A Behavioral Freight Microsimulation in U.S.

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ABSTRACT. This study embarked upon the development of a nationwide freight activity microsimulation as an acceptable analysis tool for policy assessments. Mode choice component of a large-scale behavioral microsimulation framework, named Freight Activity Microsimulation Estimator (FAME) was developed and validated in this study. A new concept for firm-types is implemented in FAME to keep the computational burden at a reasonable level and to diminish the need for highly disaggregated data. A total of ٤٦,٢٤٣ firm-types were generated in the U.S., among which more than ١٠ billion tons of domestic shipments were simulated. Total tonnage, value, and ton-mile of commodities for each mode were obtained as the final output, which showed a satisfactory match with public freight data in the U.S.

Keywords: Freight modal selection, activity-based approach, micro-simulation.

INTRODUCTION

Freight transportation is a vital element in the economic prosperity of any country and directly affects the productivity rate in many aspects. The volume of freight flows within the United States has almost doubled the rate of population increase over the past three decades (١). As the businesses increasingly adopt sophisticated supply chain management strategies, the freight shipment decision-making process is becoming even more complicated. Population increase, economic growth, proliferation of e-commerce, and greater dependence on transportation in the production process, on the other hand, are driving freight movements to reach unprecedented levels (٢).

Although the need to incorporate movement of freight in the broader framework of national transportation policy is recognized (٣), providing satisfactory analysis tools to facilitate decision making has been met with significant technical challenges. Major research efforts in travel demand modeling have mainly concentrated on the passenger transportation in the past. As a result, the state-of-the-art in behavioral freight modeling is far behind the advancements in the passenger transportation ground (٤). It has been argued that the complexity of the decision-making process, lack of an acceptable freight modeling framework, and freight data scarcity are the major obstacles that prevent advancement of freight modeling.

It is not possible to capture the strategic decisions that individual firms make regarding their supply chain design and operations using a four-step model. Even in the passenger transportation modeling, the effectiveness of the four-step framework is questioned (٥). In the past few decades, researchers have developed and advanced the Activity Based Modeling approach to take into account the way that the individuals are making decisions (٦). A limited number of studies have tried to apply the activity-based approach to freight transportation modeling, but due to the lack of data, most have not produced satisfactory results (٧).

BACKGROUND

The conventional four step approach is the state-of-the-practice in the modeling of freight transport (٨), primarily because of the simplicity of aggregate models to be developed based upon non-intensive data (٤). Liedtke and Schepperle (٩) argued that freight transportation modeling literature lacks appropriate "actor-based" micro-level models, and as a result, the role of actual decision-makers is mostly overlooked. Many others have emphasized the need for a better understanding of decision-making procedures (٢, ٧, ١٠, ١١, and ١٢). Liedtke and Schepperle (٩) argued that a sound microsimulation freight model could provide a valid forecast tool and pave the way for more reliable policy assessments compared to currently available decision tools. Simulation-based models could better account for the complex interactions among many agents by replicating the individual behavior of the decision makers (١٠) and could be integrated with passenger microsimulation models to provide a realistic picture of current and future traffic patterns.

GoodTrip was one of the early commodity-based freight microsimulation efforts in the City of Groningen. It focused on urban freight and aimed at providing reliable estimates for commodity and vehicle flow and was utilized for analyzing three alternative urban commodity distribution systems (١٣). Wisetjindawat and Sano (١٤), also, developed an urban truck microsimulation model for Tokyo, Japan based on the GoodTrip framework. This model is a modification of the conventional four-step approach but disaggregate enough to incorporate individual behaviors. They simulated five percent of the actual firms operating in the study area and reported truck origin-destination demand matrices along with the vehicle kilometer traveled by each truck type (١٥).

