) model and compared these methods with Mixed MNL (MMNL) and Cross Nested Logit (CNL) model (de Jong et. al., 2003; Bajwa et. al., 2008, Yang et. al., 2013; Ding et. al., 2014, Shakeel et. al., 2016). Few studies used either only NL model (Dissanayake and Morikawa, 2003; Debrezion et. al., 2009) or Mixed MNL model (Bhat 1998b; Hess et. al., 2007) or Cross NL model (Vega and Reynolds-Feighan, 2009) to analyze the joint decision. MNL and NL models are more often used due to their closed form structure and easy interpretation. The major limitation of classical MNL method is assumption of Independence of Irrelevant Alternatives (IIA) property which infers that distribution of random error term is independent and same across all alternatives, which eventually leads to bias estimation and prediction. The limitation of MNL model can be relaxed by using Nested Logit model which allows correlation between choices in a common group. Dissanayake and

Morikawa (2003) estimated NL model where they considered two levels in the nesting structure- in the upper level they used car ownership, motorcycle ownership and no vehicle ownership and in the lower level they represented mode choice combination. Debrizon et. al. (2009) analyzed the joint decision of access mode and station choice in two possible decision structures. In one structure alternatives having same access modes were grouped together and in another structure alternatives having same stations were grouped together. They found that access mode in upper level and station in lower level structure was more appropriate compared reverse structure in Netherlands. The main drawback of logit model is that it can not capture random taste variation due to unobserved attributes across the individuals. These limitations can be overcome in the mixed logit structure which allows taste variation, unrestricted substitution patterns and correlation among unobserved factors (McFadden and Train, 2000). Bhat (1998a) estimated a MMNL model which captured shared unobserved factor along both mode and departure time choice context in the San Francisco Bay area, USA. Also, in the Cross Nested Logit the alternatives belong to more than one nest instead of belonging to a single nest in nested logit model defining the share of each alternative going to different nests. Hence, CNL allows flexible correlation structure of the error terms among the alternatives. Ding et. al. (2014) and Bajwa et. al. (2008) investigated joint decision of mode choice and departure time using CNL and found that this model outperformed NL model. Yang et. al. (2013) analyzed three simultaneous decision- residential location, mode and departure time choice, using CNL and concluded that CNL performed better than NL models.

The joint or simultaneous decision has also been investigated employing some other methodologies. For example, Train (1980) examined the joint decision of auto ownership and mode choice employing a conditional rule where the probability of choosing the mode by worker is dependent on the auto ownership level of the household. In his proposed joint system the conditional and marginal probabilities both are in the logit form, therefore he named this model sequential or structured model which captures the correlation among decision through Θ parameter. Bhat (1997) estimated a joint MNL-Ordered Response model for the Boston Metropolitan Area, USA which showed that there exists a strong correlation among random components influencing mode choice and number of stops during work commute. Bhat (1998b) in his another study employed a joint MNL-Ordered Generalized Extreme Value (OGEV) model in a nesting structure where he used mode choice at higher level and departure time at lower level for the San Francisco Bay Area of USA. His study showed that joint MNL-OGEV performed much better than NL and MNL. Tringides et. al. (2004) in their study considered a recursive bivariate probit model with two alternative causal structures-in one structure departure time in determined first and mode choice is then influenced by departure time and vice versa. This study was conducted at tour level for Florida, USA and the result showed that for workers, the model having departure time first and mode choice later performed better and for non-worker reverse combination performed better. Habib et. al. (2009) used joint MNL-Hazard based Duration model for joint mode choice and departure time decision for Toronto, Canada. Pinjari et. al. (2011) captured correlation among residential location, car and bicycle ownership and mode choice using a mixed multidimensional choice model for San Francisco Bay Area, USA. The residential location and mode choice was analyzed using MNL and auto/bicycle ownership was analyzed using ordered response model. Then the interdependency and joint natures of the choice decisions were captured using common stochastic terms in multidimensional model system. In this model system the interdependencies allowed self-selection effects, endogeneity effects, correlated error structures and unobserved heterogeneity. Zou et. al. (2017) used agent based choice model for mode-departure time joint choice decision. More recently, to capture the impact of common unobserved factors affecting the joint decision Ermagun et. al. (2015) and Shabanpour et. al. (2017) used closed form copula structure in their studies. But, in this process, the information of one choice in not directly considered in another choice decision and the information is only treated through unobserved error correlation. Therefore, recently Chakour and Eluru (2014) established an alternative approach where they assumed that decision maker tends to make joint decision in a sequence. As the true sequence is unknown to analyst, so, they proposed a latent segmentation based approach which determines probabilistic assignment of the individual based on some exogenous variables. They applied this method on access mode and train station choice for Montreal, Canada. They developed two latent segment- in one segment station was chosen first and access mode later; and vice versa for another segment. In this process the first choice decision is assumed to be known while modeling the second choice decision and based on this condition additional information can be announced in the model structure. Anowar et. al. (2018) used this innovative latent segmentation based sequential approach in modeling joint decision of mode-departure time choice, but using regret minimization decision rule for Toronto, Canada. Angueira et. al. (2017) also used this method in modeling joint decision of vehicle type and distance traveled choice. Few studies also used machine learning techniques to capture the correlation between joint decisions of mode-departure time choice and found these techniques performed better than traditional MNl or NL models (Seyedehsan and Shafahi, 2013 used Fuzzy Decision Tree, Zhu et. al. used Decision Tree and Bayesian Network).

In the field of freight transportation, from Table 2.1, we found that shipment size is mostly used as an explanatory variable in developing mode choice models. However, there is a growing recognition of the interrelation between freight mode and shipment size in the transportation research community. Table 2.2 listed a set of studies which investigated joint decision of mode and shipment size choice. From freight transportation related studies of the table we can conclude few things. *First*, most of the studies considered mode as discrete variable and shipment size as a continuous variable. *Second*, the most commonly considered modes were truck and rail. Very few studies considered some other modes, such as, air, parcel or multiple moes. *Third*, in terms of methodology traditional MNL model has been used for analyzing mode choice and linear regression for shipment size analysis. Abdelwahab and Sargious (1992) and Abdelwahab (1998) used switching simultaneous equation to capture correlation of mode and shipment size choice decision. Classical MNL and NL model have also been utilized by many studies to capture the correlation (de Jong and Ben-Akiva, 2007; de Jong and Johnson, 2009; Habibi, 2010; Windisch et. al., 2010; Stinsosn et. al., 2017). To overcome the limitations of MNL and NL discussed earlier few studies used mixed MNL in their analysis (de Jong and Ben-Akiva, 2007; Abate and de Jong, 2014). Recently, the copula based closed form structure has been used to capture correlation between discrete-discrete choice (Pourabdollahi et. al., 2013a) and discrete-continuous choice (Irannezhad et. al., 2017) decision. Irannezhad et. al. (2017) used random regret minimization based decision rule for mode choice and linear regression for shipment size choice with Frank copula based structure. Few other methods, such as, Heteroscedastic Extreme Value model (Holguin-Veras, 2002), Game theory (Holguin-Veras, 2011) where between two experimental set-ups, in one shippers decide the shipment size and in other carriers decide the shipment size to maximize profit., Economic Ordered Quantity model

(Combes, 2012) and Freight Activity based Modeling Framework (FAME) have also been employed by some researchers.

Earlier Studies on Destination Choice Behavior

Destination choice process has gained significant attention in passenger transportation literature. However, there has been relatively little literature published on freight destination choice development. A complete review on freight mode choice studies is provided in our earlier study (Keya et. al., 2017), which provide a detail information on exogenous variables affecting mode choice process and the methodologies used. Therefore, in our review of the earlier literature, we will mainly focus on studies examining destination choice behavior. Though selecting a destination and a mode type for a trip are typically treated as two independent problems, but research shows that these two decision processes can be made simultaneously and hence joint models have been applied for prediction mode and destination choice. So, in our literature review, we will also cover the studies which evaluated joint decision of mode and destination choice employing different methodologies.

Table 2.3 depicts the earlier literature on only destination choice in both passenger and freight transportation field of research. Several observations can be made from the table related to passenger and freight destination choice studies. *First*, several studies examined destination choice by activity purpose, for example, shopping trips (Ansah, 1977; Recker and Kostyniuk, 1978; Kitakumar, 1984; Thill and Horowitz, 1997; Pallegrini et. al., 1997; Leszczyc et. al., 2000; Arentze et. al., 2005; Sivakumar and Bhat, 2007; Wang and Lo, 2007; Scott and He, 2012; Paleti et. al.; 2017); recreational trips (Pozsgay and Bhat, 2001; Simma et. al., 2002; Kemperman et. al., 2002; Molloy and Moeckel, 2017) and tourist's vacation location choice (Um and Crompton, 1990; Seddighi and Theocharous, 2002; Hong et. al., 2006; Barros et. al, 2008; Hsu et. al., 2009; Yang et. al, 2013; Wong et. al.; 2017). *Second,* in terms of considering destination alternatives, the number of choice alternatives mostly ranges between 2 to 117 for passenger's destination choice behavior. Sometimes universal set of all available destination alternatives has been considered as choice alternatives in the study (Thill and Horowitz, 1997; Simma et. al., 2002). For freight destination choice studies the number of destination choice alternatives ranges from 12 to 40. *Third*, from passenger destination choice related studies it can be observed from the table that mainly three categories of explanatory variables have been used in the studies-(1) Socio-demographic characteristics of decision maker (age gender, marital status, employment status, household income, household size, vehicle ownership); (2) Level of service variables (travel time, travel cost, distance, frequency of public transit); (3) Destination zonal attributes (area type, area size, number of shopping and recreational opportunities, no. of employment, presence of central business area, parking facilities, store's characteristics for shopping trips, entry fee for the recreational activity, cultural and climatic attributes for vacation trip). For freight destination choice studies the attributes used by the studies are travel time, loading-unloading time, waiting time, distance, type of goods to be transported, number of employment at destination and destination area type. *Fourth,* most widely used method for destination choice process is traditional multinomial logit (MNL) model in both passenger and freight transportation studies (Recker and Kostyniuk, 1978; Kitakumar, 1984; Genc et. al., 1994; Thill and Horowitz, 1997; Pellegrini et. al., 1997; Bowman and Ben-Akiva, 2000; Leszczyc et. al., 2000; Pozsgay and Bhat, 2001, Simma et. al., 2002; Kemperman et. al, 2002; Sivakumar and Bhat, 2007; Cheng et. al., 2008; Auld and Mohammadian, 2011; Scott and He, 2012; Mei, 2013; Faghih-Imani and Eluru, 2015; Molloy and Moeckel, 2017). Some studies also used nested logit

(NL) model (Ansah, 1977; Ishikawa, 1990; Arentze et. al., 2005, Hong et. al, 2006; Yang et. al, 2013) and mixed multinomial logit (MMNL) model (Sivakumar and Bhat, 2007; Barros et. al., 2008; Paleti et. al, 2017) which is more flexible than MNL and NL as it allows for heteroscedasticity in the error term.

Table 2.4 represents the studies which examined the joint decision of mode and destination choice process of passengers. The table contains information on study area, type of mode, number of destination alternatives, trip purpose, exogenous variables and methodology. From the table we can observe that almost all the studies considered car, transit, walk and bike alternatives for mode choice analysis. The number of destination in the joint decision process varied from 2 to 134, whereas few study also considered all the destination alternatives in their study area (Fox et. al, 2014). Some studies considered shopping trips (Richards and Ben-Akiva, 1974; Adler and Ben-Akiva, 1976; Timmermans, 1996; Limanond and Neimeier, 2003; Ding et. al, 2014); some studies considered work or commuter trips (Newman et. al, 2010; Chakour and Eluru, 2014; Fox et. al, 2014) and also few studies considered work, shopping, school and recreational trips together (Southworth, 1981; Jonnalagadda et. al., 2001; Yagi and Mohammadian, 2008; Seyedabrishami and Shafahi, 2013; Schimd et. al., 2018). Table 2.4 illustrates that traditionally multinomial logit (MNL) and nested logit (NL) model have been used by most of the studies due to their closed form structure and easy interpretability. Though multinomial logit model has been used mostly by various researchers (Richards and Ben-Akiva, 1974; Adler and Ben-Akiva, 1976; Southworth, 1981; LaMondia et. al., 2008; Schimed et. al., 2018), but this model has some limitations too. Conventional MNL model assumes that distribution of random error term is independent and same across all the alternatives and hence the estimation and prediction using this model can be biased. To overcome the limitation of traditional MNL model, NL has been employed by some researchers in their studies to capture the correlation among choices in a common group. Jonnalagadda et. al., (2001); Yagi and Mohammadian (2008), Newman et. al. (2010) and Fox et. al. (2014) used NL model in their studies. Ding et. al. (2014) investigated the joint mode-destination choice decision using traditional MNL, NL and cross-nested logit (CNL) model. They concluded that CNL outperformed other two models as it can capture unobserved correlation among alternatives than MNL and NL. Seyedabrishami and Shafahi (2013) used fuzzy decision tree model and compared the result with MNL. They concluded that fuzzy decision tree model gave more accurate result than MNL. Timmermans (1996) used two MNL model in sequential form to capture correlation between mode and destination choice behavior. To test the dependency, the choice alternatives of previous step are introduced in the specification of the present choice process. If the cross-effects comes out statistically insignificant then attributes of choice alternatives of first step will not influence the decision process of the second choice occasion. He assumed mode is chosen first and then the destination. More recently, Chakour and Eluru (2014) suggested a latent segmentation based sequential model which determines probabilistic assignment of individual to a segment, as the true sequence of the decision process is unknown to the researcher. They used MNL model for mode and station choice, where in one segment mode is chosen first and station later, and for other segment station is chosen first and then the access mode.

Summary

The chapter presented a summary of the existing literature of freight mode choice analysis, shipment size choice and destination decision, along with some advanced methodological literatures. Some limitations of previous studies are also identified in this chapter. Based on these observations our further studies have been conducted.

Table 2. 1: Previous Literature on Freight Mode Choice

Study	Study Area	Data Source and Type[1]	Methodology	Decision Variable	Mode[2]	Independent variables			
						Level of Service Characteristics	Freight Characteristics	Network and O-D Attributes	Other
Nam (1997)	Korea	KOTI 1990a, KNR (RP)	Binary logit	Mode choice	Rail, truck	Cost, time, service frequency	Weight		Accessibility
Abdelwahab (1998)	USA	CTS 1977 (RP)	Switching simultaneous equations (binary probit and linear regression)	Mode choice and shipment size	Rail & Truck	Cost, time	Commodity Group	Region	---
Abdelwahab and Sayed (1999)	USA	CTS 1977 (RP)	Artificial Neural Network	Mode choice	Rail & Truck	Cost, time, reliability	Size, product state, temperature, perishability,	Region, distance	Loss and damage
Jiang et al (1999)	France	INRETS 1988 (RP)	Nested logit	Mode choice	Road, rail, combined (private & public)	frequency	Type of product, value, weight, trade type	Distance, origin, destination,	Packaging, warehouse accessibility
Cullinane and Toy (2000)	---	SP	Stated Preference, statistical analysis	Route/ Mode choice	---	Cost, time, speed, service frequency	Goods characteristics	Distance,	Service, flexibility. Infrastructure availability, capability, inventory, loss/damage, sales per year, previous experience, frequency,
Sayed and Razavi (2000)	USA	CTS 1977 (RP)	1. Artificial Neural Network 2. Neurofuzzy	Mode Choice	Motor Carrier and Rail	Cost, time, reliability	Size, tonnage, value, density, product state, temperature control, protection, perishability	Origin-destination, distance,	Loss and damage
Holguin-Veras (2002)	Guatemala City	Survey in Guatemala City (RP)	1. Heteroscedastic extreme value model 2. Multinomial logit	Shipment size & Mode choice	Truck	Cost	Commodity group	Trip Length	Economic activities
Kim (2002)	UK and Continental Europe	Channel Tunnel Survey	Inherent random heterogeneity logit model	Mode choice	Rail and truck	Cost, time, reliability	---	---	---

Study	Study Area	Data Source and Type[1]	Methodology	Decision Variable	Mode[2]	Independent variables			
						Level of Service Characteristics	Freight Characteristics	Network and O-D Attributes	Other
		1996 (SP)							
Shinghal and Fowkes (2002)	India (Delhi-Bombay Corridor)	Survey on Delhi-Bombaby corridor 1998 (SP)	Multinomial Logit	Mode choice	Intermodal, rail, parcel	Cost, time, frequency	---	---	---
Norojono and Young (2003)	Indonesia (Java)	Survey from 1998 - 1999 (SP)	1. Ordered Probit 2. Heteroscedastic extreme value model	Mode choice	Rail and road	Cost, time	Commodity type, size, value, trade type	Distance	Quality, flexibility, cargo unit
Ohashi et al. (2005)	Northeast Asia	Survey 2000 (RP)	Multinomial Logit	Route choice	Air	Cost, time	---	Distance	Landing fee
Rich et al. (2009)	Sweden	FEMEX/COMVIC 1995-96, VFU (RP)	Nested logit	Mode choice	Truck, rail, ship	Cost, time	Commodity group,	---	---
Arunotayanun and Polak (2011)	Indonesia (Java)	Survey 1998-99 (SP)	1. Multinomial logit 2. Mixed multinomial logit 3. Latent class	Mode choice	Small truck, train	Cost, time	Value, frequency, commodity group	Destination	Quality, flexibility
Feo et al. (2011)	Spain (Zaragoza, Barcelona, Valencia, Madrid, Murcia)	Survey 2006 (SP)	Disaggregated behavior model	Mode Choice	Truck & Ship	Cost, time, frequency, reliability	---	---	---
Holguin-Veras et al. (2011)	USA and UK	Experiment data in USA 2007, Expermient data in UK (SP)	Game Theory	Mode choice and Shipment size	Truck, Van, combined road-rail	Cost	Shipment size, No. of shipment	---	---
Samimi et al (2011)	USA	Online survey 2009 (RP)	1. Binary logit 2. Binary probit model	Mode choice	Truck & Rail	Cost, time	Weight, value	Distance	---
Brooks et al. (2012)	Australia (Perth-Melbourne, Melbourne-	Survey (SP)	1. Mixed logit 2. Latent Class	Mode Choice	Truck, Rail, Ship	Cost, time, frequency, reliability	---	Distance, direction,	Carbon pricing,

Study	Study Area	Data Source and Type[1]	Methodology	Decision Variable	Mode[2]	Independent variables			
						Level of Service Characteristics	Freight Characteristics	Network and O-D Attributes	Other
	Brisbane, Brisbane-Townsville corridors)								
Moschovou and Giannopoulos (2012)	Greece	Survey (RP)	1. Linear regression 2. Binary Logit	Mode Choice	Truck and Rail	Cost, time, access to mode, service frequency	Shipment Type, Shipment Value, Weight,	Distance	Loading Units, Quality of Service, Probability of load Loss and Damage, availability of loading/unloading equipment
Shen and Wang (2012)	USA	FAF 2 (RP)	1. Binary logit 2. Linear Regression	Mode choice (cereal grains)	Truck, Rail	Fuel cost, time	Weight, value	Distance	---
Pourabdollahi et al. (2013)	USA	Online survey 2009-2011 (RP)	Copula based joint MNL-MNL	Mode & Shipment Size	Truck, Rail, Air, Courier	Cost	Commodity type, characteristics, value, trade type	Distance	---
Wang et al (2013)	USA (Maryland)	FAF 3, NTAD 2006 (RP)	1. Binary Probit 2. Logit Model	Mode Choice	Truck, Rail	Fuel cost, time	Commodity type, weight, value, trade type	Origin, Ratio of Highway milage and Railway milage in origin and destination zone, highway and Railway Distance	---
Boeri and Masiero (2014)	Switzerland (Ticino)	Survey 2008 (SP)	1. Random regret MNL and MXL 2. Random utility maximization MNL and MXL	Freight mode and road alternative s	Truck carried on train, combination of road and rail, best road alternative	Cost, time	---	---	Punctuality

Study	Study Area	Data Source and Type[1]	Methodology	Decision Variable	Mode[2]	Independent variables			
						Level of Service Characteristics	Freight Characteristics	Network and O-D Attributes	Other
Mitra and Leon (2014)	USA (North Dakota)	Interview of airport managers (RP)	Mixed Logit	Mode Choice	Air-cargo	Cost, time, delay	Commodity density, quantity, perishability,	---	Equipment avaibality, loss and damage
Reis (2014)	Portugal	Data provided by freight forwarder (RP)	Agent based micro simulation	Mode choice (short distance)	---	Cost, time	Weight, type of commodity,	Origin, destination	---
Yang et al. (2014)	USA (export-import)	USA Trade online database 2012(RP)	Multinomial Logit	Mode Choice	Air & Ship	---	Commodity type, weight, value	---	---
Arencibia et al (2015)	Spain	Survey 2011-2012 (SP)	1. Multinomial logit 2. Mixed logit	Mode choice	Truck, intermodal-maritime, intermodal-rail, intermodal-air	Cost, time, service frequency ,	---	---	Punctuality
Nugroho et al. (2016)	Indonesia (Java,)	Survey 2014 (SP)	1. Multinomial Logit 2. Nested Logit 3. Mixed Multinomial Logit 4. Mixed nested Logit	Mode Choice	Truck, Rail, Ship	Cost, time, frequency, reliability	---	---	Green House Gas Emission,

[1]Data Type: RP = revealed Preference, SP = Stated Preference
[2]Mode: When the study specifies particular modes.

