Development of a Freight Policy Analysis Tool for Northeastern Illinois and the United States

Freight Activity Microsimulation Estimator

Kazuya Kawamura (PI)
Abolfazl (Kouros) Mohammadian
Ammir Samimi
Zahra Pourabdollahi
Meredith Klekotka

Urban Transportation Center
The University of Illinois at Chicago

December 2011

DISCLAIMER NOTICE

Table of Contents

CHAPTER 1. INTRODUCTION

1.1. BACKGROUND

Freight flow volume within the United States has almost doubled over the past thirty years (Transportation Research Board, 2008). In 2007, over 12 billion tons of goods, valued at more than $11.6 trillion, were transported in America (Bureau of Transportation Statistics, 2009). Population growth, economic growth, the proliferation of e-commerce, and a greater dependence on transportation in the production process have driven this growth in freight volumes, especially for long-haul and international shipments (Southworth, 2003). As a national rail hub, metropolitan Chicago is sensitive to these changes in freight volumes.

Industry sectors, international trade networks, public agencies, and other policy makers need accurate information about national freight movements to continue efficiently delivering various goods within and among consumer markets,. They need to plan for future freight traffic impacts and evaluate the effectiveness of policies and projects designed to alleviate freight congestion problems.

New federal regulations mandate that state departments of transportation and metropolitan planning organizations consider these rail freight congestion problems during the long-range transportation planning process (Transportation Research Board, 2008). Bryan et al. (2007) and many others have argued that transportation planners should consider rail freight transportation's environmental, maintenance, and security costs as well as congestion costs to better formulate practical solutions to freight congestion problems.

The freight shipment decision-making process is becoming even more complex as businesses increasingly adopt sophisticated supply chain management strategies and as the demand for more accurate freight modeling and forecasting tools is growing.

To help address these needs, a research study team from the University of Illinois at Chicago has developed a forecasting tool that accurately reflects current freight flows, incorporates freight operators' complex modal-choice decisions, and estimates changes in freight movement based on a variety of variables. Creating a satisfactory freight model which reflects modal share decisions and facilitates decision making is challenging. Major research efforts in travel demand modeling have mainly concentrated on passenger transportation. A state-of-the-art, behavioral freight model is therefore far behind advancements in ground passenger transportation (Pendyala et al., 2000). The complex decision-making process, the lack of an acceptable freight modeling framework, and freight data scarcity are major obstacles that may have prevented freight modeling's advancement. This report summarizes the results of the Freight Activity Microsimulation Estimator study for which the research team developed a state-of-the-art, freight policy analysis tool for Northeastern Illinois and the United States.

1.2. SCOPE

This study introduces a nationwide behavioral microsimulation framework that has five basic modules. The first module uses agent-based modeling to replicate firms' characteristics to organize these firms according to industry type. The second module uses a fuzzy rule based model to determine the volume and type of commodity flows and replicates the supply chain design. This model is used because disaggregate data on supplier selection within the supply chain is lacking. By effectively incorporating decision making agents into the model, the results are more realistic since they are based on firms' behaviors. Incorporating firms' behavior in the freight transportation model is the essence of disaggregate freight models. A few researchers have emphasized it (RAND Europe, 2004; de Jong and Ben-Akiva, 2007; Hensher and Figliozzi, 2007).

In the third module, the study team nationally applied this framework's open structure under multiple scenarios to develop a comprehensive freight traffic study that incorporates freight firms' complex-decision-making about modal split and the influences of supply-chain demands that affect freight flows. The study team has therefore tried to fill the modeling gap in large scale freight microsimulation and has sought to promote future behavioral freight microsimulation efforts.

This report details the Freight Activity Microsimulation Estimator framework's development and documents the study team's results in determining national freight flows along the transportation network. The first application of the five Freight Activity Microsimulation Estimator modules used the County Business Pattern and Freight Analysis Framework from 2002 to analyze how freight mode choices affected the transportation network under a variety of factors.

The second application of the Freight Activity Microsimulation Estimator framework used the updated 2007 County Business Pattern and Freight Analysis Framework data sets and incorporated new infrastructure developments affecting freight flows nationally. This model covers the entire U.S. since freight policies and plans for Northeastern Illinois cannot be analyzed in isolation from national and even global trends and major projects planned elsewhere in the country, given Chicago's role as North America's major freight hub.

1.3. DATA

Data scarcity is a major issue that hinders the development of behavioral freight modeling. Aggregate data, often at the state or urban area level, are usually available but are insufficient for behavioral freight modeling efforts that need to capture decision-making processes and interactions at the firm level. This is the primary factor that hinders the development of freight studies at the disaggregate level (Kumar and Kockelman, 2008). Surveying freight firms is one option for collecting disaggregate data, but many decision-makers are unwilling to participate in surveys inquiring about their shipping decisions, since such information is an important part of their business strategies. They understandably fear that disclosing their strategies will jeopardize their competitive edge. Furthermore, knowledgeable persons who can provide input to such surveys tend to have a high value of time. This could not only seriously decrease the response rate and thereby endanger the survey's credibility, but also make such surveys very expensive in many cases, even if successful.

This study's data takes advantage of publicly available U.S. freight and business data, the Freight Analysis Framework, and County Business Pattern data and incorporates it with data from a nationwide survey of freight shippers that the University of Illinois at Chicago previously collected. The diversity of this data is sufficient to produce results indicating modal choice decisions and the distribution pattern of national freight movements. However, the highly aggregate nature of the Freight Analysis Framework data means that the results are susceptible to uncertainty. This model should therefore be considered as an exploratory effort that will need further improvements.

CHAPTER 2. LITERATURE REVIEW

This chapter provides a context for this study within the current modeling frameworks. It contains an overview of past freight demand forecasting efforts, consisting of aggregate models, disaggregate models, and freight mode choice models. Freight microsimulation efforts, however, are discussed in another chapter.

2.1. RESEARCH NEED

Supply chain management seeks to satisfy customers as a way to improve industrial competitiveness and profitability (Stadtler, 2005). Freight industry deregulation in the early 1980s, increasing globalization, and the use of information technology prompted freight industries to apply supply chain management (Rodrigue, 2006). This application of supply chain management has led to more efficient and complex behaviors in commodity production and distribution cycles. Following freight industry deregulation in the U.S, the logistics-related component's share of the GDP decreased from approximately 17% in 1980 to just above 10% in 2000 (AASHTO, 2003).

Long haul commodity flows increased when these firms sought better national or international partners to form the best possible chains. To survive in such a competitive market, these firms also had to use logistics professionals to keep transportation costs as low as possible.

The way that logistics decisions are made within production cycles influences the transportation costs for raw materials and semi-finished goods. Firms could similarly optimize the distribution costs for finished goods within a well-organized distribution system. This could lower the overall costs of goods from the producers to the consumers, causing a decrease in retail store prices (Rodrigue, 2006).

Hensher and Figliozzi (2007) argued that rapid changes in supply chain structures, logistics and technological advancements, and freight systems are the primary causes of the current freight models and policy making tools' obsolescence. They and many other researchers strongly believe that the conventional four-step approach, primarily designed for passenger transport modeling, cannot adequately capture the complexity of the international, national, and urban freight movements.

Like the passenger travel demand models, Hensher and Figliozzi's framework has four sequential modules: commercial trip generation, distribution, mode choice, and traffic assignment. However, this framework does not capture strategic decisions that individual firms make regarding their supply chain designs and operations, such as how shipping decisions are made, whether to contract out shipping tasks, and whether consolidation and/or distribution centers are needed.

Southworth (2003) argued that a successful freight forecasting tool must be able to incorporate rapid changes in supply chain logistics into the planning procedure, either by adopting traditional methodologies or introducing entirely new frameworks of freight demand forecasting tools.

Taylor (2001) highlighted the growing trend toward new delivery methods that used the intermodal transport system's uncovered capacities to place a premium on transit time and reliability. One example is just-in-time (JIT) delivery, a cornerstone of contemporary customer-order-driven markets (Hensher and Figliozzi, 2007).

As goods transportation becomes ever more complex and sophisticated, many shippers have resorted to outsourcing all or many of their supply chain functions to third-party logistics companies, or third-party logistics companies. Southworth (2003) has argued that third-party logistics companies and IT-based logistics service providers are moving toward more integration and globalization by linking different firms' logistics management. This makes predicting shipping decision behaviors even more complicated.

Gray (1982) reviewed behavioral models and highlighted the importance of identifying decision makers in freight demand modeling procedures. Even in passenger transportation modeling, the effectiveness of the four-step framework is questioned (McNally and Recker, 1986).

In the last few decades, researchers have developed and advanced the Activity Based Modeling approach (Ettema and Timmermans, 1997). In this emerging framework, the model includes how individuals (or households) are making decisions regarding activity type, destination choice, mode choice, etc. The need to incorporate changes in travel behavior, such as trip chaining, partly motivated this approach.

A limited number of studies have tried to apply the activity-based approach to freight transportation modeling, but most have not produced satisfactory results given the lack of data (Hensher and Figliozzi, 2007). In a comparison with the passenger activity-based modeling approach, Liedtke and Schepperle (2004) argued that commodity transport modeling's current state-of-the-practice lacks actor-based microsimulation.

Although there are well-developed standard techniques to model passenger transportation systems, less attention has been paid to freight demand modeling. Accordingly, there are much fewer achievements in this area.

The freight transportation decision-making process is extremely difficult to reproduce. However, freight modelers have made some strides using an agent-based approach. Behavioral freight demand modeling frameworks are at their early development stages and establishing a practical and theoretically sound method is yet to come.

2.2. FREIGHT DEMAND MODELS

The four-step freight modeling framework consists of four sequential modules and is the primary approach for freight demand forecasting in practice, especially for metropolitan and statewide planning agencies (Southworth, 2003, Cambridge Systematics, 1995).

A commonly used criteria for categorizing modeling efforts is vehicle-based versus commodity-based models. In commodity-based models, modelers estimate commodity tonnage and convert it into truck trips. They apply payload cost estimates to aggregate commodity tonnage and obtain truck trips rates (Fisher and Han, 2001).

Although it lacks consensus on using vehicle versus commodity based models, vehicle based models dominate freight research (Luk and Chen, 1997). Holguin-Veras and Thorson (2000), however, argued that both commodity-based and vehicle-based approaches lead to conceptual inconsistencies since commodity flows should represent actual freight demand and vehicles should represent logistics decisions.

Winston (1983) also classified the freight models into aggregate and disaggregate approaches based on the types of data used. This categorization method seems suitable for this study's purposes since the study team is focusing on behavioral freight models.

The study team will review aggregate and disaggregate approaches to freight modeling and provide an overview of existing research on mode-choice models and microsimulation of freight activity in the following sections.

2.2.1. Aggregate Models

Aggregate models are still the state-of-the-practice in freight transport modeling (Liedtke and Schepperle, 2004). They predominate modeling because they require simple data compared to the disaggregate approach and rely on historical trends (Pendyala et al., 2000). Although many practitioners and decision-makers are aware of the aggregate models' drawbacks, they face pressure to keep data collection costs low and must compromise between modeling quality and project expenses.

The application of the four-step modeling framework is typically aggregate in nature. Generation and attraction of commercial trips are usually based on zonal economic activity or employment (Anderson et al., 2007). Although information on an industry's economic activity is difficult to obtain, there are some publications that provide an average rate of commercial trip generation and attraction for freight planners (Fischer and Han, 2001).

The distribution of commercial trips is commonly carried out by a gravity model with shipping distance as the impedance (Auld, 2007).

Southworth (2003) discussed different approaches for commercial trip distribution, including the spatial interaction method. Mode choice is a critical component of the framework. Modelers previously estimated mode choice based on shipping costs (Cunningham, 1982).

Many four step models have now attempted to incorporate both commodity and vehicle trips by adding a fifth step that converts the commodity flow into vehicle flow, before assigning traffic (Fischer et al., 2000). Modelers, however, usually assign urban freight traffic to the cheapest or quickest path with base traffic when converting it to a passenger vehicle equivalent. This trend of not considering modal split is very common in aggregate four-step approaches and is rooted to the aggregate nature of the data that is not able to capture the behavioral complexities of modal selection decisions.

Tavasszy et al. (1998) were pioneers in considering logistics decisions in freight transportation planning. They developed the Strategic Model for Integrated Logistic Evaluations in the Netherlands for the Dutch Ministry of Transport, Public Works, and Water Management. The Strategic Model for Integrated Logistic Evaluations is an aggregate model (Yang et al., 2009), yet containing some disaggregate logistics components.

More details on four-step freight demand modeling is provided in the Quick Response Freight Manual (Cambridge Systematics, 1997) for the U.S. Department of Transportation. National Cooperative Highway Research Project (NCHRP) Report 606, Yang et al. (2009), and Pendyala et al. (2000), also provided valuable reviews of similar past practices. The American Association of State Highway and Transportation Officials (AASHTO) in cooperation with the Federal Highway Administration (Transportation Research Board, 2008) sponsored a recent study that is a comprehensive source for freight demand models in the U.S.