Hunt et al. (١٦) developed an agent-based commercial vehicle microsimulation for the Calgary region in Canada, based on information from roughly ٣٧,٠٠٠ tours and ١٨٥,٠٠٠ trips (١٧). The study provided very valuable and detailed information about commercial vehicle movements, including route choice, empty vehicle, and less-than-truck load treatment. Other regions in Canada (Edmonton) and the U.S. (Ohio) have also applied the findings of the

Calgary study (۱۸). The Oregon Department of Transportation developed a Transportation and Land Use Model Integration Program (TLUMIP) that includes a commercial travel model component (۱۹). Passenger and road freight were integrated in this economic and land use behavioral model to simulate micro-level truck movements more effectively (۲۰). Unlike the Calgary study that undertook an extensive data collection effort (۱٦), the Oregon model was based on a diverse range of data sources with different levels of spatial and temporal resolution.

Liedtke (۲۱) presented an agent-based microsimulation that accounts for logistics reaction configurations. Firm generation, supplier choice, shipment-size choice, carrier choice and tour generation are the main components of this behavioral micro model. Liedtke (۲۱) calibrated INTERLOG model with disaggregate freight data from Germany. Similar to many other microsimulation efforts, this study focused on the urban commodity movements and overlooked the rail and other freight transport markets. In a recent study Roorda et al. (۱۲) proposed a comprehensive agent-based freight microsimulation framework and discussed a diverse range of actors. Although the study is still in progress and no modeling output was reported, some new aspects of freight demand modeling was emphasized. They, however, indicate that making this conceptual framework operational is a very challenging task.

Although there are valuable findings in the literature of freight microsimulation, a vast majority of them deal with urban freight movements. Such studies are necessary for urban transportation planning, but not enough for long term policies and infrastructure investments planning. Beside the limited geographical coverage, many previous efforts only focused on the truck movements. Recent adoption of e-commerce and information technologies also affects the freight shipping behaviors and led to new partnerships between manufactures, shippers, carriers, and ۳PLs (۲). This requires the policy makers to have access to behavioral micro-level models not only in urban and regional level but also in the country level. Developing a nationwide freight microsimulation could be rewarding and provides valuable insights for future infrastructure investments, a big picture of freight modal shift, and a better understanding of potential impacts of freight activities in a larger scale.

FRAMEWORK AND DATA

Freight Activity Microsimulation Estimator (FAME) was introduced as a freight activity-based modeling framework with five basic modules (۲۲). This framework, however, is very briefly mentioned in this paper and interested readers may refer to Samimi et al. (۲۲) for further elaboration. In the first module, all the firms in the study area are recognized and their basic characteristics are identified. Based on each firm's characteristics, the types and amounts of incoming and outgoing goods are determined, and the design of the supply chains is replicated in the second module. In the third module, the shipment sizes are defined based on the acquired information on the firms' characteristics and the way that they trade commodities between each other. Logistics decisions such as shipping mode, haul time, shipping cost, warehousing, etc. are made in the fourth module. Finally, in the last module, the impact of the goods movements on transportation network is investigated.

Four categories of data are required for developing FAME: information on business establishments, aggregate freight movements, information on individual shipments and supply chains, and specifications of the transportation networks. County Business Patterns (CBP) is a publicly available dataset that reports location, industry sector, and number of employees for all the U.S. business establishments with paid employees since ۱۹٦٤ (۲۳). This information is used in the first module. To keep the computational burden at a reasonable level and diminish the need for highly disaggregate data some form of aggregation is inevitable. We proposed to aggregate the firms based on firm-types. A firm-type is a collection of firms with similar location, industry type, and establishment size.

Aggregate freight movements are required for the second module, and are obtained in the form of two sets of information: annual commodity flows between each zone pair, and relationships between different industries in the U.S economy. Annual value and tonnage of different commodity types that are traded between zone pairs are provided in the Freight Analysis Framework (FAF) by the Federal Highway Administration (٢٤). FAF estimates for the commodity flows only between the domestic zones is used in this study. Two-digit Standard Classification of Transported Goods (SCTG) that is used in FAF is also used in this study to classify the commodities. Another aggregate piece of information about freight movements that is essential in this study is the types and amount of commodities used and produced in each industry. The input-output account is a public dataset that provides this information in the U.S. (٢٥). Although this data is very fundamental in the supply chain replication module, no linkage between commodity type and industry class is provided. Therefore, a reliable crosswalk between industry and commodity is essential, since FAF O-D commodity flow is available for each type of commodity and the second module in FAME has to assign this flow to appropriate industries. A similar crosswalk that was used in FAF development is also used in this study.