Table 2. 2: Previous Literature on Joint Modeling of Mode and Other Decision Variables

Study	Study Area	Decision Variables	Level	Mode Considered	Methodology
Passenger					
Train (1980)	San Francisco Bay Area, USA	Auto Ownership-Mode	Trip	Car, Bus, Walk, Carpool	Sequential/structured Logit
Bhat (1997)	Boston Metropolitan Area, USA	Mode choice-Number of Stops during work commute	Activity	Car, Shared Ride, Transit	Joint MNL (Mode)-Ordered Response (no. of stops) Model
Bhat (1998a)	San Francisco Bay Area, USA	Mode-Departure Time	Trip	Drive Alone, Shared ride, Transit	Mixed MNL
Bhat (1998b)	San Francisco Bay Area, USA	Mode-Departure Time	Trip	Drive Alone, Shared ride, Transit	Joint MNL-Ordered Generalized Extreme Value (OGEV) model in a nesting structure
de Jong et. al. (2003)	Netherlands	Mode-Departure Time	Tour	Car, Train	• MNL • Nested Logit • Mixed MNL
Dissanayake and Morikawa (2003)	Bangkok Metropolitan Area, Thailand	Car ownership-Mode-Trip chaining	Trip	Car, Motorcycle, Bus, Motorcycle-Bus, Car-Bus, Other available modes	Combined RP/SP Nested Logit Model
Tringides et. al. (2004)	Florida, USA	Mode-Departure Time	Trip	SOV (Car, motor cycle), non SOV	Recursive Bivariate Probit Model
Hess et. al. (2007)	London, UK, West Midlands, UK, Netherlands	Mode-Departure Time	Tour	Car, Transit	Mixed MNL
Bajwa et. al. (2008)	Tokyo Metropolitan Area, Japan	Mode-Departure Time	Trip	Car, Rail	• MNL • Mixed MNL • Nested Logit • Mixed Nested Logit • Cross Nested Logit • Error Component Nested Logit
Habib et. al. (2009)	Toronto, Canada	Mode-Departure Time	Trip	Car, Passenger, Transit, Transit park and ride, GO park and ride, Walk	Joint MNL(mode)-Hazard based Duration Model
Vega and Reynolds-	Greater Dublin Area,	Mode –Residential	Trip	Car, Transit	Cross Nested Logit

Study	Study Area	Decision Variables	Level	Mode Considered	Methodology
Feighan (2009)	Ireland	Location			
Debrezion et. al. (2009)	Netherlands	Access Mode-Railway Station	Trip	Car, Public Transit, Bicycle, Walk	Nested Logit
Pinjari et. al. (2011)	Sam Francisco Bay Area, USA	Residential Location-Auto/Bicycle Ownership-Mode Choice	Tour	Car, Transit, Walk, Bicycle	• Mixed multidimensional choice model
Habib (2012)	Toronto, Canada	Mode Choice-Work Start Time,-Work Duration	Tour	Auto, Passenger, Transit, Transit park and ride, GO park and ride, Walk	Tri-variate discrete-continuous model
Habib (2013)	Toronto, Canada	Mode-Departure Time	Tour	Auto, Passenger, Transit, Transit park and ride, GO park and ride, Walk	Joint Discrete-Continuous model using RUM-based assumption
Seyedehsan and Shafahi (2013)	Shiraz, Iran	Mode-Destination	Tour	Car, Transit	• MNL • Fuzzy Decision Tree
Yang et. al. (2013)	Beijing, China	Residential Location-Mode-Departure Time	Trip	Car. Transit, Bicycle	• Nested Logit • Cross Nested Logit
Chakour and Eluru (2014)	Montreal, Canada	Access mode-Train Station	Commuter	Drive Alone, Shared ride, Transit	Latent Segmentation based Sequence Model • MNL (access mode) • MNL (station)
Ding et. al. (2014)	Maryland and Washington DC, USA	Mode-Departure Time	Trip	Drive Alone, Shared Ride, Transit, Walk, Bicycle	• MNL • Nested Logit • Cross Nested Logit
Ermagun et. al. (2015)	Tehran, Iran	Mode Choice-Accompaniment	Trip	Car, School Bus, Public Transit, Walk	• Nested Logit • Copula (MNL -Binary Logit)
Shakeel et. al. (2016)	Sydney, Australia	Mode-Route Choice	Trip	Car, Cycle, Transit	• MNL • Nested Logit • Mixed Logit
Zou et. al. (2016)	Beijing, China	Mode-Departure Time	Trip	Car, Metro, Bus, Others	Agent Based Choice Model
Shabanpour et. al. (2017)	Chicago, USA	Mode-Departure Time	Tour	Car, Transit, Walk, Bike	Copula (MNL – Log-linear Regression)
Zhu et. al. (2017)	Baltimore and Washington, DC, USA	Mode-Departure Time	Tour	Car, Transit, Carpool, Walk/Bike	• Nested Logit • Decision Tree • Two-dimensional mixed

Study	Study Area	Decision Variables	Level	Mode Considered	Methodology
					Bayesian Network
Anowar et. al. (2018)	Toronto, Canada	Mode-Departure Time	Trip	Drive Alone, Passenger(shared ride), Transit, Walk, Bike, Other modes (park and Ride, Kiss and Ride)	Latent Segmentation Based Sequential Model using Regret Minimization decision rules • MNL (mode) • MNL (departure Time)
Freight					
Hall (1985)	USA	Mode-Shipment Size	Trip	Truck and Parcel	Developed cost equations for alternative modes and plotted graphs to compare
Abdelwahab and Sargious (1992)	USA	Mode-Shipment Size	Trip	Truck and Rail	Switching Regression Model • Binary probit (mode) • Linear regression (shipment size)
Abdelwahab (1998)	USA	Mode-Shipment Size	Trip	Rail & Truck	Switching Simultaneous Equations • Binary probit (mode) • Linear regression (shipment size)
Holguin-Veras (2002)	Guatemala City	Mode-Shipment Size	Trip	Truck	• Heteroscedastic extreme value model • MNL
de Jong and Ben-Akiva (2007)	Sweden and Norway	Mode-Shipment Size	Trip	Truck, Rail, Air, Water	• Nested Logit • Mixed MNL
de Jong and Johnson (2009)	Sweden	Mode-Shipment Size	Trip	Truck, Rail, Air, Water	MNL
Cavalcante and Roorda (2010)	Toronto, Canada	Mode-Shipment Size	Trip	Single unit truck, pick up/van and truck with 1 trailer	Discrete-continuous model
Habibi (2010)	Sweden	Mode-Shipment Size	Trip	Truck, Rail, Combination of truck-rail-sea	MNL
Windisch et al. (2010)	Sweden	Mode-Shipment Size	Trip	Truck/lorry, railway, ferry, Cargo vessel, air	• MNL • Nested Logit
Holguin-Veras et al. (2011)	USA	Mode-Shipment Size	Trip	Truck, Van, road-rail	Game Theory

Study	Study Area	Decision Variables	Level	Mode Considered	Methodology
Combes (2012)	France	Mode-Shipment Size	Trip	Truck, Rail, Combined transport, Inland Waterway, Sea, Air	Economic Order Quantity Model
Pourabdollahi et al. (2013a)	USA	Mode-Shipment Size	Trip	Truck, Rail, Air, Courier	Copula based joint MNL-MNL
Pourabdollahi et al. (2013b)	USA	Mode-Shipment Size	Trip	Truck, Rail, Air, Courier	• MNL • Freight Activity Bases Modeling Framework (FAME) for simulation
Abate and de Jong (2014)	Denmark	Mode-Shipment Size	Trip	Truck	• MNL • Mixed MNL • Dubin-McFadden method
Irannezhad et al. (2017)	Mashhad, Iran	Mode-Shipment Size	Trip	Van, Truck, Heavy Truck, Trailers	Copula between Discrete-Continuous choice
Stinson et. al. (2017)	Arizona, USA	Mode-Shipment Size	Trip	Truck, Rail, Air, Parcel	Nested Logit

Table 2. 3: Previous Literature on Destination Choice Behavior

Study	Study Area	Trip Purpose	No. of Alternative	Variables Considered	Methodology
Passenger					
Ansah (1977)	Indianapolis, USA	Shopping	Within 7 miles	Uncongested road, quick parking, no. of employees, no. of outlets, distance	Crossed, nested, nested crossed
Recker and Kostyniuk (1978)	New York, USA	Grocery shopping	4	Availability of parking spot, easy accessibility to destination, nearby other shops, hours of operation, price in store, variety of goods, quality of goods, easy to find goods in store, store accepts credit card/cash, easy to exchange, not so crowded	Multinomial Logit model
Kitamura (1984)	Baltimore, USA	Shopping	9	Average travel time, population, no. of employment	Multinomial Logit model
Ishikawa (1990)	Japan	-	46	Distance, attractiveness	Production-constrained model, Competing-destination model, Nested Logit
Um and Crompton (1990)	Texas, USA	Tourism	2	Personal characteristics, motives, attitudes, values	Two stage approach
Thill and Horowitz (1997)	Minneapolis, USA	Shopping	1165	No. of employment, travel time, distance, presence of mall, age, household income, area type	Multinomial logit, approximate nested choice-set destination choice model
Pellegrini et. al. (1997)	Florida, USA	Shopping	14	Distance, store size, competition to other stores, neighborhood characteristics	Multinomial Logit model
Bowman and Ben-Akiva (2000)	Boston, USA	Home based Work, school and other	8	Travel time and cost, distance, no. of vehicle per household, household income, size of employment at destination	Multinomial logit model
Leszczyc et. al. (2000)	Missouri, USA	Grocery shopping	21	Household size, family income, shopping frequency, working hour of decision maker, trip cost	Hazard model, MNL
Pozsgay and Bhat (2001)	Texas, USA	Recreational	10	Travel cost and time, zone area, percentage of water area, age, presence of children in household, participating alone/with family and friends in recreation, no. of cars in household, household income, if decision maker in worker	Multinomial Logit model
Simma et. al. (2002)	Switzerland	Recreational	Skiing: 176 Hiking & climbing:	Distance between O-D, quality of facilities for recreational activities, cost for the activity,	Multinomial logit model

Study	Study Area	Trip Purpose	No. of Alternative	Variables Considered	Methodology
			555 Walking and swimming: 1716	area of destination, presence of forest	
Seddighi and Theocharous (2002)	Cyprus	Tourism	2	Age, gender marital status, income, education, cost of living in destination, price of tourist package, facilities, cost of transportation, quality of service and promotional activities, political instability	Multivariate Logit model
Kemperman et. al. (2002)	Netherlands	Recreational	12	Park attributes, entrance fee, season of the year, variety at destination, loyalty behavior effect	Multinomial logit model
Arentze et. al. (2005)	Netherlands	Shopping	8	Travel time to destination, floor space per goods category, no. and types of stores in the shopping center	Nested logit
Hong et. al. (2006)	Korea	Tourism	8	Park type (mountains, coastal, historical, exotic), active, pleasant, exhilarating, hectic, drowsy, repulsive, boring, serene	Nested multinomial logit model
Sivakumar and Bhat (2007)	Germany	Shopping	10	Area, population, no. of shopping and recreational opportunities, presence of central business area and daycare, distance from home and work/school zone, gender, marital status, employment status, household income, household size, time of the day, day of the week. no. of household/non-household member accompanied, activity duration	Multinomial logit, mixed multinomial logit model
Wang and Lo (2007)	Toronto, Canada	Grocery Shopping	2	Product variety and price in the store, store environment, age, household income, education level	Multinomial Logistic Regression
Cheng et. al. (2008)	South Carolina, USA	Evacuation	28	Distance, population, no. of hotels and motels, risk to hurricane, ethnic percentage at destination, if metropolitan area, if destination contains interstate highway	Multinomial Logit model
Barros et. al. (2008)	Portugal	Tourism	2	Travel budget, distance, cultural attraction, climate, gastronomy, ethnic composition, exoticism, safety, age, family composition, income, no, of people travelling, information gathered, previous experience	Mixed logit model
Hsu et. al. (2009)	Taiwan	Tourism	8	Escape, self-actuation, rest and relaxation,	4-level Analytical hierarchy

Study	Study Area	Trip Purpose	No. of Alternative	Variables Considered	Methodology
				medical treatment, health and fitness, visiting friends/relative, meeting new people, novelty seeking, culture exploration, adventure seeking, enjoying nightlife and shopping, transportation facilities, friendliness of people, quality and variety of food, accommodation facilities and price, cultural and historical resources, personal and environmental safety, environmental quality, destination image, benefits expectations	process (AHP)
Auld and Mohammadian (2011)	Chicago, USA	Non-work	100	Travel time, zonal income, land use area, employment	Multinomial Logit Model
Scott and He (2012)	Kentucky, USA	Shopping	10	Type of stores at destination, time available for shopping, age, income, gender, employment status and driving license status of the decision maker	Multinomial Logit
Yang et. al. (2013)	Nanjing, China	Tourism	10	Distance, age, no. of previous visit to destination, night of stay, vacation/sightseeing/other purpose of visit, travel with family and friends/alone/travel agency/affiliation	Nested Logit
Faghih-Imani and Eluru (2015)	Chicago, USA	-	30	Distance, age, gender, trip start time, bicycle infrastructure, distance from CBD, transit, availability, no. of restaurants, grocery store and parking area, job and population density	Multinomial logit model
Huang (2013)	Minneapolis, USA	Non-work	Destination within 100 meters	Travel time, land use, day-of-week, age, gender, income	Mixed effect linear, mixed-effect log-linear, mixed-effect negative binomial, mixed-effect ordered logit, mixed effect zero-inflated negative binomial
Molloy and Moeckel (2017)	Ontario, Canada	Business, leisure, visit	117	No. of hotel, sightseeing, outdoor activities, medical, ski area, distance	Multinomial logit model
Paleti et. al. (2017)	California, USA	Shopping, escorting, social,	50	Gender, tour type, joint tour composition, presence of CBD, intersection density, bike lane access	Mixed Multinomial logit model

Study	Study Area	Trip Purpose	No. of Alternative	Variables Considered	Methodology
		maintenance, eating out, discretionary			
Wong et. al. (2017)	Hong Kong	Tourism	3	Gender, age, monthly income, education level, unemployment rate	Hierarchical linear modeling (HLM)
Freight					
Genc et. al. (1994)	USA	-	12	Waiting time, time for loading unloading, time to travel, market boundary	Multinomial logit model
Park et. al. (2012)	Korea	-	40	Distance, no. of employment	Stratified importance sampling for destination selection
Mei (2013)	USA	-	20	Travel time, area type, type of goods, no. of employees	Multinomial logit

Table 2. 4: Previous Literature on Joint Modeling of Passenger Mode and Destination Choice

Study	Study Area	Decision Variables		Trip Purpose	Exogenous Variables	Methodology
		Mode	No. of Destination			
Richards and Ben-Akiva (1974)	Netherlands	Car, bus, train, moped, walk, bike	18	Shopping	Travel time, cost, no. of employment in destination shopping center	Multinomial Logit Model
Adler and Ben-Akiva (1976)	Washington D.C., USA	Drive alone, passenger, transit	134	Shopping	Travel time and cost, car ownership, distance, no. of retail employment, if destination in CBD, no. of persons in household, household income	Multinomial Logit Model
Southworth (1981)	England	Car, transit	14	Work, shopping, recreational	Travel time and cost, income, no. of worker in household, distance	Multinomial Logit Model
Timmermans (1996)	Netherlands	Car, bus	2	Shopping	Travel time, parking cot, travel cost, frequency of bus service, size of shopping center, price level at shopping center, parking facilities, distance	Sequential multinomial logit model
Jonnalagadda et. al. (2001)	San Francisco, USA	Drive alone, shared ride, transit, walk, bike	40	Work, school, other	No. of employment, destination household income, presence of CBD, urban/suburban area, distance, travel time, waiting time, no. of stops, vehicle ownership, no. of worker at household, destination topology, network connectivity, vitality of neighborhood	Nested logit (mode), Multinomial logit (destination)
Limanond and Niemeier (2003)	Washington, USA	Auto, bus, walk	100	Shopping	Travel time and cost, no. of retail employment in destination, household income, day of week, distance	Random utility model
LaMondia et. al. (2008)	Europe	Car, air, surface public transport	6	Tourism	Home country/abroad, distance, travel companions, age, household size, income,	Multinomial logit model

Study	Study Area	Decision Variables		Trip Purpose	Exogenous Variables	Methodology
		Mode	No. of Destination			
					employment status, student, travel planning characteristics, cost at destination, quality of facilities at destination, easily accessible from home, population density, no. of large cities, np. Of hotels, climate, activities for children, friends/family lives at destination, familiar with destination language, product available for shopping, national park/spa/coastal area	
Yagi and Mohammadian (2008)	Jakarta, Indonesia	Drive alone, shared ride, motorcycle, taxi, transit, non-motorized	11	Home based-work, school, maintenance, discretionary	Travel time, distance, time of the day, presence and location of intermediate stops, household income, household composition, vehicle ownership, age , gender, destination urban area, land use pattern, density of jobs	Nested logit
Newman et. al. (2010)	Tennessee, USA	Car, transit, school bus, walk, bike	-	Work	No. of student in household, presence of seniors, household income, gas price, bus fare, activity diversity, percent of sidewalk in the zone, household vehicle per person, no. of employment, need river and county border crossing, percent of destination zone within 0.5 mile of bus stop	Nested logit model
Seyedabrishami and Shafahi (2013)	Iran	Car, transit	15	Work, school, shopping, personal, recreation	Household car ownership, household size, trip purpose, zonal car ownership, distance from home zone to CBD, travel time	MNL, fuzzy decision tree

Study	Study Area	Decision Variables		Trip Purpose	Exogenous Variables	Methodology
		Mode	No. of Destination			
Chakour and Eluru (2014)	Montreal, Canada	Car, passenger, transit, walk, bike	18	Work	Age, gender, vehicle ownership, employment status, time left home, distance to station, parking facilities at station, travel time, land-use	Latent segmentation based sequential MNL-MNL model
Fox et. al. (2014)	Toronto, Canada	Drive alone, auto passenger, transit, walk	1404	Work	Travel time, cost, if destination is CBD, distance, car availability, age, gender, no. of employment,	Nested Logit
Ding et. al. (2014)	Maryland, Washington D.C.,USA	Car, transit, walk, bike	Within 1 mile, 1-2 miles and over 2 miles	Shopping	Household size, income, car ownership, gender, age, residential density, employment density, travel time and cost	Multinomial logit, nested logit, cross-nested logit model
Schmid et. al. (2018)	Austria	Car, transit, walk, bike	-	Work, school, other, shopping	Distance, income, area type, no. of children, working status, age, gender, education level, availability of car, travel time, travel cost, parking facility, no. of transfers, market quality, waiting time in queue of supermarket	Multinomial Logit model

CHAPTER THREE: DATA ANALYSIS

The previous chapter discussed earlier research on freight mode, shipment size and destination choice analysis. This chapter describes the data source employed for the study and descriptive statistics of the dataset. Same dataset has been used for application of advanced mode choice decision and the simultaneous decision of freight mode choice and shipment size. A discussion on data compilation procedures as well as exogenous variable generation steps is provided in this chapter.

Data Source

The main data source for this study is the 2012 Commodity Flow Survey data. The survey is conducted every 5 years since 1993 and is the only publicly available source of commodity flow information at a national level. This data was published in June 2015 and is provided by the Bureau of Transportation Statistics (BTS). CFS is a joint data collection effort by BTS, US Census Bureau, and U.S. Department of Commerce. The Public Use Microdata (PUM) file of CFS 2012 contains a total of 4,547,661 shipment records from approximately 60,000 responding industries.

Generation of Mode Variable And Alternative Availability

CFS 2012 data contains twenty-one modes of freight transportation. In this study, the reported modes were categorized into five major groups: (1) hire truck (including truck and hire truck), (2) private truck, (3) air, (4) parcel or courier service, and (5) “other” mode. Here, the hire truck represents the truck which is operated by a non-governmental business unit to provide transport services to customers. On the other hand, private truck refers to trucks owned and used by individual business entity for its own freight movement. Parcel or courier service mainly refers to a combination of modes. The air mode consists of both air and truck, as truck is needed to pick up and deliver the commodity from or to a particular place which cannot be accessed by air mode. The "other" mode consists of rail, water, pipeline or combination of non-parcel multiple modes. The weighted mode share in the original dataset is as follows: hire truck (16.55 %), private truck (26.02%), parcel (55.77%), air (1.36%), and "other" (0.30%). Within the "other" mode, rail consists 0.13 percent and rest of the other mode consists 0.17 percent. The weighted mode share is represented graphically in figure 3.1. Note that all types of shipments cannot be transported by all types of modes. For instance, it is very unlikely that a large load of 50 tons is shipped by air or parcel mode as these modes have capacity restrictions. Therefore, allowing air or parcel mode as an available option affects the accuracy of the model estimates. To account for this issue, a heuristic approach was adopted to induce availability option based on shipment weight and routed distance. . The availability of the five modes are set according to the conditions below:

- Hire truck alternative is always available.
- Private truck is available when routed distance is less than 413 miles (99 percentile of private truck observed in the data).
- Air is set available when the shipment weight is less than 914 lbs (99 percentile).
- Parcel/Courier service is set available when shipment weight is less than 131 lbs (99 percentile).
- Other mode is always available.

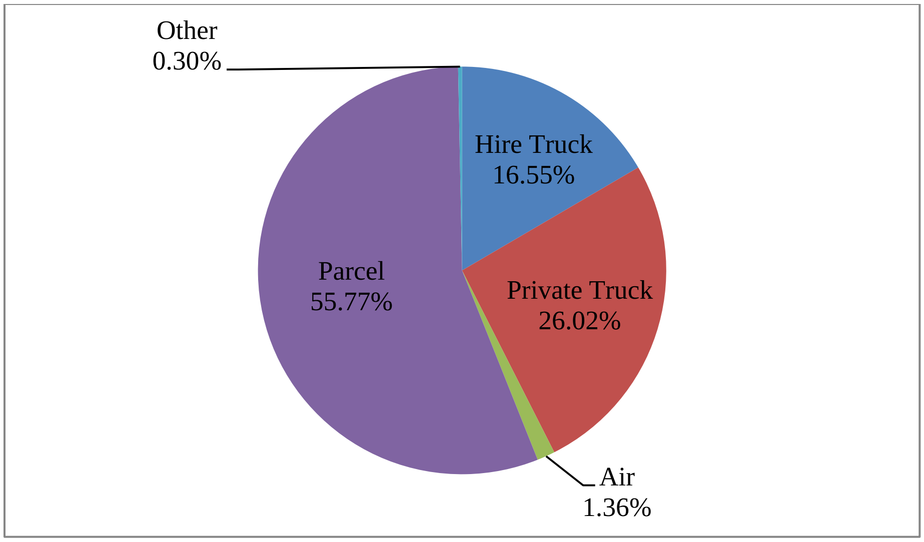


Figure 3. 1: Weighted Distribution of Freight Mode Share

Sample Selection And Dependent Variable Generation

For different chapters, we have used different sample size, geographical location and dependent variables along with mode. The following sections describe the sample selection and dependent variable generation for each of the chapters.

For Regret Minimization and Utility Maximization Based Hybrid Model for Freight Mode Choice Study

For this study a sample of 5,565 records is drawn from the original dataset to manage the burden of generating level of service variables (shipping cost and shipping time) ensuring that the weighted mode share in the random sample is the same as the weighted mode share in the original dataset. Of this, 4,000 records were randomly chosen for estimation purpose and 1,565 records were set aside for validation exercise. The weighted mode share in the sample is as follows: hire truck (16.57 %), private truck (25.97%), parcel (55.73%), air (1.42%), and "other" (0.31%).

For A Copula-Based Random Regret Minimization Joint Model Of Freight Mode Choice And Shipment Size Study

To reduce the data processing and model estimation burden, a random sample of 15,000 records was carefully drawn from the PUM database ensuring that the mode share of the extracted sample was the same as the weighted mode share of the original database for this study. From this sample, 10000 data records were randomly chosen for estimation and 5,000 records were set aside for validation exercise. The weighted mode share in the estimation sample is as follows: for-hire truck (16.47%), private truck (26.23%), parcel (55.64%), air (1.36%), and other (0.29%).

Shipment size is reported as a continuous variable in the CFS data. In our study, we categorized it into seven groups from very small to very large shipment size. These are: (1) category 1 (<=30 lb), (2) category 2 (30-200 lb), (3) category 3 (200-1,000 lb), (4) category 4 (1,000-5,000 lb), (5) category 5 (5,000-30,000 lb), (6) category 6 (30,000-45,000 lb), and (7) category 7 (>45,000 lb). Table 3.1 presents the weighted distribution of shipment sizes across five chosen modes considered. We can see from the table that across these two modes, the shipment sizes are quite evenly distributed with the highest percentage share for 5,001-30,000 lb category for for-hire truck (18.59%) and for 201-1,000 lb category for private truck (19.46%). Therefore, for hire and private truck, we considered all seven of the shipment size categories. It is also evident from the table that air and parcel modes primarily carry smaller shipments weighing less than 30 lb (59.6% and 78.81%, respectively). Hence, only two categories of shipment size were assigned to air and parcel mode – less than or equal to 30 lb and greater than 30 lb. We can also see that the other mode mainly contain large shipment sizes in categories 6 and 7. Since other mode consists primarily of rail, this is expected. Based on weight distributions, for "other mode", we considered three shipment size categories (less than or equal to 30 lb (3.06%), 31-5,000 lb (9.17%), and greater than 5,000 lb (87.78%).

For The Joint Decision Of Mode And Shipment Size Choice Behavior Using Sequential Model Framework Study

This study covers the data from Alabama, Florida, Georgia, North Carolina, South Carolina and Tennessee. In our analysis we have considered only the flows within these states as the weighted percentage share of shipment weight within these regions is much higher (56.72%) compared to the inbound shipment weight (24.65%) and outbound shipment weight (18.63%) to and from these regions respectively. Also, the shipment records which used “other” mode for freight transportation have been discarded from this study as the weighted mode share of “other” mode by shipment records within these regions is very low (0.08%). Therefore, finally a total of 295,618 shipment flows are found available within these regions. To reduce the load of data processing (such as, generation of level of service variables) we have randomly selected a sample of 10,399 records ensuring the consistency of the weighted mode shares of the original data and sample data within these regions. From this sample, then we have randomly separated an estimation sample with 7,805 records and a validation sample with 2,594 records. As discussed earlier, in this study we have considered only hire truck, private truck, air and parcel mode. The weighted percentage share of the freight transportation modes in the estimation sample is as follows: hire truck (21.48%), private truck (40.40%), Air (0.62%) and parcel mode (37.50%).

In the 2012 CFS data, shipment weight has been reported as a continuous variable. In this study we categorized shipment size into seven groups: Category 1 (<=30 lbs), Category 2 (30-

200 lbs), Category 3 (200-1000 lbs), Category 4 (1000-5000 lbs), Category 5 (5000-30000 lbs), Category 6 (30000-45000 lbs), and Category 7 (>45000 lbs). Table 3.2 depicts the weighted shipment size distribution across the four considered modes. From the table we can observe that hire and private truck has a reasonable distribution in all seven shipment size categories. Hire trucks have the highest percentage category in the shipment size group 5,001-30,000 lbs and private trucks have highest percentage of shipment size share in 201-1,000 lbs group. For air and parcel mode the table clearly indicates that these modes mainly carry smaller size shipment (≤ 30lbs). Therefore, these modes have been categorized into two major shipment size groups: less than or equal to 30 lbs and greater than 30 lbs. The weighted shipment size share of less than or equal to 30 lbs for air and parcel mode are 45.51 percent and 79.11 percent respectively.

