Joint Model of Freight Mode Choice and Shipment Size: A Copula-based Random Regret Minimization Framework

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ABSTRACT
In our study, we examine the joint choice of freight transportation mode and shipment size. 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. 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. Further, we explore alternatives to the traditional random utility structure in modeling mode choice. Specifically, 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 shipment size is analyzed using ordered logit (OL) model within the copula structure. The RU and RR MNL structures are explored for several copula-based structures including Gaussian, Farlie-Gumbel-Morgenstern (FGM), Clayton, Gumbel, Frank and Joe. The proposed approach considers copula models with multiple copula-based dependencies within a single model. The copula-based model dependency is also allowed to vary across the data by parameterizing the dependency as a function of observed attributes. The models are estimated based on the data from 2012 U.S. Commodity Flow Survey data. The copula RRM based MNL-OL copula with Frank and Joe copula dependencies offered the best data fit indicating the strong interconnectedness between shipment mode and shipment size choice decisions. A validation exercise provides further evidence of the joint model superiority for overall sample level and freight characteristics variables specific sub-samples.

Keywords: Freight Mode Choice; Shipment Size; Random Regret Minimization; Copula

INTRODUCTION

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. In fact, with increasing online purchases (promoted by Amazon, e-Bay, Walmart and other retailers), it is expected that, there will be a reduction in personal travel while an increased frequency of freight movements is expected. Overall, the combined outcome of several factors can potentially lead to increased travel (Anderson et al., 2003; Mokhtarian, 2004). According to Bureau of Transportation Statistics (BTS) (2004), smaller sized shipments (less than 500 pounds) increased 56 percent by shipment value (net dollar sale value of the entire shipment or commodity, excluding freight shipping cost or excise vat) 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 shipped were under 500 pounds and worth 25 percent by shipment value ($). The proclivity toward smaller shipment sizes will result in increased truck and parcel mode usage. The growth in truck and parcel flows will likely result in increasing the movement of light commercial vehicles on residential streets and heavy vehicles on major roads (accelerating road surface deterioration, creating safety hazards, causing congestion and increasing emissions).

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. However, 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, in our study, we employ an ordered representation of shipment size that groups the variable in meaningful categories. 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 U.S. CFS data. The rest of the paper is organized as follows. The literature review section provides a brief discussion of earlier research on joint decision of shipping mode and shipment size choice while positioning the current research in context. Next, the details of the econometric framework used in the analysis are discussed. The empirical data section contains discussion on the data source, data preparation, and descriptive analysis results. Model comparison results, model estimation results, and model validation results are presented in the empirical analysis section followed by the conclusion section.

LITERATURE REVIEW

Earlier Research

Two of the most important and critical logistics decisions in freight transportation market are the mode of transportation and quantity of freight to be shipped (shipment size). There have been several studies examining freight mode and shipment size choice. An extensive review of all these studies is beyond the scope of the paper (see Keya et al., 2017 for a summary of studies on mode choice). In our earlier study (Keya et al., 2017), we found that shipment size is mostly used as an explanatory variable in mode choice models (Abdelwahab and Sayed, 1999; Jiang et al., 1999; Sayed and Razavi, 2000; Norojono and Young, 2003). However, there is a growing recognition of the interrelation between freight mode and shipment size in the transportation research community. For example, in an effort to reduce inventory costs, a shipper might decide to ship smaller sized shipments and then choose the shipment mode appropriate to the quantity to be shipped; meaning that choice of transportation mode is dependent on shipment size. On the other hand, the choice of shipment size might be dictated by the shipper's goal of reducing the transportation/operating costs associated with the shipment modes. Table 1 provides a brief summary of earlier research on joint modeling of shipment size and mode choice. The information in the table includes study area, data elicitation approach (revealed preference (RP) versus stated preference (SP)), modeling methodology, decision variables of interest, types of mode considered, and the category of exogenous variables used.

Several observations can be made from the Table. First, in terms of mode, most of the studies considered truck and rail for modeling. Very few studies considered other modes such as air, water, and courier mode in their analysis. Second, in the majority of the studies, mode is characterized as a discrete variable and shipment size as a continuous variable. Third, four types of exogenous variables are usually considered in the reviewed studies: (1) level of service measures (shipping cost, operating cost, shipping time); (2) freight characteristics (commodity size, commodity group, commodity density, commodity value, commodity weight, product state, hazardous product or not, temperature controlled or not, perishability, quantity); (3) transportation network and origin-destination (O-D) attributes (O-D distance, O-D region); and (4) other characteristics (percentage of loss and damage, reliability of service, company size, access to rail track or piers, economic activities of firms, fleet size, number of employees in firm, season of the year, number of intermediate agents, number of trips, shipment operation type, rate of commodity flow, carrying capacity of vehicle, time of day). Fourth, classical random utility based MNL model (and its variants) is most commonly used to analyze the mode choice part while shipment size is analyzed using linear regression approach. . In recent years, some researchers have proposed the application of random regret based MNL models for analyzing freight mode choice (Keya et al., 2018; Boeri and Masiero, 2014; Irannezhad et al., 2017). Finally, findings from these earlier studies clearly highlight the interconnectedness of mode choice and shipment size decisions. For instance, Holguin-Veras et al. (2011) concluded (based on the outcome of their game theory application) that shippers and carriers cooperate with each other for mode choice and the choice of mode largely depends on shipment size. To be sure, we do recognize that joint modeling of mode and shipment size might not be applicable to all kinds of freight flows; particularly so for foreign transactions (see Abdelwahab and Sargious, 1990 and Zhang and Zhu, 2018 for a discussion)

Current Study Context

The literature most relevant to the current study includes Pourabdollahi et al. (2013a), Pourabdollahi et al. (2013b), and Irannezhad et al. (2017). In these studies, mode and shipment size choice dimensions were jointly examined employing a copula-based system. Pourabdollahi and colleagues used RU based approach while Irannezhad et al. (2017) used RR based approach for mode choice with Frank copula correlation structure. As mentioned before, the shipment size variable was either examined using a continuous form or unordered discrete variable form. 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. Figure 1 represents the frequency of shipment size observed from 2012 Commodity Flow Survey data. From the figure we can observe that high frequency for weight occurs around round numbers such as 250 pounds and 3000 pounds. Further, employing linear regression (or log-linear) imposes a strict linearity (or exponential structure) on parameter effects. To address these limitations, we consider an ordered representation for the shipment size variable. The specific categories considered are customized by mode under consideration. Thus, in our study, we explore an unordered-ordered discrete model structure embedded within a copula-based joint system. Further, we compare the random utility model system with a random regret model structure for the mode choice dimension. 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.