Information on individual shipments and supply chains is another category of information that is required for the second, third, and fourth modules. This information was obtained through an online survey that was conducted by our research team. This survey was specifically designed to collect some information on shipments and to facilitate the development of FAME. This survey was carried out in April and May of ٢٠٠٩. In total, ٣١٦ establishments participated in the survey providing information on ٨٨١ shipments across the country. Further information about this survey is discussed elsewhere (٢٦).

Specifications of the transportation networks are the last pieces of information, required to run FAME. This is not only needed in the fifth module, but a rough estimate of the network characteristics is also required in other modules. For instance, accessibility to truck-rail intermodal facilities is a critical element in a mode choice model, and should be obtained from the transportation network data. The Oak Ridge National Laboratory (٢٧) has provided county-to-county distance matrix for the entire U.S. Millage and impedance of every county pairs are estimated in rail, highway, water, and highway-rail networks.

Impedance values are mode specific and calculated for each link based on several specifications.

MODE CHOICE MODEL

Two freight mode choice models were calibrated based on the UIC National Freight Survey. An explanatory model was discussed to shed light on truck and rail (including truck-rail intermodal) competition in U.S. freight transportation market. Furthermore, a parsimonious mode choice model was proposed and implemented in the microsimulation. Although the latter had easy-to-generate input variables, its overall goodness of fit was slightly less than the explanatory model. The explanatory model is further discussed elsewhere (٢٨) and is not the focus of this paper. Meanwhile, it is briefly mentioned here for the sake of comparison with the parsimonious model.

Method

The most common framework used for choice behavior analysis in recent years has been discrete choice modeling approach. Various forms of discreet choice models are proposed in the literature depending on underlying assumptions concerning the distribution of the unobserved utility. Two widely used forms of the discrete choice models are logit and probit models. While logit model assumes independent and identically distributed (IID) error terms in the utility function, the probit model assumes normal distribution for the error terms (٢٩). Newey and McFadden (٣٠) and Train (٢٩) include detailed discussions on binary choice models. The Limdep econometrics software (٣١) was used in this study for model calibration. Akaike and McFadden values are among many fit measures offered for binary choice models, which were used along with the chi-squared values for model selection (٢٩). The higher the McFadden value and the lower the Akaike measure, the better the explanatory power of the model. Standard t-statistics are used to test whether each coefficient has a non-zero effect on the choice probability. Wald, Likelihood Ratio, and Lagrange Multiplier tests, known as

Neyman-Pearson tests (۳۱), were also carried out to show the overall significance of the final models. Percentage of correctly predicted observations is usually high in binary choice models that predict a rare event, and in many cases this number could be misrepresented as the general explanatory power of the model. When the two possible outcomes are either rare or common events, binary models tend to over predict the latter, resulting in high rates of correct predictions at the expense of largely ignoring the rare event outcomes. For example, if ۹۹ out of ۱۰۰ choices are common and only ۱ is a rare event, the model can attain ۹۹% accuracy by simply predicting all cases to be common. Thus the percentage of rare events that are correctly predicted is a more valuable measure of predictive power for such models. In our case, choosing rail over truck could be considered as a rare event with less than ۱۰% chance of occurrence in our data. Potential multicollinearity between explanatory variables is also controlled in two ways. Large off-diagonal values were searched in the variance-covariance matrices as the primary effect of multicollinearity. Meanwhile, variance inflation factors (VIF) were estimated for all the independent variables to detect any severe multicollinearity. Kutner et al. (۳۲) suggested a VIF of ۵ as the threshold that indicates a presence of serious multicollinearity.

Descriptive Model

Variables that are used in this part of the analysis are summarized in Table ۱, while the final logit model that estimate the probability of choosing between truck and rail is presented in Table ۲. All the estimated parameters in the final models turn out to be significant with a p-value of less than ۰.۰۵, and most of them are significant with a ۹۹% confidence interval. The model has a pseudo R-squared value of more than ۵۷%, and correctly predicts ۹۵% of the observations. The model predicted more than ۷۲% of rail shipments correctly, which is quite impressive. None of the variables, however, had the VIF in excess of ۳.۵, and thus, multicollinearity is not an issue in this model (Table ۲).