2.2.1. Disaggregate Models

This section provides a short review of some disaggregate modeling efforts in previous freight demand studies. Although disaggregate models are more appealing and considered theoretically sounder, the limited availability of disaggregate data often prevents development and implementation of these models. Nevertheless, a considerable number of disaggregate models have focused on urban freight movement and modal selection, and recently on supply chain and logistic decisions.

Regan and Garrido (2001) pointed out several general drawbacks of aggregate models and discussed behavioral and inventory disaggregate freight models. Behavioral disaggregate freight models strive to capture the utility maximization process for certain decision-makers. Inventory disaggregate freight models, however, attempt to model firms' production and logistic decisions based on economic optimization.

Pendyala et al. (2000) argued that approximations are unavoidable in developing logistics cost functions for practical inventory models.

Inventory disaggregate freight models treat production-related variables, such as shipment size, endogenously with mode choice decisions (Pendyala et al., 2000). They argued that some approximations in these models could make them very similar to behavioral disaggregate freight models.

Baumol and Vinod (1970) are among the pioneers in modeling both mode choice and demands for links on a freight network. They used the same approach that had been developed for the analysis of passenger transportation. Their mode choice model considers the trade-off between transportation cost, time, reliability, and safety. It also accounts for carrier and commodity heterogeneity.

Harker and Friesz (1986) also applied the conventional four-step approach with substantial modifications to the supply and demand models.

Hunt and Stefan (2007) developed a behavioral urban freight model, capable of predicting commercial vehicle movements under different policy scenarios. This model shed light on some urban freight movements, including the treatment of empty trips, less than truck load movements, shipment allocation to vehicles, and conversion of commodity flows to shipments. It also integrated an aggregate passenger travel component to account for the interdependencies of urban freight movement and passenger transportation.

Recently, there has been a growing interest in supply chain and logistics modeling. Some of these models were developed for urban freight studies. Fischer et al. (2005) and Yang et al. (2009) provided summaries of recent developments in supply chain models. Tavasszy et al. (1998) is a prominent example of supply chain and logistics modeling efforts. They developed a series of disaggregate logistics models, called the Strategic Model for Integrated Logistics Evaluations, together with an economic input-output model to provide a decision tool for policy evaluation for the Netherlands. Also, Boerkamps et al. (2000) developed an urban supply chain model, called GoodTrip, for the city of Groningen in the Netherlands. The GoodTrip is a disaggregate model that defines supply chain patterns and urban truck tours to provide insights into how logistics decisions affect urban truck traffic. De Jong and Ben-Akiva (2007) also embarked upon the development of a logistics module to be included in the existing freight demand model for Norway and Sweden.

Behavioral freight models are extremely scarce in the literature and a limited number of such studies are found among recent works. Companies have become increasingly customer-order-driven and new production systems such as Just-in-Time (JIT) are now common. De Jong and Ben-Akiva (2007) stated that almost all the existing freight transportation studies are missing supply chain and logistics components. They introduced some behavioral models that incorporated firms' characteristics, which were a substantial step toward establishing a feasible framework for a behavioral freight model.

Hensher and Figliozzi (2007) highlighted the importance of disaggregate behavioral freight models in mitigating traffic congestion and maintaining the freight transportation system's efficiency and reliability. Holguin-Veras (2000) also discussed an urban freight modeling framework capable of incorporating logistics information and trip chaining behaviors.

2.2.2. Freight Mode Choice Models

Mode choice is one of the most critical parts of any freight demand modeling framework, and Freight Activity Microsimulation Estimator is no exception. The amount of literature on this issue is surprisingly modest mainly given the absence of suitable data to estimate such models. A direct comparison of shipment costs was the primary method in the earliest freight mode choice models (Cunningham, 1982).

Reliability, flexibility, safety, and some other non-cost factors entered the analysis when the random utility models emerged (Norojono and Young, 2003). Random utility models become outdated, however, when supply chain concepts required the development of actor-based models that incorporated the role of actual decision-makers in freight movement determination. Many companies adopted new supply chain concepts, which have influenced shipping preferences (Hensher and Figliozzi, 2007) and therefore require a fundamental revision of the existing approach to freight demand modeling.

Freight mode choice models vary greatly in scope and design. Whether logit versus probit or aggregate versus disaggregate, each model calibrates the impact of various factors on freight firms' mode choice decisions

Based on a review of these studies, the dominant factors impacting freight mode choice in the literature can be summarized as: accessibility, reliability, cost, time, flexibility, and past experience with each mode.

2.3. FREIGHT MICROSIMULATION EFFORTS

Many previous studies have called for a behavioral freight microsimulation model. Liedtke and Schepperle (2004) argued that freight transportation modeling literature lacks appropriate "actor-based" micro-level models. Actual decision-makers' roles are therefore mostly overlooked.

Many other studies have emphasized the need for a better understanding of decision-making procedures including Gray (1982), Southworth (2003), Wisetjindawat et al. (2005), de Jong and Ben-Akiva (2007), Hensher and Figliozzi (2007), Yang et al. (2009), and Roorda et al. (2010). Liedtke and Schepperle (2004) 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. Today, various factors enhance the prospect for developing a disaggregate freight simulation model. They include high-speed computing devices, a growing number of potential data sources, the emergence of online surveys as an affordable data collection technique, and successful microsimulation practices in passenger transportation. Modelers can adopt some of these practices for freight modeling.

Simulation-based models can replicate decision makers' individual behavior (Wisetjindawat et al., 2005) and integrate 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. It focused on urban freight and considered some market, actor, and supply chain characteristics. (Supply chains are formed between different entities, such as consumers, stores, distribution centers, and factories.) This model simulated consumer commodity demand and commodity flows in different mode and supply chains, which resulted in vehicle tours in the city. GoodTrip provided reliable estimates for commodity and vehicle flows and was used to analyze three alternative urban commodity distribution systems. As Boerkamps et al. (2000) noted, GoodTrip has an open architecture that modelers could expand.

Wisetjindawat and Sano (2003) developed an urban truck microsimulation model for Tokyo building on the GoodTrip framework. They modified the conventional four-step approach in their model but kept it disaggregate enough to incorporate individual behaviors. They only focused on urban truck movements and used observed truck volumes from the Road Traffic Census survey to validate their model. They simulated five percent of the actual firms operating in the study area and reported truck origin-destination demand matrices and vehicle kilometer traveled by each truck type (Wisetjindawat et al., 2007). However, they left complex supply chain consideration (e.g. role of third-party logistics companies, JIT) for future improvement.

Hunt et al. (2006) undertook an extensive establishment survey and developed an agent-based commercial vehicle microsimulation for the Calgary region in Canada, based on information from roughly 37,000 tours and 185,000 trips (Stefan at al., 2005). They developed a series of logit models to account for service delivery, trip chaining behaviors, vehicle type, tour duration, etc. (Hunt and Stefan, 2007).

These models provided very valuable and detailed information about commercial vehicle movements, including route choice, and the activities of empty vehicles and less-than-truckload vehicles. They also integrated commercial vehicle movements with an aggregate passenger travel model. Other regions in Canada (Edmonton) and the U.S. (Ohio) have applied this model's techniques (Yang et al., 2009).

The Oregon Department of Transportation developed a Transportation and Land Use Model Integration Program that included a commercial travel model component (Donnelly, 2007). The Department integrated passenger and road freight in this economic and land use behavioral model to more effectively simulate micro-level truck movements (Hunt et al., 2001). They used economic models to generate commodity flows and then converted these flows into vehicle flows using land use activities and zonal data. Unlike the Calgary study that undertook an extensive data collection effort (Hunt et al., 2006), the Oregon model was based on a diverse range of data sources with different levels of spatial and temporal resolution.

Liedtke (2009) presented an agent-based microsimulation behavioral model called INTERLOG that accounted for logistics configurations. This model contained the following major components: firm generation, supplier choice, shipment-size choice, carrier choice, and tour generation. Liedtke calibrated the INTERLOG model with disaggregate freight data from Germany. Similar to many other microsimulation efforts, this study focused on urban commodity movements and overlooked the rail and other freight transport markets.

In a recent study, Roorda et al. (2010) proposed a comprehensive agent-based freight microsimulation framework and talked about a diverse range of actors that can be included in the model. Although this study is still in progress, its authors have emphasized some new aspects of freight demand modeling.

The proposed framework has explicit treatments to handle the outsourcing of logistics services to third-party logistics companies, the impacts of new supply channels, and general logistics costs. This proposed framework has differentiated it from other studies, although Roorda et al. (2010) have indicated that making this conceptual framework operational is a challenging task.

This firm-level microsimulation would be able to predict the effects of different scenarios on explicit firms with a known location, industry type, and size. Since the current freight market has a growing tendency in outsourcing freight services to third-party logistics companies, this framework seems suitable for obtaining insights and creating future policies.

Although there are valuable findings in the literature of freight microsimulation, most of them deal with urban freight movements. These studies are necessary for urban transportation planning, but are inadequate for long-term policies and infrastructure investment planning, especially in areas like Northeastern Illinois where a significant share of the region's freight traffic is associated with the national or even global economy.

Besides the limited geographical coverage, many previous efforts only focused on truck movements. Recent adoption of e-commerce and information technologies have affected freight shipping behaviors and have led to new partnerships between manufactures, shippers, carriers, and third-party logistics companies (Southworth, 2003).

This requires policy makers to access behavioral micro-level models not only in an urban and regional level but also at the national level. Developing a nationwide freight microsimulation could be rewarding and provide valuable insights for future infrastructure investments, a big picture of freight modal shift, and a better understanding of potential impacts of freight activities on a larger scale.

CHAPTER 3. MODEL FRAMEWORK

3.1 OVERVIEW

The previous chapter shows that the study team must effectively incorporate decision making agents' behavior into the Freight Activity Microsimulation Estimator (Freight Activity Microsimulation Estimator) model to produce more realistic and accurate results that reflect changes in freight flows, policies, and infrastructure. Incorporating firms' behaviors in the freight transportation model is the essence of the disaggregate freight models. Very few researchers, such as de Jong and Ben-Akiva (2007) have followed this practice.

Freight Activity Microsimulation Estimator has five basic modules (Figure 1). In the first module, Freight Activity Microsimulation Estimator recognizes all the firms in the study area and identifies their basic characteristics. In the second module, Freight Activity Microsimulation Estimator determines the types and amounts of incoming and outgoing goods based on each firm's characteristics and replicates their supply chain designs. In the third module, Freight Activity Microsimulation Estimator defines shipment sizes based on the previously collected data about the firms' characteristics and the way they trade commodities with each other. In the fourth module, Freight Activity Microsimulation Estimator makes decisions regarding such areas as shipping mode, haul time, shipping cost, warehousing, etc. Sophisticated firms simultaneously make decisions on the supply chain's physical infrastructure and logistics strategies. The study team has treated these decisions separately in Freight Activity Microsimulation Estimator to make the modeling structure compatible with the available data. In the last module, Freight Activity Microsimulation Estimator investigates the goods movements' impacts on the transportation network.

In an ideal modeling structure, the above-mentioned modules are interrelated with a recursive structure leading to more realistic results. For example, the results of the last module, the network analysis, could help the model to better determine the shipping mode. Similarly, the way logistic decisions are made in the fourth module could affect the supply chain formation in the second module. Also, the general cost of commodity transportation from the last module could be fed back into the second, third, and forth modules, through numerous iterations, until a stabilized set of commodity flows and costs are obtained. However, the chosen modeling framework is appropriate based on data availability and the project's scope of creating a forecasting tool that estimates national movement and modal split. The effects of congestion are an important factor in route selection at the urban area-level, but not at the national level.