In summary, the proposed approach makes the following methodological and empirical contributions. Methodologically, 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). We also 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. 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. The proposed model is also validated using a hold-out sample to evaluate model performance. Empirically, the proposed model system is employed to study mode choice and shipment size decisions. The comparison will allow us to identify the appropriate model structure for studying these choices. The resulting model estimates provide more accurate variable impacts on the choice dimensions. The models developed are used to generate money value of time measures for both random utility and regret model structures.

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

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

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

$$P_{ni} = \frac{e^{(-R_{ni})}}{\sum_{j=1}^{J} e^{(-R_{nj})}} \tag{2}$$

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

$$s_{ni}^* = \alpha_i z_{ni} + \zeta_{ni}, \quad s_{ni}^* = s_i, \qquad if\ \tau_{i,s-1} < s_{ni}^* < \tau_{i,s} \tag{3}$$

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

$$P_{ni} = \Lambda_i\left(\tau_{i,s} - \alpha_i z_{ni}\right) - \Lambda_i\left(\tau_{i,s-1} - \alpha_i z_{ni}\right) \tag{4}$$

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:

$$\Lambda_{\xi_{ni},\zeta_{ni}}(U_1, U_2) = C_{\theta_n}(U_1 = \Lambda_{\xi_{ni}}(\xi), U_2 = \Lambda_{\zeta_{ni}}(\zeta)) \tag{5}$$

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 parameterize the dependence parameter θ_n as a function of freight characteristics. The equation is:

$$\theta_n = f(\gamma_i \vartheta_{ni}) \tag{6}$$

where ϑ_{ni} is a column vector of exogenous variables, γ_i is a row vector of unknown parameters (including a constant) specific to mode i and f represent 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:

$$\theta_n = f(\gamma_i \vartheta_{ni}) \tag{7}$$

While for Clayton we use:

$$\theta_n = exp(\gamma_i \vartheta_{ni}) \tag{8}$$

and for Gumbel and Joe the function is:

$$\theta_n = 1 + exp(\gamma_i \vartheta_{ni}) \tag{9}$$

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 the independent copula model.

EMPIRICAL DATA

Data Source and Data Preparation

The data for our analysis is drawn from the 2012 US CFS data available at www.census.gov/econ/cfs/pums.html. This survey is the joint data collection effort of Bureau of Transportation Statistics (BTS) and U.S. Census Bureau. The survey is conducted every 5 years since 1993. Although several data sources are available for freight planning purposes, this is the only freely available source that portray a detailed picture of freight movement at national level. A total of 4,547,661 shipment records from approximately 60,000 responding businesses and industries are recorded (including some important freight characteristics) in the Public Use Microdata (PUM) file of the 2012 CFS. 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. From this sample, 10000 data records were randomly chosen for estimation and 5,000 records were set aside for validation exercise.

Dependent Variable Generation

The 2012 CFS PUM file reports twenty-one modes of transport. In this study, the reported modes were categorized into five major groups: (1) for-hire truck, (2) private truck, (3) air, (4) parcel service, and (5) "other mode". Here, for-hire truck mode represents the trucks operated by a non-governmental business unit to provide transport services to customers under a negotiated rate. On the other hand, private truck refers to trucks owned and used by an individual business entity for its own freight movement. Parcel service mainly refers to a combination of modes (on ground/air/express carrier). Air mode consists of both air and truck, as truck is needed to pick up and/or deliver the commodity from and/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 by number of shipments 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%). The reader would note that certain types of shipments can be transported by only a subset of the 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 for such shipments affects the accuracy of the model estimates. To account for this issue, a heuristic approach was adopted to define the mode availability option based on shipment weight and routed distance (see Keya et al., 2017 for details). After carefully examining the freight characteristics of the chosen mode, following guidelines have been developed for alternative availability: for-hire truck and other mode have been considered always available; private truck is set available when routed distance is less than 413 miles (99 percentile of private truck observed in the data); air and parcel mode are considered available when shipment weight is less than 914 lb and less than 131 lb respectively (99 percentile observed in the data).

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 based on the observed frequency distribution of shipment size from the CFS data. We have categorized the shipment size in such a way that there exists a reasonable share of shipment size in each category for each shipping mode. 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 2 presents the weighted distribution of shipment sizes across five modes considered by number of shipments. We can see from the table that across for-hire truck and private truck 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 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 contains 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%). Table 3 presents the weighted mode share across the seven shipment size groups. It can be observed from the table that in general truck modes have the largest share across all shipment sizes (except when shipment size is less than 200 lb). On the other hand, air and parcel mode mainly carry smaller shipment size (less than 200 lb). It is also clear from the table that other mode, which is dominated by rail, transports larger shipment size. The distribution clearly shows how by mode, shipment size varies substantially highlighting the potential interconnectedness.

Independent Variable Generation

While the CFS data contains important freight attributes, level of service (LOS) variables, such as shipment time and shipment cost, are not available in the data. Therefore, we augmented the data with a host of secondary data sources. First, LOS variables were generated for each mode based on the origin and destination locations, routed distance and the shipment weight reported in the data. We generated shipping time for for-hire and private truck considering three different travel speed bands based on trip distance. In this procedure, we also considered the required break times for the truck drivers according to the service regulations, suggested by Federal Motor Carrier Safety Administration (FMCSA). Based on the share of shipping speed from FedEx 2015 annual report, we generated the shipping time by parcel mode- express overnight (1day), express deferred (3 days) and ground service (5days). Shipping time of air and "other mode" (considering rail, as rail contains major share within other mode) was calculated based on the average speed obtained from different sources. For shipping cost by parcel mode we developed pricing functions considering shipping distance and shipment weight and using shipping cost information available from FedEx. We also considered the shipping speed in calculation of shipping cost by parcel mode based on the share of shipping speed from FedEx 2015 annual report. Shipping cost for for-hire truck, private truck and "other mode" (mainly rail) was calculated based on the 2007 average freight revenue information obtained from the National Transportation Statistics (NTS) website with appropriate regional and temporal correction factors. The shipping cost per pound for air was estimated based on cost documentation obtained from a U.S. based cargo company- Southwest Cargo Company. For more details on level of service generations see Keya et al, 2017. Second, a number of O-D attributes were compiled utilizing different sources which include National Transportation Atlas Database (NTAD) 2012, National Bridge Inventory (NBI) data, National Highway Freight Network (NHFN) data, Highway Performance Monitoring System (HPMS) data, and Freight Analysis Framework – version 4 (FAF^4) network data. The transportation network attributes generated are: roadway length per 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, and length of intermodal connectors. Several CFS zonal level variables (both at origin and destination) have also been generated including 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), income categories based on mean income of an area (low (< $50,000), medium ($50,000-$80,000) and high (>$80,000)), number of warehouses and super centers, major industry type in an area (based on the majority of existing industries in an area), 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 60^{o}F; warm if the temperature is greater than 60^{o}F). To generate the zonal level variables, at first we collected the county level data. Then, we aggregated these information from the counties within each CFS area to obtain the CFS area level data.