During the model fitting process, many different combinations of the independent variables were tested. We found that a broad range of variables to be influential on the mode selection process, but due to some interdependencies not all of them turned out to be significant in the final model. A detailed discussion on the modeling approach, interpretation of the coefficients, effect of each explanatory variable, and sensitivity analysis is discussed elsewhere (۲۸).

Parsimonious Model

An explanatory mode choice model was developed and discussed in the previous chapter, the primary goal of which was to shed light on the modal selection behaviors in freight transportation. Although that model revealed some behavioral aspects of modal selection such as different levels of sensitivity to travel time and cost for truck and rail users, it is not necessarily a good model to be implemented in a microsimulation or forecast. Contradictory to explanatory models, microsimulation or forecast models have to be applied on a different set of input variables and the new set of input variables should be collected, estimated, or imputed. Therefore, an essential characteristic for such models is to have easy-to-obtain explanatory variables. Otherwise, estimated dependent variable will be affected by the errors and assumptions associated with independent variables' estimation. The explanatory mode choice model could not be used in a nationwide microsimulation effectively, since time and cost of each mode should be estimated for all the simulated shipments prior to determining the mode, which seems quite questionable. Therefore, another model is discussed here with a slightly less goodness of fit, but much easier to obtain explanatory variables. Basic descriptive statistics of variables that are used in this model are summarized in Table ۳.

A discrete choice modeling approach is preferred for this model with a probit specification. As stated earlier the logit model assumes independent and identically distributed (IID) error terms in the utility function but has a closed form equation for estimating the probability of each choice. This makes logit models very convenient to use, especially in microsimulations that a specific decision has to be made several times. Probit models, on the other hand, do not have the IID assumption but a normal distribution for the error terms, and require a numerical method for estimating the probability of each choice.

Table ٤ shows the final probit model that estimates the probability of choosing between truck and rail / truck-rail. All the estimated parameters in the final models turn out to be significant with a p-value of less than ۰.۰٥, and most of them are significant at a ۹۹% confidence level. The model has a pseudo R-squared value of ٥٤%, and correctly predicts ۹٦% of the observations. Furthermore, more than ٥۸% of rail or truck-rail shipments are correctly predicted. As shown in Table ٤, all the VIFs are less than five, and thus, a serious multicollinearity issue is not detected (۳۲).

SIMULATION

This section of the paper discusses the development of the first four modules of FAME. Firm-types generation, supply chains replication, and shipment size determination are performed to provide necessary information for modal split in the fourth module. Finally the mode choice results are validated with some reliable public freight data sources in the U.S.

Firm-types Generation

A total of ٤٦,۲٤۳ firm-types were generated for this microsimulation in the domestic FAF zones. ۱۳۰ domestic FAF zones, ۳۲۷ industry classes (six digit NAICS classification), and eight size groups (Table ٥) were considered in this simulation as well. All the industry classes in FAF are considered in this study, and the industry classes for which no business establishment is reported in CBP ۲۰۰۲ are excluded. For example, NAICS ۱۱۱ is observed in FAF but not in this study, since information for business establishments in the crop production industry are not reported in CBP ۲۰۰۲. The size of establishments, however, was defined according to the number of paid employees.

Supply Chains Replication

Supply chains were replicated based on a fuzzy expert system that is developed and discussed elsewhere (٣٣). This model scores the appropriateness of all the possible suppliers for a given firm-type. Having the likelihood of partnership for any pair of supplier and buyer, annual commodity flows is disaggregated from geographic zone level into firm-type level. For a given origin, destination, and commodity type, the value of total annual tonnage was obtained from FAF data and disaggregated between the top five percent of supplier and buyer pairs with the highest appropriateness score. However, this score was weighted by the total number of actual firms within the supplying and buying firm-type before disaggregation. This was to distinguish between a pair of supplier and buyer with only one actual firm in each side of the chain and a pair of supplier and buyer with several actual firms in each side. Obviously, the latter should receive a higher share of commodity fellow.