For Sequential Decision of Freight Mode and Destination Choice Behavior Study

For this study a random sample of 15,000 records was carefully drawn from the PUM database to reduce the data processing and model estimation burden. During the random sampling, it was ensured that the mode share of the extracted sample was as same as the weighted mode share of the original data. From this sample, 5,000 data records were randomly chosen for estimation and 10,000 records were set aside for validation exercise. The weighted mode shares by shipment records in the estimation sample are as follows: for-hire truck (16.71%), private truck (25.55%), air (1.36%), parcel (56.06%) and “other” mode (0.33%).

To generate the destination choice set we have randomly chosen 30 destinations from 132 available CFS areas. Out of these 30 destination CFS areas one is chosen and rest of the 29 destinations are unique and not same as the chosen destination. Therefore, the number of destination alternatives considered in the analysis are 30, when destination is chosen first and mode second. But, this may lead to potentially inaccurate analysis when mode is chosen first and destination second, as irrespective of the chosen mode the destination choice set would be same for all individual. For example, if a shipment is carried by private truck then it is possible the destination choice would be narrowed and only those destinations would be more preferable which are within a shorter distance from the origin. To address this issue a new set of viable destination CFS areas is generated based on chosen mode. For the mode choice analysis private truck has been considered available when the routed distance is less than 413 miles. We have considered only the destinations which have network distance within 413 miles from origin and randomly chose the destinations to create private truck mode specific destination choice set. When private truck is chosen, there were some origins which have less than 30 available destination choices. In these cases we kept the chosen one and used all other available destinations in the choice set ensuring all the destination alternatives from a particular origin is unique. For the origins having more than 30 available alternatives we followed the same procedure as described for the destination choice set not having any mode specific issue. For-hire truck, air, parcel and "other" mode has not any restrictions on distance shipped and therefore for these modes we randomly chose 30 unique destinations from 132 CFs areas where is chosen destination. This destination choice set is exclusively used when mode is modeled first and destination second. In this mode specific destination choice set the number of alternatives varies from 5 to 30. When destination is chosen first and mode second, mode to destination is unknown to the analyst and hence mode specific destination choice set will not be employed in this case.

Exogenous Variable Summary

The information on freight characteristics provided in CFS 2012 dataset includes shipment value, shipment weight, North American Industry Classification System (NAICS) - industry classification of the shipper, quarter in which the shipment was made in 2012, Standard Classification of Transported Goods (SCTG) - commodity type, whether or not the shipment required temperature control, hazardous material code, whether or not the shipment was an export. The shipment value has been further categorized into four groups: shipment value < $300, $300-$1,000, $1,001-$5,000 and > $5,000. The reason of categorization of the continuous shipment value is after a certain threshold the value is not anymore continuous, but discrete. The shipment value is likely to be bunched together at various value limit. The O-D variables include shipment origin (State, Metropolitan and CFS Area), shipment destination (State, Metropolitan and CFS Area), great circle distance between the shipment origin and US destination, and routed distance between the shipment origin and US destination. The states and CFS areas are categorized into ten mega regions using geographical information system (GIS). The GIS shape file of mega regions has been obtained from http://www.america2050.org/maps/. The states which do not fall into any mega region have been categorized as non-mega region. The details on states comprising each mega region are presented in Table 3.3. The SCTG commodities are also regrouped into nine major categories described in Table 3.4. The categories are raw food, prepared products, stone and non-metallic minerals, petroleum and coal, chemical products, wood, paper and textile, metals and machinery, electronics, furniture and others.

The CFS data was further augmented with information from a host of secondary GIS and Census data sources. First, we generated level of service variables employing information from several sources for all available modes. For instance, shipping cost by hire truck and private truck was estimated using the 2007 revenue per ton-mile from National Transportation Statistics (NTS) with appropriate regional and temporal correction factors. For parcel mode, using FedEx, pricing functions were generated with distance and weight as variables for the seven zones in the US. The pricing functions also accommodated for shipping speed - express overnight (1day), express deferred (3 days), and ground service (5days) - based on observed shares of these shipping options from FedEx 2015 annual report. For shipping time by hire and private truck, three different speed bands were considered based on trip distance while considering the required break times according to the service regulations provided by Federal Motor Carrier Safety Administration (FMCSA) (see Keya et. al., 2017 for a detailed discussion on how shipping time and cost variables were generated for each mode).

Second, we augmented the 2012 CFS dataset with a host of origin-destination attributes and network characteristics using information from different sources, such as, National Transportation Atlas Database (NTAD) 2012, National Bridge Inventory (NBI) data, National Highway Freight Network (NHFN) data, Highway Performance Monitoring System (HPMS) data, Federal Highway Administration (FHWA), and Freight Analysis Framework – version 4 (FAF4) network data. The zonal level variables generated include: population density, number of employees and number of establishments by North American Industry Classification System (NAICS) (manufacturing, mining, retail trade, warehouse and storage, company and enterprise, wholesale, information), ratio of number of employment to the population of age between 15 to 65, income categories based on mean income of an area (low (< $50,000), medium ($50,000-$80,000) and high (>$80,000)), urban or rural area type based on the percentage of population residing in each area, number of warehouses and super centers, percentage of population below poverty level, and annual average temperature (www.currentresults.com/Weather/US/average-annual-state-temperatures.php) (cold if the average annual temperature is less than or equal to 60oF; warm if the temperature is greater than 60oF). Also indicator variable was generated for identifying major industry type in each CFS area depending on the highest number of industries among the industries stated above. For instance if the number of manufacturing, mining and wholesale industries are 70, 20 and 50 respectively in a particular CFS area, then the major industry type of that area will be manufacturing having the highest number of industries.

The transportation network attributes generated at CFS area level are: roadway length by functional classification (interstate highway, freeway and expressway, principal arterial, minor arterial, major and minor collector), railway length, number of airports, number of seaports, number of intermodal facilities, number of bridges, truck annual average daily traffic (AADT), length of tolled road, length of truck route, number of truck parking locations, number of truck parking spaces in rest area and non-rest area, ratio of length of intermodal connectors to total roadway length and ratio of the length of primary highway freight system (PHFS) and other interstates portions not on PHFS (NPHFS) to total roadway length .

Descriptive Analysis

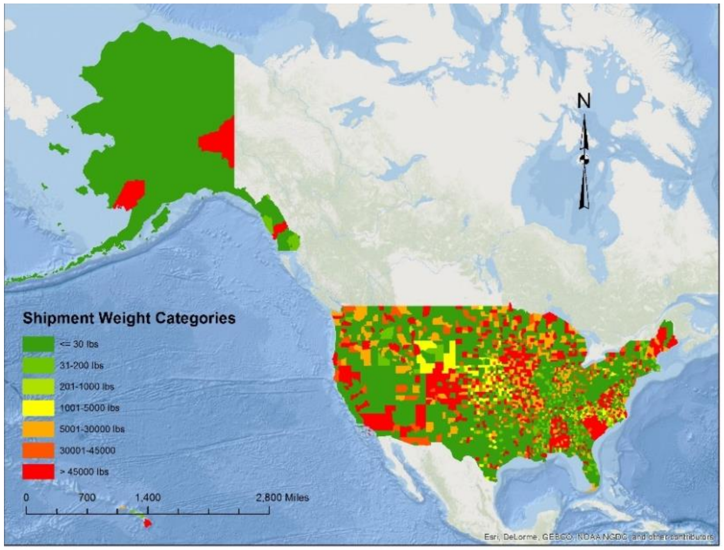
Table 3.5 summarizes the characteristics of explanatory variables from weighted estimation dataset used for the copula-based joint model of mode-shipment size choice decision. Descriptive analysis of the sample reveals that almost all the shipments are transported within the US (95.9%). Also, the shipment share of temperature controlled products and hazardous material is very low (4.2% and 4.4% respectively) compared to other commodity types. Most of the shipments are originating and terminating in non-mega regions (32.4% and 34.9% respectively). The mostly shipped commodity types in 2012 were electronics (20.2%), wood, paper and textiles

(19.3%) and metals and machinery (18.3%). The least transported commodity was raw food (1.9%) and stone and non-metallic minerals (2.4%). The percentage share of shipment by value is the highest for shipment value less than $300 (44.4 %). The mean shipping cost is highest ($277.36) for air mode, with the lowest mean shipping time (1.03 hours). On the other hand, shipping cost is the lowest for other modes ($10.83) and mean shipping time is the highest for parcel mode (66.18 hours).

Figure 3.2 illustrates the shipment weight distribution by mode. It shows that private trucks carry increased tonnages in the California, Piedmont Atlantic and Gulf Coast regions. Air and parcel modes mainly carry loads less than or equal to 30 lbs in majority of the CFS areas. In Figure 3.3, the shipping cost by different modes across the CFS areas are presented. It can be observed from the figure that the shipping cost is comparatively higher in California and Great Lake mega regions for hire and private truck (more than $370 and $100 respectively). The shipping cost by air mode is relatively higher in Northern states (> $450). The reason might be the cold weather in these states. Shipping cost by parcel mode is lower than other modes across whole USA with very few CFS areas with shipping cost more than $80. The shipping cost by parcel mode in most of the areas is less than $80. Figure 3.4 demonstrates the shipping time distribution by mode across entire USA. In most of the regions the shipping time varies between 12 to 63 hours for hire truck and 1 to 3 hours for private truck. Very few regions have shipping time as high as 100 hours by hire truck. Shipping time by private truck is more than 6 hours in very few areas, because private truck usually travels shorter distance compared to hire truck. The shipping time by air mode in most CFS areas is less than 3 hours by air mode. For parcel mode shipping time is greater than 94 hours in majority of the CFS areas, as typically parcel mode takes 3 to 5 days to deliver a product without exception for express delivery option (usually takes 1 or 2 days). Barely some areas can be found from the figure where shipping time is 1 to 3 days.

Summary

In this chapter the source of different variables and preparation of the data employed for the studies have been discussed. Further, descriptive statistics of estimation sample for the five freight modes and exogenous variables were provided. The next four chapters describe the application of different methods on freight transportation analysis employing the estimation dataset generated.



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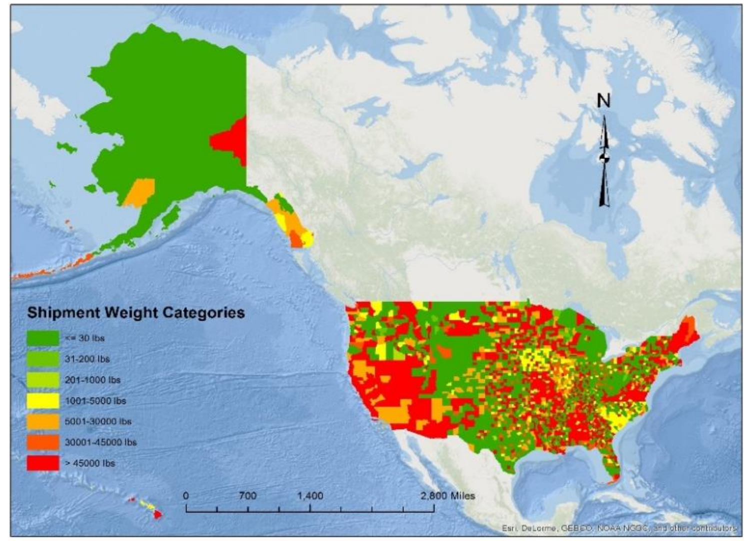

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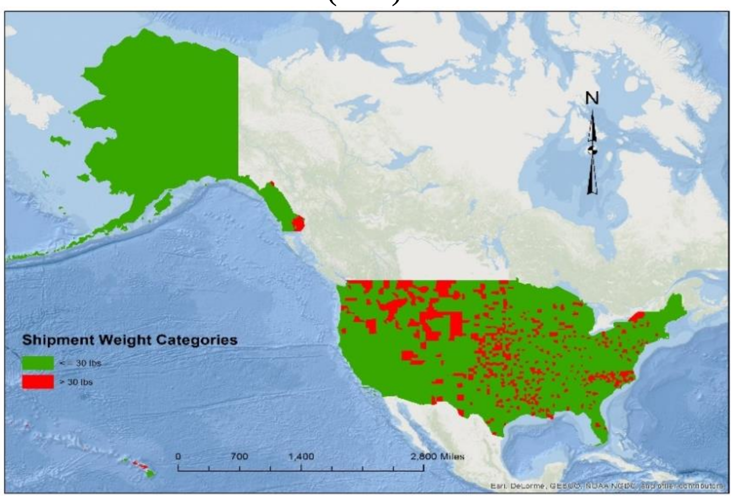

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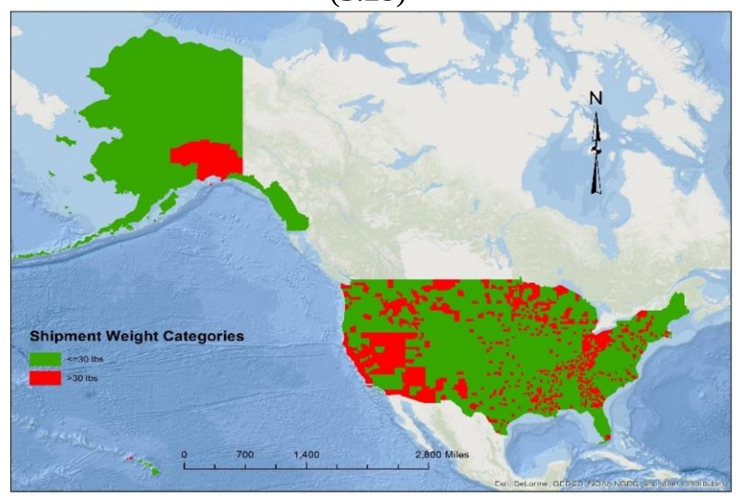
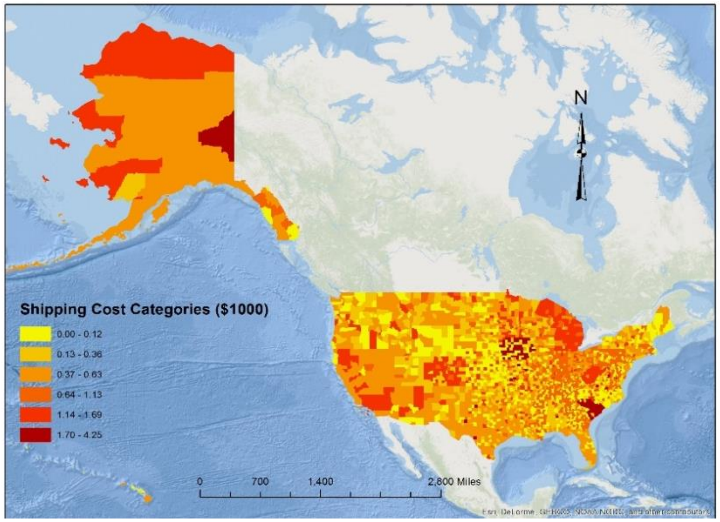


(3.2d)

Figure 3. 2: Shipment Weight Distribution in CFS Areas (3.2a) Hire Truck; (3.2b) Private Truck; (3.2c) Air; (3.2d) Parcel



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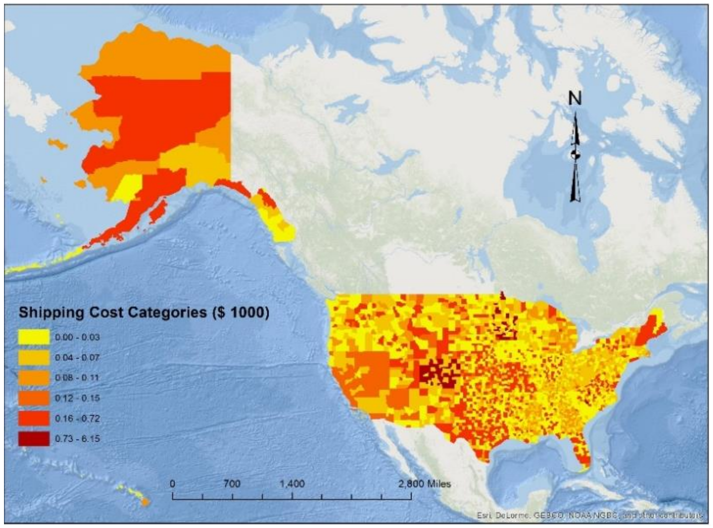

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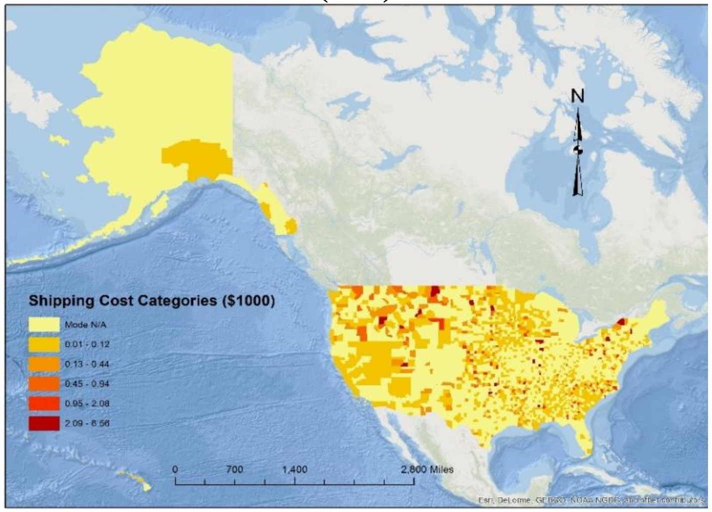

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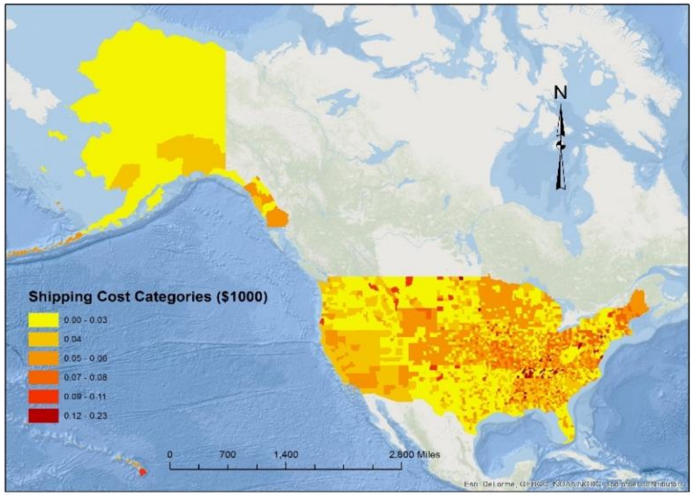
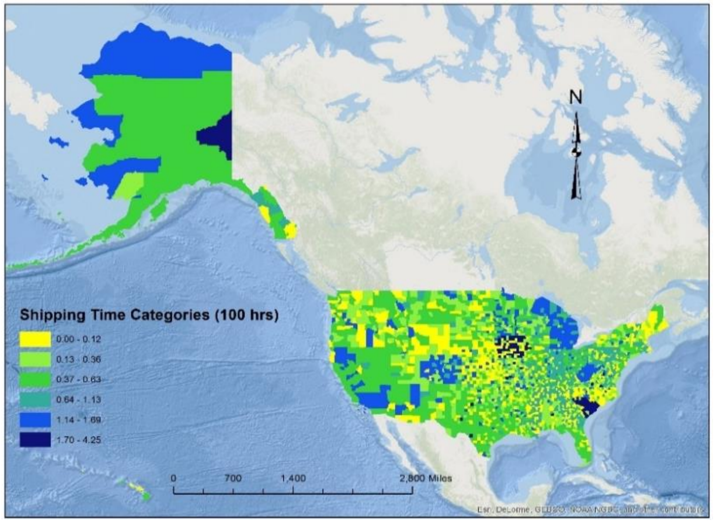


(3.3d)

Figure 3. 3: Shipping Cost($1,000) Distribution in CFS Areas (3.3a) Hire Truck;(3.3b) Private Truck;(3.3c) Air;(3.3d) Parcel



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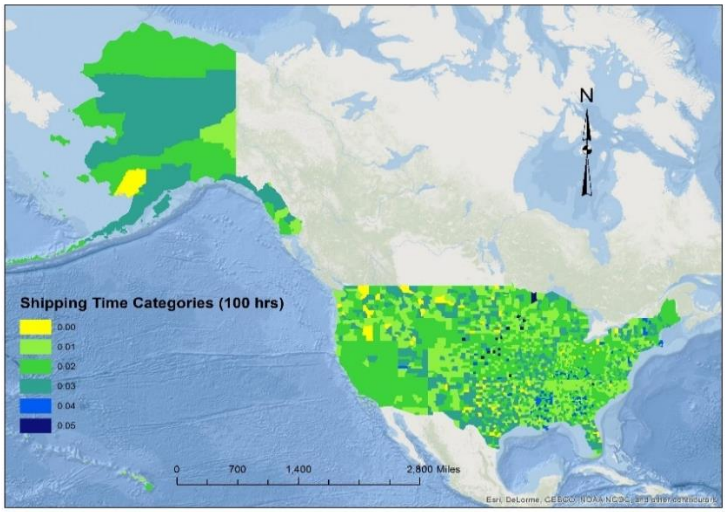

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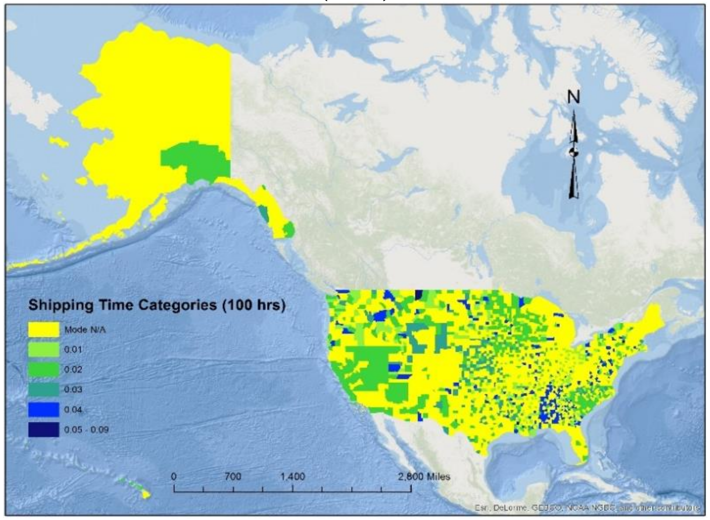

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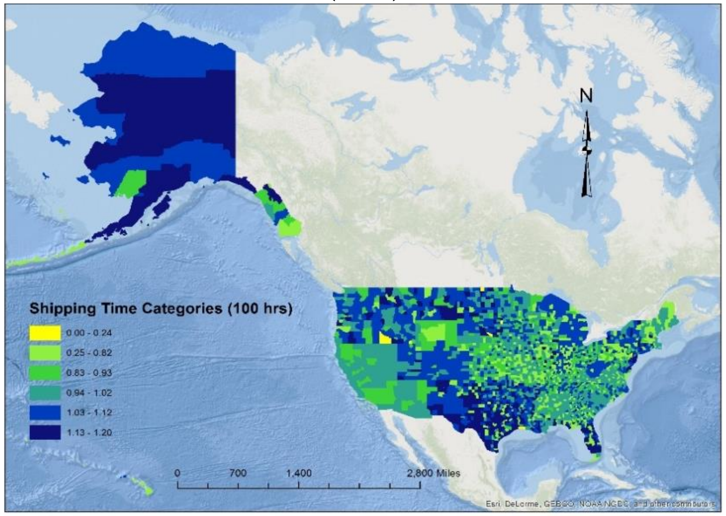

(3.4d)

Figure 3. 4: Shipping Time (100 hrs) in CFS Areas (3.4a) Hire Truck; (3.4b) Private Truck; (3.4c) Air; (3.4d) Parcel

Table 3. 1: Weighted Shipment Size Distribution (%) Across Modes for Entire USA

Mode	Mode Share (%)	Shipment Size								Total
		Categories	1	2	3	4	5	6	7	
		Weight Range (lb)	<= 30	31-200	201-1,000	1,001-5,000	5,001-30,000	30,001-45,000	> 45,000	
For-hire truck	16.47		11.05%	10.38%	17.66%	15.33%	18.59%	14.27%	12.71%	100.00
Private truck	26.23		17.30%	18.41%	19.46%	16.15%	13.88%	7.36%	7.44%	100.00
Air	1.36		59.60%	18.30%	15.00%	4.70%	2.30%	-	-	100.00
Parcel	55.64		78.81%	21.19%	-	-	-	-	-	100.00
Other	0.29		3.06%	2.50%	2.22%	4.44%	9.44%	13.33%	65.00%	100.00
Average weight (lb)			7.87	77.63	488.11	2377.40	14721.61	38625.86	153730.75	-