Descriptive Statistics

Table 4 of descriptive analysis of the estimation sample reveals that the majority of the shipments are domestic – transported within the US (95.8%). Moreover, the shipment shares of both temperature controlled products and hazardous materials are very low (4.7% each) compared to other commodity types. We also found that most of the shipments are originating and terminating in non-mega regions[1] (36.1% and 33.9%, respectively). The most commonly shipped commodity types by frequency of shipment in 2012 were electronics (20.2%), metals and machinery (18.8%), and wood, paper and textiles (17.9%). The least transported commodity type was stone and non-metallic minerals (2.1%) and raw food (2.6%). The percentage share of shipment by value is the highest for shipment value less than $300 (44.5%). The mean shipping cost is the highest ($276.53) for air mode, with the lowest mean shipping time (1.30 hours). On the other hand, shipping cost is the lowest for other modes ($13.71) and mean shipping time is the highest for parcel mode (98.84 hours).

EMPIRICAL ANALYSIS

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

[1] The entire USA is divided into eleven megaregions which are expected to share common economic growth, natural resources and environmental system, topography, and transportation system. These eleven megaregions are: Arizona Sun Corridor, Cascadia, Florida, Front Range, Great Lakes, Gulf Coast, Northeast, Northern California, Piedmont Atlantic, Southern California, and Texas Triangle. The remainder of the USA has been considered as non-mega region (http://www.america2050.org/content/megaregions.html).

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) and Akaike Information Criterion (AIC). 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. While, AIC value is calculated using the following equation for a given empirical model: $[2\ K -\ 2\ ln\ (LL)]$, where K is the number of parameters and LL is the log likelihood at convergence. The model with the lowest BIC and AIC value is the preferred model. The BIC and AIC values obtained are presented in Table 5. 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 (25765.36 (93)). Also, the AIC (no. of parameters) values for the RRM based and RU based MNL-OL Frank–Frank-Frank-Joe-Independent copula model are 25084.80(94) and 25094.80(93) respectively. The BIC and AIC values indicate that the random regret based copula model outperformed its random utility counterpart. The copula model BIC and AIC 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 RRM based copula model (Frank-Frank-Frank-Joe-Independent) with parameterization provided the best data fit amongst all the copulas (BIC value: 25713.41 (98) and AIC value: 25006.80(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 6(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 negative coefficients (-001 per hour and -0.134 per $1000 respectively) 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). 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 shipping 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). The value of the coefficient for export trade by air mode is 1.125, which implies that 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, the coefficient for export trade by private truck (-0.220) indicates that, 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 O-D Attributes

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 (coefficient value: -0.88) or when the percentage of population living below poverty level is high at origin (coefficient value: -4.006). 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 (coefficient value: -0.091); 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 6(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

The coefficient (0.946) of non-flammable liquid and other hazardous materials indicates that, these products 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 (coefficient value: -0.853) 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 O-D Attributes

Several transportation networks and O-D attributes were considered in the shipment size models. For 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 (coefficient value: 0.617) increases the propensity for larger shipments since increased roadway coverage facilitates movement of goods in large quantity. On the other hand, density of management companies and enterprises 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 (coefficient value: -0.094) or increased number of seaports at origin (coefficients value: -0.001) 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 6(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. The reader would note that accounting for the flexible specification for common unobserved factors enhances model fit. At the same time, it is important to recognize that ignoring for the presence of these common unobserved factors is likely to result in biased and/or inconsistent estimates for all other parameters. Hence, the copula model offers a twofold benefit: (1) improve model fit and (2) allows for enhanced parameter estimation of the data under consideration.

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 7. 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. A prediction exercise has been conducted to compare actual and predicted mode and shipment size share. From Figure 2, we can clearly observe that the actual and predicted mode share are almost similar indicating a satisfactory predictive ability of our model. The predicted shipment size share has been provided in Table 8 and the results are quite reasonable highlighting the appropriateness of the joint model.

Value of Time (VOT)

We also have estimated the value of time (VOT). In the random regret minimization approach, the value of time (VOT) is calculated using the following equation (Chorus, 2012):

$$\mathrm{VOT} = \frac{\sum_{j\neq i} -\beta_t/(1+1/\exp[\beta_t(TT_j-TT_i)]))}{\sum_{j\neq i} -\beta_c/(1+1/\exp[\beta_c(TC_j-TC_i)]))} \tag{10}$$

Where, β_t and β_c are the estimated coefficients of shipping time and shipping cost respectively. In the RRM based approach, the shipping time and shipping cost of both the chosen alternative and the competitor alternatives enter into the VOT equation. Figure 3 represents the value of time analysis across different modes, where the blue plane with a single value represents VOT obtained from RUM model and the colored plane with varying values represents VOT values obtained from RRM model. From the figure, we can observe that the VOT obtained from random utility model in not sensitive to any change in the attributes. However, random regret formulation based VOT changes across the mode and is affected by the change in attribute levels. The results from VOT analysis highlight that while RUM and RRM based analysis provide similar ranges of VOT, the inherent variation allowed in RRM models enhances data fit.