All the FAF industry sectors were considered in FAME, but some of them were not present in specific zones in the simulation. This is due to the limitations of business establishment data sources and also the crosswalks that were used in the second module. As a result, not all of the FAF commodity flows between the zone pairs was allocated to firm-types. A total of ١٣,١٤٠ millions of tons of commodity valued at around ٨,٧٩٤ billion dollars is transported between the domestic origin and destinations on truck, rail, or truck-rail intermodal. However, ١٠,٥٨٣ millions of tons of commodity valued at around ٦,٩٤٤ billion dollars are simulated in FAME. Thus, around ٨٠% of FAF domestic tonnage and ٧٩% of commodity values are simulated in this study.

Shipment Size Determination

A shipment size model was developed by Samimi et al. (٣٣), that provides a categorical output variable with three clusters: small, medium, and large. Establishment size of the supplier and buyer, shipping distance and commodity type, on the other hand, are the inputs. This model was applied on the annual commodity flow between each pair of supplier and buyer from the former section and determined share of small, medium, and large shipments accordingly. However, knowing that a shipment is small is not enough to run the modal split in the next module and a crisp value should be assigned as well. In order to do so, a distribution of observed shipment sizes from the UIC National Freight Survey was obtained for each class of shipment size. Details of the shipment size model and the shipment size distributions are elaborated in a separate study (٣٣).

Modal Split

The parsimonious binary mode choice model that was introduced in the previous section was deployed in this simulation to determine the share of truck and rail (including truck-rail intermodal) for each shipment. This model has GCD, weight, relative impedance between truck and rail, a dummy for containerized shipments and commodity type as input variables all of which have to be determined for every simulated shipment. Since the origin and destination zone of all the shipments are known, GCD and the relative impedance between truck and rail could be easily obtained from the inter-county distance matrix, provided by the Oak Ridge National Laboratory (٢٧). The two-digit SCTG commodity type is also known for each simulated shipment, and therefore the dummy for commodity type could be determined accordingly. Weight of the shipment, on the other hand, was obtained from the shipment size model. And finally dummies for the containerized shipments were drawn from a Bernoulli distribution. Bernoulli is a discrete probability distribution with a given success probability. In this simulation the overall probability of having containerized shipments was assumed to be ١١.٨%, according to the UIC National Freight Survey. This figure, however, was weighted by the normalized highway impedance between each origin and destination that was provided by the Oak Ridge National Laboratory (٢٧). Since the weight factors were normalized, the average chance of having a containerized shipment remained the same. However, this chance was higher for long haul shipments. Although the binary mode choice overall has a satisfactory goodness of fit, it underestimates the total number of rail shipments.

Therefore, the estimated probability of a rail shipment is increased by a ١.٣ factor to cover this underestimation in general.

Modal split of domestic freight movements in the U.S. was performed by calibrating and simulating the first four modules of FAME. As mentioned, only truck and rail (including truck-rail intermodal) are covered as the primary modes of freight transportation in America, and the relative percentages of total tonnage, value, and ton-mile of commodities between the two modes are estimated. Due to the random nature of the microsimulation, the simulation was repeated several times, the results of which are reported in Table ٦. Although the tonnage of the shipments carried by each mode is obtained directly from the model, the dollar value of the shipment is approximated. Average dollar per ton for each commodity type was obtained from FAF data and applied to the tonnage of the shipments carried by each mode to estimate the dollar value. The ton-mile of the shipments, on the other hand was simply estimated by using the inter-county distance matrix, provided by the Oak Ridge National Laboratory (٢٧).

Validation

The primary objective of this study was to develop a behavioral mode choice model for freight transportation, focusing on truck and rail. Therefore, the relative percentages of total tonnage, value, and ton-mile of commodities between the two modes (Table ٦) are validated in this section. These relative percentages can be obtained from FAF and CFS, as two major public sources of freight data in America. It should be noted, however, that the modal split information of none of these datasets has been used in model calibration and thus can be an appropriate base lines for validation. Table ٧ compares the percentages of the two modes according to FAF, CFS ٢٠٠٢, CFS ٢٠٠٧, and FAME.