Table 3. 2 Weighted Shipment Size Distribution (%) for Florida and Piedmont Atlantic Region

Mode	Mode Share (%)		Shipment Size							Total
		Group	1	2	3	4	5	6	7	
		Weight (lbs)	<= 30	31-200	201-1,000	1,001-5,000	5,001-30,000	30,001-45,000	> 45,000	
Hire Truck	21.48		12.51	10.34	11.46	12.82	19.32	15.98	17.59	100.00
Private Truck	40.40		15.81	17.52	20.81	15.77	14.36	8.82	6.91	100.00
Air	0.62		45.51	26.65	20.06	5.99	1.50	0.30	---	100.00
Parcel	37.50		79.11	20.89	---	---	---	---	---	100.00

Table 3. 3: States Comprising Mega Regions

Mega Region	States
Arizona	Arizona, Partially Utah, Partially New Mexico
California	California, Partially Nevada
Cascadia	Washington, Oregon
Florida	Florida
Front Range	South of Colorado, Wyoming area, Part of New Mexico
Great Lake	Minnesota, Wisconsin, Michigan, Illinois, Indiana, Ohio, west Pennsylvania, Kentucky, East part of Missouri, Iowa, West Virginia
Gulf Coast	Part of Mississippi, Partially Louisiana and Alabama
Northeast	East Pennsylvania, New York, Maine, New Hampshire, Massachusetts, Connecticut, Rhode Island, New Jersey, Delaware, Maryland, Delaware, Maryland, Virginia
Piedmont Atlantic	North Carolina, South Carolina, Georgia, Alabama, Tennessee, South part of Kentucky
Texas Triangle	Texas, South West Part of Louisiana, Little part of south Oklahoma
Non-Mega region	Idaho, Montana, North Dakota, South Dakota, Nebraska, Hawaii, Alaska, Mississippi, Vermont

Table 3. 4: Newly Grouped SCTG Commodity Type

SCTG Code	Description	New SCTG Group
01	Animals and Fish (live)	Raw Food
02	Cereal Grains (includes seed)	
03	Agricultural Products (excludes Animal Feed, Cereal Grains, and Forage Products)	
04	Animal Feed, Eggs, Honey, and Other Products of Animal Origin	
05	Meat, Poultry, Fish, Seafood, and Their Preparations	
06	Milled Grain Products and Preparations, and Bakery Products	Prepared Products
07	Other Prepared Foodstuffs, and Fats and Oils	
08	Alcoholic Beverages and Denatured Alcohol	
09	Tobacco Products	
10	Monumental or Building Stone	Materials
11	Natural Sands	
12	Gravel and Crushed Stone (excludes Dolomite and Slate)	
13	Other Non-Metallic Minerals not elsewhere classified	
14	Metallic Ores and Concentrates	
15	Coal	Petroleum & Coal
16	Crude Petroleum	
17	Gasoline, Aviation Turbine Fuel, and Ethanol (includes Kerosene, and Fuel Alcohols)	
18	Fuel Oils (includes Diesel, Bunker C, and Biodiesel)	
19	Other Coal and Petroleum Products, not elsewhere classified	
20	Basic Chemicals	Chemical
21	Pharmaceutical Products	
22	Fertilizers	
23	Other Chemical Products and Preparations	
24	Plastics and Rubber	
25	Logs and Other Wood in the Rough	Wood &

SCTG Code	Description	New SCTG Group
26	Wood Products	papers
27	Pulp, Newsprint, Paper, and Paperboard	
28	Paper or Paperboard Articles	
29	Printed Products	
30	Textiles, Leather, and Articles of Textiles or Leather	
31	Non-Metallic Mineral Products	Metal and Machinery
32	Base Metal in Primary or Semi-Finished Forms and in Finished Basic Shapes	
33	Articles of Base Metal	
34	Machinery	
35	Electronic and Other Electrical Equipment and Components, and Office Equipment	Electronics
36	Motorized and Other Vehicles (includes parts)	
37	Transportation Equipment, not elsewhere classified	
38	Precision Instruments and Apparatus	
39	Furniture, Mattresses and Mattress Supports, Lamps, Lighting Fittings, and Illuminated Signs	Furniture & Others
40	Miscellaneous Manufactured Products	
41	Waste and Scrap (excludes of agriculture or food, see 041xx)	
43	Mixed Freight	
99	Missing Code	
00	Commodity code suppressed	

Table 3. 5: Summary Statistics of Exogenous Variables

Total Sample Size, N = 15,000		
Variables	**Sample Size**	**Sample Characteristics**
Categorical Variables		**Percentage**
Export		
Yes	615	4.1
No	14,385	95.9
Temperature Controlled		
Yes	630	4.2
No	14,370	95.8
Hazardous Materials		
Flammable Liquids	255	1.7
Non-flammable Liquid and Other Hazardous Material	405	2.7
Non Hazardous Materials	14,340	95.6
SCTG Commodity Type		
Raw Food	285	1.9
Prepared Products	810	5.4
Stone and Non-Metallic Minerals	360	2.4
Petroleum and Coal	495	3.3
Chemical Products	1,860	12.4
Wood, papers and Textiles	2,895	19.3
Metals and Machinery	2,745	18.3
Electronics	3,030	20.2
Furniture and Others	2,505	16.7
Shipment Value		
Value < $300	6,660	44.4
$300 ≤ Value ≤ $1,000	3,180	21.2
$1,000 < Value ≤ $5,000	2,715	18.1
Value > $5,000	2,445	16.3
Continuous Variables	**Mean**	
Shipping Cost ($)		
Hire Truck	37.33	

Private Truck	23.10
Air	277.36
Parcel	42.60
Other	10.83
Shipping Time (hour)	
Hire Truck	19.22
Private Truck	1.69
Air	1.03
Parcel	66.18
Other	23.23

CHAPTER FOUR: FREIGHT MODE CHOICE – A REGRET MINIMIZATION AND UTILITY MAXIMIZATION BASED HYBRID MODEL

Introduction

An efficient and cost-effective freight transportation system is the prerequisite for a region's economic growth and prosperity. About 122.5 million households, 7.5 million businesses and 90 thousand government units, daily depend on the efficient movement of about 55 million tons of freight valued at around $49 billion (Freight Facts and Figure, 2015). In the US, the demand for goods has grown steadily over the past half century and is expected to increase with the growth in population. The percentage share of freight transported in 2013 by weight and value by mode are as follows: truck (70 and 64), rail (9 and 3), water (4 and 1.5), air (0.1 and 6.5), and pipeline (7.7 and 6.0) (Freight Facts and Figures, 2015). The remainder of the freight is transported by multiple modes, mail and unknown modes. This percentage clearly indicates that, road based freight transportation is an important component of supply chain in the US and trucks are the preferred mode of shipping for most manufacturers and distributors in the country. Higher percentage of truck mode share is associated with negative externalities including, air pollution, traffic congestion, increase in accident severity, and expeditious deterioration of road and bridge infrastructure. Though heavy trucks consist only 3 percent of the total registered vehicles in the US and comprise 7 percent of the total vehicle miles driven, yet they are involved in 11 percent of the total road fatalities (Bezwada, 2010). Usually multiple axle trucks produce rutting damage and single and tandem axles cause cracking on road surface (Salama, et. al., 2006).

There is growing recognition among transportation researchers that addressing the freight industry associated challenges needs us to examine several dimensions including freight mode choice, freight infrastructure, pricing strategies across modes, and wages. In our research, we focus our attention on identifying and quantifying the influence of factors affecting mode choice for freight shipments. With the emerging advances in vehicle technology – connected and autonomous vehicles – there is likely to be a seismic shift in the freight industry in the near future. While level 4 adoption which is a fully self-driving vehicle in all conditions, (as defined by NHTSA, 2013) is likely to take time, several intermediate levels of vehicle technologies are already being introduced by private and public companies. These vehicular advances offer significant advantages to the trucking industry in terms of fuel, time, and labor cost savings. For instance, a platoon of connected trucks in a formation can reduce the impact of wind resistance by maintaining a shorter distance between them (15m instead of 50m) thus saving fuel and reducing CO_2 emission by around 7 percent for a platoon of three trucks (Daimler Blog). Further, adoption of fully autonomous vehicles will allow the trucking industry to circumvent the need for federally mandated driver breaks for long-haul trips. These are instances of how vehicle technology can offer environmental and financial benefits. While these changes are likely to improve the performance of the trucking industry, their impact on the overall shipment mode choice is less straightforward.

The proposed research effort contributes to our understanding of the impact of these technological adoptions, by developing advanced discrete choice models for freight mode choice analysis. Toward that end, we adopt a three-pronged research approach. First, we contribute to the existing literature by examining freight mode choice from the perspectives of alternative behavioral paradigms including classical random utility (RU) framework, newly emerging random regret (RR) framework, and hybrid framework (that builds on both utility and regret). Two kinds of hybrid models are considered: (1) hybrid framework with single utility equation accommodating regret and utility terms, and (2) latent class model with one segment following RU structure and another following RR structure. Second, a national level dataset drawn from Commodity Flow Survey (CFS) 2012 is augmented with a host of exogenous variables generated at origin and destination CFS areas and used for model building exercise. Finally, based on these variable effects, a host of policy scenarios are identified and evaluated employing the best-specified model structure. Based on the policy scenario outcomes, recommendations for freight planning process are given.

The rest of the chapter is organized as follows. The next section provides details of the econometric model framework used in the analysis. This section is followed by the section, which describes the empirical analysis of this study including model comparison and description of the empirical results. The policy analysis is presented in the following section. The last section concludes the chapter by summarizing the important findings from this analysis.

Econometric Model Framework

In this section, the details of econometric frameworks considered to evaluate freight transportation model have been discussed. At first, the traditional multinomial logit (MNL) model has been described, then we discuss the mixed multinomial logit (MMNL) model, random regret minimization (RRM) model, mixed random regret minimization (MRRM) model and a hybrid model-combination of RUM and RRM approaches. Also, a latent class two segment model RUM and RRM model has been analysed which is also discussed.

Multinomial Logit (MNL) Model

In the random utility approach it is assumed that a decision maker always chooses the alternative with the highest utility. Let s ($s = 1,2, \dots \dots, S$) be the index for shippers, and i ($i = 1,2, \dots \dots, I$) be the index for freight mode alternatives. With this notation, the random utility formulation takes the following familiar form:

$$u_{is} = \beta' x_{is} + \varepsilon_{is} \tag{4.1}$$

In the above equation, u_{is} represents the total utility obtained by the s^{th} shipper in choosing the i^{th} alternative. x_{is} is a vector of exogenous variables. β' is a vector of coefficients to be estimated. ε_{is} is an idiosyncratic error term assumed to be standard type-1 extreme value distributed. The probability expression for choosing alternative i is given by:

$$P_{is} = \frac{e^{(\beta' x_{is})}}{\sum_{i=1}^{I} e^{(\beta' x_{is})}} \tag{4.2}$$

The log-likelihood function is constructed based on the above probability expression. The strengths of multinomial logit model are probability computation is free from integration and simulation, if linear utility specification is maintained the optimal solution will be reached irrespective of where we began and it is easy to interpret because of the utility structure.

Mixed Multinomial Logit (MMNL) Model

The traditional logit model cannot accommodate taste variation based on unobserved attributes and assume homogenous preference across all shippers. To overcome this issue, mixed multinomial logit model is applied. Let s ($s = 1,2, \dots \dots, S$) be the index for shippers, and i ($i = 1,2, \dots \dots, I$) be the index for freight mode alternatives. With this notation, the random utility formulation for MMNL takes the following familiar form:

$$v_{is} = (\beta' + \delta'_s)x_{is} + \varepsilon_{is} \tag{4.3}$$

In the above equation, v_{is} represents the total utility obtained by the s^{th} shipper in choosing the i^{th} alternative. x_{is} is a vector of exogenous variables (including constants), β' and δ'_s are the column vector of parameters to be estimated, β' represents the mean effect, and δ'_s represents the shipper level disturbance of the coefficient, ε_{is} is an idiosyncratic error term assumed to be standard type-1 extreme value distributed. In the current paper, we assume that δ'_s are independent realizations from normal population distribution; $\delta'_s \sim S(0, \sigma_m^2)$. The probability expression for choosing alternative i is given by:

$$P_{in} = \int \frac{e^{(\beta' + \delta'_s)}}{\sum_{i=1}^{I} e^{(\beta' + \delta'_s)}} * dF(\delta'_s)d(\delta'_s) \tag{4.4}$$

Maximum simulated likelihood (MSL) estimation is employed to estimate β' parameters. For this particular study, we use a quasi-Monte Carlo (QMC) approach (Scrambled Halton draws) with 200 draws for the MSL estimation (see Bhat, 2001 for more details).

Random Regret Minimization (RRM) Model

Another concept has been developed to analyze choice behavior which is based on the idea of decision maker's regret minimization when making choices among different alternatives. Basically, regret is a feeling which a decision maker experiences when a non-chosen alternative performs better than a chosen alternative. The idea of this model is that, when multiple attributes are present a decision maker's aim is to reduce the anticipated random regret by making some trade-off between these attributes. The total regret associated with an alternative i among j alternatives, can be denoted with following equation:

$$R_i = \sum_{m=1,\ldots,M} \sum_{j \neq i} ln\{1 + exp[\,\beta_m\,(x_{jm} - x_{im})]\} + \varepsilon_{is} \tag{4.5}$$

This formulation infers that the regret is zero when alternative j does not perform better compared to chosen alternative i in terms of a particular alternative specific attribute x_m. If the alternative i performs better than alternative j then regret becomes a function of attribute importance and difference in the performance between the alternatives for a particular attribute. Here, ε_{is} represents an idiosyncratic error term for unobserved heterogeneity in regret, assumed to be standard type-1 extreme value distributed. Assuming that an individual will make a decision to choose the alternative with minimum regret, the choice probability of alternative i is given by the following equation:

$$P_i = \frac{e^{(-R_i)}}{\sum_{j=1}^{J} e^{(-R_j)}} \tag{4.6}$$

Mixed Random Regret Minimization Model

In this study we have also applied mixed formulation to the RRM model to capture unobserved heterogeneity. In this method random variation is allowed to accommodate the heterogeneity for all respondents. The mixed formulation is flexible in nature and provides practical computation in econometric discrete choice modeling. The probability of respondent s's choices over the distribution of θ would be as follows:

$$P_i = \int \frac{e^{(-R_{ist})}}{\sum_{j=1}^{J} e^{(-R_{jst})}} * f(\theta) d(\theta) \tag{4.7}$$

Mixed Hybrid Model – Combination Of RUM And RRM

Let s $(s = 1,2, \dots \dots, S)$ be the index for shippers, and i $(i = 1,2, \dots \dots, I)$ be the index for freight mode alternatives characterized by m $(m = 1,2, \dots N, \dots, M)$ attributes. Let us also consider, N are evaluated following utility maximization principle while the rest $(M - N)$ are evaluated following random regret minimization principle. With these notations, the systematic part of the hybrid (or modified) utility/regret equation would take the following form:

$$HU_i = \sum_{m=1}^{N} \beta'_m \, x_i - \sum_{j \neq i} \sum_{m=N+1}^{M} \ln\left[1 + exp\left\{\beta'_m\left(x_{jm} - x_{im}\right)\right\}\right] \tag{4.8}$$

In the above formula the linear in parameter portion represents random utility maximization and the non-linear part represents random regret minimization attribute processing. Considering, the error term to be standard type-1 extreme value distributed, the mathematical expression for the unconditional probability of the hybrid utility/regret model could be written (accommodating for unobserved heterogeneity) as:

$$P_i^{HU} = \int \left(\left[\frac{exp(HU_i)}{\sum_{i=1}^{I} exp\,(HU_i)} \right]^{d_i} \right) f(\beta) d\beta \tag{4.9}$$

where $f(\beta)$ is a density function specified to be normally distributed with mean 0 and variance σ^2 and d_i is a binary variable which is equal to 1 if shipper s choose mode i or 0 otherwise. There is no *a priori* expectation regarding which attributes are likely to be processed in utility theoretic fashion and which are likely to be processed by random regret approach. If all parameters are evaluated based on utility maximization principle, then the model collapses to traditional random utility based mixed MNL model and if all parameters are evaluated based on regret minimization principle, then hybrid model collapses to regret based mixed MNL model. To estimate parameters, maximum simulated likelihood (MSL) estimation technique is employed. For this particular study, we use a quasi-Monte Carlo (QMC) approach (Scrambled Halton draws) with 200 draws for the MSL estimation (see Bhat, 2001 for more details).

Latent Class Two Segment Model With RUM And RRM

In the two class latent segment model, Segment 1 follows random utility principle and segment 2 follows a regret based decision rule. The latent segmentation based models assign shipments probabilistically into k (k = 1, 2) segments based on a host of explanatory variables (for example, freight characteristics). The mathematical expression for the probability of a shipment *s* belonging to segment *k* can be expressed as follows:

$$P_{sk} = \frac{\exp(\gamma_k' z_s)}{\sum_{k=1}^{2} \exp(\gamma_k' z_s)} \tag{4.10}$$

where, z_s is a vector of shipment attributes that influences the propensity of belonging to segment k, γ_k' is a vector of estimable coefficients. Within the latent class approach, the unconditional probability of a shipment s being shipped by mode i is given as:

$$P_s(i) = \sum_{k=1}^{2} (P_s(i) \mid k)(P_{sk}) \tag{4.11}$$

where $P_s(i)|k$ represents the conditional probability of shipment s being shipped by mode i within the segment k. Using the notations mentioned above, the conditional probability for segment 1 (considering random utility maximization principle) would be as follows:

$$P_s(i) \mid 1 = \frac{\exp(\alpha_k' x_{si})}{\sum_{i=1}^{I} \exp(\alpha_k' x_{si}))} \tag{4.12}$$

Here, α_s' represents a vector of coefficients, and x_{si} is a vector of attributes influencing mode choice. On the other hand, for segment 2 (considering random regret based decision), the conditional probability would be given as:

$$P_s(i) | 2 = \frac{\exp(-R_{si})}{\sum_{i=1}^{I} \exp(-R_{si})} \tag{4.13}$$

Here, $R_{si} = \sum_{j \neq i} \sum_{m=1}^{M} \ln\left[1 + \exp\left\{\delta_m\left(x_{sjm} - x_{sim}\right)\right\}\right]$; δ_m is (Lx1) column vector of estimable coefficients associated with attribute x_m; x_{im} and x_{jm} are (Lx1) column vector of mode attributes for the considered alternative i and another alternative j, respectively. The log-likelihood function for the entire dataset with appropriate $P_s(i)|k$ is as follows:

$$LL = \sum_{s=1}^{S} \log(P_s(i)) \tag{4.14}$$

Empirical Analysis

Model Fit

In this study, a series of models was estimated including traditional RU maximization based MNL (RUMNL), RR minimization based MNL (RRMNL), RU based mixed MNL (RUMMNL), RR based mixed MNL (RRMNL), hybrid utility-regret based MNL (HUMNL), hybrid utility-regret based mixed MNL (HUMMNL), and latent class two segment (RU and RR) model (LSRURR). To compare these models, Bayesian Information Criterion (BIC) values were computed (presented in Table 4.1). The BIC value for a given empirical model can be calculated using [– 2 (LL) + K ln (Q)], where (LL) is the log-likelihood value at convergence, K is the number of parameters, and Q is the number of observations. The lowest BIC value was found for HUMMNL (3840.49). Therefore, we present and discuss the results obtained from this model only (Table 4.2). Please note that we considered a 90 percent significance level. The last column of Table 4.2 identifies whether the variable was evaluated following RU structure or RR structure. We discuss the results for RUM variables followed by RRM variables.

Exogenous Variable Effects (RU)

The level of service variables (shipping cost and shipping time) negatively influence mode share. This is expected, as shippers naturally would prefer modes offering faster shipping time and lower carrying cost. We also allowed for the presence of the unobserved heterogeneity across shipping cost and time. From analysis result, it was found that shipping cost has a statistically significant standard deviation. The coefficient of cost follows a normal distribution with mean value of -0.8097 and standard deviation of 0.4639. The distribution infers that shipping cost impact most of the observation negatively with a very small proportion (4.09%) of cases having the positive impact of cost. In addition to an overall shipping time coefficient, shipping time interactions with different commodity types were examined (observed and unobserved). Of the various commodity types, only the shipping time for raw food and shipping time for prepared products presented a statistically significant result for observed effects. The estimated parameters imply that raw and prepared foods are more sensitive to shipping time compared to other commodity types. The result is reasonable because these products are usually perishable and require timely delivery. For export freight, air is more likely to be the preferred alternative compared to hire truck (see 31 for similar result). Private truck is more likely to be chosen when the shipment value is less than $5000.

The transportation network and demographic attributes offer intuitive results as well. With increasing highway density at origin, the propensity to choose parcel mode increases. The result indicates that increasing roadway connectivity increases the accessibility for the parcel mode. Densely populated area attracts more freight flows; hence, the probability of choosing private truck, air, and parcel mode also increases with increasing population density at destination. The utility for using private trucks decreases with increase in inter-modal facilities in the area. The result also shows that probability of choosing private truck decreases when density of warehouse and super center increases at origin. Air mode is less likely to be chosen for destinations with population below poverty level presumably, since shipping through air mode is expensive. Moreover, the impoverished destinations may not have necessary provisions for air mode as well (airports or freight airstrips). With increasing number of employee density in manufacturing industries at origin, the probability of choosing private truck decreases.

Exogenous Variable Effects (RR)

The constants do not possesses any substantive interpretation after introducing other exogenous variables. The coefficients of freight characteristics treated with RRM approach bears intuitive results. The probability of choosing parcel mode decreases when the commodity is non-flammable liquid or other hazardous material. It is expected because this type of commodity needs special care for handling and advanced safety precautions. Probability of choosing private truck increases when the commodity to be shipped needs temperature control as desired temperature control facilities can be provided by private truck providers. Hence, regret would be lesser compared to any other mode when private truck is chosen for temperature controlled products. In addition, the probability of choosing private truck increases when the commodity is prepared products, petroleum and coals or furniture and other commodities. On the other hand, private truck is not preferred when the commodity is stone and non-metallic minerals, chemicals or electronics. Our findings are in line with the results reported in previous studies (17 and 31). Eelectronic products are comparatively light weight, expensive and need special care while transporting (see 17 for the same finding) and hence, there would be lesser regret associated with choosing air mode for transporting these commodity type. Parcel mode is less likely to be chosen when the shipment is expensive in terms of its value (more than $5000) (see 16, 19 and 32 for similar results).

When the origin mega region is Florida, private truck is more likely to be chosen. Again, when destination is northeast region, parcel mode is less likely to be chosen. The probability of choosing private truck increases when the origin is urban area. In cold areas with average temperature below or equal to 60^0F, parcel mode is more likely to be chosen. The reason may be in colder areas people are more dependent on purchasing products online than going out by themselves to purchase that commodity. Hence, the regret would be lesser for this case. The probability of choosing private truck increases when the major industry type at origin is wholesale, but probability of choosing private truck decreases when the major industry type at destination is wholesale. One plausible explanation might be that wholesale dominating origins produce bulk amount of products, which are required to ship by truck than air or parcel mode. When the density of interstate highways and freeways at destination increases, the probability of choosing air mode decreases which is expected. With increasing density of warehouse and super centers at destination, the probability of choosing parcel mode decreases. If there are more number of seaports at destination, it is less likely to choose private truck as the shipment mode.

Policy Analysis

To illustrate the applicability of the proposed model, a host of policy analysis has been conducted. The policy scenarios considered include the following changes to the attributes while all other attributes remain constant:

(1) a carbon tax on truck mode increasing the shipping cost by 25%, 35% and 50%,

(2) a reduction in truck shipping time due to introduction of automated truck fleets in trucking industry (by eliminating the heavy vehicle driver's resting time),

(3) re-routing of trucks away from the urban region resulting an increased travel time by 15%, 25% and 50%,

(4) a carbon tax measure of 50% increase in truck shipping cost and reduction of travel time from scenario 2, and

(5) a carbon tax on air mode of 25% and 50%.