In our analysis, we also calculated the VOT per ton using the weighted average shipment weight across all modes (4.93 ton). Based on the data used to generate Figure 3, the VOT per ton for RRM based model results in different range of values. For for-hire truck and private truck the VOT per ton value ranges between 1.50 to 1.52; for air this value ranges between 1.48 to 1.49; for parcel VOT per ton ranges between 1.56 and 1.65; and for other mode this value ranges between 1.50 to 1.57. The value of VOT per ton for the RUM based analysis is obtained as 1.50 (same for all modes). The range of VOT per ton values are reasonable and are similar to values reported in earlier literature. For example, Fowkes et al. (1991) and Kurri et al. (2000) found the values as €1.18 ($1.33) per ton and €1.53 ($1.73) per ton respectively, whereas de Jong et al. (2004) found a comparatively higher value of €4.7 ($5.36) per ton.

CONCLUSION

In our study, 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. Any information of trip chaining or intermediate modes used sequentially in a particular shipping trip from one origin to destination is also not available in the dataset. Availability of such information in future, will enhance the model estimation results. Additionally, evidence of shipper level reliability, shipment frequency, shipping time delay, ownership of the vehicle fleet by the shipping firms will enhance the model results. In the future, accommodating more detailed land use attributes will provide the policy makers more interesting insights.

In terms of econometric methodology, two possible challenges can be fruitful avenues for future research. First, to accommodate the inherent discretization of the shipment size variable we developed the ordered logit model that provides additional flexibility by allowing for a non-linear specification (as opposed to linear model). However, the approach can result in loss of information as we convert the continuous value to a discrete variable. In scenarios where the loss of information is likely to be a challenge, it might be useful to consider increasing the number of alternatives in modeling shipment size and estimating an advanced version of the ordered logit (see Rahman et al., 2019 for an example). Second, the dependency of copula model does not accommodate for random taste variations attribute impacts. Therefore, accommodating random taste variations within a copula based structure may be an avenue for future research.

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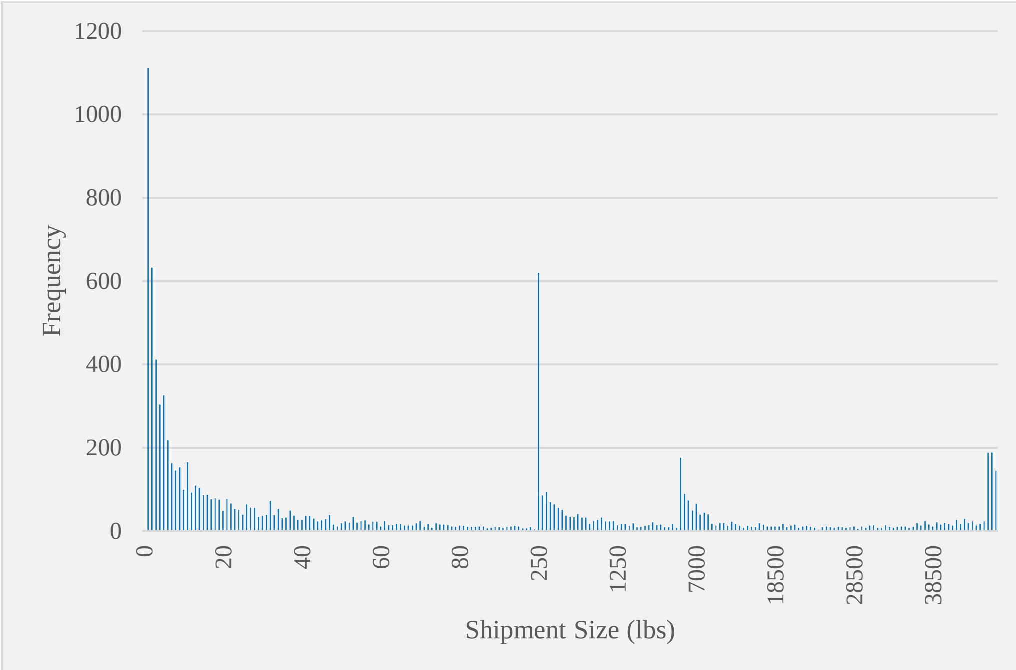


FIGURE 1: Frequency Distribution of Shipment Size (lbs)

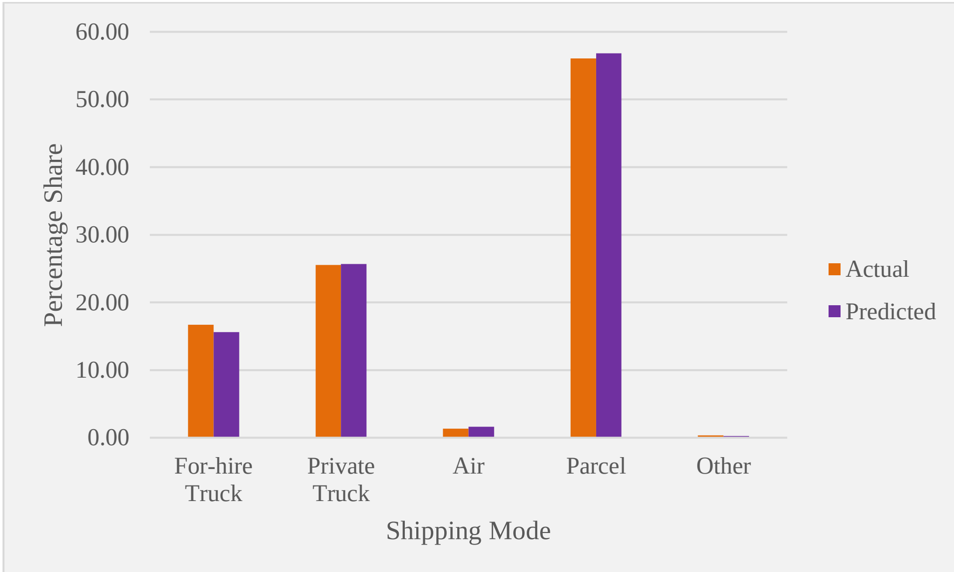
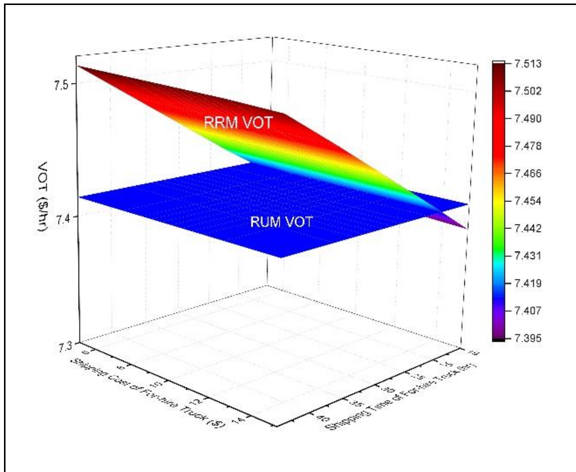
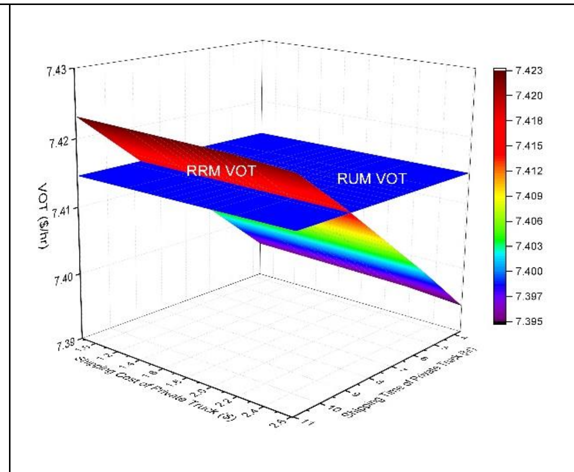