CONCLUSION

The primary motivation for this research was to develop a behavioral freight mode choice model in the U.S. and therefore, a nationwide freight activity microsimulation was conducted. A major drawback of many previous studies of this kind was their aggregate nature which prevents the development of an actor-based microsimulation. This is a key downside that seriously questioned practicability of the models in current freight markets in which an increase in globalization is increasingly prompting the firms to apply supply chain management concepts. A large-scale behavioral microsimulation framework, named Freight Activity Microsimulation Estimator (FAME) was developed in this study. This framework incorporates firms' characteristics in replicating shipping behaviors, and aimed at paving the way for future behavioral freight microsimulation efforts. A total of ٤٦,٢٤٣ firm-types were generated for this microsimulation in the domestic geographic FAF zones. ٣٢٧ industry classes and eight establishment size groups were considered in this simulation as well. Final results of the modal split showed a close match with CFS ٢٠٠٢, CFS ٢٠٠٧, and FAF data. This study aimed at facilitating a sound microsimulation freight model as a valid forecast tool that eventually could contribute to more reliable policy assessments compared to currently available decision tools.

FAME is largely based on public freight data in the U.S. and therefore data collection costs are substantially mitigated. It is also one of the early efforts in freight demand modeling that has a separate component for supply chain configuration. Furthermore, this study covered almost all the industry classes. FAME has a unique geographic coverage, as well, and to the best of the authors' knowledge, it is the first comprehensive nationwide freight microsimulation in the U.S. This study presented the first steps toward a comprehensive activity-based freight microsimulation. There are still several components that need further exploration. Although this study focused on domestic shipments in the U.S., this framework could be run for international and domestic flows. However, some additional information for the international commodity movement has to be collected. This includes country of origin and/or destination, port of entry and/or departure etc. Upon data availability, FAME could also be calibrated and simulated with a county-level geographic resolution. Although this requires a rich set of data for calibration and will have a heavy computational burden in simulation, the results are rewarding and enlightening particularly for regional studies. Considering other modes of transportation in the framework is another area for improvement, which of course requires extra data sources.

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FIGURES AND TABLES

TABLE ١. VARIABLES USED IN THE EXPLANATORY ANALYSIS

Variable	Definition	Mean	Standard deviation
MODE	١: rail or any combination of that with other modes / ٠: truck	٠.٠٨٩	٠.٢٨٥
DISTANCE	Suggested distance between origin and destination by Google Map (miles)	١٠٧٧.٩٤٠	٢٢٢١.١٠٠
WEIGHT	Weight of the shipment (lbs)	٢٢٩٠١.١٠٠	٢٥٢٧٥.١٠٠
VALUE	Value of the shipment (USD)	٤٨١٠١.٣٨٩	١٣٠١٥٠.٢٥١
TRUCK-COST	Shipping cost by truck (USD)	١٣٣١.٧٦٠	٤٠٩٣.٣٩٠
RAIL-COST	Shipping cost by rail (USD)	٢٠١٦.٨٨٠	١١٢٨.١٦٠
TRUCK-TIME	Shipping time by truck (days)	٢.٠١٢	١.٣٥٧
RAIL-TIME	Shipping time by rail (days)	٧.٢٨١	٦.٦٦٢
TRUCK-COST-INDEX	= Ln (TRUCK-COST / (TRUCK-TIME * VALUE))	-٣.٥٤٢	١.٥٢١
RAIL-COST-INDEX	= Ln (RAIL-COST / (RAIL-TIME * VALUE))	-٣.٧٠٥	١.٩٤٠
SAME-DECISION	١: if the same mode was preferred TWO years ago for a similar shipment / ٠: otherwise	٠.٩٣٤	٠.٢٤٨
ACCESS	٠: firm has easy access to truck rail intermodal facilities / ١: neutral access / ٢: difficult access	٠.٧٨٠	٠.٤١٥
POTENTIAL-INTERMODAL	١: truck-rail intermodal is considered always or often as a potential transportation mode / ٠: otherwise	٠.٣٤٩	٠.٤٧٧
PERISHABLE	١: if the commodity is perishable / ٠: otherwise	٠.١٦٠	٠.٣٦٧
CONSOLIDATION-CENTER	١: if the shipment has gone through a consolidation center / ٠: otherwise	٠.١٤٣	٠.٣٥٠
DISTRIBUTION-CENTER	١: if the shipment has gone through a distribution center / ٠: otherwise	٠.٢٧٠	٠.٤٤٥
WAREHOUSE	١: if the shipment has gone through a warehouse / ٠: otherwise	٠.٣٤٧	٠.٤٧٧
DECISION-MAKER	١: if a ٣PL company has make the shipping decision / ٠: otherwise	٠.١٠٤	٠.٣٠٥