Table 4.3 illustrates the changes in predicted mode shares from base shares for different policy scenarios. In the table, a positive (negative) sign specifies an increase (decrease) from the base mode share. When the shipping cost increases due to carbon tax measure, as expected, the mode share of hire truck and private truck decreases. This reduction ranges from 1.93 percent to 2.96 percent for hire truck and 1.08 percent to 1.77 percent for private truck. Moreover, percentage share of "other" mode increases significantly under this policy scenario. This is not surprising, because trucks usually carry larger loads which can only be substituted by rail. In the second scenario, the shipping times by hire and private trucks are reduced by eliminating the mandatory rest and break times for long haul drivers. As expected, the results illustrate a potential increase in hire truck share (by 6.91%). However, there is a slight increment in private truck share because these trucks usually run shorter distance compared to hire truck and hence, rest or break time is not usually needed for the drivers. This essentially signifies that vehicle automation might be more beneficial for long-haul modes. On the other hand, reduction in truck shipping time decreases the share of air and parcel mode substantially. To reduce congestion, to reduce conflicts between heavy vehicle and automobiles and pedestrians/cyclists on the roadways within cities, and to reduce air pollution, city officials might decide to reroute truck flows to by-pass roadways located at the periphery of the cities. This will apparently benefit passenger traffic but will lead to increased shipping time for trucks. We capture the effect of such rerouting in the third scenario. As expected, increase in shipping time leads to a substantial decrease in truck share. More specifically, hire truck share decreases between the ranges of 2.35 percent to 7.85 percent. In contrast, share of private trucks does not decrease remarkably. Under this scenario, shippers are more likely to opt for parcel and other modes if truck flows are rerouted. More interestingly, a simultaneous increase in truck shipping cost (carbon tax) and reduction in shipping time leads to an increase in share of hire truck indicating that shippers are usually more sensitive to shipping time than shipping cost. At the same time, share of “other” mode increases by almost 72 percent under this policy scenario. Finally, a carbon tax measure of 25% and 50% on air mode reduces the air mode share by 7.71 percent and 11.92 percent, respectively, while increasing parcel and “other” mode share.

Summary

This chapter describes the analysis of mode choice decision using different model paradigms and also presents the change in mode share under different policy scenarios. The advanced technology adoption and implementation in trucking industry benefits the industry both financially and environmentally. Hence, this change may influence overall freight industry in a complex way. The proposed research effort contributes to our understanding of the impact of these technological adoptions, by developing advanced discrete choice models for freight mode choice analysis.

We contribute to the existing literature by examining freight mode choice from alternative behavioral paradigms-random utility maximization and random regret minimization.

To capture unobserved heterogeneity of level of service variables, a mixed hybrid model was estimated. The applicability of these behavioral paradigms and the corresponding changes predicted to freight mode choice under future vehicle technology adoption are evaluated. In our empirical analysis, the hybrid utility-regret mixed MNL model performed better compared to all other models. Our finding lends credence to the growing recognition that attributes impacting choice behavior could be treated either by heterogeneously – using either utility theoretic manner or regret minimization orientation. Overall, the estimated results offer plausible interpretation of the choice behavior. The evaluations of policy scenarios offer reasonable and intuitive results in terms of modal shifts. We found that introduction of automation in the freight industry would be more beneficial for long-haul hire truck mode than short-haul private truck mode. An increase in travel time by truck due to re-routing of truck flows away from urban region clearly indicates a modal shift from truck to parcel or “other” mode which includes rail, water or multiple modes. Also, implementation of carbon tax should be accompanied by travel time penalty, if modal shift from road based transportation to rail or water vessel based transportation is to be achieved. These policy insights can be helpful for transportation planner and urban policy makers to provide adequate physical facilities and services for truck transportation. Designated truck route, controlled access to urban area and selected parking and loading-unloading infrastructural facilities can improve truck transportation significantly. Also adopting automated truck fleets can cut off the economic and environmental impacts associated with trucking industry to a greater extent.

Table 4. 1: Comparison of Different Models

Model	Log-likelihood at Convergence	No. of Parameters	No. of Observation	BIC Values
RUMNL	-1782.95	41	4000	3905.96
RRMNL	-1769.30	40	4000	3870.36
HUMNL	-1769.69	38	4000	3854.55
RUMMNL	-1772.06	42	4000	3892.75
RRMMNL	-1759.83	41	4000	3859.72
HUMMNL	-1758.52	39	4000	**3840.52**
LSRURR	-1857.98	36	4000	4014.55

Table 4. 2: Estimation Result of Mixed Hybrid Model-Combination of RUM and RRM Based Approaches

Explanatory Variables	Hire Truck		Private Truck		Air		Parcel/Courier		Other		Type
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	
Constant	0	– [1]	0.2222	2.680	-0.3997	-1.021	1.3049	7.959	-1.7770	-3.532	RRM[2]
Level of Service variables											
Shipping Cost (1000 $)	-0.8097	-2.239	-0.8097	-2.239	-0.8097	-2.239	-0.8097	-2.239	-0.8097	-2.239	RUM[3]
Std. Dev.	0.4639	1.751	0.4639	1.751	0.4639	1.751	0.4639	1.751	0.4639	1.751	RUM
Shipping Time (hrs)	-0.0059	-3.648	-0.0059	-3.648	-0.0059	-3.648	-0.0059	-3.648	-0.0059	-3.648	RUM
Interaction Variables											
Interaction of Travel Time with Raw Food (hrs)	-0.0169	-2.625	-0.0169	-2.625	-0.0169	-2.625	-0.0169	-2.625	-0.0169	-2.625	RUM
Interaction of Travel Time with Prepared Products (hrs)	-0.0086	-2.129	-0.0086	-2.129	-0.0086	-2.129	-0.0086	-2.129	-0.0086	-2.129	RUM
Freight Characteristics											
Hazardous Material (Base: Not Hazardous)											
Non-flammable Liquid and Other Hazardous Material	–	–	–	–	–	–	-0.6022	-3.557	–	–	RRM
Temperature Controlled (Base: No)											
Yes	–	–	0.2743	2.366	–	–	–	–	–	–	RRM
Export (Base: No)											
Yes	–	–	–	–	2.4275	5.664	–	–	–	–	RUM
SCTG Commodity Type (Base: Wood, Papers and Textile)											
Prepared Products	–	–	0.5488	4.064	–	–	–	–	–	–	RRM
Stone & Non-Metallic Minerals	–	–	-0.3178	-3.381	–	–	–	–	–	–	RRM

Explanatory Variables	Hire Truck		Private Truck		Air		Parcel/Courier		Other		Type
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	
Petroleum and Coals	–	–	0.5279	3.220	–	–	–	–	–	–	RRM
Chemicals	–	–	-0.1538	-2.300	–	–	–	–	–	–	RRM
Electronics	–	–	-0.1552	-2.354	0.6292	3.146	–	–	–	–	RRM
Furniture and Others	–	–	0.1544	2.394	–	–	–	–	–	–	RRM
Shipment Value ($) *(Base: Value >5000)*	–	–			–	–	–	–	–	–	
Value ≤ 1000	–	–	1.6217	10.484	–	–	–	–	–	–	RUM
1000 < Value ≤ 5000	–	–	0.9355	5.254	–	–	–	–	–	–	RUM
Value > 5000	–	–	–	–	–	–	-0.3176	-2.787	–	–	RRM
Transportation Network and Demographic Variables											
Origin Mega Region *(Base: Non Mega Region)*											
Florida	–	–	0.2998	2.198	–	–	–	–	–	–	RRM
Destination Mega Region *(Base: Non Mega Region)*											
North-East	–	–	–	–	–	–	-0.1356	-1.653	–	–	RRM
Origin Area Type (Base: Rural)											
Urban	–	–	0.2787	2.593	–	–	–	–	–	–	RRM
Avg. Temperature at Origin *(Base: Warm; $>60^0$ F)*											
Cold (≤ 60^0 F)	–	–	–	–	–	–	0.1850	2.826	–	–	RRM
Major Industry at Origin *(Base: Manufacturing)*											
Wholesale	–	–	0.1209	1.850	–	–	–	–	–	–	RRM
Major Industry at Destination *(Base: Manufacturing)*											
Wholesale	–	–	-0.1093	-1.788	–	–	–	–	–	–	RRM

Explanatory Variables	Hire Truck		Private Truck		Air		Parcel/Courier		Other		Type
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	
Origin Highway Density (mi/mi^2)	–	–	–	–	–	–	2.2970	1.974	–	–	RUM
Density Interstate Highways and Freeways at Destination (mi/mi^2)	–	–	–	–	-0.0283	-1.785	-	-	–	–	RRM
Destination Population Density (pop/mi^2)	–	–	0.0011	3.500	0.0011	3.500	0.0007	3.733	–	–	RUM
No. of Inter Modal Facility at Destination	–	–	-0.0067	-2.869	–	–	–	–	–	–	RUM
Density of Warehouse and Super Center at Origin (per mi^2)	–	–	-0.4361	-2.356	–	–	–	–	–	–	RUM
	–	–	-	-	–	–	-0.1903	-2.210	–	–	RRM
Density of Wholesale Industry at Destination (per mi^2)	–	–	-0.2117	-2.978	–	–	–	–	–	–	RRM
Percentage of Population below Poverty Level at Destination	–	–	–	–	-10.7827	-1.744	–	–	–	–	RUM
Density of Employees in Manufacturing Industry at Origin (per mi^2)	–	–	-0.4453	-7.936	–	–	–	–	–	–	RUM
No. of Seaports at Destination	–	–	-0.0003	-2.924	–	–	–	–	–	–	RRM
Number of cases	4000										
Log Likelihood for Constant only Model	-2063.51										
Log Likelihood at Convergence	-1758.52										
No. of Parameter	39										
Adjusted rho-square	0.1313										

[1] - = Variable insignificant at 90 percent confidence level
[2] RRM = Random Regret Minimization
[3] RUM = Random Utility Maximization

Table 4. 3: Percentage Changes of Mode Share from Base Prediction Under Different Policy Scenarios

Mode (Base % Share)	**Truck Shipping Cost 25% Increase**	**Truck Shipping Cost 35% Increase**	**Truck Shipping Cost 50% Increase**	**Truck Shipping Time Under Automated Vehicles**	**Truck Shipping Time 15% Increase**	**Truck Shipping Time 25% Increase**	**Truck Shipping Time 50 % Increase**	**Truck Shipping Cost 50% Increase and Truck Shipping Time Reduction**	**Air Shipping Cost 25% Increase**	**Air Shipping Cost 50% Increase**
Hire Truck (16.57%)	-1.93	-2.41	-2.96	6.91	-2.35	-3.68	-7.85	4.83	0.42	0.48
Private Truck (25.92%)	-1.08	-1.54	-1.77	0.27	-1.09	-1.13	-1.21	0.08	-1.16	-1.14
Air (1.51%)	-4.39	-4.29	-4.15	-7.16	-2.70	-2.04	-0.33	-6.22	-7.71	-11.92
Parcel (55.71%)	1.01	1.29	1.42	-2.20	1.22	1.60	2.82	-1.69	0.72	0.75
Other (0.29%)	35.75	51.55	76.23	0.68	12.74	13.82	16.63	72.12	3.45	3.45

CHAPTER FIVE: JOINT MODEL OF FREIGHT MODE CHOICE AND SHIPMENT SIZE – A COPULA BASED RANDOM REGRET FRAMEWORK

Introduction

Economic globalization, e-commerce and internet based shopping are growing speedily in recent years. This shopping pattern results in higher percentage of smaller size shipment. While online shopping is resulting in a drop in passenger travel an increase in freight movements is occurring. As a result, freight movement in residential areas is impacting road surface, increasing emission, increasing establishment of intermodal hubs, increasing congestion and traffic safety concerns arising from collisions of trucks and other road users.

Given the importance of freight mode and shipment size decisions, we enhance current approaches used to model these two choice dimensions. In modeling mode choice, we explore alternatives to the traditional random utility (RU) structure. The commonly employed decision rule for developing discrete choice models for unordered alternatives such as mode choice, is the random utility maximization (RUM). RUM based approaches hypothesize that decision makers opt for alternatives that offer them the highest utility or satisfaction (Ben-Akiva and Lerman, 1985; McFadden, 1974; Train, 2009). The framework allows for the consideration of trade-offs across various attributes affecting the choice process. This implicit compensatory nature of the formulation allows for a poor performance on an attribute to be compensated by a positive performance on another attribute (Chorus et al., 2008). Several researchers, motivated by research in behavioral economics, have considered alternative decision rules for developing discrete choice models such as relative advantage maximization (Leong and Hensher, 2015), contextual concavity (Kivetz et al., 2004), fully-compensatory decision making (Arentze and

Timmermans, 2007; Swait, 2001), prospect theory (PT) (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), and random regret minimization (RRM) (Chorus et al., 2008; Chorus, 2010). Of these approaches, we adopt regret minimization approach for our analysis due to its mathematical simplicity within a semi-compensatory decision framework. In our study, we explore both RU based multinomial logit (MNL) and random regret (RR) minimization based MNL models within a copula-based structure.

The shipment size variable is examined using an ordered logit (OL) model. Given the continuous reporting of shipment size, the most common approach to modeling shipment size in the literature includes employing a linear (or log-linear) formulation. While it is intuitive to consider a continuous representation, the assumption could potentially be restrictive. The shipment size data is likely to be reported as continuous values but with significant rounding as the shipment size increases. Effectively, after passing a certain threshold, the reported data is no longer continuous but discrete in nature. The shipment weight data is likely to be bunched together at various weight limits (such as 500 pounds or 1 ton). Given the inherent bunching of the shipment weight variable, the consideration of linear or log-linear models is not appropriate. Further, linear models restrict the impact of explanatory variables to be linear in nature (or exponential in log-linear models). Hence, to address these limitations, we consider an ordered representation for the shipment size variable. The specific categories considered are customized by mode under consideration. The grouping approach also allows for non-linear variable impacts in examining shipment size (for example, see Chakour and Eluru, 2016 for a similar approach in another context).

In addition to improving the individual model components, we also develop a joint model of shipment mode and shipment size. For the joint model, we adopt a closed form copula-based model structure for capturing the impact of common unobserved factors affecting these two choice dimensions. Copula-based structures tested include Gaussian, Farlie-Gumbel-Morgenstern (FGM), Clayton, Gumbel, Frank, and Joe. In applying copula models, we contribute along two main directions. First, we allow the copula dependency to vary across each shipment mode alternative and shipment size combination. To elaborate, for capturing the dependency between the mode (five alternatives) and shipment size we allow for various combinations of copula dependencies. Second, within the copula structure, we consider the possibility that copula dependency does not remain the same for all data points. Thus, we customize the dependency profile based on a host of freight characteristics; thus enhancing the relevance of the dependency profile. The proposed copula-based RU and RR multinomial logit and ordered logit models are estimated based on the data from 2012 CFS data.

In summary, the proposed approach makes the following contributions. First, we propose and estimate a closed form copula-based framework for mode and shipment size choice considering six different copulas (earlier work focused only on Frank Copula). Second, we allow for different copulas by mode choice alternative within a single model. Thus, we allow for symmetric dependencies for some alternatives and dependency on tails for others. Third, within the copula structure, we do not impose the same dependency on all records; rather, we allow the dependency to vary across the records by parameterizing the dependency profile. This allows for an accurate estimation of the dependency profile. A restrictive approach, as employed in earlier research, simply estimates an average dependency profile across all data points. Thus, the dependency profile obtained might not be representative and could result in biased model estimates. Finally, the proposed model is also validated using a hold-out sample to evaluate model performance.

The rest of the chapter is organized as follows: the econometric framework used for the analysis is discussed in the following section. The following sections describe empirical result of the analysis and present model validation. The chapter is concluded then discussing the important finding from the analysis.

Econometric Model Framework

Copula Based Joint MNL-OL Model

In our empirical analysis, we considered two dependent variables – shipment mode and shipment size. The former is modeled using both RU based and RR based MNL structure proposed by Chorus (2010), and the latter is modeled using traditional OL structure. These two dependent variables are jointly analyzed using a copula approach (see Anowar and Eluru, 2017; Yasmin et al., 2014; Rana et al., 2010; Portoghese et al., 2011 for a similar modeling technique in different transportation contexts). To conserve on space, we only discuss the joint model framework with RR based system.

Let i (i=1,2,…,I) and s (s=1,2,…,S) be the indices representing mode and shipment size choices of shippers n (n=1,2,…,…,N), respectively. With these notations, the random regret associated with the choice of mode i among j modes, each characterized by m (m=1,2,…,…,M) attributes, can be written as:

$$RR_{ni} = \sum_{j \neq i} \sum_{m=1,2,\dots,M} ln\{1 + exp[\, \beta_m \,(x_{njm} - x_{nim})]\} + \xi_{ni} \qquad (5.1)$$

where β_m denotes the estimable parameter associated with attribute x_m, x_{im} and x_{jm} denote the values associated with attribute x_m for chosen mode i and considered mode j. The choice probability with Type 1 extreme value distributed error term (ξ_i) is as follows:

$$P_{ni} = \frac{e^{(-R_{ni})}}{\sum_{j=1}^{J} e^{(-R_{nj})}} \tag{5.2}$$

We considered the shipment size to be ordered. The underlying propensity (s_{ni}^*) of choosing shipment size s choice for mode i can be specified as:

$$s_{ni}^* = \alpha_i z_{ni} + \zeta_{ni}, \quad s_{ni}^* = s_i, \qquad if\ \tau_{i,s-1} < s_{ni}^* < \tau_{i,s} \tag{5.3}$$

Considering a standard logistic distributed error term(ζ_{ni}), the probability of shipper n choosing shipment size s for mode i can be expressed as:

$$P_{ni} = \Lambda_i\left(\tau_{i,s} - \alpha_i z_{ni}\right) - \Lambda_i\left(\tau_{i,s-1} - \alpha_i z_{ni}\right) \tag{5.4}$$

where, Λ represents the cumulative density function for standard logistic distribution, $\tau_{i,s}$ $\left(\tau_{i,0} = -\infty, \tau_{i,S} = +\infty\right)$ represents the thresholds associated with shipment size s for mode i with the following ordering condition $\left(-\infty < \tau_{i,1} < \tau_{i,2} < \cdots < \tau_{i,S-1} < +\infty\right)$; α_i are the estimable parameters, z_{ni} are vector of attributes.

The shipment size and mode component may be coupled together through their stochastic error terms using the copula approach. The joint distribution (of uniform marginal variables) can be generated by a function $C_{\theta n}(.,.)$ (Sklar, 1973), such that:

$$\Lambda_{\xi_{ni},\zeta_{ni}}(U_1, U_2) = C_{\theta_n}({}_1{=}\ \Lambda_{\xi_{ni}}(\xi), U_2 = \Lambda_{\zeta_{ni}}(\zeta)) \tag{5.5}$$

where $C_{\theta n}(.,.)$ is a copula function and θ_n the dependence parameter defining the link between ξ_{ni} and ζ_{ni}. Level of dependence between shipment mode and size might vary across shippers. Recognizing that, we parameterized the dependence parameter θ_n as a function of freight characteristics. The equation is:

$$\theta_n = f(\gamma_i \vartheta_{ni}) \tag{5.6}$$

where $\vartheta_{ni}$is a column vector of exogenous variable, γ_i is a row vector of unknown parameters (including a constant) specific to mode i and f represents the functional form of parameterization. The parameterization was carefully done for each of the six copula types considering the permissible limits of the dependency parameters. More specifically, for normal, FGM and Frank copulas we use the following functional form:

$$\theta_n = f(\gamma_i \vartheta_{ni}) \tag{5.7}$$

While for Clayton we use:

$$\theta_n = exp(\gamma_i \vartheta_{ni}) \tag{5.8}$$

and for Gumbel and Joe the function use is:

$$\theta_n = 1 + exp(\gamma_i \vartheta_{ni}) \tag{5.9}$$

All the models are estimated by maximizing the log-likelihood function coded in GAUSS matrix programming language. In our analysis, we employ six different copula structures – Gaussian copula, Farlie-Gumbel-Morgenstern (FGM) copula, and a set of Archimedean copulas including Frank, Clayton, Joe and Gumbel copulas (a detailed discussion of these copulas is available in Bhat and Eluru, 2009). Please note that restricting the copula structure to have no correlation between the error terms of shipping mode and shipment size choices would result in independent copula model.

Empirical Result

Model Fit

A series of models were estimated in the current study. First, we developed independent discrete choice models of mode and shipment size choice. For mode choice analysis, both RU based as well as RR based MNL models were estimated while for shipment size we estimated traditional OL models for each mode. The log-likelihood values of the independent models can be appropriately summed up to obtain the independent copula model log-likelihood. These models were estimated to establish a benchmark for model performance evaluation. Second, we estimated a copula-based joint mode and shipment size choice model considering both decision rules for the mode choice decision. In our study, we considered six different copula structures: (1) Gaussian, (2) FGM, (3) Clayton, (4) Gumbel, (5) Frank, and (6) Joe. We also estimated models allowing different dependency structures (for example Frank copula for the first three mode types, and Joe copula for parcel mode). Third, rather than imposing a single dependency parameter across the dataset, we allow for the copula dependency to vary as a function of exogenous variables. Please note that we did not estimate any dependency parameter for “other” mode since it had too few observations for model estimation. Finally, to determine the most suitable copula model (including the independent copula model), a comparison exercise was undertaken.

Since the alternative copula models are non-nested, we compared their performance using Bayesian Information Criterion (BIC). The BIC value for a given empirical model can be calculated as: $[-\ 2\ (LL)\ +\ K\ ln\ (Q)]$, where LL is the log-likelihood value at convergence, K is the number of parameters and Q is the number of observations. The model with the lowest BIC value is the preferred model. The BIC values obtained are presented in Table 5.1. We can see from the table that the combination of Frank-Frank-Frank-Joe-Independent for RRM based MNL-OL copula provided the best data fit. The BIC (number of parameters) values for the RRM based MNL-OL Frank-Frank-Frank-Joe-Independent copula model and independent model are 25762.57 (94) and 26473.42 (99), respectively. From the RU regime as well, a similar combination of copulas (Frank-Frank-Frank-Joe-Independent) provided the best data fit (25765.97 (93)). The BIC values indicate that the random regret based copula model outperformed its random utility counterpart. The copula model BIC comparisons confirms the importance of accommodating dependence between mode type and shipment size choice dimensions in the analysis of freight mode choice. In addition, we found that the copula model (Frank-Frank-Frank-Joe-Independent) with parameterization provided the best data fit amongst all the copulas (25713.41 (98)). Therefore, in the subsequent sections, we will only discuss about the results for this model. In our analysis, variable selection was guided by a 90 percent significance level and variable impact expectations from past research.

Mode Choice Component

Table 5.2(a) represents the results of the RR based mode choice component. A positive (negative) sign for the coefficients indicates that an increase (decrease) in the corresponding attribute increases (decreases) the regret associated with not participating in the alternative and contributes to an increase (decrease) in the probability for participating in the alternative. In the following section, the estimation results are discussed by variable groups.

Level Of Service Variables

In our empirical analysis, shipment time and cost variables have a negative effect indicating that regret is higher if the competitor mode has lower travel time or lower shipment cost (see Boeri and Masiero, 2014 for similar results). The magnitudes of the coefficients indicate that shippers are more concerned with shipping cost than shipping time. In our model, we also tested for several first order interactions of travel time with commodity types; only two interactions were significant. The signs of the coefficients of the interaction terms of travel time with raw food and prepared products are found to be intuitive. Relative to other commodities, shipping of these two commodities are more time sensitive as indicated by worsening regret with increase in travel time. The magnitude of sensitivity is larger for raw food commodity. This result is reasonable because raw food products are perishable and require timely delivery.

Freight Characteristics

The effects of the freight attributes provide interesting results. Both non-flammable liquid and other hazardous materials, and temperature controlled products are more likely to be shipped by private truck. These type of shipments require special handling and safety precautions which can be accommodated by private truck operators. In addition, temperature controlled products can be delivered to its destination without any transfer time (as required for other modes). Air is the preferred mode for transporting export shipments. It is expected, as shipping overseas is more convenient by air mode (see Wang et al., 2013 for similar result). However, it is less likely that private truck would be chosen for export purposes as private trucks are more likely to be used for shorter shipping distances. Private truck is preferred for commodities such as prepared food and products, petroleum and coal, and furniture and other miscellaneous commodities. Private trucks are more likely to be used to carry small quantities of refined petroleum to the gasoline distribution locations, such as gas stations within shorter distances. On the other hand, private truck is less preferred for transporting stone and non-metallic minerals and electronic products. Air mode is preferred for transporting electronic products which are lightweight, costly and require special care to prevent any damage due to shock while transporting. Similar finding is reported by Pouraabdollahi et al. (2013a). In terms of shipment value, for shipments valued under $5000, private truck is more likely to be chosen. Regret gradually decreases for higher value merchandise (see Sayed and Razavi, 2000; Norojono and Young, 2003; Arunotayanun and Polak, 2011; Moschovou and Giannopoulos, 2012 for similar findings).