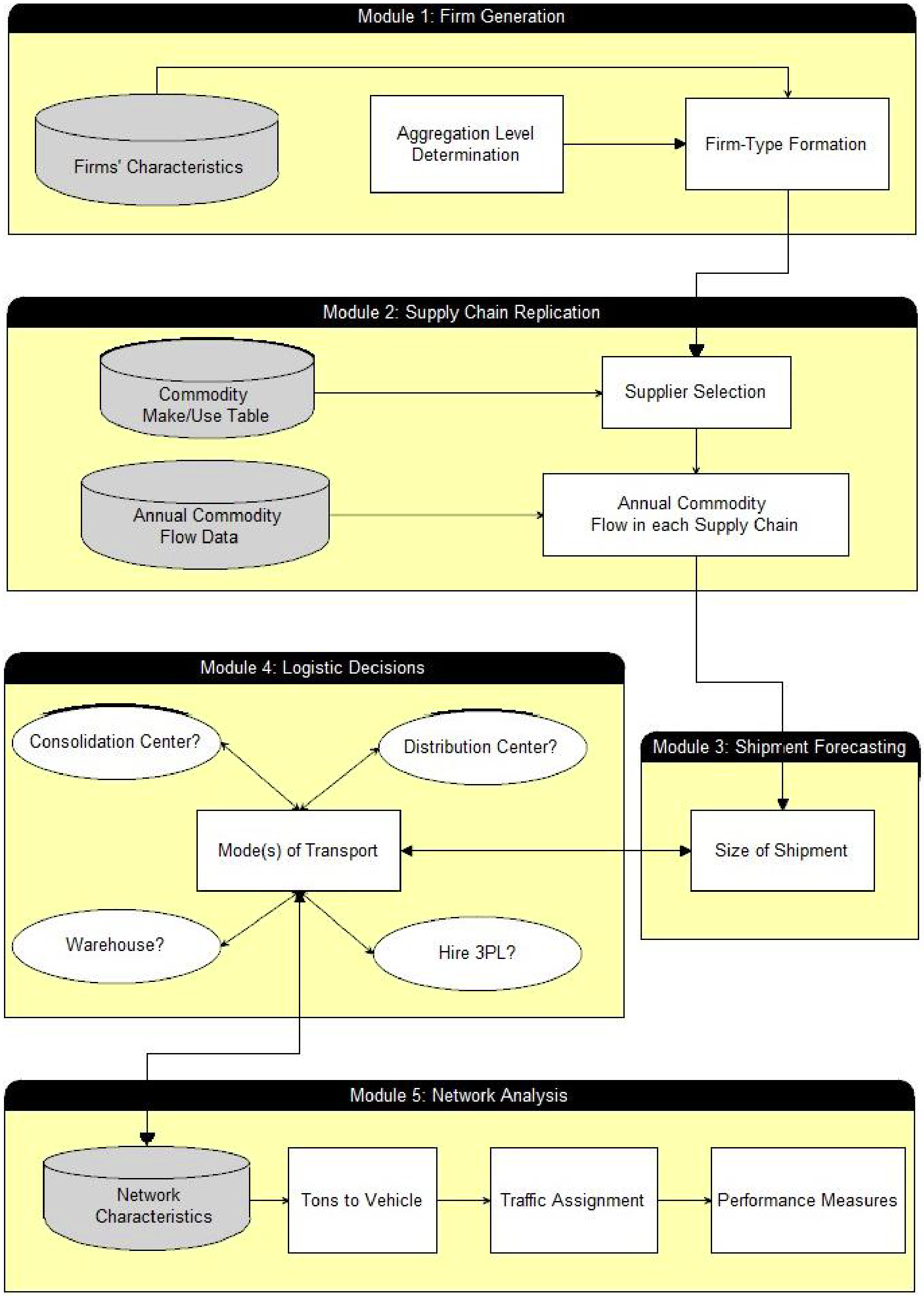

FIGURE 1. FRAMEWORK OF THE FREIGHT ACTIVITY MICROSIMULATION ESTIMATOR (FREIGHT ACTIVITY MICROSIMULATION ESTIMATOR)

3.2 MODEL ASSUMPTIONS

This study aims at modeling domestic freight flow in the entire U.S. According to the 2009 Economic Census, the U.S. had over 7.4 million firms with paid employees (U.S. Census Bureau, 2011). Theoretically, Freight Activity Microsimulation Estimator is capable of synthesizing all these firms, but this level of disaggregation requires robust and detailed data for calibration and presents a computational burden. To keep the computational burden reasonable and to lessen the need for highly disaggregate data, Freight Activity Microsimulation Estimator aggregates the firms based on firm-type. A firm-type is a collection of firms with similar location, industry type, and establishment size.

The second type of aggregation in this study is the treatment of firms' behavior based on zoning level. Freight Activity Microsimulation Estimator ignores intra-zonal interactions and assumes that all the firms in the same zone with similar characteristics (i.e. size and industry type) behave similarly.

The zoning strategy that the research team uses is complex and based on data availability. The lower the zoning level, the more accurate the final estimates. Ideally, zones could be defined at zip code level, so local interactions could be captured in all the modules. However, data availability and computational burden are tough barriers for disaggregation, so any customized zoning system may be used.

3.3. DATA

An accurate, comprehensive, and reliable dataset is a fundamental part of any travel demand analysis, and the lack of such data could make the study unfruitful. Obtaining a realistic picture of national freight movements requires a very large scale freight survey with broad industry type coverage.

This study has avoided proprietary commercial data to the extent possible and relied on publicly available freight data. States and planning agencies will more likely adopt models that can be developed using only widely available data. This section elaborates data needs for Freight Activity Microsimulation Estimator and reviews some data sets that the study team used in the model's estimation.

The study team was required to gather the following: background on business establishments, aggregate freight movement information, detailed information on a sample of individual shipments and supply chains, and specifications on transportation networks. Figure 2 summarizes where each data set is applied to the Freight Activity Microsimulation Estimator framework.

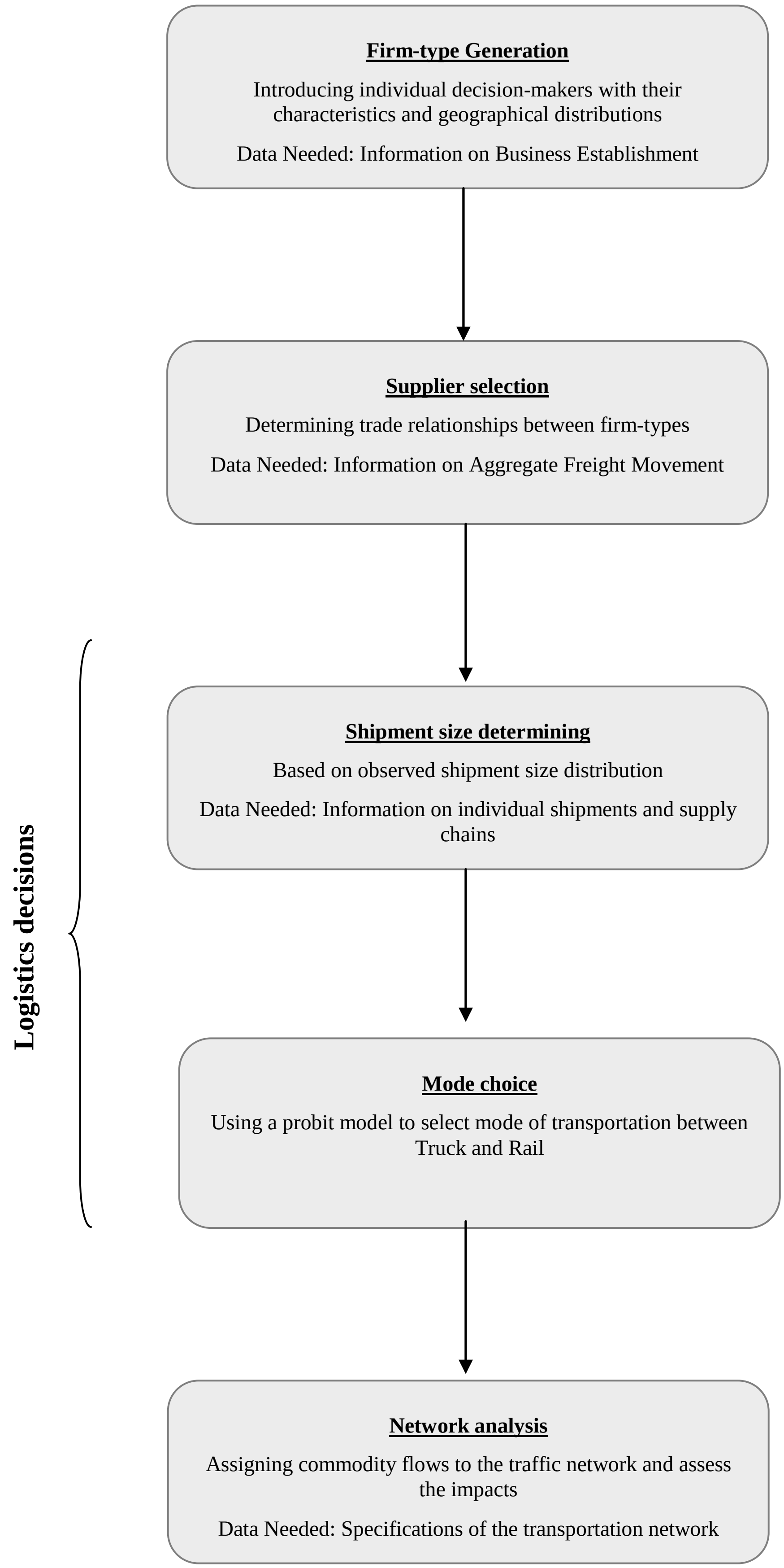
Firm-type Generation
Introducing individual decision-makers with their characteristics and geographical distributions
Data Needed: Information on Business Establishment
Supplier selection
Determining trade relationships between firm-types
Data Needed: Information on Aggregate Freight Movement
Shipment size determining
Based on observed shipment size distribution
Data Needed: Information on individual shipments and supply chains
Mode choice
Using a probit model to select mode of transportation between Truck and Rail
Network analysis
Assigning commodity flows to the traffic network and assess the impacts
Data Needed: Specifications of the transportation network
Logistics decisions

FIGURE 2: FREIGHT ACTIVITY MICROSIMULATION ESTIMATOR FRAMEWORK AND DATA NEEDS

3.3.1. Information on Business Establishments

An enormous number of American firms annually send or receive many shipments. However, getting and processing this data is too difficult. The study team, therefore, relied on firm-types for Freight Activity Microsimulation Estimator. They used firm type, location, and number of employees to estimate the number of firms in each type and assigned them to a particular geographic zone or zones. The publicly available County Business Patterns dataset contains this data. The U.S. Census Bureau has published the County Business Patterns dataset since 1964 (U.S. Census Bureau, 2008).

Annual information for all the U.S. business establishments with paid employees during the week of March 12 is provided at the county level. This data is also available for different geographic zones ranging from state to ZIP code levels. County Business Patterns dataset provides the number of establishments, first quarter and annual payroll by geographic area, industry, and employment size class. The County Business Patterns dataset is the only complete and consistent source of county-level annual data for business establishments with detail industry specification in the U.S. (U.S. Census Bureau, 2009). A well-known problem with the County Business Patterns dataset's disaggregate dataset is that a considerable number of values are not released due to confidentiality issue. When the number of establishments drops below a predefined value, the numbers are not reported. Although this is not a problem at the level of aggregation used in this study, the missing values could be approximated using the conventional methods, such as iterative proportional fitting if there is a need. Since most of the aggregate numbers are provided for larger geographic areas and also for larger industry classifications, the iterative proportional fitting is a promising approach to address the issue of missing values (Auld et al., 2009).

With almost 1200 categories, the 2002 North American Industry Classification System (NAICS) is used to classify industry type of businesses in the County Business Patterns dataset (U.S. Census Bureau, 2010). The County Business Patterns dataset provides a diverse range of industry classification resolution, from aggregate two-digit North American Industry Classification System number to a fairly disaggregate six-digit North American Industry Classification System number that is used in this study. Table 1 shows the two-digit industry codes and descriptions that is used in Freight Activity Microsimulation Estimator. Table 2 presents summary statistics about U.S. business establishments for the year 2002, obtained from the County Business Patterns dataset. There were more than 7.2 million firms in the U.S. in the County Business Patterns dataset 2002. The figure increased to around 7.7 million in 2007.