TABLE ٢. EXPLANATORY MODE CHOICE PROBIT MODEL

	Item	Value	t-ratio	VIF
Coefficient	CONSTANT	-٥.٩٠٢*	-٦.٠٥٠	-
	DISTANCE	٠.٢٣٧E-٠٣**	٢.٢٧٣	٢.٧٧٦
	WEIGHT	٠.٣١٠E-٠٤*	٤.٢٩٣	١.٥٦٤
	TRUCK-TIME	٠.٦٢٢*	٥.٠١٩	١.٦٤٨
	RAIL-TIME	-٠.٠٩٤*	-٢.٥٧٩	٢.٣٨٧
	TRUCK-COST-INDEX	٠.٣٨٨**	٢.٥٣٢	٣.٤٠٨
	RAIL-COST-INDEX	-٠.٦٥٩*	-٣.٤٧٤	١.٠٩٩
	POTENTIAL-INTERMODAL	١.٢١٤*	٣.٤٦٨	٢.٧٧٦
Fit Measures	Log likelihood	-٤٧.١٤١	-	-
	Model Chi-squared	١٢٨.٥٧٧	-	-
	Akaike I.C.	٠.٢٩٦	-	-
	Pseudo R-squared	٠.٥٧٧	-	-
	Correctly Predicted (%)	٩٥.٤٣٠	-	-
	Correctly Predicted (%) –rail	٧٢.٧٢٧	-	-

*Significant at ٩٩% confidence interval.
**Significant at ٩٥% confidence interval.

TABLE ٣. VARIABLES USED IN MODE CHOICE MODEL IN FAME

Variable	Definition	Mean	Standard deviation
MODE	١: truck / ٠: rail or any combination of that with truck	٠.٩٢٤٨٤٣	٠.٢٦٣٩١٩
GCD	Great circle distance (miles)	٦١٦.٥٦٣	٦٤٠.٣٢٨
WEIGHT	Weight of the shipment (lbs)	٢٣٤٥٧.٦	٢٨٩٥٩
IMPEDANCE	= EXP (H_IMP/R_IMP)	٦.١٨٦٦	٣.٣٣٨٣٩
H_IMP	Highway impedance	٨٩٧.٧٠٢	٤٥٨٩.٤٨
R_IMP	Rail impedance	١١٧٦.١٦	٩٠٨٢.٠٨
CONTAINERIZED	١: if the shipment is containerized / ٠: otherwise	٠.٠٢٢٩٦٤٥	٠.١٤٩٩٤٧
COMMODITY	١: if the commodity is agricultural, chemical, pharmaceutical, gravel, natural sands, cement, machinery, metal, mixed freight, miscellaneous, or preparedfoodstuffs / ٠: otherwise.	٠.٦٥٥٥٣٢	٠.٤٧٥٦٩١