Transportation Network And Origin Destination Characteristics

Private truck is less preferred when the density of railways or number of intermodal facilities at destination zone increases. The possibility of choosing air mode decreases when density of railway at origin increases or when the percentage of population living below poverty level is high at origin. Air mode is typically expensive and hence, shippers in the impoverished regions are less likely to ship/receive products by this mode. Higher population density is a proxy for higher demand for service. Hence, with increasing population density at destination CFS zone, the probability of choosing air and parcel mode increases. If shipment's originating zone has higher highway density or increased number of warehouse and supercenters parcel mode is also more likely to be chosen. The result is expected because parcel mode requires greater accessibility through roadway network. Moreover, warehouses are generally situated in locations with better highway accessibility, allowing for faster access by parcel mode. However, parcel mode is less preferred when the density of wholesale industry at origin increases; possibly because wholesale industries generally ship bulk loads and for bulk loads, parcel is not a convenient mode option.

Shipment Size Component

The results of ordered logit models for each mode type are presented in Table 5.2(b). A positive (negative) coefficient increases (decreases) the shipper's propensity for choosing a larger (smaller) shipment size category. The results are discussed by variable groups in the following section. Please note that the threshold variables do not have any substantive interpretation.

Freight Characteristics

Non-inflammable liquid and other hazardous materials are more likely to be shipped in larger volume using for-hire trucks. Trucks can be specially equipped and operated to carry hazardous materials to ensure safe transportation of such commodities. As expected, shipment size of commodities requiring temperature control is likely to be smaller for parcels as it may not be able to offer the special handling care required for these commodities. Commodities, such as raw food, prepared products, stone and non-metallic minerals, and petroleum and coals, are likely to be shipped in large amounts by for-hire and private trucks. Both for-hire and private trucks offer unhindered movement of these commodities without needing any transfers. On the other hand, chemicals, furniture and other products might be shipped in smaller quantities when using private truck as a mode of transportation. Also, electronics tend to be shipped in smaller amounts by for-hire truck, private truck, air and parcel modes. Parcel mode may have weight restrictions for shipping; hence, shipment size for furniture, and metals and machinery are likely to be on the smaller side. However, for prepared products, the shipment sizes are likely to be on larger side. Shipment value and its size are negatively correlated for all modes.

Transportation Network And Origin Destination Characteristics

Several transportation networks and O-D attributes were considered in the shipment size models. For hire truck, density of employees in mining industry at origin increased the propensity for larger shipments. This possibly reflects the nature of industry in the region. In addition, density of bridges at destination, cold climate at origin (average annual temperature $\leq 60^0$F), and increased routed distance reduces the propensity for large shipments using for-hire trucks. For private truck, density of highways in the destination zone increases the propensity for larger shipments since increased roadway coverage facilitates movement of goods in large quantity. On the other hand, density of management company and enterprise at destination decreases the propensity for large shipments, as this type of establishments normally attracts commodities with smaller weight including office supplies and electronics. For parcel mode, the propensity of large shipment increases when mean zonal income at origin is less than $50,000. However, increased density of wholesale industries at destination or increased number of seaports at origin reduces the propensity for large shipments by parcel mode. Wholesale industries potentially generate bulk weight that is less convenient to be transported by parcel mode. Shipping large amount of freight through seaports is cost effective.

Copula Parameters

The last panel of Table 5.2(b) presents the copula parameters estimated. The statistically significant dependency parameters imply the existence of unobserved factors strongly influencing the mode and shipment size choice decision simultaneously. Further, the results clearly highlight how the dependence varies across the dataset. The Frank copula is associated with for-hire truck, private truck, and air modes while Joe copula is associated with parcel mode. For the “other” mode alternative, dependency could not be captured due to the small sample size. The Frank copula provides symmetric dependency; i.e. the positive copula parameter specifies that the dependency caused by the common unobserved factors for the specific mode is positive, and a negative copula specifies that the dependency is negative. In our case, the constant parameter in Frank is negative indicating that the common unobserved factors that increase the probability of choosing the mode are likely to reduce the probability that larger shipment size is chosen. The Joe copula is only associated with positive dependency and proposes a stronger right tail dependency. The positive sign of Joe copula associated with parcel mode implies that the common unobserved factors that increase the propensity of choosing parcel mode also increase the propensity of choosing a larger shipment size. Several freight characteristics influence the dependency across the mode and shipment size categories. The variables include raw food, stone and non-metallic minerals, shipment value less than $300 and shipment value from $300 to $1000 (for-hire truck); metals and machinery (private truck); and export trade type (parcel). The parameter values provide customized dependency values across the dataset.

Model Validation

To evaluate the performance of the estimated models, we also performed a validation exercise. Specifically, we employed the final parameters obtained from the models to compute the predictive log-likelihood (LL) and BIC values for four models: (1) RRM based MNL-OL Copula (Frank-Frank-Frank-Joe-Independent) with parameterization, (2) RUM based MNL-OL Copula (Frank-Frank-Frank-Joe-Independent) with parameterization, (3) RRM based MNL-OL Independent Copula, and (4) RUM based MNL-OL Independent Copula. The results are reported in Table 5.3. The overall predictive log-likelihood and BIC values clearly indicate that RR based MNL-OL copula (Frank-Frank-Frank-Joe) with parameterization performs better than other models. Further, to illustrate the performance, we generate predicted LL values for several sub-samples including freight characteristics such as flammable liquid, commodity type (such as raw food, prepared products, chemicals). Except for a few instances, the RRM based MNL-OL copula model offers improved fit in the majority of the cases. Overall, the validation results also confirm the value of considering dependency across mode choice and shipment size.

Summary

In this chapter, a joint model system is developed in the form of an unordered choice model for mode and an ordered choice model for shipment size. We adopt a closed form copula-based model structure for capturing the impact of common unobserved factors affecting these two choices. We explore both the random utility (RU) based multinomial logit and the random regret (RR) minimization based multinomial logit (MNL) within a copula-based model. The RU and RR MNL structure are explored for several copula-based structures including Gaussian, Farlie-Gumbel-Morgenstern (FGM), Clayton, Gumbel, Frank and Joe. Finally, we consider six different copula structures while allowing for different copula structures within the same model (as opposed to a single copula form for all dimensions). For all the copula models, a more flexible approach that allows for exogenous variables to influence dependency structure is also estimated. The models are estimated based on the data from 2012 Commodity Flow Survey data. The estimated results obtained from this study clearly indicates the importance of accommodating dependencies between shipment mode and shipment size choice decisions. Of the copula models, RR based MNL-OL Frank-Frank-Frank-Joe copula model with parameterization offered the best fit. The estimated coefficients exhibited plausible interpretations too. The validation exercise performed to evaluate the model fit for overall sample and sub-samples based on freight characteristics suggests that RR based MNL-OL copula (Frank-Frank-Frank-Joe-Independent) model with parameterization significantly outperforms other models.

Certain drawbacks of this study need to be acknowledged. PUM CFS data does not contain exact geo-coded locations of origin and destination of freight movement. Advanced approaches to augment the data set with this information will improve the calculation of LOS variables and alternative availability matrices. Additionally, evidence of shipper level reliability, shipment frequency, shipping time delay, ownership of the vehicle fleet by the shipping firms will enhance the model result. In the future, accommodating more detailed land use attributes will provide the policy makers more interesting insights.

Table 5. 1: Comparison of Different Copula Models

MNL Decision Rule	Copula	LL at Convergence	No. of Parameters	No. of Observation	BIC
RRM	Frank-Frank-Frank-Joe-Independent	-12448.40	94	10000	25762.57
RUM	Frank-Frank-Frank-Joe-Independent	-12454.40	93	10000	25765.36
RRM	Frank[1]	-12450.10	94	10000	25765.97
RUM	Frank	-12456.20	93	10000	25768.96
RUM	FGM	-12656.40	95	10000	26187.78
RRM	FGM	-12655.60	96	10000	26195.39
RRM	Normal	-12741.10	94	10000	26347.97
RUM	Normal	-12809.50	86	10000	26411.09
RUM	Clayton	-12787.10	93	10000	26430.76
RUM	Gumbel	-12788.70	93	10000	26433.96
RRM	Clayton	-12786.50	94	10000	26438.77
RRM	Joe	-12788.10	94	10000	26441.97
RRM	Gumbel	-12788.20	94	10000	26442.17
RUM	Joe	-12788.50	94	10000	26442.77
RRM	Independent	-12780.80	99	10000	26473.42
RUM	Independent	-12782.40	99	10000	26476.62
Parameterization					
RRM	Frank-Frank-Frank-Joe-Independent	-12405.40	98	10000	25713.41
RRM	Frank	-12413.70	97	10000	25720.80
RUM	Frank-Frank-Frank-Joe-Independent	-12409.10	98	10000	25720.81

[1] Please note that the copula parameter for “Other” mode was set to 0 with FGM copula to ensure independence between “Other” mode and its corresponding shipping size.

Table 5.2 (a): Estimation Copula RRM Based MNL (Shipping Mode Choice) Model Estimation Results

Explanatory Variables	For-hire truck		Private Truck		Air		Parcel/Courier		Other	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Constant	0	–[1]	0.082	2.199	-0.046	-0.220	1.334	16.796	-1.500	-22.221
Level of Service Variables										
Shipping Cost (1000 $)	-0.134	-6.829	-0.134	-6.829	-0.134	-6.829	-0.134	-6.829	-0.134	-6.829
Shipping Time (hrs)	-0.001	-3.214	-0.001	-3.214	-0.001	-3.214	-0.001	-3.214	-0.001	-3.214
Travel Time * Raw Food	-0.005	-3.430	-0.005	-3.430	-0.005	-3.430	-0.005	-3.430	-0.005	-3.430
Travel Time * Prepared Products	-0.002	-3.281	-0.002	-3.281	-0.002	-3.281	-0.002	-3.281	-0.002	-3.281
Freight Characteristics										
Hazardous Material (Base: Not Hazardous)										
Non-flammable Liquid and Other Hazardous Materials	–	–	0.366	4.593	–	–	–	–	–	–
Export (Base: No)										
Yes	–	–	-0.220	-3.018	1.125	9.177	–	–	–	–
Temperature Controlled (Base: No)										
Yes	–	–	0.092	1.908	–	–	–	–	–	–
SCTG Commodity Type (Base: Wood, Papers and Textile)										
Prepared Food and Products	–	–	0.261	4.332	–	–	–	–	–	–
Stone & Non-Metallic Minerals	–	–	-0.462	-8.122	–	–	–	–	–	–
Petroleum and Coals	–	–	0.244	3.767	–	–	–	–	–	–

Explanatory Variables	For-hire truck		Private Truck		Air		Parcel/Courier		Other	
	Parameter	**t-stat**	**Parameter**	**t-stat**	**Parameter**	**t-stat**	**Parameter**	**t-stat**	**Parameter**	**t-stat**
Electronics	–	–	-0.171	-4.287	0.267	3.163	–	–	–	–
Furniture and Others	–	–	0.110	3.144	–	–	–	–	–	–
Shipment Value ($) (Base: Value >5000)										
Value ≤ 300	–	–	0.899	17.399	–	–	–	–	–	–
300 < Value ≤ 1000	–	–	0.745	14.071	–	–	–	–	–	–
1000 < Value ≤ 5000	–	–	0.435	9.717	–	–	–	–	–	–
Transportation Network and O-D Attributes										
Origin Highway Density (mi/mi^2)	–	–	–	–	–	–	0.500	4.142	–	–
Density of Railway at Origin (mi/mi^2)	–	–	–	–	-0.088	-2.855	–	–	–	
Density of Railway at Destination (mi/mi^2)	–	–	-0.020	-2.112	–	–	–	–	–	–
Destination Population Density (10 pop/mi^2)	–	–	–	–	0.002	2.661	0.001	3.195	–	
No. of Inter-Modal Facility at Destination	–	–	-0.001	-1.743	–	–	–	–	–	–
No. of Warehouse and Super Center at Origin	–	–	–	–	–	–	0.001	2.784	–	–
Density of Whole Sale Industry at Origin (per mi^2)	–	–	–	–	–	–	-0.091	-4.386	–	–
Percentage of Population below Poverty Level at Origin	–	–	–	–	-4.006	-3.808	–	–	–	–

[1] – = variable insignificant at 90 percent confidence level

Table 5.2 (b): Copula OL (Shipment Size) Model Estimation Results

Explanatory Variables	For-hire truck		Private Truck		Air		Parcel/Courier		Other	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Thresholds										
Threshold 1	-6.279	-28.075	-5.789	-39.179	-3.823	-8.563	-0.706	-4.665	-5.624	-2.841
Threshold 2	-4.796	-24.398	-4.235	-31.818	–[1]	–	–	–	-2.979	-3.171
Threshold 3	-3.029	-17.646	-2.704	-22.587	–	–	–	–	–	–
Threshold 4	-1.780	-11.045	-1.656	-15.220	–	–	–	–	–	–
Threshold 5	-0.442	-2.728	-0.641	-6.201	–	–	–	–	–	–
Threshold 6	0.850	4.767	-0.028	-0.258	–	–	–	–	–	–
Freight Characteristics										
Hazardous Material (Base: Not Hazardous)										
Non-flammable Liquid and Other Hazardous Material	0.946	2.647	–	–	–	–	–	–	–	–
Temperature Controlled (Base: No)										
Yes	–	–	–	–	–	–	-0.853	-2.883	–	–
SCTG Commodity Type (Base: Wood, Papers and Textile)										
Raw Food	0.505	2.024	0.309	2.741	–	–	–	–	–	–
Prepared Food and Products	0.853	4.875	0.276	2.654	–	–	0.554	2.011	–	–
Stone & Non-Metallic Minerals	3.127	9.884	4.443	21.490	–	–	–	–	–	–
Petroleum and Coals	1.675	6.126	0.317	2.757	–	–	–	–	–	–
Chemicals	–	–	-0.167	-1.899	–	–	–	–	–	–
Metals and Machinery	–	–	–	–	–	–	-0.407	-3.887	–	–

Explanatory Variables	For-hire truck		Private Truck		Air		Parcel/Courier		Other	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Electronics	-1.107	-8.001	-0.376	-2.859	-0.639	-2.226	-1.027	-10.189	–	–
Furniture and Others	–	–	-0.349	-3.676	–	–	-0.406	-3.818	–	–
Shipment Value ($) (Base:Value >5000)										
Value ≤ 300	-3.678	-11.895	-4.344	-31.332	-1.585	-3.740	-2.484	-17.023	-5.210	-2.131
300 < Value ≤ 1000	-2.929	-13.233	-3.185	-25.294	-1.169	-2.819	-0.874	-6.129	-3.393	-1.855
1000 < Value ≤ 5000	-2.100	-15.030	-1.807	-16.824	-1.136	-2.805	-0.424	-2.939	–	–
Transportation Network and O-D Attributes										
Mean Household Income at Origin ($) (Base: ≥ $50,000)										
< $50,000	–	–	–	–	–	–	0.346	2.233	–	–
Density of Employees in Mining Industry at Origin (per mi^2)	1.100	3.240	–	–	–	–	–	–	–	–
Density of Management Company and Enterprise at Destination (per mi^2)	–	–	-1.010	-2.959	–	–	–	–	–	–
Density of Wholesale Industries at Destination (per mi^2)	–	–	–	–	–	–	-0.094	-2.561	–	–
Density of Highway at Destination (mi/mi^2)	–	–	0.617	2.867	–	–	–	–	–	–
Density of Bridges at Destination (per mi^2)	-0.314	-1.896	–	–	–	–	–	–	–	–
Origin Avg. Temperature (Base: Warm; > 60^0 F)										
Cold; <= 60^0 F	-0.353	-3.425	–	–	–	–	–	–	–	–
No. of seaports at	–	–	–	–	–	–	-0.001	-3.499	–	–

Explanatory Variables	For-hire truck		Private Truck		Air		Parcel/Courier		Other	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Origin										
Routed Distance Between O-D (miles)	-0.001	-8.086	–	–	–	–	–	–	–	–
Copula Parameters										
Copula	Frank		Frank		Frank		Joe			
Correlation Parameters	-1.862	-4.047	-18.615	-8.804	-27.518	-2.580	1.351	5.652	0	–
Raw Food	3.864	3.734	–	–	–	–	–	–	–	–
Stone & Non-Metallic Minerals	13.362	6.866	–	–	–	–	–	–	–	–
Metals and Machinery	–	–	8.773	4.236	–	–	–	–	–	–
Shipment Value ≤ \$300	-6.079	-3.823	–	–	–	–	–	–	–	–
\$300 < Shipment Value ≤ \$1000	-3.090	-3.391	–	–	–	–	–	–	–	–
Export	–	–	–	–	–	–	-0.8539	-3.420	–	–
No. of Parameters	98									
Log-likelihood at Convergence	-12405.40									

[1] – = variable insignificant at 90 percent confidence level

Table 5. 3: Prediction Comparison (Validation Sample)

Summary statistics	**RRM based MNL-OL Copula with Parametrization (Frank-Frank-Frank-Joe-Independent)**	**RUM based MNL-OL Copula with Parameterization (Frank-Frank-Frank-Joe-Independent)**	**RRM based MNL-OL Independent Copula**	**RUM based MNL-OL Independent Copula**
No. of parameters	98	98	99	99
Log-likelihood at constants	-7790.63	-7790.63	-7790.63	-7790.63
Predictive log-likelihood	**-6189.38**	-6197.95	-6364.32	-6378.69
BIC	**13099.55**	13116.68	13456.78	13485.53
Predictive Log-likelihood at Variable Specific Level				
Freight Characteristics	**RRM based MNL-OL Copula (Frank-Frank-Frank-Joe-Independent)**	**RUM based MNL-OL Copula (Frank-Frank-Frank-Joe-Independent)**	**RRM based MNL-OL Independent Copula**	**RUM based MNL-OL Independent Copula**
Flammable liquid	-149.64	-150.43	**-149.46**	-149.79
Non-flammable liquid and other hazardous material	**-231.23**	-231.26	-239.23	-239.76
Temperature controlled products	**-380.78**	-381.10	-391.23	-392.90
Export	-250.12	-248.85	**-247.11**	-252.69
Raw food	**-205.08**	-205.26	-209.01	-208.57
Prepared food and products	**-395.25**	-395.44	-410.33	-410.26
Stone and non-metallic minerals	-203.48	-203.41	-202.61	**-202.57**
Petroleum and coals	**-297.80**	-298.43	-302.32	-302.18
Chemicals	**-849.81**	-852.97	-884.40	-889.21
Metals and machinery	**-1345.29**	-1347.29	-1382.86	-1384.44
Electronics	-921.78	**-920.83**	-948.91	-955.81
Furniture and others	**-910.42**	-913.14	-938.63	-940.68

CHAPTER SIX: A JOINT DECISION OF MODE AND SHIPMENT SIZE CHOICE BEHAVIOR IN FREIGHT TRANSPORTATION USING SEQUENTIAL MODEL FRAMEWORK

Introduction

The volume of freight transportation has grown significantly in last few decades in USA. The tons of domestic, export and import freight flow grew almost 18 percent between 1998 and 2015 and is expected to increase by almost 40 percent from 2015 to 2045 (Freight Facts and Figures, 2017). The highly developed transportation system in USA facilitates the urban goods movement, domestic freight flow and international supply chains and logistics. In recent years, with increasing popularity of e-commerce and internet based shopping, the traditional freight flow is gradually shifting towards smaller size freight movement. With the growing freight movement, the existing congested highways are already facing enormous pressure due to increasing movement of trucks. In 2013 the total number of registered public and private trucks was almost 133 million in USA, which was almost 50 percent greater than the total number of trucks in 2000 (U.S. Highway Statistics, FHWA, 2017). Therefore it is important to maintain and improve an efficient and effective freight transportation system to meet the increased demand of the projected population growth.

In freight transportation planning, decisions of mode and shipment size choice are two very critical issues. Traditionally, shipment size has been used as an exogenous variables in estimating mode choice models (Abdel Wahab and Sayed, 1999; Jiang et. al., 1999; Sayed and Razavi, 2000 and Norojono and Young, 2003). But, existing literature review infers that these two logistic decision are mutually correlated and should be studied together. The most common approach used in the mode choice analysis part of joint decision studies is traditional

Multinomial Logit (MNL) logit model considering mode as discrete variable. For shipment size choice analysis part of the joint decision Linear Regression model has been used mostly considering shipment size it as a continuous variable. Though MNL models are easily interpretable, yet due to the assumption that distribution of error term is same across all alternatives, classical MNL can lead to bias estimation and prediction. To overcome this limitation few studies estimated Nested Logit (NL) models (de Jong and Ben-Akiva, 2007; de Jong and Johnson, 2009; Habibi, 2010; Windisch et. al., 2010; Stinsosn et. al., 2017). To capture the random taste variation due to unobserved factors across individuals Mixed MNL model is used by several researches in freight mode choice studies (de Jong and Ben-Akiva, 2007; Abate and de Jong, 2014), as classical logit models can not accommodate this effect. More recently, a random regret minimization based decision rule has been used by Irannezhad et. al., 2017 in mode choice analysis of the joint decision of mode and shipment size choice study. This decision rule allows for pairwise alternative attribute comparison and is semi-compensatory. Whereas, the mostly used utility maximization rule is compensatory and decision maker's decision is made upon the performance of the considered alternative only assuming the utility of the chosen alternative is not affected by other alternatives and their features. Though, most of the studies analyzed the joint decision of mode and shipment size choice using MNL, NL or some advanced forms of MNL, few studies adopted copula based system introduced by Bhat and Eluru (2009) in analyzing the joint decision (Pourabdollahi et al., 2013a; Pourabdollahi et al., 2013b; Irannezhad et al., 2017). The copula based structure can capture the influence of common unobserved factors affecting the two choice decisions. But, in this process the information of one choice in not directly considered in another choice decision. Recently, an alternative approach has been recognized by Chakour and Eluru (2014), where they assumed that decision maker tends to make joint decision in a sequence. They proposed a latent segmentation based approach which determines probabilistic assignment of the individual as the true sequence of choices is unknown to analyst.

While it is beneficial to analyze a copula based joint model system in the form of an unordered choice model for mode and an ordered choice model for shipment size. Alternatively, this simultaneous decision of mode choice and shipment size decision can be analyzed based on a sequential approach developed by Chakour and Eluru (2014). Hence, we will compare the performance of the joint assumption based copula model with a sequence based model. It is important to note that for the two choices under consideration, two unique sequences are possible. Also, the sequence of choices made by the shippers is unknown to analyst. For this purpose a latent segmentation based approach is developed, where in Segment 1 a random utility (RU) maximization based multinomial logit (MNL) model is established for shipment mode and an ordered logit model is established for shipment size and; and vice versa in Segment 2. In our study we used the freight flows only within Alabama, Florida, Georgia, North Carolina, South Carolina and Tennessee, as the percentage share of shipment flow within these states by shipment weight is more than 50 percent, while inbound and outbound share of shipment weight is 26.45 percent and 18.62 percent respectively. Among all the 50 states of USA, Florida, Georgia, North Carolina, South Carolina and Tennessee are in the top 20 densely populated states, while Florida is at number 8 with population density 375.9 per square mile (https://state.1keydata.com/state-population-density.php). Among these states Alabama, Florida and Georgia have some major sea ports which handles enormous amount of freight each year. In 2013, the Port of Mobile in Alabama ranked 13 among top 100 sea ports in USA where almost 54 million tons of freights were traded ("U.S. Port Ranking By Cargo Volume". American

Association of Port Authorities, 2013). In 2014, among these six states Florida contributed highest (4.9%) in national economy of US followed by Georgia (2.8%) and North Carolina (2.8%) (https://blogs.voanews.com/all-about-america/2015/09/18/heres-how-much-each-state-contributes-to-us-economy/). Florida ranked 4 in contribution to USA economy among all 50 states. Tourism is the largest industry of Florida followed by agriculture. Alabama's major economical source is crop and animal production and heavy industries, which includes automobile manufacturing, mineral extraction, steel production and fabrication. Along with agricultural industry Georgia also includes mineral industry. Tobacco and Cotton are the major types of agricultural products produced by North Carolina, South Carolina and Tennessee. Crushed stones are the mostly valuable mine product of North Carolina. In terms of mode share, from Figure 6.1 we can observe that the weighted share of hire and private truck is higher in these regions, whereas, weighted share of parcel mode is lower compared to the mode share of entire USA. Hire and private trucks comprise almost 62 percent of total mode share in these regions. Also, weighted share of air mode in these regions is almost half compared to the entire USA as it is not reasonable to ship a product by an expensive mode in shorter distance. On the other hand, Figure 6.2 depicts that weighted share of shipment size is higher within these regions compared to entire USA for all the categories except when shipment size is less than or equal to 30 lbs. Also, the shipment size within these regions is reasonably distributed among all seven categories. Therefore, the evidences described above reflect that investigation of mode and shipment size choice decisions within these states may provide interesting insights in freight transportation behaviors.