TABLE 1. TWO-DIGIT NORTH AMERICAN INDUSTRY CLASSIFICATION SYSTEM[1]

NAICS Code	Description
11	Agriculture, Forestry, Fishing and Hunting
21	Mining
22	Utilities
23	Construction
31-33	Manufacturing
42	Wholesale Trade
44-45	Retail Trade
48-49	Transportation and Warehousing
51	Information
52	Finance and Insurance
53	Real Estate and Rental and Leasing
54	Professional, Scientific, and Technical Services
55	Management of Companies and Enterprises
56	Administrative and Support and Waste Management and Remediation Services
61	Educational Services
62	Health Care and Social Assistance
71	Arts, Entertainment, and Recreation
72	Accommodation and Food Services
81	Other Services (except Public Administration)
92	Public Administration

[1] Source: http://www.census.gov/naics/

TABLE 2. U.S. BUSINESS ESTABLISHMENTS STATISTICS FOR THE YEAR 2002[1]

NAICS	Employees[2]	Annual payroll ($1000)	Number of establishment by employment-size class								
			1-4[3]	5-9	10-19	20-49	50-99	100-249	250-499	500-999	1000<
Total	112400654	3943179606	3900755	1384960	912797	624628	210577	118724	30220	11377	6732
11	181162	4978291	17735	4641	2507	1219	289	126	26	7	2
21	465775	23961694	12389	3775	3386	2647	904	516	164	59	31
22	648254	41844745	7714	3060	2442	2553	1316	899	267	124	57
23	6307370	247302462	456597	119620	71197	43195	12444	5623	1182	339	128
31-33	14393609	580356005	123326	59889	53286	52301	25301	19748	6656	2638	1196
42	5860256	262527777	227405	85422	61877	41821	12406	6006	1391	435	137
44-45	14819904	320707026	517258	290121	170153	92079	31487	20326	3677	534	58
48-49	3581013	127251855	113061	29270	22721	18310	6757	3685	806	279	254
51	3536120	188076999	69551	21978	18365	15374	6669	4370	1347	652	284
52	6414583	372656276	258426	91878	53293	29660	8812	5189	1712	907	545
53	2017347	65241211	226343	53650	27786	10598	2826	1334	349	106	32
54	7046205	368778137	530713	113555	67898	39943	11672	6051	1649	597	287
55	2913798	204802311	19073	7128	6891	7031	3845	2967	1319	723	406
56	8299217	212189377	198062	50905	35732	28971	14442	10536	3120	1082	694
61	2701675	71961852	34326	11519	9901	10238	4078	2273	637	378	351
62	14900148	499177227	327337	166757	105986	60178	20687	15613	3519	1668	1795
71	1800991	47724377	65361	15093	11776	10869	4460	2073	462	164	117
72	10048875	131110795	202967	96210	106176	118831	32504	7096	903	290	172
81	5420087	118899903	455258	156968	78870	36479	8475	3339	558	125	46
95	1011496	52670905	3893	2236	2149	2265	1201	950	476	270	140
99	32769	960381	33960	1285	405	66	2	4	0	0	0

[1] Source: http://www.census.gov/econ/cbp/
[2] Number of paid employees for the pay period that includes March 12.
[3] Number of business establishment with less than five paid employees.

3.3.2. Aggregate Freight Movements

Two sets of information are explored in this section: annual commodity flows between each zone pair, and relationship between different industries in the U.S. economy.

3.3.2.1. Freight Analysis FrameworkAnnual value and tonnage of different commodity types that are traded between the zone pairs are needed for the supply chain replication in Freight Activity Microsimulation Estimator. The Federal Highway Administration

(2006) has utilized many freight data sources including but not limited to Commodity Flow Survey (U.S. Census Bureau, 2007), Transborder Freight Transportation Data (*Bureau of Transportation Statistics, 2009*)*, and Surface Transportation Board's Rail Waybill Sample to develop the Freight Analysis Framework. This dataset has the total tonnage and value of shipments for each commodity type that are transported between all the Freight Analysis Framework zone pairs for each mode of transportation. Some federal publications, such as the annual Freight Facts and Figures (U.S. Department of Transportation, 2009), provide descriptive statistics from the Freight Analysis Framework. Even though the Freight Analysis Framework is the most comprehensive publicly available freight dataset, it has a few limitations that make it insufficient for some applications. One drawback is the level of geographical aggregation. The Freight Analysis Framework divides the United States into 114 domestic regions and also includes 17 international gateways, which is too large to use for local studies. Although possible application of disaggregation methods to the Freight Analysis Framework dataset has been examined to resolve this issue, no credible disaggregate Freight Analysis Framework data has been made available at this time.*

For a national level freight study; however, the Freight Analysis Framework dataset provides valuable and creditable information. Therefore, the Freight Analysis Framework estimates for the commodity flows between domestic zones is used as an input. Two-digit Standard Classification of Transported Goods with 43 categories is used in the Freight Analysis Framework to classify the commodities. The list of Standard Classification of Transported Goods commodities is provided in Table 3. The same commodity classification, i.e. 2-digit Standard Classification of Transported Goods, is used in Freight Activity Microsimulation Estimator. Annual tonnage by commodity for each domestic Freight Analysis Framework zone pair are imputed to the second module of Freight Activity Microsimulation Estimator.

TABLE 3. STANDARD CLASSIFICATION OF TRANSPORTED GOODS

STANDARD CLASSIFICATION OF TRANSPORTED GOODS (SCTG)

2-DIGIT COMMODITY TYPES

SCTG Code	Commodity Description
1	Live animals and live fish
2	Cereal grains
3	Other agricultural products
4	Animal feed and products of animal origin, n.e.c.1
5	Meat, fish, seafood, and their preparations
6	Milled grain products and preparations, bakery products
7	Other prepared foodstuffs and fats and oils
8	Alcoholic beverages
9	Tobacco products
10	Monumental or building stone
11	Natural sands
12	Gravel and crushed stone
13	Nonmetallic minerals n.e.c.[1]
14	Metallic ores and concentrates
15	Coal
16	Crude Petroleum
17	Gasoline and aviation turbine fuel
18	Fuel oils
19	Coal and petroleum products, n.e.c.[1]
20	Basic chemicals
21	Pharmaceutical products
22	Fertilizers
23	Chemical products and preparations, n.e.c.[1]
24	Plastics and rubber
25	Logs and other wood in the rough
26	Wood products

27	Pulp, newsprint, paper, and paperboard
28	Paper or paperboard articles
29	Printed products
30	Textiles, leather, and articles of textiles or leather
31	Nonmetallic mineral products
32	Base metal in primary or semi-finished forms and in finished basic shapes
33	Articles of base metal
34	Machinery
35	Electronic and other electrical equipment and components and office equipment
36	Motorized and other vehicles (including parts)
37	Transportation equipment, n.e.c.[1]
38	Precision instruments and apparatus
39	Furniture, mattresses and mattress supports, lamps, lighting fittings
40	Miscellaneous manufactured products
41	Waste and scrap
42	Commodity unknown
43	Mixed freight

3.3.2.2. Benchmark Input-Output Account

Additional information that are needed in the supply chain replication module are amount of commodities that are used and produced by each industry as well as the pattern of exchange of goods among them. The input-output account is a public dataset that provides this information at the national level (Bureau of Economic Analysis, 2008) although county-level dataset are available from commercial venders. It also provides information on the values of the required commodities to produce a unit output by each industry. There are two main problems with this dataset. First, the figures are the average values for the entire country and do not capture the geographical heterogeneity. A related issue is that the pattern of commodity use and production is not homogenous within all the firms within a particular industry sector. Another problem is that for the warehousing sector, the figures reported in the input-output table represent the amount of value-added operations performed at facilities, instead of the value of the goods being stored or transported through. There are county-level input-output data available from commercial venders, but they are imputed from the national data and the accuracy of the county-level data is unknown. Despite its drawbacks, considering the resources required to collect data on economic activities throughout the country, national input-output account provides rich information that can be used in the Freight Activity Microsimulation Estimator model.

The 2002 benchmark input-output account covers more than 400 industries and has its own industry classification system. The classification used for the input-output account is similar to the six-digit North American industry classification system number, but at a slightly higher aggregation level. To cope with this problem, the Bureau of Economic Analysis has developed a crosswalk (i.e. an equivalency table) between the six-digit North American industry classification system and this study's input-output account industry classification system.

The input-output account industry classification system provides information on the transactions between the industries in monetary terms. Although this data is extremely useful in the supply chain replication module, the input-output account does not provide information on the linkages between commodity types and industry classes. This information is critical since the Freight Analysis Framework data is provided for commodity types instead of industry classes, and the Freight Activity Microsimulation Estimator uses them to appropriate firm-types with specific industries. Fortunately, the crosswalk that connects industry to commodity was developed during the Freight Analysis Framework's development; it has been incorporated into the Freight Activity Microsimulation Estimator. This classification method for industry and commodity is compatible with other data sources that are used in the Freight Activity Microsimulation Estimator. It eliminates the error of making questionable assumptions and self-defined crosswalks to link different data sources.

3.4. INFORMATION ON INDIVIDUAL SHIPMENTS AND SUPPLY CHAINS

After forming trade relationships between firm-types and determining annual commodity flows between each pair of suppliers, the next step is to determine the logistics choices (shipment characteristics, such as shipment size, mode, etc.) for these flows. To develop logistics choice models in the third and forth modules, information on individual shipments, such as shipping time, costs, mode, etc. are required. The detailed specifications of the sending and receiving agents at different segments of the whole shipping process should be collected to provide insights on the firms that are forming the supply chain. For each acting agent in the whole shipping process, some information including primary activity, employee size, annual turnover, establishment square footage, number of franchises, etc. are of interest. Moreover, the shipment characteristics and shipping specifications are needed. The former include the commodity's weight, value, dimensions, time sensitivity, type, origin, and destination, and the latter may be comprised of the shipping process' haul time, cost, mode, and damage risk.

Since there is no publically available data source of data for this data type,the UIC team conducted an online business survey. This survey was specifically designed to collect some information on shipments and facilitate development of the Freight Activity Microsimulation Estimator. The study team carried out this survey in April and May of 2009. In total, 316 businesses participated in the survey and provided information on 881 shipments across the country. The survey detail and data quality analysis are included in Appendix C.

3.5. SPECIFICATIONS OF THE TRANSPORTATION NETWORKS

Specifications of transportation networks are primarily needed for the fifth module, network analysis. However, a rough estimate of the network characteristics for each transportation mode is required in other modules as well. Accessibility to truck-rail intermodal facilities, for example, is a critical element in a mode choice model and should be obtained from transportation network data. The Oak Ridge National

Laboratory (2006) has developed a county-to-county distance matrix for the entire U.S. Millage and impedance of all county pairs are estimated for rail, highway, water, and highway-rail networks. Impedance values are mode specific and calculated for each link based on several specifications. For example, impedance value for a link in the highway network is affected by The presence of a divided roadway, level of access to the road, rural or urban classification of the link, congestion level, etc. An intermodal link's impedance of is estimated in a way that accounts for the transfer time from truck to rail or vice versa and that provides a more realistic general cost for using a transfer facility. This data offers adequately accurate estimates for the characteristics of different transportation networks, and has also been implemented in the 2002 Commodity Flow Survey for estimating each mode's ton-mile share.

CHAPTER 4. MODEL ESTIMATION

This chapter discusses the estimation of each module in the Freight Activity Microsimulation Estimator model, except for the network analysis. A model's estimation involves finding the correct specification of mathematical equations and determining the appropriate parameter values.

4.1. FIRM-TYPES GENERATION

As discussed earlier, the Freight Activity Microsimulation Estimator simulates freight flows at the firm-to-firm level. Thus, the decision makers in this microsimulation are individual firms in the U.S. There are more than 239,000 firms in the County Business Patterns dataset. To keep the computational burden at a reasonable level and diminish the need for highly disaggregate data, some form of aggregation is inevitable. The Freight Activity Microsimulation Estimator uses firm types to aggregate firms with similar characteristics into groups. A firm-type is a collection of firms with similar location, industry type, and establishment size. It is assumed that firms with the same characteristics have similar behavior in the freight decision-making process. Number of firm-types can differ based on the number of industry types, establishment size, and geographic zones in the study area.

4.2. SUPPLY CHAIN REPLICATION

In this step, supply chains are created by matching suppliers and buyers of goods. All the potential suppliers for a given firm-type are determined in the first step and each supplier's suitability is assessed in the second step. Due to the modeling process' technical nature, the study team only provides an overview of the approach they used for this module . A detailed description of the modeling procedure involving the fuzzy expert system's development and application is included in Appendix A.

4.2.1. Generation of Candidate Suppliers

This procedure consists of two steps. In the first step, for a given type of commodity, potential suppliers, expressed in terms of firm types, are determined. In other words, the first stage of the supplier selection model is to list all the firm-types that can sell a given product to a specific firm-type. Two conditions have to be met for a firm-type to be eligible for such a list. First, the supplier should produce the commodity. Second, the buyer has to need the supplier's product as an input. The first step of the supplier selection model estimates a probability for each of those two conditions for a given supplier, buyer, and commodity type, and provides a degree of feasibility for a certain supply chain to form by multiplying those figures. The method of estimating each of the two probabilities is elaborated below.

The Freight Analysis Framework industry-to-commodity crosswalk was used to estimate the probability that a supplier produces a given commodity, which is the first condition. Almost all industry classes are linked to only one commodity type and thus most of these probabilities are either zero or one.

The second step in determining supplier feasibility is to assess the probability that the potential buyer's industry class can use the supplier's product. This figure is estimated based on the supplier and buyer's industry types, using the 2002 Benchmark Input-Output Account. The standard use tables were applied at the six-digit North American industry classification system level. This table contains the total value of a given industry sector's output that was used in different industry classes during 2002. For example, the *Glass Container Manufacturing* sector sold 526.0 million dollars of its products to the *Fruit and Vegetable Canning, Pickling, and Drying* sector; 13.5 million dollars to the *Cheese Manufacturing* sector ; 2,042.4 million dollars to the *Breweries* sector; 552.2 million dollars to the *Wineries* sector; and so on. These figures were used to calculate the percentage of a given industry's output that other industry sectors used.

4.2.2. Evaluation of Candidate Suppliers

The second stage in the supplier selection model is to assess the candidate suppliers' suitability. As argued earlier, there is no comprehensive dataset with specific information about supplier selection behaviors in different industry sectors across the country. Therefore, the study team used a fuzzy rule-based expert system, which is not data intensive to evaluate each potential supplier's suitability.