TABLE ٤. MODE CHOICE PROBIT MODEL IN FAME

	Item	Value	t-ratio	VIF
Coefficient	CONSTANT	٤.٨٣٢٧١٣٧٤٢	٨.١٧٠	-
	GCD *	-.١٠٤٢٣٨٥٨١٨E-٠٢	-٤.٨٥٦	٢.٠٧٨٦٦٠٦
	WEIGHT*	-.٢٥٤٣٨٠٥٥٢٨E-٠٤	-٥.٠٧٥	١.٠٢٩٦٤٧٦
	IMPEDANCE **	-.٩٨٨٩٧٧١٩٤٤E-٠١	-١.٩٧٨	٢.٠٢١١٤٩٣
	CONTAINERIZED*	-١.٢٧١٠٥٢٦٤٣	-٢.٦١٢	١.٠٥٥٠٧٢٦
	COMMODITY*	-.٩٤٠٣٠٤٤٦٥١	-٢.٩٨٥	١.٠٤٦٣٧٠٩
Fit Measures	Log likelihood	-٥٨.٥٦٧٤٢	-	-
	Model Chi-squared	١٣٨.٤٣٨٢	-	-
	Akaike I.C.	٠.٢٦٩٥٩	-	-
	Pseudo R-squared	٠.٥٤١٦٨	-	-
	Correctly Predicted (%)	٩٥.٦١٥٨٦٦	-	-
	Correctly Predicted (%) –rail	٥٨.٣٣٣٣	-	-

*Significant at ٩٩% confidence interval.
** Significant at ٩٥% confidence interval.

TABLE ٥. DEFINITION FOR ESTABLISHMENT SIZE CLASSIFICATION

Establishment size category	Range of number of employees
١	١ – ١٩
٢	٢٠ – ٩٩
٣	١٠٠ – ٢٤٩
٤	٢٥٠ – ٤٩٩
٥	٥٠٠ – ٩٩٩
٦	١٠٠٠ – ٢٤٩٩
٧	٢٥٠٠ – ٤٩٩٩
٨	٤٩٩٩ <

TABLE ٦. RELATIVE PERCENTAGE OF TRUCK-ONLY SHIPMENTS IN DIFFERENT SIMULATION RUNS

Simulation Run	Ton	Value	Ton-mile
١	٧٩.٦٣%	٨٩.٩٢%	٦٥.٦٢%
٢	٧٩.٨٧%	٩٠.١٩%	٦٦.٣٧%
٣	٧٩.٢٦%	٩٠.١٤%	٦٧.٤٣%
٤	٧٩.٦٥%	٨٩.٧٩%	٦٨.١٨%
٥	٧٨.٣٤%	٨٩.٧٢%	٦٠.٩٩%
٦	٧٨.٣٩%	٨٩.٨٢%	٦٥.٢١%
٧	٧٨.٠٤%	٨٩.٨٢%	٦٠.٧٥%
٨	٧٨.٩٨%	٨٩.٨٥%	٦٥.٢٠%
٩	٧٨.٨٥%	٨٩.٨٥%	٦٢.٨٦%
١٠	٧٨.٧٣%	٨٩.٩٢%	٦٦.١٦%
١١	٧٩.٧٧%	٨٩.٨٩%	٦٤.٦٠%
١٢	٨٠.٢١%	٩٠.٢٦%	٦٢.٤٨%
١٣	٨٠.١٤%	٨٩.٨٧%	٦٥.٢٢%
١٤	٧٩.١٠%	٨٩.٩٧%	٦٣.٣٥%
١٥	٧٧.٣٩%	٨٩.٧٨%	٦٣.٦١%
١٦	٧٩.٧٠%	٨٩.٩٣%	٦٤.١٥%
١٧	٧٨.٤٣%	٨٩.٥١%	٦٤.٢٢%
١٨	٧٩.٠٤%	٩٠.٠٣%	٦٧.٤٣%
١٩	٨٠.٤٩%	٩٠.٢٣%	٦٨.١١%
٢٠	٧٩.٥٧%	٩٠.٣٠%	٦٢.٨٢%
Mean	٧٩.١٨%	٨٩.٩٤%	٦٤.٧٤%
Coefficient of Variation	٠.٩٨%	٠.٢٢%	٣.٢٨%

TABLE ٧. MODAL SPLIT VALIDATION IN FAME

Item		**CFS ٢٠٠٢**	**CFS ٢٠٠٧**	**FAF**	**FAME**
Tonnage	Rail	٢٠%	١٩%	١٥%	٢١%
	Truck	٨٠%	٨١%	٥٨%	٧٩%
Value	Rail	٦%	٧%	٥%	١٠%
	Truck	٩٤%	٩٣%	٩٥%	٩٠%
Ton-mile	Rail	٥١%	٥٣%	٤٣%	٣٥%
	Truck	٤٩%	٤٧%	٥٧%	٦٥%