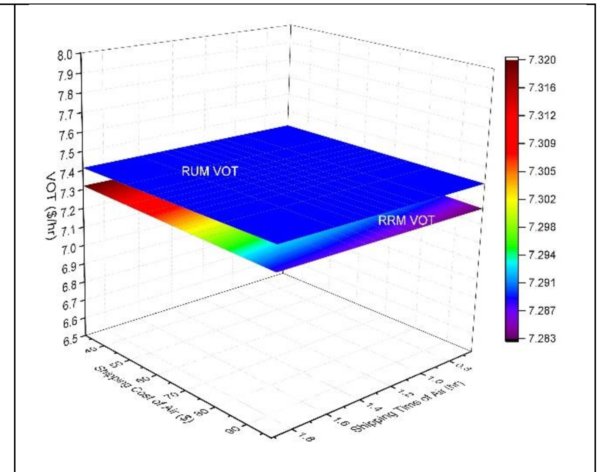
FIGURE 2: Actual vs. Predicted Mode Share



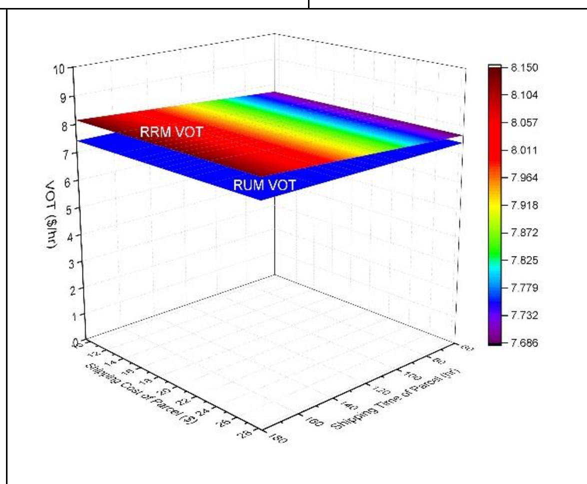
(a) For-Hire Truck



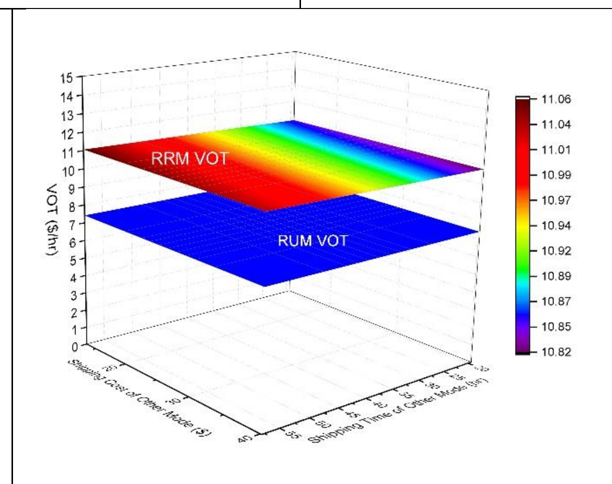
(b) Private Truck



(c) Air



(d) Parcel



(e) Other Mode

FIGURE 3: VOT for Different Shipping Modes

TABLE 1: Previous Literature on Joint Modeling of Freight Mode Choice and Shipment Size

Study	Study Area	Data Type[1]	Methodology[2]	Decision Variable	Modes Considered[3]	Independent Variables Considered			
						Level of Service Measures	Freight Characteristics	Network and O-D Attributes	Other Characteristics
Hall (1985)	USA	–[4]	Cost equations for alternative modes	Mode, shipment size	Truck, parcel	Cost, time	–	Distance	–
Abdelwahab and Sargious (1992)	USA	RP	Switching simultaneous equations (binary probit for mode choice and linear regression for shipment size)	Mode, shipment size	Truck, rail	Cost, time	Shipment size, commodity density, value, commodity type, hazardous, temperature controlled	Destination territory	Loss and damage percentage, reliability
Abdelwahab (1998)	USA	RP	Switching simultaneous equations (binary probit for mode and linear regression for shipment size)	Mode, shipment size	Rail, truck	Freight charges, transit time	Commodity category	Origin-destination territory	–
Holguin-Veras (2002)	Guatemala City, Guatemala	RP	Heteroscedastic extreme value model (HEV), MNL	Mode, shipment size	Truck	Unit cost	Commodity category	Distance	Economic activities
de Jong and Ben-Akiva (2007)	Sweden, Norway	RP	MNL for mode and shipment size choice, NL model, mixed MNL	Mode, shipment size, transportation chain	Truck, rail, air, water	Cost, time	Commodity category, shipment value/weight ratio	–	Company size, access to rail track and piers
de Jong and Johnson (2009)	Sweden	RP	MNL, two step model (mode discrete, size continuous)	Mode, shipment size	Truck, rail, air, water	Cost, time	Commodity category, shipment value/weight ratio	–	Company size