Some recent supply chain management studies have highlighted the benefits of fuzzy rule-based systems compared to mathematical optimization approaches. Altinoz (2008) argued that incomplete information about the candidate suppliers and the methodology's complexity seriously limit the usability of mathematical optimization approaches. He evaluated the usability level of different supplier selection methodologies by practitioners and proposed a fuzzy rule-based expert system. According to Zadeh (1965), the fuzzy logic system could effectively model a complex system, while avoiding explicit mathematical formulations. The major components of the fuzzy rule-based systems, introduced here are discussed in Appendix A.

4.3. SHIPMENT SIZE DETERMINATION

A shipment size model provides a categorical output variable with three clusters: small (less than 1,000 lb), medium (1,000-50,000 lb), and large (more than 50,000 lb). This model is required for the Freight Activity Microsimulation Estimator's third module, where the sizes of individual shipments are determined. In other words, annual flow of a specific commodity between a given supplier and buyer pair has to be broken down into single shipments. Such model's output could be each shipment's weight in pounds or just a categorical variable in the form of weight range. The former, being a continuous variable, provides richer information for each shipment, but requires more precise data and method for estimation. The latter is less data intensive but has a higher uncertainty level. Given this study's nationwide scope and data limitation, the study team could not carry out the logistic cost minimization approach. Instead, the study team obtained the distribution of the shipment size for each commodity type and shipping distance category from the 2002 Commodity Flow Survey. This information was used with other procedures to determine the sizes of individual shipments in a categorical output variable in three weight ranges: *small*, *medium*, and *large*.

Shipment size distribution in this study is initially set in a way that larger suppliers and buyers tend to ship their annual commodity flow in larger shipments. After initialization, a modified iterative proportional fitting approach was applied to replicate the shipment size distribution that was observed in the 2002 Commodity Flow Survey to the extent possible. The Commodity Flow Survey data has reported nationwide annual tonnage of transported commodities in a three dimensional table: commodity type, shipping distance, and shipment size. Similar to this study, commodities are classified in two digits Standard Classification of Transported Goods. Shipping distance is provided in nine categories (<50 miles, 50-99, 100-249, 250-499, 500-749, 750-999, 1000-1499, 1500-2000, >2000), and shipment size is also given in nine categories (<50 lbs., 50-99, 100-499, 500-749, 750-999, 1000-9999, 10000-49999, 50000-99999, 100,000<). The supplier and buyer's establishment size, shipping distance, and commodity type are inputs to this process. The model was applied on the annual commodity flow between each supplier and buyer pair from the supply chain replication module to determine the shares of small, medium, and large shipments accordingly. However, knowing that a shipment is small is not sufficient for the modal split in the next module. Mode split requires a crisp value for the shipment size. Conversion of the shipment size class to specific value was carried out using the distribution of observed shipment sizes from the UIC National Freight Survey. Details of the shipment size model and shipment size distributions are elaborated in Appendix B.

4.4. MODE CHOICE MODEL

Mode choice is the most critical logistics decision. A proper choice model should be sensitive to the decision-maker's attributes and to the choice alternatives. Unlike the decision-maker's characteristics, the attributes of choice alternatives vary significantly from one alternative to the other. As previously mentioned, to obtain the necessary information for developing the modal split model of the Freight Activity Microsimulation Estimator, the study team carried out a nationwide survey of businesses. The survey data satisfied the data needs for developing a mode choice model and also other components of the Freight Activity Microsimulation Estimator framework. The detail of the survey and the survey results analysis are included in Appendix C.

The survey is the only data source for the Freight Activity Microsimulation Estimator that is not publically available. To achieve the goal of developing a model that can only be used only with publicly available data, this document includes the two freight mode choice model specifications that were calibrated based on the UIC National Freight Survey. Depending on the availability of input variables, agencies will be able to select the powerful yet data hungry model or the parsimonious model that requires a limited number of input variables.

First, the consultant team developed an explanatory model to shed light on truck and rail (including truck-rail intermodal) competition in the U.S. freight transportation market. Some of the explanatory variables in the model were not available, however, from publically available sources. The study team proposed a parsimonious mode choice model that is better suited for practical use the microsimulation. Although the latter had a modest set of input variables, its overall goodness of fit was slightly less than the explanatory model.

The Limdep econometrics software (Greene, 2002) was used in this study for the mode choice model calibration. Akaike and McFadden values along with the chi-squared values were used for model selection (Train, 2003). The higher the McFadden value and the lower the Akaike measure, the better the explanatory power of the model. Standard t-statistics were used to test whether each coefficient had a non-zero effect on the choice probability. Wald, Likelihood Ratio, and Lagrange Multiplier tests, known as Neyman-

Pearson tests (Greene, 2002), were also carried out to assess the overall significance of the final models.

Percentage of correctly predicted observations, which is often used to validate mode choice models, is usually high in binary choice models that include a rare event as one of the choices. In many cases, the high accuracy figure could be misinterpreted as the indicative of the general explanatory power of the model. When one of the two possible choices is very rare and the other is common, binary models tend to over-predict the latter, resulting in a high rate of correct predictions at the expense of largely ignoring the rare event outcomes. For example, if 99 out of 100 data points in the dataset chose the common alternative, the model can attain 99% accuracy by simply predicting all cases to be common, but the model lacks the sensitivity to its input variables and consequently provides very little information. In Freight Activity Microsimulation Estimator, choosing the rail mode over truck could be considered as a rare event with less than 10% chance of occurrence in the data. Both mode choice models developed for Freight Activity Microsimulation Estimator achieved satisfactory accuracy in predicting rail shipments.

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 (VIFs) were estimated for all the independent variables to detect any severe multicollinearity among the explanatory variables. Kutner et al. (2004) suggested a variance inflation factor of 5 as the threshold that indicates a presence of serious multicollinearity. Following sections provides a detailed discussion of the development of the mode choice models.

4.4.1. Explanatory Model

Variables that were used in the development of the mode choice models are shown in Table 4. Table 5 shows the specifications of the exploratory model along with the assessment of it performance. All the estimated parameters in the exploratory models turned out to be significant with a p-value of less than 0.05, and most of them are significant with a 99% confidence interval. The model has a pseudo R-squared value of over 57%, and are able to correctly predict 95% of the observations. As noted before, the model predicted more than 72% of rail shipments correctly. As shown in Table 5, none of the variables had a variance inflation factor in excess of 3.5, and thus, multicollinearity is not an issue in this model.

4.4.2.Parsimonious Model

Although the exploratory 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 forecasting. For example, 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 is an extremely challenging if not impossible task. Therefore, another model with a parsimonious nature is discussed here. The model achieved a slightly less goodness of fit, but only uses a set of explanatory variables that are much easier to obtain. Basic descriptive statistics of variables that are used in this model are summarized in Table 6.

TABLE 4. VARIABLES USED IN THE EXPLANATORY MODEL

Variable	Definition	Mean	Standard deviation
MODE	1: rail or any combination of that with other modes / 0: truck	0.089	0.285
DISTANCE	Suggested distance between origin and destination by Google Map (miles)	1077	2221
WEIGHT	Weight of the shipment (lbs)	22901	25275
VALUE	Value of the shipment (USD)	48101	130150
TRUCK-COST	Shipping cost by truck (USD)	1331	4093
RAIL-COST	Shipping cost by rail (USD)	2016	1128
TRUCK-TIME	Shipping time by truck (days)	2.012	1.357
RAIL-TIME	Shipping time by rail (days)	7.281	6.662
TRUCK-COST-INDEX	= Ln (TRUCK-COST / (TRUCK-TIME * VALUE))	-3.542	1.521
RAIL-COST-INDEX	= Ln (RAIL-COST / (RAIL-TIME * VALUE))	-3.705	1.940
SAME-DECISION	1: if the same mode was preferred TWO years ago	0.934	0.248

	for a similar shipment / 0: otherwise		
ACCESS	0: firm has easy access to truck rail intermodal facilities / 1: neutral access / 2: difficult access	0.780	0.415
POTENTIAL-INTERMODAL	1: truck-rail intermodal is considered always or often as a potential transportation mode / 0: otherwise	0.349	0.477
PERISHABLE	1: if the commodity is perishable / 0: otherwise	0.160	0.367
CONSOLIDATION-CENTER	1: if the shipment has gone through a consolidation center / 0: otherwise	0.143	0.350
DISTRIBUTION-CENTER	1: if the shipment has gone through a distribution center / 0: otherwise	0.270	0.445
WAREHOUSE	1: if the shipment has gone through a warehouse / 0: otherwise	0.347	0.477
DECISION-MAKER	1: if a 3PL company has make the shipping decision / 0: otherwise	0.104	0.305

TABLE 5. EXPLANATORY MODE CHOICE PROBIT MODEL

Item		Value	t-ratio	VIF
Coefficient	CONSTANT	-5.902 *	-6.050	-
	DISTANCE	0.237E-03 **	2.273	2.776
	WEIGHT	0.310E-04 *	4.293	1.564
	TRUCK-TIME	0.622 *	5.019	1.648
	RAIL-TIME	-0.094 *	-2.579	2.387
	TRUCK-COST-INDEX	0.388 **	2.532	3.408
	RAIL-COST-INDEX	-0.659 *	-3.474	1.099
	POTENTIAL-INTERMODAL	1.214 *	3.468	2.776
Fit Measures	Log likelihood	-47.1	-	-
	Model Chi-squared	128	-	-
	Akaike I.C.	0.296	-	-
	Pseudo R-squared	0.577	-	-
	Correctly Predicted (%)	95.4	-	-
	Correctly Predicted (%) – rail	72.7	-	-

TABLE 6. VARIABLES USED IN THE PARSIMONIOUS MODEL

Variable	Definition	Mean	Standard deviation
MODE	1: truck / 0: rail or any combination of that with truck	0.924	0.263
GCD	Great circle distance (miles)	616	640
WEIGHT	Weight of the shipment (lbs)	23457	28959
IMPEDANCE*	= EXP (H_IMP/R_IMP)	6.186	3.338
H_IMP	Highway impedance	897	4589
R_IMP	Rail impedance	1176	9082
CONTAINERIZED	1: if the shipment is containerized / 0: otherwise	0.0229	0.149
COMMODITY	1: if the commodity is agricultural, chemical, pharmaceutical, gravel, natural sands, cement, machinery, metal, mixed freight, or prepared foodstuffs / 0: otherwise.	0.655	0.475

* The Oak Ridge National Laboratory (27) has provided county-to-county distance matrix for the entire U.S. and impedance for every county pairs are estimated in rail, highway, water, and highway-rail networks. Impedance units are mode specific and Impedance values are mode specific and calculated for each link based on several specifications such as length and type of a road to bring the approximate costs into common units. For example, impossible routes (eg,

highway from California to Hawaii) have a mileage of -1.0 and an impedance of 99999.9 in this dataset.

The study team prefers a probit specification for this model What is a probit specification? Although logit models assume the error terms in the utility function to be independently and identically distributed (commonly referred to as an "IID. assumption"), it has a closed-form equation for estimating the probability of each choice. This makes logit models convenient to use, especially in microsimulations that requires numerous iterations. Probit models do not require the IID assumption, but do require a numerical method for estimating the probability of each choice. For binary probit models such as the Freight Activity Microsimulation Estimator mode choice models, however, the task does not pose an insurmountable challenge.

Table 7 shows the parsimonious probit model that estimates the probability of choosing between truck and rail / truck-rail modes. All of the estimated parameters in the model are significant with a p-value of less than 0.05. The model has a pseudo R-squared value of 54%, and correctly predicts 96% of the observations. Furthermore, more than 58% of rail or truck-rail shipments are correctly predicted. As shown in Table 7, all the variance inflation factors are less than five. Thus, a serious multicollinearity is not detected.

TABLE 7. PARSIMONIOUS MODE CHOICE PROBIT MODEL

Item		Value	t-ratio	VIF
Coefficient	CONSTANT	4.83	8.170	-
	GCD *	-.104E-02	-4.856	2.078
	WEIGHT*	-.254E-04	-5.075	1.029
	IMPEDANCE **	-.988E-01	-1.978	2.021
	CONTAINERIZED*	-1.27	-2.612	1.055
	COMMODITY*	-.940	-2.985	1.046
Fit Measures	Log likelihood	-58.5	-	-
	Model Chi-squared	138.4	-	-
	Akaike I.C.	0.269	-	-
	Pseudo R-squared	0.541	-	-
	Correctly Predicted (%)	95.61	-	-
	Correctly Predicted (%) –rail	58.33	-	-

CHAPTER 5. MODEL IMPLEMENTATION AND VALIDATION

This chapter discusses the procedures used to apply a complete set of data to the Freight Activity Microsimulation Estimator. The outputs from each module of the Freight Activity Microsimulation Estimator are compared against real-world data to assess the models' validity.