The rest of chapter is organized as follows. The second contains the details of econometric framework used in the analysis followed by the model estimation result and model validation. Finally the last section concludes the paper with some future directions.

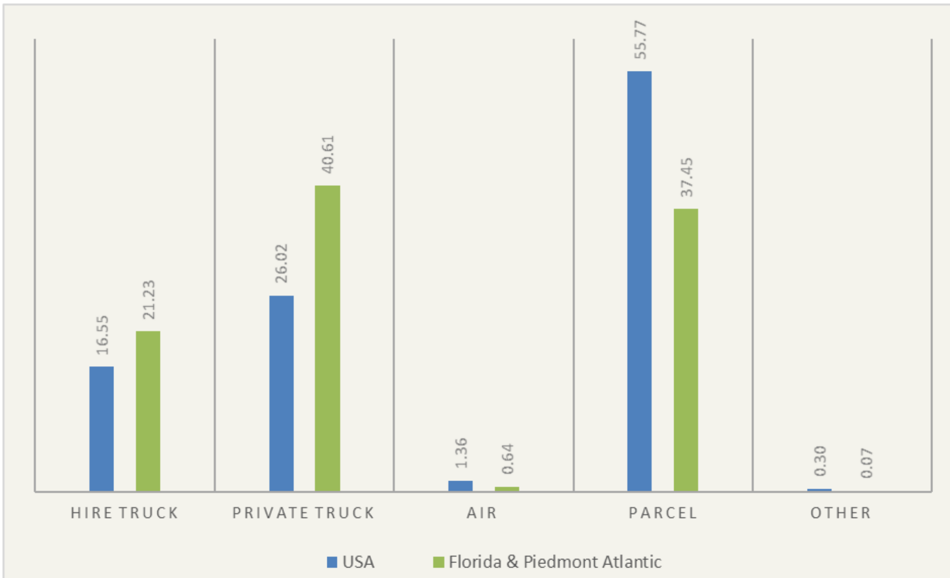

Figure 6. 1 Weighted Mode Share (%) Comparison of USA Vs. Florida and Piedmont Atlantic Region

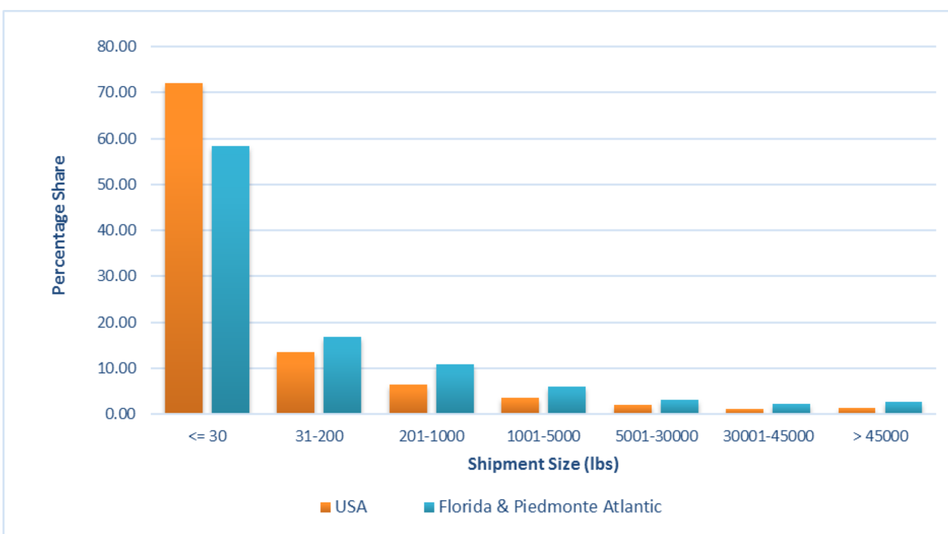

Figure 6. 2 Weighted Shipment Size (%) Distribution of USA Vs. Florida and Piedmont Atlantic Region

Econometric Model Framework

The simultaneous decision of mode choice and shipment size choice can be analyzed based on a sequence method where the decisions are considered in a sequence. It is important to note that for the two choices under consideration, two unique sequences are possible. The analyst does not observe the order of decision made by the shipper. Hence, we consider a latent segmentation based probabilistic approach that accommodates for the two sequences in a unified model with two segments and assigns the decision maker or the shipper in any of the two segments as a function of multivariate characteristics. In our analysis, in the first segment, mode is chosen first and then shipment size; in the second segment shipment size is chosen first and then the mode.

This modelling approach includes three components: (1) latent segmentation component, (2) mode choice component for each segment, and (3) shipment size component for each segment. In our study the first component embodies basically a binary logit model, while the second component represents multinomial logit model (random utility maximization based) and the third one represents ordered logit model. Let us assume, q be the index for segments $(q = 1 \; and \; 2)$, i be the index of the shipper $(i = 1,2, \ldots, I)$, m be the index for mode alternatives $(m = 1,2, \ldots, M)$ characterized by k attributes $(k = 1,2, \ldots, K)$, and s be the index for shipment size $(s = 1,2, \ldots, S)$ characterized by l attributes $(l = 1,2, \ldots, L)$. Considering the RU principle, the latent segmentation probability (P_{ims}) for joint choice of mode m and shipment size s can be written as:

$$P_{ims} = P_{i1} P_{i1m} P_{i1s} + P_{i2} P_{i2s} P_{i2m} \tag{6.1}$$

where P_{i1} and P_{i2} represent the probability of choosing segment 1 and segment 2 by the qth shipper respectively; P_{i1m}, P_{i2m} represent the probability of choosing mode m in segment 1 and segment 2 respectively, and P_{i1s}, P_{i2s} represent the probability of choosing shipment size s in segment 1 and segment 2 respectively. In this equation, the first term represents the first sequence-mode first and shipment size second, while the second term represents the second sequence-shipment size first and mode second. Segmentation probability is modeled using MNL models. So, following the RU decision rule, the segmentation probability (P_{iq}) can be expressed as:

$$P_{iq} = \frac{exp(\beta_q' x_{iq})}{\sum_{q=1,2} exp(\beta_q' x_{iq})} \tag{6.2}$$

where x_{iq} is a vector of features influencing the choice of segment, and β_q' is the vector of corresponding coefficients of the parameters to be estimated.

Following the RU decision rule and using the notation mentioned above, the choice probability for mode choice model in each segment takes the following form:

$$P_{iqm} = \frac{exp(\gamma_i' x_{iqm})}{\sum_{m=1}^{M} exp(\gamma_i' x_{iqm})} \tag{6.3}$$

We considered the shipment size to be an ordered variable. For the first segment when shipment mode is already chosen then the ordered logit model for shipment size should be mode specific. Considering a standard logistic distributed error term (ζ_{ni}), the probability of shipper i choosing shipment size s for mode m can be expressed as:

$$P_{i1s} = \Lambda_m(\tau_{m,s} - \alpha_m z_{im}) - \Lambda_m(\tau_{m,s-1} - \alpha_m z_{im}) \tag{6.4}$$

For the second segment the mode is not known when the decision of shipment size is made. Therefore, the probability expression for shipper i choosing shipment size s takes the following form:

$$P_{i2s}(y_i = s) = \Lambda\,(\tau_s - \alpha x_i) - \Lambda(\tau_{s-1} - \alpha x_i) \tag{6.5}$$

where, $\Lambda(.)$ is the standard logistic cumulative distribution function, τ_s denotes the thresholds associated with the shipment size s and α is the unknown parameter to be estimated associated with exogenous variables. Note that the attributes associated with equation (6.2), (6.3) (6.4) and (6.5) includes the information available to the shipper at that instant in the choice process. For example, when mode choice decision is made first then the LOS attributes are unavailable to the chosen shipment size by the chosen mode in the model. Also, the choice alternative of the first model in each segment can be used as an input variable in the second model.

Now, the log-likelihood at the individual shipper level i can be expressed as follows:

$$L_i = \delta_{ms} * \ln(P_{ims}) \tag{6.6}$$

where δ_{ms} = 1 if the mode and shipment size combination is the chosen alternative and 0 otherwise.

$$L = \sum_{i=1}^{I} L_i \tag{6.7}$$

The log-likelihood function is constructed based on above probability expressions and all the co-efficient parameters in the models are estimated by maximizing the log-likelihood function. The models are programmed in GAUSS matrix programming language.

Empirical Analysis

In the latent segmentation part freight characteristics have been used to estimate the model. In the mode choice and shipment size model estimation variables were used considering the sequence of choice decisions. The variables significant at 80 percent confidence interval have been retained in the model estimation process and hence only the impacts of these variables have been discussed in this section.

Model Fit

In this analysis at first we estimated copula based joint mode choice and shipment size model considering random utility based multinomial logit (MNL) model for mode choice part and mode specific ordered logit model for shipment size part. Six different copula structure have been considered in this study – FGM, Frank, Clayton, Gumbel, Gaussian and Joe. For Clayton and Gaussian copula no significant copula parameter was found. Then we estimated model using different dependency structure. For example Frank copula for hire and private truck and Joe copula for parcel mode. No copula parameter was found significant for air mode. Therefore, copula for air mode was set to independence. Then we employed the alternative decision rule and estimated Mode-Shipment Size sequence (MS) model, Shipment Size-Mode (SM) sequence model and Latent segmentation based sequence model.

To evaluate the performance of the models we calculated Bayesian Information Criterion (BIC) as the models are not nested. The BIC value for a given empirical model can be calculated as: $[-\ 2\ (LL)\ +\ K\ ln\ (Q)]$, where LL is the log-likelihood value at convergence, K is the number of parameters and Q is the number of observations. The model with the lowest BIC value is the preferred model. Table 6.1 represents the BIC value of different models estimated. From the table we can see that Frank-Frank-Joe copula outperforms the latent segmentation model. As the result of the copula is similar as described in Chapter Five, in this chapter we will discuss about the result obtained from latent segmentation based sequence model only.

Latent Segmentation Shares Analysis

Prior to evaluating the impacts of various parameters on segmentation and mode-shipment size decisions, it is important to discuss the overall aggregate share of the two segments to have a better behavioral understanding of the two segments. From Table 6.2 we can observe that approximately 79.29 percent of the shippers are likely to be in MS segment, while the probability of shippers belonging to SM segment is around 20.71 percent only. As the population share for MS and SM segments is significant, therefore careful consideration in needed for policy analysis. The table also depicts the mode share within each segment. We can observe that when mode is chosen first and shipment size is not known to the shipper then the mode share is highest for parcel mode (54.30%) followed by private truck (27.14%) and hire truck (18.18%). But when shipment size known to the decision maker then the mode share changes significantly. The share of private truck, hire truck and air mode increases, while share of parcel mode decreases substantially.

Model Results

Sequence Choice Component

The latent segmentation component determines the probability of a shipper to be in one of the two choice segments. In our analysis we considered mode first – shipment size second segment as the base segment and used freight characteristics as segmentation variables. Table 6.3 (a) illustrates some interesting result. When shipment value is greater than $1,000 shippers have inclination in choosing mode first and shipment size second. When the commodity is hazardous material or temperature controlled products then probability of choosing shipment size first and mode second is higher. The reason is probably these type of shipments require special handling and transporting care and shipping smaller or larger amount might cost the same. Therefore, it would be more reasonable to decide on the amount to be shipped first and then the mode. Also, when the commodity is stone and non-metallic minerals or wood, paper and textiles probability of choosing mode first and shipment size second increases.

Mode-Shipment Size Segment

Table 6.3 (b) and 6.3 (c) illustrates the result of mode-shipment size segment. When mode in chosen first, shipment size is not known to the decision maker. Therefore, we did not introduce shipping cost variable in the mode choice part. Shipping time variable negatively impacts the mode choice which is intuitive. As shipper wants to deliver the freight faster, therefore, probability of choosing a particular mode decreases when shipping time increases. When the number of warehouse and supercenter increases at origin probability of choosing private truck increases. The reason may be warehouse and super centers are the storage and distribution center, hence private truck are more likely to be chosen to carry the freight in the closer proximity. Also when the mean household income at destination is less than $50,000 at destination, average temperature at origin is less than 60^0F and population density at origin increases then private truck is more likely to be chosen. With increasing number of parking spot in rest area at destination the probability of choosing hire truck increases. The reason may be, being larger vehicles trucks need special parking location including loading-unloading area. Also truck drivers requires break time according to Federal Motor Carrier Safety Administration (FMCSA). Therefore, if the rest area along with adequate parking spaces are available at the destination, then the probability of choosing hire truck increases. But, probability of choosing private truck decreases when density of intermodal connectors at origin increases.

When mode is chosen first, shipment size analysis is performed specific to mode. Column two to column nine of table 6.3(c) represents the mode specific OL model result for shipment size choice. For hire truck propensity of choosing larger shipment size decreases when average temperature at origin is less than 60^0F and destination is urban area. Urban area usually is more congested having restriction in heavy vehicle movement and also there is not enough spaces for heavy vehicle parking and loading-unloading area. Therefore, it is less likely to choose larger shipment size when destination is urban area. On the other hand propensity of choosing larger shipment increases when manufacturing industry is the major industry type at origin and proportion of employees to the population of age between 15 to 65 years increases at destination. As manufacturing industries produces bulk amount of product therefore it is more likely to ship larger shipment by hire truck. For private truck propensity of choosing larger shipment weight increases when number of truck parking location at destination increases. But, when density of intermodal connectors at destination increases and commodity type is electronics then the propensity of choosing smaller size shipment increases. For air mode propensity of choosing larger size shipment decreases when shipment value is less than $300. Electronic products are usually light weight and parcel mode has weight restriction. Therefore, for parcel mode when commodity type is electronics then propensity of choosing smaller size shipment increases. Propensity of choosing larger size shipment increases for parcel mode when ratio of primary highway freight system (PHFS) length to total roadway length at origin increases.

Shipment Size-Mode Segment

In this segment shipment size is chosen first and mode second. In this segment we did not estimate mode specific OL model for shipment size as the mode is not known while the decision of shipment size is taken. We considered seven shipment size categories similar to the shipment size categories for hire and private truck described in Chapter three and considered all modes together. The results of OL model for shipment size choice first are represented in the last two columns of Table 6.3(c). Please note that the threshold value of this model was fixed to the value obtained from the threshold only OL model to avoid the complication in model estimation procedure. The result shows that propensity of choosing larger size shipment decreases when the product is electronics. The reason may be electronic products are light weight, costly and requires special care to prevent any damage due to shock while transporting. Also origin cold states with average annual temperature less than or equal to 60^0F reduces propensity for large shipments. The number of truck parking location at destination and ratio of the length of other interstates portions not on PHFS to total roadway length at origin increases propensity of choosing larger size shipment.

The fourth and fifth column of Table 6.3(b) represents the mode choice analysis result when mode is chosen first. As the shipment size is already known the impact of shipping cost is estimated in the model and it has a negative effect on the mode choice which is reasonable. When the average temperature at origin is less than 60^0F at origin and the origin is colder area then probability of choosing private truck increases. On the other hand, with increasing density of intermodal connectors at origin probability of choosing private truck decreases. In this segment, since shippers have made their decision regarding the shipment size, we can estimate coefficients for shipment size categories. From the table we can illustrate that when shipment size is less than 200lbs probability of choosing private truck decreases. The reason is trucks are usually used for shipping bulk amount of products. On the other hand, air mode is more likely to be chosen when shipment weight is less than 30 lbs. Air mode is expensive and also it has weight limitation. Therefore the result shows intuitive interpretation.

Summary

In this chapter we proposed an alternative methodology to investigate the joint decision of mode-shipment size choice. We analyzed copula based joint model in the form of MNL model for mode choice and ordered logit model for shipment size choice. Alternatively, this simultaneous decision of mode choice and shipment size decision is also analyzed based on a sequential approach. In this approach two unique sequence has been considered: mode is chosen first and shipment size second; and shipment size is chosen first and mode second. Also, the sequence of choices made by the shippers is unknown to analyst. For this purpose a latent segmentation based approach is developed, where in Segment 1 a random utility (RU) maximization based multinomial logit (MNL) model is established for shipment mode and an ordered logit model is established for shipment size and; and vice versa in Segment 2. In our study we used the freight flows only within Alabama, Florida, Georgia, North Carolina, South Carolina and Tennessee considering hire truck, private truck, air and parcel mode. The model analysis results provide interesting insights in freight transportation behavior. The Frank-Frank-Joe copula model outperformed the latent segmentation based sequence model. As our objective of this study was to evaluate the joint decision of mode and shipment size choice in a sequential framework, in this chapter we discussed about the results obtained from the latent segmentation based sequence model. The result indicates that shippers are more likely to choose mode first and shipment second. The mode share within the segments are significantly different depending on the mode choice decision is made first or second. When mode choice decision is made second and shipment size is already chosen then probability of choosing private truck decreases, but probability of choosing air mode increases when shipment size is smaller. Also the freight characteristics and origin-destination demographic and transportation network attributes impact reasonably the propensity of choosing shipment size. The findings from the model analysis indicate the requirement of a careful consideration of the choice decision in policy analysis.

Table 6. 1: Model Performance Evaluation

Model	Log-likelihood at convergence (ln(L))	No. of Parameters	No. of observation	BIC
Shipment Size First-Mode Second Sequence Model	-15652.77	41	7805	31673.01
Mode First-Shipment Size second Sequence Model	-14202.13	70	7805	29031.64
Independent Copula	-14202.13	70	7805	29031.64
Latent Segmentation Based Sequence Model	-14116.68	59	7805	28762.13
Frank-Frank-Joe Copula	-13262.49	66	7805	**27116.51**

Table 6. 2: Segmentation Characteristics

	Mode-Shipment Size Segment (%)	Shipment Size-Mode Segment (%)
Segment Shares	79.29	20.71
Mode Share		
Modes	**Mode-Shipment Size Segment (%)**	**Shipment Size-Mode Segment (%)**
Hire Truck	18.18	23.56
Private Truck	27.14	74.32
Air	0.37	1.93
Parcel	54.30	0.19

Table 6.3 (a): Latent Segmentation Based Mode-Shipment Size Choice Model Results: Sequence Choice Results

Variables	Sequence Choice			
	Mode First-Shipment Size Second (MS)		Shipment Size First-Mode Second (SM)	
	Co-efficient	t-stat	Co-efficient	t-stat
Constant	0.716	17.829	-	-
Freight Characteristics				
Shipment Value				
$1,001-$5,000	1.429	12.266	-	-
> $5,000	2.925	14.475	-	-
Temperature Controlled Products	-0.540	-3.500	-	-
Hazardous Material	-0.391	-2.747	-	-
SCTG Commodity Type				
Stone and Non-Metallic Minerals	5.968	2.718	-	-
Wood Papers and Textiles	0.721	7.359	-	-

Table 6.3 (b): Latent Segmentation Based Mode-Shipment Size Choice Model Results: Mode Choice Results

Variables	First (Mode-Destination Sequence)		Second (Destination-Mode Sequence)	
	Co-efficient	t-stat	Co-efficient	t-stat
Alternative Specific Constants				
Private Truck	-0.007	-0.066	7.190	1.680
Air	-3.102	-10.012	-2.767	-8.916
Parcel Mode	13.716	4.440	-13.778	-0.080
Level of Service Variables				
Shipping Cost ($1000)	-	-	-3.0469	-1.744
Shipping Time (100 hrs)	-3.578	-2.114	-	-
Freight Characteristics				
Shipment Size: <= 200 lbs				
Private Truck	-	-	-5.9192	-1.384
Shipment Size: <= 30 lbs				
Air	-	-	0.6038	1.576
Transportation Network & Demographic Variables				
No. of Warehouse and Superstores at Origin (per sqmi)				
Private Truck	0.081	2.307	-	-
Mean Household Income at Destination: < $50,000				
Private Truck	0.164	1.560	-	-

Average Temperature at Origin: < 60F				
Private Truck	0.623	5.818	0.2297	1.411
No. of Parking Spot in Rest Area at Destination				
Hire Truck	0.097	2.621	-	-
Population Density at Origin (per sqmi)				
Private Truck	0.003	3.665	-	-
Density of Intermodal Connectors at Origin (mi/sqmi)				
Private Truck	-6.887	-3.754	-4.8871	-2.066

Table 6.3 (c): Latent Segmentation Based Mode-Shipment Size Choice Model Results: Shipment Size Choice Results

Explanatory Variables	Second (Mode-Shipment Size)								First (Shipment Size-Mode)	
	For-hire truck		Private Truck		Air		Parcel/Courier		Other	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Thresholds										
Threshold 1	-9.705	-0.847	-9.789	-2.949	-5.597	-1.354	1.623	10.724	-0.478	-
Threshold 2	-2.076	-2.908	-4.389	-10.000	-	-	-	-	0.224	-
Threshold 3	0.592	0.971	-0.694	-5.997	-	-	-	-	0.693	-
Threshold 4	1.541	2.532	0.310	2.739	-	-	-	-	1.150	-
Threshold 5	2.592	4.239	1.334	11.389	-	-	-	-	1.823	-
Threshold 6	3.570	5.797	2.336	18.195	-	-	-	-	2.626	-
Freight Characteristics										
SCTG Commodity Type: Electronics	-	-	-1.301	-4.871	-	-	-0.555	-4.884	-1.143	-8.069
Shipment Value: < $300	-	-	-	-	-6.280	-1.221	-	-	-	-
Transportation Network & Demographic Variables										
Average Temperature at Origin: < 60F	-0.361	-2.203	-	-	-	-	-	-	-0.289	-2.393
Destination is Urban Area	-0.845	-5.441	-	-	-	-	-	-	-	-
Major Industry Type at Origin : Manufacturing Industry	0.439	2.947	-	-	-	-	-	-	-	-
Proportion of employees to the population of age between 15 to 65 years at	5.357	4.044	-	-	-	-	-	-	-	-

Explanatory Variables	Second (Mode-Shipment Size)								First (Shipment Size-Mode)	
	For-hire truck		Private Truck		Air		Parcel/Courier		Other	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Destination										
No. of Truck Parking Location at Destination	-	-	3.561	4.504	-	-	-	-	5.033	7.894
Density of Intermodal Connectors at Destination (mi/sqmi)	-	-	-10.001	-1.898	-	-	-	-	-	-
Ratio of PHFS to Total Roadway Length at Origin	-	-	-	-	-	-	4.758	2.992	-	-
Ratio of NPHFS to Total Roadway Length at Origin	-	-	-	-	-	-	-	-	7.597	1.379

CHAPTER SEVEN: A SEQUENTIAL DECISION OF MODE AND DESTINATION CHOICE IN FREIGHT TRANSPORTATION

Introduction

The choice of destination in the context of freight transportation behaviour is also a vital issue. Based on the spatial and economic attributes of an area the demand of freight varies. Orientation of urban infrastructure, such as, distribution centers, number of warehouse and storages, shop location determines the freight demand. For instance, an industrial area might attract more raw materials and the urban areas or market places would have more demand of finished products. Therefore, demands at destination determine the sales of the products. Also, the transportation facilities, such as, roadway or parking pricing, loading/unloading area at destination would also have impact on mode choice decision. Suppliers or freight carriers always try to maximize their profit by minimizing the transportation cost. Therefore, to fulfill the demand of the destination and at the same time to make the most of the profit the decision of mode and destination choice are more logical to be made simultaneously. But, all the modes cannot be chosen for all destination area. For example, choosing ship or rail as a shipping mode where there is no port or rail yard is not rational. The above discussion surely emphasises the importance of investigating the connection between shipping mode and destination choice. Here, two sequences are possible for the two choices under consideration – shipping mode and shipment destination. As the analyst does not observe the sequence for the shipper, we consider a probabilistic approach that accommodates for the two sequences in a unified model with two segments. In the first segment, shipment destination is chosen first and then the mode; in the second segment mode is chosen first and then shipment destination. The earlier studies described in chapter two clearly shows that in the field of freight transportation the mode and destination choice have not been analyzed together, whereas this decision process can have significant impact on a regions transportation system. Therefore, the objective of this chapter is to explore the joint decision of mode choice and destination of shipment in a sequential form under the same motivational paradigms.

The rest of the chapter is organized as follows: the next section describes econometric framework of model used in this study. The section after that represents the model results and the last section concludes the chapter.

Econometric Model Framework

The proposed modeling approach consists of three components: (1) latent segmentation component, (2) Mode choice component for each segment and (3) Destination choice component for each segment. The first component represents a binary logit model and the latter two components are two multinomial logit models (see Waddell et al., 2007 for a similar approach).