Cavalcante and Roorda (2010)	Toronto, Canada	RP	Discrete-continuous model	Mode, shipment size	Passenger car, single unit truck, pick up/van and truck with 1 trailer	Operating cost	Commodity category, value to weight ratio, time sensitivity of commodity	Distance	Fleet size
Habibi (2010)	Sweden	RP	MNL (for mode and shipment size choice)	Mode, shipment size, transport chain	Truck, rail, combination of truck-rail-sea	Cost, time	Value to weight ratio, commodity category	–	No. of employees in firm, season
Windisch et al. (2010)	Sweden	RP	MNL (for mode and shipment size choice) , NL (to find correlation between mode and shipment size choice)	Mode, shipment size	Truck/lorry, railway, ferry, cargo vessel, air	Cost	Commodity characteristics	–	Time of the year, proximity of rail/sea pier
Holguin-Veras et al. (2011)	USA	SP	Game Theory – cooperative game between shippers and carriers to maximize profit. Set two experimental set-up where in one shippers decide the shipment size and in other carriers decide the shipment size.	Mode, shipment size	Truck, van, road-rail	Cost	Shipment size, no. of shipment	–	–
Combes (2012)	France	RP	Economic Order Quantity Model	Mode, shipment size	Truck, rail, combined transport, inland	–	–	Distance	No. of intervening agents, no. of trips, shipment operation type,

					waterway, sea, air				rate of commodity flow
Pourabdollahi et al. (2013a)	USA	RP	Copula-based joint MNL-MNL	Mode, shipment size	Truck, rail, air, parcel	Cost	Commodity category, commodity characteristics, value, trade type	Distance	No. of employees
Pourabdollahi et al. (2013b)	USA	SP	MNL for mode and shipment size choice, Freight Activity Bases Modeling Framework (FAME) for simulation	Mode, shipment size	Truck, rail, air, parcel	Cost	Commodity category, commodity characteristics, value, shipment size	Distance	No. of employees
Abate and de Jong (2014)	Denmark	RP	MNL, Mixed MNL, Dubin-McFadden method	Truck size, shipment size	Truck	Shipping cost, fuel cost	Weight	Distance, shipment demand at origin	Carrying capacity, fleet size, age of vehicle, hire vehicle or not
Irannezhad et al. (2017)	Mashhad, Iran	RP	Copula based joint hybrid RU-RR MNL and log-linear regression	Mode, shipment size	Truck, van, heavy truck, trailers	Hire rate of vehicle	Commodity category	Distance	Time of day, external trip
Stinson et. al. (2017)	Arizona, USA	RP	NL	Mode, shipment size	Truck, rail, air, parcel	Cost, time	Commodity category, export	–	–

[1] Data Type: RP = Revealed Preference, SP = Stated Preference
[2] Methodology: MNL = Multinomial Logit Model, NL = Nested Logit
[3] Mode: When the study specifies particular modes
[4] – = not available

TABLE 2: Weighted Shipment Size Distribution (%) Across Modes

Mode	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		11.05%	10.38%	17.66%	15.33%	18.59%	14.27%	12.71%	100.00
Private truck		17.30%	18.41%	19.46%	16.15%	13.88%	7.36%	7.44%	100.00
Air		59.60%	18.30%	15.00%	4.70%	2.30%	-	-	100.00
Parcel		78.81%	21.19%	-	-	-	-	-	100.00
Other		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: Weighted Modal Split (%) Across Shipment Size (lbs)

Shipment Size (lbs)	Shipping Mode					Total
	For-Hire Truck	Private Truck	Air	Parcel	Other	
<= 30	3.59%	9.00%	1.55%	85.84%	0.02%	100.00
31-200	9.68%	25.28%	1.34%	63.65%	0.06%	100.00
201-1,000	35.45%	61.95%	2.60%	0.00%	0.00%	100.00
1,001-5,000	37.68%	61.21%	0.95%	0.00%	0.16%	100.00
5,001-30,000	43.28%	55.82%	0.45%	0.00%	0.45%	100.00
30,001-45,000	54.55%	44.52%	0.00%	0.00%	0.93%	100.00
> 45,000	48.32%	47.03%	0.00%	0.00%	4.65%	100.00

Table 4: Summary Statistics of Exogenous Variables

Variables	Sample Characteristics
Categorical Variables	**Percentage**
Export	
Yes	4.2
No	95.8
Temperature Controlled	
Yes	4.7
No	95.3
Hazardous Materials	
Flammable Liquids	2.1
Non-flammable Liquid and Other Hazardous Material	2.6
Non Hazardous Materials	95.3
SCTG Commodity Type	
Raw Food	2.6
Prepared Products	5.6
Stone and Non-Metallic Minerals	2.1
Petroleum and Coal	3.7
Chemical Products	12.8
Wood, papers and Textiles	18.1
Metals and Machinery	18.7
Electronics	20.2
Furniture and Others	16.2
Shipment Value	
Value < $300	44.5
$300 ≤ Value ≤ $1,000	20.2
$1,000 < Value ≤ $5,000	18.2
Value > $5,000	17.1
Continuous Variables	**Mean**
Shipping Cost ($)	
Hire Truck	37.33
Private Truck	23.10
Air	276.53
Parcel	42.6

Other	13.71
Shipping Time (hour)	
Hire Truck	17.83
Private Truck	1.78
Air	1.30
Parcel	98.84
Other	23.23