5.1. FIRM-TYPES GENERATION

A total of 45,206 firm-types were generated for the microsimulation of the domestic Freight Analysis Framework zones. The study team considered 123 domestic Freight Analysis Framework zones, 328 industry classes (North American Industry Classification System), and eight employee size groups (Table 8) in this simulation. All the industry classes in the Freight Analysis Framework, at the 2-digit Standard Classification of Transported Goods, are considered in Freight Activity Microsimulation Estimator, but the industry classes for which no business establishment was reported in 2007 County Business Patterns dataset are excluded except for North American Industry Classification System 111150 (corn farms) which is considered in the simulation process by using a calibration method in the Freight Activity Microsimulation Estimator input data.

TABLE 8. DEFINITION FOR ESTABLISHMENT SIZE CLASSIFICATION

Establishment size category	Range of number of employees
1	1 – 19
2	20 – 99
3	100 – 249
4	250 – 499
5	500 – 999
6	1000 – 2499
7	2500 – 4999

8	4999 <

5.2. SUPPLY CHAINS REPLICATION

Supply chains were replicated using the approach that was explained in the previous chapter. As a quick reminding note, this model scores the appropriateness of all the possible suppliers for a given firm-type. Using the likelihood of partnership for any pair of supplier and buyer, annual commodity flows can be disaggregated from the Freight Analysis Framework zone level into the firm-type level. For a given origin, destination, and commodity type combination, value of total annual tonnage was disaggregated among the top 5% of supplier and buyer pairs with the highest appropriateness score. 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 from those with several actual firms in each side. Obviously, the latter should receive a higher share of commodity fellow.

As mentioned previously, all the Freight Analysis Framework industry sectors were considered in Freight Activity Microsimulation Estimator, but some of them were not present in some of the zones in the simulation. This is due to the limitations in the business establishment data sources and also the crosswalks that were used in the second module. As a result, not all of the Freight Analysis Framework commodity flows between the zone pairs was allocated to firm-types. In some rare cases, a specific type of commodity is entirely ignored. For instance, alcoholic beverages were not simulated from zone number 79 to 48. This is because there was no provider for that specific commodity in the origin nor a buyer in the destination zone according to the County Business Patterns dataset. Furthermore, there is no flow of live animals and live fish, unknown commodities, and mixed freight in the microsimulation, although those are reported in the Freight Analysis Framework. This is because industry that is associated with the aforementioned commodity types are not covered by the County Business Patterns dataset. In the Freight Analysis Framework, a total of 13,140,649,051 tons of commodity valued at around 8,794,018 billion dollars is transported between the domestic origin and destinations on truck, rail, or truck-rail intermodal. In contrast, 10,583,089,838 tons of commodity valued at around 6,944,709 billion dollars is simulated in Freight Activity Microsimulation Estimator. Thus, around 80% of the Freight Analysis Framework domestic tonnage and 79% of commodity values are simulated in this study.

5.3. SHIPMENT SIZE DETERMINATION

The proposed shipment size model estimates a categorical output variable with three clusters: small, medium, and large. This model was applied to the annual commodity flow between each pair of supplier and buyer to determine the shares of small, medium, and large shipments accordingly. Then, the data from the survey were used to estimate the actual value of the shipments. We found that Beta distribution produced a good fit with the surveyed data. Beta distribution has the added benefit of having lower and upper bounds on the distribution. A Q-Q plot for each shipment size class, depicted in Figures 3, 4, and 5, show the fit of the model for small, medium, and large shipment size, respectively. In Q-Q plots, observed values are plotted against fitted values. Q-Q plots could be used as a nonparametric approach to compare shapes of two distributions, providing a graphical assessment of goodness of fit. In our case, if the specified distribution is a decent model, the Q-Q plot will be approximately lying on the line 45-degree line. This reference diagonal line is also drawn in the figures to indicate where the graph points should ideally fall. The shape parameters of each beta distribution that are used in this simulation are provided in Table 9.

TABLE 9. SHAPE PARAMETERS OF THE BETA DISTRIBUTIONS FOR SHIPMENT SIZE

Shipment Size	Alpha	Beta	Upper Limit	Lower Limit
Small	0.436	0.914	1	1000
Medium	0.530	0.593	1001	50000
Large	0.090	0.243	50001	200000

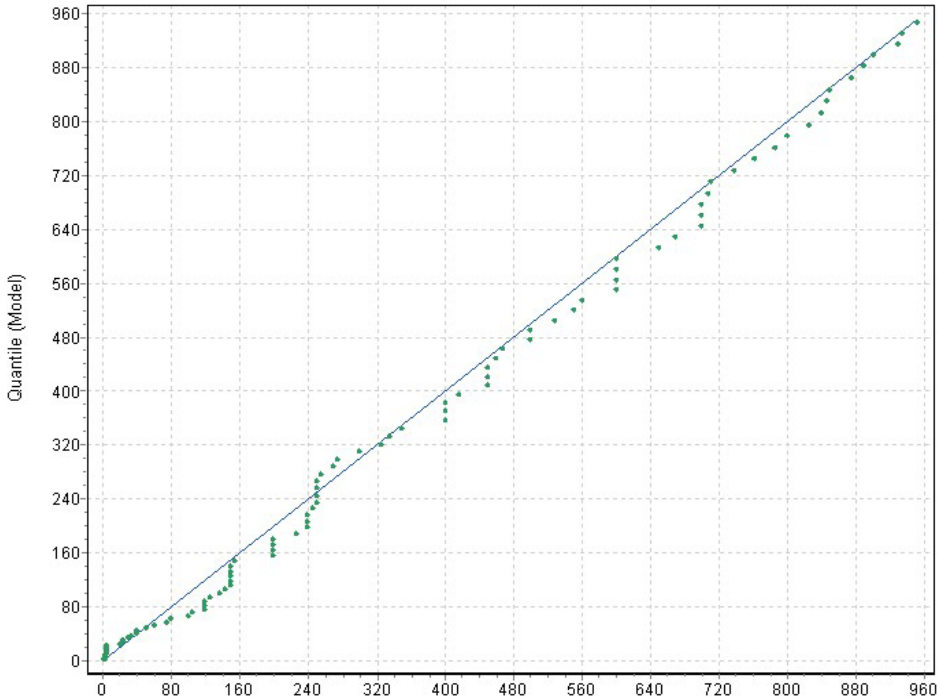

FIGURE 6. Q-Q PLOT, COMPARING OBSERVED AND PROPOSED DISTRIBUTION FOR SMALL SHIPMENTS

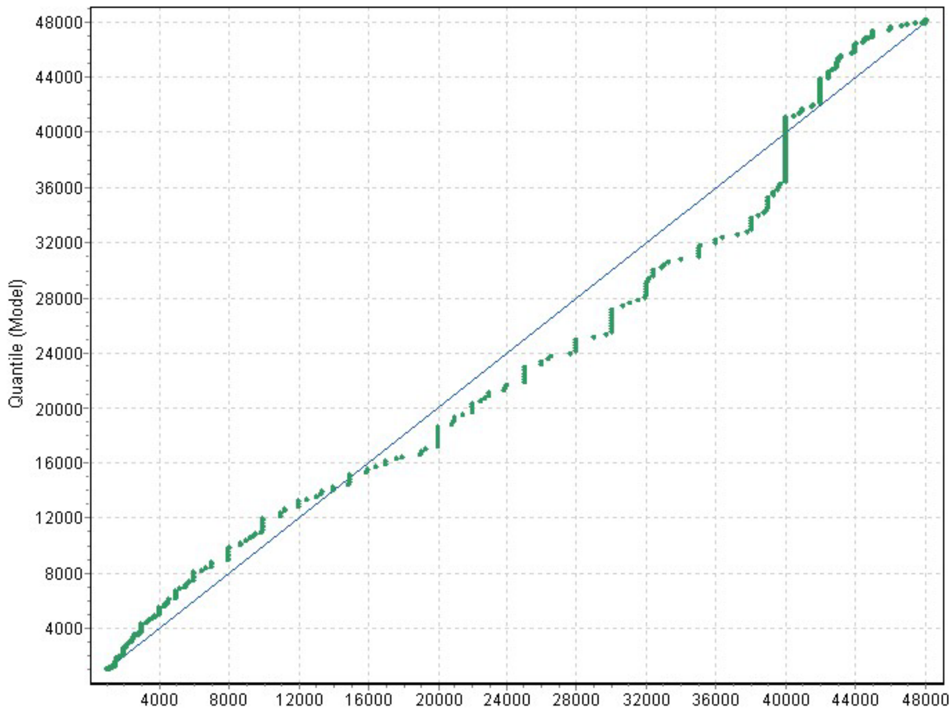

FIGURE 7. Q-Q PLOT, COMPARING OBSERVED AND PROPOSED DISTRIBUTION FOR MEDIUM SHIPMENTS

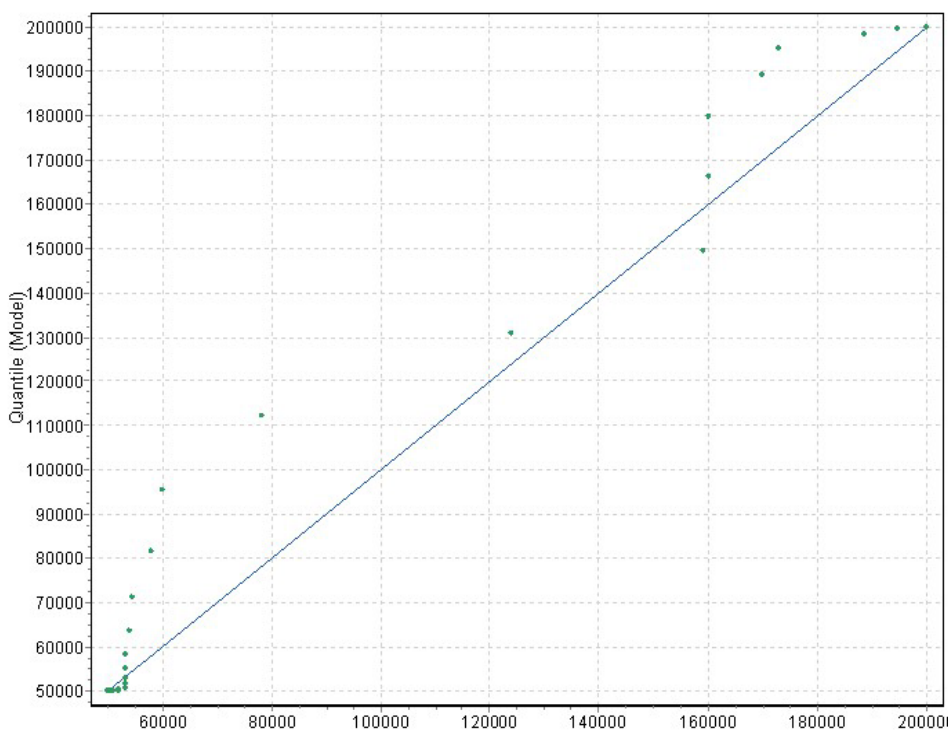

FIGURE 8. Q-Q PLOT, COMPARING OBSERVED AND PROPOSED DISTRIBUTION FOR LARGE SHIPMENTS.

5.4. MODE SPLIT

The research team used a binary mode choice model in this simulation to determine the share of truck and rail (including truck-rail intermodal) used for each shipment. The research team had to determine all of the following variables for each simulated shipment: shipment distance measured in great circle distance, weight, relative impedance between truck and rail, a dummy for containerized shipments, and commodity type.

Since the origin and destination zones are known, the research team could obtain the great circle distance and relative impedance from the intercounty distance matrix, which the Oak Ridge National Laboratory provided in 2006.

The research team also estimated each shipment's weight in the shipment size module.

The research team also knew the two-digit Standard Classification of Transported Goods commodity type for each simulated shipment and therefore could accordingly determine the dummy variable for each commodity type's containerized shipments. These variables were drawn from Bernoulli distributions. Bernoulli is a discrete probability distribution with a given success probability.

In this simulation, the research team assumed that the overall probability of having containerized shipments was 11.8%, based on the UIC National Freight Survey. The research team, however, weighted this figure by the normalized highway impedance between each origin and destination that the Oak Ridge National Laboratory (2006) provided to account for the relationship between shipment distance and the probability of containerization. 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 tends to underestimate the total number of rail shipments. Therefore, the research team multiplied the estimated probability of a rail shipment by 1.3 to adjust for this underestimation.

Given the microsimulation's random nature, the research team repeated the simulation 20 times. Table 10 shows each run's results, mean, and variation coefficient.

Although the model provided each mode's shipment tonnage, the research team estimated each shipment's dollar value. They multiplied the average dollar per ton to the shipment tonnage for each commodity type in the Freight Analysis Framework's Standard Classification of Transported Goods. They also estimated the shipment ton-miles using the intercounty distance matrix, which the Oak Ridge National Laboratory provided in 2006.