Let i be the index for shippers (i = 1, 2, ...,I) and q be the index for segment (q = 1 or 2), m be the index for mode choice alternative (m = 1, 2…M), and d be the index for station alternative (d = 1, 2…D). With this symbolization, the random utility formulation takes the following form:

$$u_{iq}^{*} = \alpha_q{}' x_{iq} + \varepsilon_{iq} \tag{7.1}$$

$$u_{iqm}^{*} = \beta_q{}' x_{iqm} + \varepsilon_{iqm} \tag{7.2}$$

$$u_{iqd}^{*} = \gamma_q{}' x_{iqd} + \varepsilon_{iqd} \tag{7.3}$$

where u_{iq}^{*} denotes the utility obtained by the i^{th} shipper in selecting the q^{th} segment, u_{iqm}^{*} denotes the utility obtained by choosing mode alternative m in the q^{th} segment, and u_{iqd}^{*} denotes the utility obtained by choosing destination alternative d in the q^{th} segment. x_{iq}, x_{iqm}, x_{iqd} are column vector of attributes which influence the choice framework. ε_{iq}, ε_{iqm} and ε_{iqd} are assumed to follow Type 1 Gumbel distribution. The shipper i will choose the alternative that offers the highest utility. $\alpha, \beta_q, \gamma_q$ are corresponding coefficient column vectors of parameters to be estimated. The second model in each segment is conditional on the first model in the segment. x_{iqm}, x_{iqd} incorporate the information available to the shipper at that instant in the choice process. For example, if the mode choice is the first alternative, level of service attributes to the chosen destination by the chosen mode are unavailable in the model.

The probability expression for each model component takes the usual multinomial logit form given by:

$$P_{iq} = \frac{\exp(\alpha_q{}' x_{iq})}{\sum_{q=1,2} \exp(\alpha_q{}' x_{iq})} \tag{7.4}$$

$$P_{iqm} = \frac{\exp(\beta_q{}' x_{iqm})}{\sum_{m=1}^{M} \exp(\beta_q{}' x_{iqm})} \tag{7.5}$$

$$P_{iqd} = \frac{\exp(\gamma_q{}' x_{iqd})}{\sum_{d=1}^{D} \exp(\gamma_q{}' x_{iqd})} \tag{7.6}$$

With these preliminaries, the latent segmentation based probability for joint choice of mode m and destination d with two segments can be formulated as follows:

$$P_{imd} = P_{i1} P_{i1m} P_{i1d} + P_{i2} P_{i2d} P_{i2m} \tag{7.7}$$

The first term in Equation (7.7) reflects the first sequence - mode first and destination second while the second term reflects the second sequence - destination first and mode second.

The exogenous variables in the second choice are generated while recognizing the chosen alternative attributes from the first choice process in the segment.

The log-likelihood at the individual q is defined as:

$$L_q = \delta_{md} * \ln(P_{imd}) \quad (7.8)$$

where δ_{md}= 1 if the mode and destination combination is the chosen alternative and 0 otherwise.

$$L = \sum_q Lq \quad (7.9)$$

The log-likelihood function is constructed based on the above probability expression, and maximum likelihood estimation is employed to estimate the $\alpha_q, \beta_q, \gamma_q$ parameters. The model is programmed in GAUSS matrix programming language.

Empirical Analysis

Freight characteristics are used for estimation of latent segmentation sequence choice. For mode choice and destination choice model estimation variables were carefully chosen corresponding to the sequence under consideration. The variables which are significant at 80 percent confidence interval have been retained in the model estimation process. Hence, in this section only the impact of these variables have been discussed.

Model Fit

As the models are not nested within each other, we have calculated the Bayesian Information Criterion (BIC) for separate mode-destination (MD) sequence, destination-mode (DM) sequence and the latent segmentation model (where segment one MD and segment 2 is DM) to evaluate the statistical significance of these models. The BIC value for a given empirical model can be calculated as: $[-\,2\,(LL)\,+\,K\,ln\,(Q)]$, where LL is the log-likelihood value at convergence, K is the number of parameters and Q is the number of observations. The model with the lowest BIC value is the preferred model. The corresponding BIC values of the MD sequence, DM sequence and latent segmentation models are 33,805.96, 31,587.80 and 28,342.14. The lowest BIC value of latent segmentation model clarifies the advantages associated with the latent segmentation model. Also the DM sequence model offers better model fit compared to the MD sequence model. In the following sections the estimated result of latent segmentation model has been discussed in detail.

Latent Segmentation Shares

From the aggregated population share of the two segments it is found that almost 53% population is allocated to MD segment and rest of the population is allocated to DM segment. As MD segment occupies a bit higher population share therefore a careful consideration is needed for policy analysis. In the MD segment the freight shipping mode share has been found as follows: for-hire truck (25.5%), private truck (8.6%), air (3.0%), parcel (62.4%) and “other” mode (0.5%). In the DM segment this share has been found as follows: for-hire truck (16.6%), private truck (29.0%), air (0.9%), parcel (51.1%) and “other” mode (2.4%). These shares clearly illustrates that there is a significant difference in freight mode share across the two segments. In both segments parcel mode occupies a larger share. But share of for-hire truck is higher in MD segment than DM segment, while share of private truck in higher in DM segment than MD segment.

Model Result

Sequence Choice Component

Table 7.1(a) represents the result of sequence choice component. The latent segmentation component examines that whether the decision maker will choose mode first and destination second; or will decide on destination first and mode second. The positive value of the constant illustrates that when everything remains the same the probability of choosing MD segment by the shipper is higher than choosing DM segment. Only the freight characteristics have been tested as the segmentation component. When the shipment value is less than < $300 shipper is more inclined to DM segment as higher shipment value might need specific modes to ship. When the commodity in hazardous material the probability of choosing MD section decreases. The reason of inclination to choose destination first might be that not all the destination would have demand of hazardous material. These types of materials might have demand in the manufacturing or mining industries. Also hazardous material needs special care for handling. Therefore once the destination is chosen then depending on the modes availability and facilities for loading-unloading in the destination zone, decision of choosing mode becomes easier. Also when the commodity is prepared foods and products, shippers are more tend to choose DM segment. The flow of these commodity depends on the destination area type. If the destination is market area then the demand of prepared foods and products increases compared to any industrial area. Hence once the destination is chosen, it becomes easier for the shipper to decide on shipping mode.

Mode-Destination Segment

The second and third column of Table 7.1(b) and 7.1(c) illustrates the result of first segment where mode is chosen first and destination second respectively. When mode is chosen first the destination attributes are not known to the decision maker. Therefore, any destination characteristics or level-of-service variables which are dependent on the distance from origin to destination, are not been examined in the model. When the major industry type at origin is manufacturing industry then probability of choosing hire truck increases. The capacity of carrying larger load from manufacturing industries and better accessibility compared to other modes, might be the reason of this inclination. With increasing number of intermodal facilities at origin probability of choosing private truck decreases. Intermodal facilities are usually referred to the transportation facilities which connects and accommodates different modes. As private trucks are usually used for shipping within a shorter distance therefore chances of interchanging of modes are lower. Shipments originating from an area with higher highway density is more likely shipped by parcel mode as parcel mode requires greater accessibility through roadway network. When the railway density increases at origin probability of choosing air mode decreases, which is expected. When the population density increases at origin probability of generating more freight increases and also the probability of choosing air mode increases.

When destination is chosen second the chosen mode is already known to the decision maker. Therefore, the shipping cost of chosen mode to destination has been found significant with a negative sign. With increasing density of manufacturing industry and number of warehouse and supercenter the probability of choosing a particular destination increases. But the density of management company and enterprise influence the destination choice negatively. Higher household income, truck AADT, proportion of employees to the population of age between 15 to 65 years and number of truck parking location at destination also influence the destination choice positively. These variables represents the higher demand of goods and better facilities for transportation modes. We also tested the interaction of some destination attributes with the chosen mode. When private truck is chosen and destination is urban the impact is negative. The reason is probably in the urban area the accessibility of truck mode is limited due to the weight restriction. The interaction of number of truck parking location at destination with for-hire truck and private truck impacts destination choice positively. As parking facility of heavy and large vehicles is different than the regular automobile parking area.

Destination-Mode Segment

In this segment destination is chosen first and then the mode. The fourth and fifth column of Table 7.1(b) and 7.1(c) represents the effects of various variables on mode and destination choice respectively. The mode choice component depicts similar result as the mode is chosen first. As destination is already chosen in this segment therefore the shipping time, shipping cost and destination attributes are known to decision maker and hence the effects of these variables have been tested in the mode choice model. The negative sign associated with shipping time and shipping cost clearly shows that probability of choosing a particular mode decreases with increasing shipping time and cost by that particular mode. When manufacturing industry is the major industry type at origin probability of choosing hire truck increases. The shipper is less likely to choose private truck when number of intermodal facilities at destination increases. With increasing roadway density at origin probability of choosing parcel mode increases. When destination is an urban area probability of choosing air mode increases. The reason may be airports are mainly situated near the proximity of urban area. Also with increasing population density at destination probability of choosing air mode increases.

When destination is chosen first in DM segment, the impacts of the variables are quite intuitive. As the mode in unknown to the decision maker therefore the average shipping time of all mode was considered in model. The impact of average shipping time to destination is found negative which is reasonable. When the density of manufacturing industries and number of warehouse and supercenter at destination increases the probability of choosing that particular destination increases. The reason of probably the manufacturing industries required raw materials to manufacture different products and also the number of warehouse and supercenters serves as storage and distribution centers of the goods. But, management company and enterprise relative attracts lesser freight. Destination areas with high household income attracts more freight as consumption of goods may increase with higher income. Also ratio of employees to the population of age between 15 to 65 years impacts the destination choice positively. The reason is probably the mean income at the area increases with higher proportion working population and hence the demand of goods increases in that particular area. Also the truck AADT and number of truck parking location at destination impacts destination choice positively. As with increasing truck parking location the accessibility of truck increases.

Summary

This chapter investigates the joint decision of mode and destination choice. Here, two sequences are considered for the two choices – shipping mode and shipment destination. As the analyst does not observe the sequence for the shipper, we considered a probabilistic approach that accommodates for the two sequences in a unified model with two segments. In the first segment, shipment destination is chosen first and then the mode; in the second segment mode is chosen first and then shipment destination. The earlier studies described in chapter two clearly shows that in the field of freight transportation the mode and destination choice have not been analyzed together, whereas this decision process can have significant impact on a regions transportation system. The model estimation represents intuitive results. The model fit clearly shows that the latent segmentation based sequence model performs better than the individual sequence model (MD or DM). The population shares in two segment are different with significant difference in mode share. This implies that when destination is chosen first the share of private truck increases and share of hire truck and parcel decreases. The reason may be if the destination is closer then probability of choosing private truck increases. The coefficient values also shows plausible interpretation of the factors affecting the choice decisions. Commercial vehicles transporting freight from one place to another have significant impact on traffic condition, infrastructure, safety, environmental quality and human health. The results obtained from this chapter represents a clear insight how the demand of freight varies depending on the spatial and economic attributes of an area and how the mode share changes whether mode is chosen first or second. The results will eventually give advantages to the transportation policy makers and urban planners.

Table 7.1 (a): Latent Segmentation Based Mode-Destination Choice Model Result: Sequence Choice Results

Variables	Mode First-Destination Second		Destination First-Mode second	
	Co-efficient	t-stat	Co-efficient	t-stat
Constant	0.207	3.709	-	-
Freight Characteristics				
Shipment Value				
< $ 300	-0.026	1.379	-	-
Hazardous Material	-1.575	-8.182	-	-
SCTG Commodity Type				
Prepared Foods and Products	-1.498	-8.197	-	-

Table 7.1 (b): Latent Segmentation Based Mode-Destination Choice Model Result: Shipping Mode Choice Results

Variables	First (Mode-Destination Sequence)		Second (Destination-Mode Sequence)	
	Co-efficient	t-stat	Co-efficient	t-stat
Constants				
Private Truck	-0.912	-1.704	1.768	13.164
Air	-0.690	-2.343	-11.525	-0.074
Parcel	3.180	12.691	3.406	9.601
"Other" Mode	-3.874	-11.688	-27.795	-3.521
Level of Service Variables				
Shipping Cost ($1000)	-	-	-14.383	-4.498
Shipping Time (100 hrs)	-	-	-1.131	-4.375
Transportation Network & Demographic Variables				
Major Industry in Manufacturing Industry at Origin				
Hire Truck	0.012	1.353	0.326	1.973
No. of Intermodal Facility at Origin				
Private Truck	-0.006	-1.631	-	-
No. of Intermodal Facility at Destination				
Private Truck	-	-	-0.008	-3.312
Roadway Density at Origin (mi/sqmi)				
Parcel	0.090	1.23	1.060	3.237

Variables	First (Mode-Destination Sequence)		Second (Destination-Mode Sequence)	
	Co-efficient	t-stat	Co-efficient	t-stat
Railway Density at Origin (mi/sqmi)				
Air	-3.761	-2.537	-	-
Population Density at Origin (1000 per sqmi)				
Air	0.793	2.289	-	-
Destination Urban Area				
Air	-	-	9.772	1.36
Population Density at Destination (1000 per sqmi)				
Air	-	-	0.804	1.871

Table 7.1 (c): Latent Segmentation Based Mode-Destination Choice Model Results: Destination Choice Results

Variables	Second (Mode-Destination Sequence)		First (Destination-Mode Sequence)	
	Co-efficient	t-stat	Co-efficient	t-stat
Level of Service Variables				
Shipping Cost for chosen mode to destination ($1000)	-0.658	-9.547	-	-
Average Shipping Time To Destination (100 hrs)	-	-	-1.815	-18.247
Transportation Network & Demographic Variables				
Density of Manufacturing Industry at Destination	0.503	5.609	1.810	7.807
Density of Management Company and Enterprise at Destination	-0.408	-2.951	-5.330	-4.509
No. of Warehouse and Supercenter at Destination	0.014	17.466	0.011	5.854
Household Income Level at Destination				
> $ 80,000	0.441	4.973	0.935	4.863
Truck AADT at Destination (million)	0.006	3.817	0.029	5.391
Proportion of employees to the population of age between 15 to 65 years at Destination	1.154	3.146	6.156	8.452
No. of Truck Parking Location at Destination	1.262	3.06	10.301	10.588
Interaction Terms with Chosen Mode				
Destination Urban Area*Private Truck	-0.707	-1.466	-	-
No. of Truck Parking Location at Destination*Private Truck	7.455	1.294	-	-
No. of Truck Parking Location at Destination*Hire Truck	2.295	3.299	-	-

CHAPTER EIGHT: CONCLUSIONS AND DIRECTIONS FOR FUTURE WORKS

Introduction

Reliable and effective freight transportation planning is becoming a vital issue in urban transportation planning sector. The objective of the dissertation is to explore how, where and how much of freight flows in the US. The literature related to freight transportation is limited compared to passenger transportation and travel behaviour literature. Therefore, the primary aim of the current dissertation is to address the methodological and empirical gaps in existing body of freight transportation literature and hence, to employ advanced econometric frameworks to investigate important empirical issues, contributing to the current body of freight transportation and travel behavior literature. The analysis for the dissertation is conducted using 2012 Commodity Flow Survey (CFS) data. CFS is a joint data collection effort by BTS, US Census Bureau, and U.S. Department of Commerce. The Public Use Microdata (PUM) file of CFS 2012 contains a total of 4,547,661 shipment records from approximately 60,000 responding industries. The data was further augmented with level of service variables, origin-destination demographic and transportation attributes.

For analyzing mode choice, an advanced discrete freight mode choice model- a hybrid utility-regret based model system has been estimated while accommodating for shipper level unobserved heterogeneity. To demonstrate the applicability of the proposed model system, detailed policy analyses examining the implementation of vehicle fleet automation and rerouting of freight movements away from a region were considered. While shipment weight could be considered as an explanatory variable in modeling mode choice (or vice-versa), it is more likely that the decision of mode and shipment choice is a simultaneous process. This joint decision is investigated both simultaneously employing a closed form copula structure and sequentially employing latent segmentation based sequence model. For destination choice, we investigated the connection between shipping mode and destination choice of shipment in a latent segmentation based sequential form.

This chapter summarizes the major conclusions obtained from the earlier chapters. The next four sections discuss the findings from each chapter briefly. The last sections concludes the dissertation by presenting some directions to future research.

Freight Mode Choice-A Regret Minimization And Utility Maximization Based Hybrid Model

Chapter Four describes the analysis of mode choice decision using different model paradigms and also presents the change in mode share under different policy scenarios. The advanced technology adoption and implementation in trucking industry benefits the industry both financially and environmentally. Hence, this change may influence overall freight industry in a complex way. The proposed research effort contributes to our understanding of the impact of these technological adoptions, by developing advanced discrete choice models for freight mode choice analysis.

We contribute to the existing literature by examining freight mode choice from alternative behavioral paradigms-random utility maximization and random regret minimization. To capture unobserved heterogeneity of level of service variables, a mixed hybrid model was estimated. The applicability of these behavioral paradigms and the corresponding changes predicted to freight mode choice under future vehicle technology adoption are evaluated. In our empirical analysis, the hybrid utility-regret mixed MNL model performed better compared to all other models. Our finding lends credence to the growing recognition that attributes impacting choice behavior could be treated either by heterogeneously – using either utility theoretic manner or regret minimization orientation. Overall, the estimated results offer plausible interpretation of the choice behavior. The evaluations of policy scenarios offer reasonable and intuitive results in terms of modal shifts. We found that introduction of automation in the freight industry would be more beneficial for long-haul hire truck mode than short-haul private truck mode. An increase in travel time by truck due to re-routing of truck flows away from urban region clearly indicates a modal shift from truck to parcel or "other" mode which includes rail, water or multiple modes. Also, implementation of carbon tax should be accompanied by travel time penalty, if modal shift from road based transportation to rail or water vessel based transportation is to be achieved. These policy insights can be helpful for transportation planner and urban policy makers to provide adequate physical facilities and services for truck transportation. Designated truck route, controlled access to urban area and selected parking and loading-unloading infrastructural facilities can improve truck transportation significantly. Also adopting automated truck fleets can cut off the economic and environmental impacts associated with trucking industry to a greater extent.

Joint Model Of Freight Mode Choice And Shipment Size-A Copula Based Random Regret Framework

In Chapter Five, a joint model system is developed in the form of an unordered choice model for mode and an ordered choice model for shipment size. We adopt a closed form copula-based model structure for capturing the impact of common unobserved factors affecting these two choices. We explore both the random utility (RU) based multinomial logit and the random regret (RR) minimization based multinomial logit (MNL) within a copula-based model. The RU and RR MNL structure are explored for several copula-based structures including Gaussian, Farlie-Gumbel-Morgenstern (FGM), Clayton, Gumbel, Frank and Joe. Finally, we consider six different copula structures while allowing for different copula structures within the same model (as opposed to a single copula form for all dimensions). For all the copula models, a more flexible approach that allows for exogenous variables to influence dependency structure is also estimated. The models are estimated based on the data from 2012 Commodity Flow Survey data. The estimated results obtained from this study clearly indicates the importance of accommodating dependencies between shipment mode and shipment size choice decisions. Of the copula models, RR based MNL-OL Frank-Frank-Frank-Joe copula model with parameterization offered the best fit. The estimated coefficients exhibited plausible interpretations too. The validation exercise performed to evaluate the model fit for overall sample and sub-samples based on freight characteristics suggests that RR based MNL-OL copula (Frank-Frank-Frank-Joe-Independent) model with parameterization significantly outperforms other models.

A Joint Decision Of Mode And Shipment Size Choice Behavior In Freight Transportation Using Sequential Model Framework

Chapter Six Focuses on the proposed alternative methodology to investigate the joint decision of mode-shipment size choice. We analyzed copula based joint model in the form of MNL model for mode choice and ordered logit model for shipment size choice. Alternatively, this simultaneous decision of mode choice and shipment size decision is also analyzed based on a sequential approach. In this approach two unique sequence has been considered: mode is chosen first and shipment size second; and shipment size is chosen first and mode second. Also, the sequence of choices made by the shippers is unknown to analyst. For this purpose a latent segmentation based approach is developed, where in Segment 1 a random utility (RU) maximization based multinomial logit (MNL) model is established for shipment mode and an ordered logit model is established for shipment size and; and vice versa in Segment 2. In our study we used the freight flows only within Alabama, Florida, Georgia, North Carolina, South Carolina and Tennessee considering hire truck, private truck, air and parcel mode. The model analysis results provide interesting insights in freight transportation behavior. The Frank-Frank-Joe copula model outperformed the latent segmentation based sequence model. As our objective of this study was to evaluate the joint decision of mode and shipment size choice in a sequential framework, in this chapter we discussed about the results obtained from the latent segmentation based sequence model. The result indicates that shippers are more likely to choose mode first and shipment second. The mode share within the segments are significantly different depending on the mode choice decision is made first or second. The impacts of various exogenous variables are also intuitive. The findings from the model analysis indicate the requirement of a careful consideration of the choice decision in policy analysis.

A Sequential Decision of Mode And Destination Choice in Freight Transportation

Chapter Seven investigates the joint decision of mode and destination choice. Here, two sequences are considered for the two choices – shipping mode and shipment destination. As the analyst does not observe the sequence for the shipper, we considered a probabilistic approach that accommodates for the two sequences in a unified model with two segments. In the first segment, shipment destination is chosen first and then the mode; in the second segment mode is chosen first and then shipment destination. The earlier studies described in chapter two clearly shows that in the field of freight transportation the mode and destination choice have not been analyzed together, whereas this decision process can have significant impact on a regions transportation system. The model estimation represents intuitive results. The model fit clearly shows that the latent segmentation based sequence model performs better than the individual sequence model (MD or DM). The population shares in two segment are different with significant difference in mode share. This implies that when destination is chosen first the share of private truck increases and share of hire truck and parcel decreases. The reason may be if the destination is closer then probability of choosing private truck increases. The coefficient values also shows plausible interpretation of the factors affecting the choice decisions. Commercial vehicles transporting freight from one place to another have significant impact on traffic condition, infrastructure, safety, environmental quality and human health. The results obtained from this chapter represents a clear insight how the demand of freight varies depending on the spatial and economic attributes of an area and how the mode share changes whether mode is chosen first or second. The results will eventually give advantages to the transportation policy makers and urban planners.

Research Impact

The growing freight demand impacts the environment, infrastructure and the overall transportation system. Therefore, understanding the overall freight movement in terms of freight mode, shipment size and destination choice is very important for operating a cost effective and efficient freight transportation system. Our research clearly indicates that the introduction of automated trucks in the freight industry would be more beneficial for long-haul hire truck mode than short-haul private truck mode. An increase in travel time by truck due to re-routing of truck flows away from urban region clearly indicates a modal shift from truck to parcel or rail, water or other multiple modes. Also, implementation of carbon tax results in a modal shift from road based transportation to rail or water vessel based transportation. The research clearly specifies the connection between the decisions of shipment size choice and freight shipment mode choice; as it is directly related to logistical and technical requirements for both shippers and carriers.

Specifically, shipment size choice is closely related to transportation mode as different shipment size demands different vehicle types. The joint sequential model system provides us a better understanding of the decision process and the factors affecting choice decision in a particular sequence indicates the requirement of a careful consideration of the choice decisions in policy analysis. Also, the connection between shipping mode and destination choice implies that depending on the spatial, transportation, infrastructural and economic attributes of the particular destination, demand of freight may vary and hence different destinations would have different types of freight flow and modal distribution. The policy insights from our work can be helpful for transportation planners and urban policy makers to provide adequate physical facilities and services for freight transportation. Designated truck routes, controlled access to urban area and selected parking and loading-unloading infrastructural facilities can improve truck transportation significantly. Also adopting automated truck fleets can reduce the economic and environmental impacts associated with trucking industry to a large extent.

Direction For Future Research

Certain drawbacks of this study need to be acknowledged. PUM CFS data does not contain exact geo-coded locations of origin and destination of freight movement, rather it contains the origin and destination at CFS area level. Any information of trip chaining or any intermediate location of the trip is unavailable in the dataset. In future, availability of this kind of information will lead to have more accurate analysis of freight demand modeling. Also the shipping time and shipping cost variables are not available in the dataset, where these variables play significant role in mode choice analysis. Advanced approaches to augment the data set with origin-destination information will improve the calculation of LOS variables and alternative availability matrices. Additionally, evidence of shipper level reliability, shipment frequency, shipping time delay, ownership of the vehicle fleet by the shipping firms will enhance the model result. In the future, accommodating more detailed land use attributes will provide the policy makers more interesting insights.

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