TABLE 5: Comparison of Different Copula Models

MNL Decision Rule	Copula	LL at Constants	LL at Convergence	No. of Parameters	No. of Observation	Rho-square	Adjusted Rho-square	BIC	AIC
RRM	Frank-Frank-Frank-Joe-Independent	-15732.83	-12448.40	94	10000	0.2088	0.2028	25762.57	25084.80
RUM	Frank-Frank-Frank-Joe-Independent	-15732.83	-12454.40	93	10000	0.2084	0.2025	25765.36	25094.80
RRM	Frank[2]	-15732.83	-12450.10	94	10000	0.2087	0.2027	25765.97	25088.20
RUM	Frank	-15732.83	-12456.20	93	10000	0.2083	0.2024	25768.96	25098.40
RUM	FGM	-15732.83	-12656.40	95	10000	0.1955	0.1895	26187.78	25502.80
RRM	FGM	-15732.83	-12655.60	96	10000	0.1956	0.1895	26195.39	25503.20
RRM	Normal	-15732.83	-12741.10	94	10000	0.1902	0.1842	26347.97	25670.20
RUM	Normal	-15732.83	-12809.50	86	10000	0.1858	0.1803	26411.09	25791.00
RUM	Clayton	-15732.83	-12787.10	93	10000	0.1872	0.1813	26430.76	25760.20
RUM	Gumbel	-15732.83	-12788.70	93	10000	0.1871	0.1812	26433.96	25763.40
RRM	Clayton	-15732.83	-12786.50	94	10000	0.1873	0.1813	26438.77	25761.00
RRM	Joe	-15732.83	-12788.10	94	10000	0.1872	0.1812	26441.97	25764.20
RRM	Gumbel	-15732.83	-12788.20	94	10000	0.1872	0.1812	26442.17	25764.40
RUM	Joe	-15732.83	-12788.50	94	10000	0.1871	0.1812	26442.77	25765.00
RRM	Independent	-15732.83	-12780.80	99	10000	0.1876	0.1813	26473.42	25759.60
RUM	Independent	-15732.83	-12782.40	99	10000	0.1875	0.1812	26476.62	25762.80
Parameterization									
RRM	Frank-Frank-Frank-Joe-Independent	-15732.83	-12405.40	98	10000	0.2115	0.2053	**25713.41**	**25006.80**
RRM	Frank	-15732.83	-12413.70	97	10000	0.2110	0.2048	25720.80	25021.40
RUM	Frank-Frank-Frank-Joe-Independent	-15732.83	-12409.10	98	10000	0.2113	0.2050	25720.81	25014.20

[2] 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 6(a): Copula RRM Based MNL (Shipping Mode Choice) Model Estimation Results

Explanatory Variables	For-hire truck		Private Truck		Air		Parcel		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
Shipping Time * Raw Food	-0.005	-3.430	-0.005	-3.430	-0.005	-3.430	-0.005	-3.430	-0.005	-3.430
Shipping 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		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 (1000 pop/mi^2)	–	–	–	–	0.200	2.661	0.100	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 6(b): Copula OL (Shipment Size) Model Estimation Results

Explanatory Variables	For-hire truck		Private Truck		Air		Parcel		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	–	–	–	–	–	–

Explanatory Variables	For-hire truck		Private Truck		Air		Parcel		Other	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Metals and Machinery	–	–	–	–	–	–	-0.407	-3.887	–	–
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)										

Explanatory Variables	For-hire truck		Private Truck		Air		Parcel		Other	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Cold; <= 60^0 F	-0.353	-3.425	–	–	–	–	–	–	–	–
No. of seaports at Origin	–	–	–	–	–	–	-0.001	-3.499	–	–
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 constants	-15732.83									
Log-likelihood at Convergence	-12405.40									
Rho-square	0.2115									
Adjusted Rho-square	0.2053									

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

TABLE 7: 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
Rho-square	**0.2055**	0.2044	0.1831	0.1812
Adjusted Rho-square	**0.1930**	0.1919	0.1704	0.1685
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

TABLE 8: Actual vs. Predicted Shipment Size Share (Validation Sample)

<table>
<tr><th rowspan="2">Shipment Size (lbs)</th><th colspan="2">For-hire Truck</th><th colspan="2">Private Truck</th><th colspan="2">Air</th><th colspan="2">Parcel</th><th colspan="2">Other Mode</th></tr>
<tr><th>Actual</th><th>Predicted</th><th>Actual</th><th>Predicted</th><th>Actual</th><th>Predicted</th><th>Actual</th><th>Predicted</th><th>Actual</th><th>Predicted</th></tr>
<tr><td><= 30</td><td>10.97</td><td>10.31</td><td>16.98</td><td>15.29</td><td>62.56</td><td>66.28</td><td>79.41</td><td>71.62</td><td>3.85</td><td>4.96</td></tr>
<tr><td>31-200</td><td>9.08</td><td>11.48</td><td>19.04</td><td>19.73</td><td rowspan="6">37.44</td><td rowspan="6">33.72</td><td rowspan="6">20.59</td><td rowspan="6">28.38</td><td rowspan="3">9.23</td><td rowspan="3">10.60</td></tr>
<tr><td>201-1,000</td><td>18.16</td><td>19.08</td><td>20.20</td><td>22.95</td></tr>
<tr><td>1,001-5,000</td><td>15.76</td><td>17.12</td><td>17.64</td><td>16.36</td></tr>
<tr><td>5,001-30,000</td><td>18.79</td><td>16.81</td><td>11.62</td><td>11.08</td><td rowspan="3">86.92</td><td rowspan="3">84.44</td></tr>
<tr><td>30,001-45,000</td><td>12.99</td><td>11.57</td><td>6.76</td><td>5.47</td></tr>
<tr><td>> 45,000</td><td>14.25</td><td>13.63</td><td>7.75</td><td>9.12</td></tr>
<tr><td>Total</td><td>100.00</td><td>100.00</td><td>100.00</td><td>100.00</td><td>100.00</td><td>100.00</td><td>100.00</td><td>100.00</td><td>100.00</td><td>100.00</td></tr>
</table>

APPENDIX

TABLE A(i): Copula RUM Based MNL (Shipping Mode Choice) Model Estimation Results

Explanatory Variables	For-hire truck		Private Truck		Air		Parcel		Other	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Constant	0	–[1]	0.200	2.220	-0.943	-2.177	2.700	21.721	-4.579	-19.087
Level of Service Variables										
Shipping Cost (1000 $)	-0.287	-6.952	-0.287	-6.952	-0.287	-6.952	-0.287	-6.952	-0.287	-6.952
Shipping Time (hrs)	-0.002	-3.130	-0.002	-3.130	-0.002	-3.130	-0.002	-3.130	-0.002	-3.130
Travel Time * Raw Food	-1.269	-3.276	-1.269	-3.276	-1.269	-3.276	-1.269	-3.276	-1.269	-3.276
Travel Time * Prepared Products	-0.583	-3.169	-0.583	-3.169	-0.583	-3.169	-0.583	-3.169	-0.583	-3.169
Freight Characteristics										
Hazardous Material (Base: Not Hazardous)										
Non-flammable Liquid and Other Hazardous Materials	–	–	0.866	4.880	–	–	–	–	–	–
Export (Base: No)										
Yes	–	–	-0.568	-2.912	2.338	11.088	–	–	–	–
Temperature Controlled (Base: No)										
Yes	–	–	0.227	1.944	–	–	–	–	–	–
SCTG Commodity Type (Base: Wood, Papers and Textile)										
Prepared Food and Products	–	–	0.626	4.506	–	–	–	–	–	–
Stone & Non-Metallic Minerals	–	–	-1.231	-7.624	–	–	–	–	–	–