TABLE 10 RELATIVE PERCENTAGE OF TRUCK-ONLY SHIPMENTS IN DIFFERENT SIMULATION RUNS

Simulation Run	Ton	Value	Ton-mile
1	79.63%	89.92%	65.62%
2	79.87%	90.19%	66.37%
3	79.26%	90.14%	67.43%
4	79.65%	89.79%	68.18%
5	78.34%	89.72%	60.99%
6	78.39%	89.82%	65.21%
7	78.04%	89.82%	60.75%
8	78.98%	89.85%	65.20%
9	78.85%	89.85%	62.86%
10	78.73%	89.92%	66.16%
11	79.77%	89.89%	64.60%
12	80.21%	90.26%	62.48%
13	80.14%	89.87%	65.22%
14	79.10%	89.97%	63.35%
15	77.39%	89.78%	63.61%
16	79.70%	89.93%	64.15%
17	78.43%	89.51%	64.22%
18	79.04%	90.03%	67.43%
19	80.49%	90.23%	68.11%
20	79.57%	90.30%	62.82%
Mean	79.18%	89.94%	64.74%
Coefficient of Variation	0.98%	0.22%	3.28%

5.5. VALIDATION

This study's primary objective was to develop a behavioral freight model that focuses on truck and rail modes. The mode share for the two modes is therefore expressed in total tonnage, value, and ton-mile of commodities (Table 11) and is validated in this section. The research team compared the Freight Activity Microsimulation Estimator's estimated values against those from the Freight Analysis Framework and the Commodity Flow Survey, two major public freight data sources in the U.S. It should be noted that modal split information from these datasets have not been used to estimate the model split module, and thus it is appropriate to use them as the base lines for validation. TABLE 11 and Figure 6 compare the percentages of the two modes according to Freight Analysis Framework 3, COMMODITY FLOW SURVEY 2002, COMMODITY FLOW SURVEY 2007, and the Freight Activity Microsimulation Estimator.

TABLE 11. MODAL SPLIT VALIDATION IN Freight Activity Microsimulation Estimator

Item		**Commodity Flow Survey 2002**	**Commodity Flow Survey 2007**	**FAF3**	**Freight Activity Microsimulation Estimator**
Tonnage	Rail	20%	19%	15%	21%
	Truck	80%	81%	58%	79%
Value	Rail	6%	7%	5%	10%
	Truck	94%	93%	95%	90%
Ton-mile	Rail	51%	53%	43%	35%
	Truck	49%	47%	57%	65%

The data indicate that Freight Activity Microsimulation Estimator is able to accurately replicate the mode shares especially when they are measured in terms of weight or value. Since the Commodity Flow Survey excludes certain industries from the survey frame, the Freight Analysis Framework is the most meaningful baseline of comparison. The Freight Activity Microsimulation Estimator was able to replicate the mode shares of Freight Analysis Framework 3 with perfect accuracy.

CHAPTER 6. CONCLUSION

The primary motivation for this research was to develop a behavioral freight mode choice model for Northeastern Illinois. Since the freight flow in Northeastern Illinois is intimately connected to the national movement of goods, the research team developed a nationwide freight activity microsimulation model. This is a monumental achievement as in the past. Although the need to incorporate freight movement in the broader national transportation policy framework is recognized, development of satisfactory analysis tools to facilitate decision-making is highly challenging given the complexity of the decision-making process, a lack of an acceptable freight modeling framework, and scarcity of freight data.

This report's modeling framework replicates shipping behaviors to incorporate firms' characteristics and seeks to pave the way for future behavioral freight microsimulation efforts. This research has already made significant impacts in freight demand analysis in the Chicago region as two ambitious efforts, one by the Chicago Metropolitan Agency for Planning (CMAP), and the other by the Federal Highway Administration (FHWA), rely heavily on this study's approach, and its output, in some cases.

A major drawback of many previous efforts of this kind was their aggregate nature which prevented the development of an actor-based microsimulation. This limitation has seriously affected the models' reliability and applicability in the environment where firms are increasingly relying on supply chain management concepts to remain competitive. The conventional models are not able to reconcile the proliferation of e-commerce, information technologies, and sophisticated supply chain management strategies with freight shipment decision-making processes.

The Freight Activity Microsimulation Estimator is one of the first attempts to address these problems by incorporating behavioral factors in a microsimulation framework. Its geographical coverage also is broader than most of the past models, thus giving policymakers and agencies a powerful tool for analyzing and evaluating potential courses of action to meet the many challenges facing the movement of goods in the U.S. and Northeastern Illinois in particular.

The research team strived to develop a sound microsimulation freight model in this study as a valid forecasting tool that could contribute to more reliable policy assessments compared to existing decision-making tools. The proposed framework (the Freight Activity Microsimulation Estimator) has some remarkable characteristics that distinguish it from other frameworks:

- The Freight Activity Microsimulation Estimator is mostly based on publicly available freight data. Combined with the on-line survey that was developed to collect key pieces of data that were not publicly available, the Freight Activity Microsimulation Estimator's data collection cost is modest compared to that of other behavioral models.
- It is one of the early efforts in freight demand modeling that has a separate component for simulating the formation of supply chain configurations. A fuzzy expert system was developed for supplier selection. This approach could be used in the absence of disaggregate data on supply chain formation.
- The Freight Activity Microsimulation Estimator has an open structure and could accept other components that may become available later.
- The Freight Activity Microsimulation Estimator covers almost all the industry classes in the U.S.
- The Freight Activity Microsimulation Estimator has a unique geographic coverage and is probably the first comprehensive nationwide freight microsimulation in the U.S.

This study designed and implemented a cost-effective way of collecting disaggregate freight data for running this simulation. An online establishment survey that was conducted as part of this research provided valuable disaggregate information that was necessary for developing a behavioral freight model. The research team looked for the presence of a selection bias that is common in surveys with low response rates, but found no serious issues.

The research team also calibrated two freight mode choice models based on the UIC National Freight Survey. They first developed an explanatory model to gain insights on truck and rail (including truck-rail intermodal) competition in the U.S. freight transportation market. They later developed a parsimonious mode choice model for use in the microsimulation. They built this model using only variables that are easy-to-obtain or estimate from existing data. Its overall goodness of fit was only slightly less than the explanatory model. We believe that this model is superior to the existing mode choice models used in practice, and should attract interest from agencies around the country.

CITED LITERATURE

AASHTO, Invest in America- Freight Rail Bottom Line Report. January 2003.

Abdelwahab, W. M. (1998) Elasticities of Mode Choice Probabilities and Market Elasticities of Demand: Evidence from a Simultaneous Mode Choice/Shipment-Size Freight Transport Model. Transportation Research Part E: Logistics and Transportation Review 34(4): 257-266.

Abdelwahab, W., and M. Sargious (1992) Modelling the Demand for Freight Transport: A New Approach. Journal of Transport Economics and Policy, 26(1): 49-70.

Ahanotu, D., and A. Mani (2008) Freight Data Synthesis. Final Report No. CDOT-2008-3, Colorado Department of Transportation Research Branch.

Al-Deek, H. Comparison of Two Approaches for Modeling Freight Movement at Seaports. The ASCE Journal of Computing in Civil Engineering, 15(4), pp. 284-291, 2001.

Allen, J. and M. Browne (2008) Review of Survey Techniques Used in Urban Freight Studies. Project Report of the Green Logistics: Work Module 9 (Urban Freight Transport).

Arunotayanun, K., and J. W. Polak (2007) Taste Heterogeneity in Freight Shippers' Mode Choice Behaviour. Proceedings, 86th Annual Meeting of the Transportation Research Board, Washington DC, 21–25 January 2007.

Altinoz, C., (2008) Supplier selection for industry: a fuzzy rule-based scoring approach with a focus on usability. International Journal of Integrated Supply Management, Vol. 4, pp. 303 - 321.

Auld, J., Mohammadian A. and Kermit, W. (2009). "Population Synthesis with Subregion-Level Control Variable Aggregation." *Journal of Transportation Engineering*, 135(9), 632-639.

Baumol, W. J., and H. D. Vinod (1970) An Inventory Theoretic Model of Freight Transport Demand. Management Science, 16(7): 413–421.

Bezdek, J. C. (1981) Pattern Recognition with Fuzzy Objective Function Algorithms. Plenum Press, New York.

Boerkamps, J. H. K., A. J. van Binsbergen, and P. H. L. Bovy (2000) Modeling Behavioral Aspects of Urban Freight Movement in Supply Chains. Transportation Research Record, 1725: 17-25.

Brogan, J. J., S. C. Brich, and M. J. Demetsky (2001) Application of a Statewide Intermodal Freight Planning Methodology. Final Report VTRC 02-R5.

Bryan, J., G. Weisbrod, C. D. Martland (2007) Rail Freight as a Means of Reducing Roadway Congestion: Feasibility Considerations for Transportation Planning. Transportation Research Record, 2008: 75-83.

Bureau of Economic Analysis. 2008. Revised 2002 Benchmark Input-Output Make and Use Tables. http://www.bea.gov/industry/Make_Use_table_revisions.htm, Accessed December 24, 2008.

Bureau of Transportation Statistics. 2004. 2002 Commodity Flow Survey (COMMODITY FLOW SURVEY) United States. http://www.bts.gov/publications/commodity_flow_survey/2002/united_states, Accessed May 2, 2008.

Bureau of Transportation Statistics. 2007 Commodity Flow Survey (COMMODITY FLOW SURVEY) Preliminary Tables. United States, 2008. http://www.bts.gov/publications/commodity_flow_survey/preliminary_tables_december_2008/index.html, accessed July 17, 2009.

Bureau of Transportation Statistics (BTS): North American Transborder Freight Data (2009). Available at: http://www.bts.gov/programs/international/transborder/, accessed February 2010.

Bureau of Transportation Statistics (BTS). North American Transportation Atlas Data. Available at: http://www.bts.gov/publications/north_american_transportation_atlas_data/, accessed June 2008.

Cambridge Systematics, Inc., COMSIS Corporation, and University of Wisconsin-Milwaukee (1997) Quick Response Freight Manual. Final Report DOT-T-97-10 prepared for U.S. Department of Transportation and U.S. Environmental Protection Agency. Technology Sharing Program, U.S. Department of Transportation.

Cambridge Systematics, Inc., Global Insight, H. Cohen, A. Horowitz, and R. Pendyala (2008) NCHRP Report 606: Forecasting Statewide Freight Toolkit, TRB, National Research Council, Washington, D.C.

Catalani, M. (2001) A model of shipper behaviour choice in a domestic freight transport system. Proceeding of the 9th World Conference on Transport Research in Seoul.

Choi, T.Y. and Hartley, J.L. (1996) An exploration of supplier selection practices across the supply chain. *Journal of Operations Management*, Volume 14, Issue 4, Pages 333-343.

Chow, G. Regional Freight Modelling, Potential Directions for the Vancouver Lower Mainland, Prepared for Transport Canada and Trans Link, 2004.

Coogan, M. A. (1996) Freight Transportation Planning in the Public Sector. NCHRP Synthesis 230. Transportation Research Board, Washington, D.C.

Couper, M. P., M. W. Traugott, and M. J. Lamias, Web Survey Design and Administration, The Public Opinion Quarterly. Vol. 65, No. 2, pp. 230-253. 2001.

Daughety, A. F., and F. S. Inaba (1978) Estimating Service-Differentiated Transport Demand Functions. Transportation Research Record, 668: 23-30.

Davidsson, P., Henesey, L., Ramstedt, L., Tornquist, J., and Wernstedt, F., An Analysis of Agent-Based Approaches to Transport Logistics, Transportation Research Part C: Emerging Technologies. Vol. 13 No. 4, pp 255-271. 2005.

de Jong, G., and M. Ben-Akiva (2007) A micro-simulation model of shipment size and transport chain choice. Transportation Research Part B 41: 950–965.

Donnelly, R. (2007) A Hybrid Microsimulation Model of Freight Flows. Proceedings of the 4th International Conference on City Logistics, July 11-13, 2007. Taniguchi, E. and R.G. Thompson (Ed.). Crete, Greece, Institute for City Logistics, pp: 235-246.

Dunn, J. C. (1973) A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters. *Cybernetics and Systems*, Volume 3, Issue 3, Pages 32 – 57.

Evers, P. T., D. V. Harper, and P. M. Needham (1996) The Determinants of Shipper Perceptions of Modes. Transportation Journal 36(2): 13-25.

Ettema, D.F., and H.J.P. Timmermans. Activity Based Approaches to Travel Analysis, Elsevier Science, 1997, Tarrytown, New York.

Federal Highway Administration (2006) Commodity Origin-Destination Database: 2002-2035. Freight Analysis Framework (FAF) Version 2.2, User Guide.

Figliozzi, M. A. (2007) Analysis of the efficiency of urban commercial vehicle tours: Data collection, methodology, and policy implications. Transportation Research Part B 41: 1014–1032.