Explanatory Variables	For-hire truck		Private Truck		Air		Parcel		Other	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Petroleum and Coals	–	–	0.588	3.920	–	–	–	–	–	–
Electronics	–	–	-0.440	-4.201	0.599	3.083	–	–	–	–
Furniture and Others	–	–	0.270	3.185	–	–	–	–	–	–
Transportation Network and O-D Attributes										
Origin Highway Density (mi/mi^2)	–	–	–	–	–	–	0.125	4.718	–	–
Density of Railway at Origin (mi/mi^2)	–	–	-0.049	-2.001	–	–	–	–	–	
Density of Railway at Destination (mi/mi^2)	–	–	–	–	–	–	–	–	–	–
Destination Population Density (10 /mi^2)	–	–	–	–	0.300	2.604	0.200	3.111	–	
No. of Inter-Modal Facility at Destination	–	–	-0.002	-1.760	–	–	–	–	–	–
No. of Warehouse and Super Center at Origin	–	–	–	–	–	–	0.003	2.953	–	–
Density of Whole Sale Industry at Origin (per mi^2)	–	–	–	–	–	–	-0.246	-4.073	–	–
Percentage of Population below Poverty Level at Origin	–	–	–	–	-7.724	-2.601	–	–	–	–

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

TABLE A(ii): Copula OL (Shipment Size) Model Estimation Results

Explanatory Variables	For-hire truck		Private Truck		Air		Parcel		Other	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Thresholds										
Threshold 1	-6.283	-28.205	-5.790	-39.591	-3.896	-8.943	-0.705	-4.635	-5.631	-2.838
Threshold 2	-4.799	-24.534	-4.235	-32.314	– [1]	–	–	–	-2.982	-3.166
Threshold 3	-3.030	-17.773	-2.704	-23.065	–	–	–	–	–	–
Threshold 4	-1.782	-11.143	-1.656	-15.689	–	–	–	–	–	–
Threshold 5	-0.445	-2.765	-0.641	-6.495	–	–	–	–	–	–
Threshold 6	0.847	4.784	-0.027	-0.261	–	–	–	–	–	–
Freight Characteristics										
Hazardous Material (Base: Not Hazardous)										
Non-flammable Liquid and Other Hazardous Material	0.951	2.662	–	–	–	–	–	–	–	–
Temperature Controlled (Base: No)										
Yes	–	–	–	–	–	–	-0.854	-2.883	–	–
SCTG Commodity Type (Base: Wood, Papers and Textile)										
Raw Food	0.516	2.065	0.309	2.759	–	–	–	–	–	–
Prepared Food and Products	0.856	4.890	-0.275	-2.660	–	–	0.553	1.999	–	–
Stone & Non-Metallic Minerals	3.131	9.910	4.447	21.648	–	–	–	–	–	–
Petroleum and Coals	1.674	6.124	0.318	2.788	–	–	–	–	–	–
Chemicals	–	–	-0.169	-1.926	–	–	–	–	–	–

Explanatory Variables	For-hire truck		Private Truck		Air		Parcel		Other	
	Parameter	**t-stat**	**Parameter**	**t-stat**	**Parameter**	**t-stat**	**Parameter**	**t-stat**	**Parameter**	**t-stat**
Metals and Machinery	–	–	–	–	–	–	-0.409	-3.892	–	–
Electronics	-1.104	-7.976	-0.378	-2.874	-0.628	-2.226	-1.032	-10.191	–	–
Furniture and Others			-0.349	-3.691	–	–	-0.406	-3.808	–	–
Shipment Value ($) (Base:Value >5000)										
Value ≤ 300	-3.692	-12.028	-4.348	-31.358	-1.546	-3.714	-2.489	-17.048	-5.206	-2.127
300 < Value ≤ 1000	-2.934	-13.292	-3.187	-25.322	-1.166	-2.847	-0.874	-6.109	-3.390	-1.848
1000 < Value ≤ 5000	-2.097	-14.993	-1.808	-16.871	-1.131	-2.812	-0.423	-2.918	–	–
Transportation Network and O-D Attributes										
Mean Household Income at Origin ($) (Base: ≥ $50,000)										
< $50,000	–	–	–	–	–	–	0.347	2.235	–	–
Density of Employees in Mining Industry at Origin (per mi^2)	1.108	3.260	–	–	–	–	–	–	–	–
Density of Management Company and Enterprise at Destination (per mi^2)	–	–	-1.028	-3.026	–	–	–	–	–	–
Density of Wholesale Industries at Destination (per mi^2)	–	–	–	–	–	–	-0.097	-2.632	–	–
Density of Highway at Destination (mi/mi^2)	–	–	0.062	2.926	–	–	–	–	–	–
Density of Bridges at Destination (per mi^2)	-0.320	-1.963	–	–	–	–	–	–	–	–
Origin Avg. Temperature (Base: Warm; > 60^0 F)										

Explanatory Variables	For-hire truck		Private Truck		Air		Parcel		Other	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Cold; <= 60^0 F	-0.352	-3.403	–	–	–	–	–	–	–	–
No. of seaports at Origin	–	–	–	–	–	–	-0.001	-3.494	–	–
Routed Distance Between O-D (miles)	-0.001	-8.125	–	–	–	–	–	–	–	–
Copula Parameters										
Copula	Frank		Frank		Frank		Joe			
Correlation Parameters	-1.868	-4.059	-18.525	-8.895	-30.642	-2.724	1.369	5.613	0	–
Raw Food	3.768	3.676	–	–	–	–	–	–	–	–
Stone & Non-Metallic Minerals	13.321	6.871	–	–	–	–	–	–	–	–
Metals and Machinery	–	–	8.717	4.248	–	–	–	–	–	–
Shipment Value ≤ $300	-6.004	-3.844	–	–	–	–	–	–	–	–
$300 < Shipment Value ≤ $1000	-3.068	-3.389	–	–	–	–	–	–	–	–
Export	–	–	–	–	–	–	-0.756	-2.878	–	–
No. of Parameters	98									
Log-likelihood at constants	-15732.83									
Log-likelihood at Convergence	-12409.10									
Rho-square	0.2113									
Adjusted Rho-square	0.2050									

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