Fisher, M.J. and Han, M. (2001) Truck Trip Generation Data (NCHRP Report 298). Washington, D.C: TRB, National Research Council.

Fischer, M. J., M. L. Outwater, L. L. Cheng, D. N. Ahanotu, and R. Calix (2005) Innovative Framework for Modeling Freight Transportation in Los Angeles County, California. Transportation Research Record, 1906: 105-112.

Gray, R. (1982) Behavioural Approaches to Freight Transport Modal Choice. Transport Reviews, 2(2), pp. 161-184.

Greene, H.W. LIMDEP Version 8.0 User's Manual. Econometric Software Inc., Plainview, NY, USA, 2002.

Gujarati, D. N. Basic Econometrics, 4th edition, McGraw–Hill, Inc., New York, 2003.

Harker, P. (1985) The state of the art in the predictive analysis of freight transport systems. Transport Review, 5(2): 143-164.

Heckman, J. (1990) Varieties of Selection Bias. American Economic Review, 80(2): 313-318.

Hensher, D., and M. Figliozzi (2007) Behavioural insights into the modelling of freight transportation and distribution systems. Transportation Research Part B 41: 921–923.

Higginson, J.K., and J.H. Bookbinder. Policy recommendations for a shipment-consolidation program. *Journal of Business Logistics*, 15(1), pp. 87–112, 1994.

Holguin-Veras, J. (2000) A framework for an integrative freight market simulation. IEEE 3rd Annual Intelligent Transportation Systems Conference, Dearborn, Michigan.

Holguin-Veras, J., and G. Patil (2005) Observed trip chain behavior of commercial vehicles. Transportation Research Record, 1906: 74–80.

Holguin-Veras, J., N. Pérez, B. Cruz, and J. Polimeni. Effectiveness of Financial Incentives for Off-Peak Deliveries to Restaurants in Manhattan, New York. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1966, pp. 51–59, 2006.

Holguin-Veras, J. and E. Thorston (2000) Trip Length Distributions in Commodity-Based and Trip-Based Freight Demand Modeling: Investigation of Relationships. Transportation Research Record, 1707: 37-48.

Hunt, J.D., and K.J. Stefan (2007) Tour-based microsimulation of urban commercial movements. Transportation Research Part B 41: 981–1013.

Hunt, J. D., K. J. Stefan, and A. T. Brownlee (2006) Establishment-Based Survey of Urban Commercial Vehicle Movements in Alberta, Canada: Survey Design, Implementation, and Results. Transportation Research Record, 1957: 75-83.

Hunt, J.D., R. Donnelly, J.E. Abraham, C. Batten, J. Freedman, J. Hicks, P.J. Costinett, and W.J. Upton (2001) Design of a Statewide Land Use Transport Interaction Model for Oregon. Proceedings of World Conference on Transportation Research, Seoul, South Korea.

Iding, M., W. Meester, and L. Tavasszy. Freight trip generation by firms. *42nd European Congress of the Regional Science Association*, Dortmund, 2002.

IHS Global Insight's (2010), U.S. County-level Freight-movement Data by Commodity Group and Mode of Transportation. http://www.ihsglobalinsight.com/ProductsServices/ProductDetail2322.htm, Accessed February 2, 2010.

Jessep, E., K. Casavant, and C. Lawson. Truck Trip Data Collection Methods. Final Report SP343, for Oregon Department of Transport and Federal Highway Administration, 2004.

Jiang, F., P. Johnson, and C. Calzada (1999) Freight Demand Characteristics and Mode Choice: An Analysis of the Results of Modeling with Disaggregate Revealed Preference Data. Journal of Transportation and Statistics 2(2): 149-158.

Jin, Y., R.M. Rejesus, and B.B. Little. Binary Choice Models for Rare Events Data: A Crop Insurance Fraud Application, *Applied Economics*, 37, pp. 841-848, 2005

Kumar, S., and K. M. Kockelman (2008). Tracking Size, Location, and Interactions of Businesses: Microsimulation of Firm Behavior in Austin, Texas. Transportation Research Record, 2077: 113-121.

Kutner, M. H., C.J. Nachtsheim, and J. Neter. Applied Linear Regression Models, 4th edition, McGraw-Hill Irwin, 2004.

Kwan, H. (2007) A Combined GPS, Mail-out/mail-back Survey of Commercial Vehicle Movements in Region of Peel. Masters of Applied Science Thesis, Department of Civil Engineering, University of Toronto, Canada.

Lawson, C., J. Strathman, E. Riis. Survey Methods for Assessing Freight Industry Opinions. Final Report SPR 328 to the Oregon DOT and FHWA. 2002.

Lewis, K. and D. P. Widup (1982) Deregulation and rail-truck competition: evidence from a translog transport demand for assembled automobiles. Journal of Transport Economics and Policy, 16(2): 139-149.

Liedtke, G. (2009) Principles of micro-behavior commodity transport modeling. Transportation Research Part E: Logistics and Transportation Review, Vol. 45(5), pp. 795–809.

Liedtke, G., and H. Schepperle (2004) Segmentation of the Transportation Market with Regard to Activity–based Freight Transport Modelling, International Journal of Logistics: Research and Applications, Vol. 7, No. 3, pp. 199-218.

Luk, J. and B. Chen (1997) Evaluation of Information Available to Asses Road Freight Transport Demand. ARRB Transport Research Report ARR 308.

MATLAB 7.9, (2009) The MathWorks, Inc. http://www.mathworks.com/, accessed February 2010.

McCabe, S. (2007) The Region of Peel Commercial Travel Survey: Mailout–Mailback Survey Design and Preliminary Analysis. Masters of Applied Science Thesis, Department of Civil Engineering, University of Toronto, Canada.

McFadden, D., C. Winston, and A. Boersh-supan (1985) Joint Estimation of Freight Transportation Decisions under Nomrandom Sampling. In: Analytical Studies in Transport Economics (edited by A. F. Daughety), 137-157. Cambridge University Press.

McGinnis, M. A. (1989) A Comparative Evaluation of Freight Transportation Choice Models. Transportation Journal 29(2): 36-46.

McNally, M.G., and W.W.Recker (1986). On the Formation of Household Travel/Activity Pattern: A Simulation Approach, Final Report to USDoT, University of California.

Miao, X., and B. Xi. Agile Forecasting of Dynamic Logistics Demand. Transport, Vol. 23 No. 1, pp 26-30. 2008.

Mohammadian, A. and E.J. Miller. Nested Logit Models and Artificial Neural Networks for Predicting Household Automobile Choices: A Comparison of the Performance. Transportation Research Record, No.1807, pp. 92-100, 2003.

Nam, K. (1997) A Study on the Estimation and Aggregation of Disaggregate Models of Mode Choice for Freight Transport. Transportation Research Part E: Logistics and Transportation Review 33(3): 223-231.

Neuro Dimension Corporate. NeuroSolutions: Premier Neural Network Development Environment. <http://www.neurosolutions.com>, accessed July 15, 2009.

Newell, A. and H.A. Simon. Human Problem Solving. Englewood Cliffs, NJ: Prentice Hall. 1972.

Newey, W.K., and D. McFadden. Large Sample Estimation and Hypothesis Testing, in R. Engle, and D. McFadden, Handbook of Econometrics, Vol. 4, pp. 2111-2245, North Holland: Amsterdam, 1994.

Norojono, O., and W. Young (2003) A Stated Preference Freight Mode Choice Model. Transportation Planning and Technology, 26(2): 195–212.

Oak Ridge National Laboratory (2006), CTA Transportation Networks. http://cta.ornl.gov/transnet/, accessed February 2010.

Ohio Department of Transportation. Office of Urban and Corridor Planning. http://www2.dot.state.oh.us/research/Implementation/Implementation%20Plans/14766IP.pdf Accessed October 26, 2009.

Oum, T.H. A Cross Sectional Study of Freight Transport Demand and Rail-Truck Competition in Canada. *Bell Journal of Economics*, 10, pp. 463-482, 1979.

Parks, R.W., D.S. Levine, and D.L. Long. Fundamentals of Neural Network Modeling. MIT Press, Cambridge, MA, 1998.

Parsons, K., and E. Cleckley. New Orleans Intra-City Truck Freight Study. USDOT Talking Freight seminar on Small MPOs and Innovative Freight Projects, April 2006.

Patterson, Z., G. O. Ewing, and M. Haider (2007) Shipper Preferences Suggest Strong Mistrust of Rail: Results from Stated Preference Carrier Choice Survey for Quebec City–Windsor Corridor in Canada. Transportation Research Record, 2008.

Patterson, Z., G. O. Ewing, and M. Haider (2008) How Different Is Carrier Choice for Third-Party Logistics Companies? Mixed-Logit Approach. Proceedings, 87th Annual Meeting of the Transportation Research Board, Washington DC, 13–17 January 2008.

Pendyala, R.M., Shankar, V.N., and R.G. McCullough (2000) Freight Travel Demand Modeling: Synthesis of Approaches and Development of a Framework. Transportation Research Record 1725, National Research Council, Washington, D.C., 2000, pp. 9-16.

Principe, J.C., N.R. Euliano, and W.C. Lefebvre. Neural and Adaptive Systems: Fundamentals through Simulations. John Wiley & Sons, New York, 2000.

Proussaloglou, K., Y. Popuri, D. Tempesta, K. Kasturirangan, and D. Cipra (2007) Wisconsin Passenger and Freight Statewide Model: Case Study in Statewide Model Validation. Transportation Research Record, 2003: 120-129.

Qian, W., and J. Holguin-Veras (2008). Investigation of Attributes Determining Trip Chaining Behavior in Hybrid Microsimulation Urban Freight Models. Transportation Research Record, 2066: 1-8.

RAND Europe, Solving, INRO. The specification of logistics in the Norwegian and Swedish national freight model systems, model scope, structure and implementation plan. Report for the NTP and Samgods group, TR-225-SIKA, RAND Europe, Leiden, 2004.

Regan, A.C., and R.A. Garrido (2001) Modeling freight demand and shipper behavior: state of the art, future directions. In: D. Hensher, Editor, Travel Behavior Research: The Leading Edge, Pergamon, Amsterdam, pp. 1–30.

Rodrigue, J. P., Commodity Chains and Freight Transportation, Chapter 5, Concept 3, in *The Geography of Transport Systems*, by J. P. Rodrigue, C. Comtois and B. Slack, New York: Routledge, 2006.

Roorda, M.J., S. McCabe and H. Kwan (2007) A Shipper-Based Survey of Goods and Service Movements in the Greater Golden Horseshoe: Report II. Preliminary Analysis of Results and Comparison of Survey Techniques.

Roorda, M. J., R. Cavalcante, S. McCabe, and H. Kwan (2010) A conceptual framework for agent-based modelling of logistics services. Transportation Research Part E: Logistics and Transportation Review, Vol. 46(1), pp. 18-31.

Schmedding, D., G.T. Liedtke, and J. Babani. The Rule-Based Freight Transport Simulation System InterLOG, in the Proc. of 85th Annual Meeting of the Transportation Research Board, (CD-ROM), Washington D.C., January 2006.

Shinghal, N., and T. Fowkes (2002) Freight mode choice and adaptive stated preferences. Transportation Research Part E 38: 367–378.

Silva, J.M.C.S. A score test for non–nested hypotheses with applications to discrete data models. *Journal of Applied Econometrics*, 16(5), pp. 577–597, 2001.

Southworth, F. (2003) Freight Transportation Planning: Models and Methods. Transportation systems planning: methods and applications, by K. G. Goulias.

Spekman, R.E. (1988) Strategic supplier selection. *Business Horizons*, Volume 31, Issue 4, Pages 75-81.

Stadtler, H. 2005. Supply chain management and advanced planning - basics, overview and challenges. *European Journal of Operational Research*, Vol. 163, pp. 575-588.

Stefan, K. J., J. D. P. McMillan, and J. D. Hunt (2005) An Urban Commercial Vehicle Movement Model for Calgary. Transportation Research Record, 1921: 1-10.

Strong, C. K., R. Harrison, and H. S. Mahmassani (1996). A methodology for determining the freight border transportation impact of the North American free trade agreement. University of texas, Center for Transportation Research Report 1319-4.

Tavasszy, L.A., B. Smeenk, and C.J. Ruijgrok. (1998) A DSS for Modeling Logistic Chains in Freight Transport Policy Analysis. Intelligent Transportation Operational Research, 5(6): 447-459.

Train, E. K. Discrete Choice Methods with Simulation. Cambridge University Press, 2003.

Transport Canada. National Roadside Survey. 1999. <http://www.tc.gc.ca/policy/acg/acgc/NRSIndex_e.htm>, accessed July 2009.

Transportation Research Board: National Cooperative Highway Research Program, Report 606. Forecasting Statewide Freight Toolkit. Washington D.C., 2008.

Tyworth, J. T. (1991) The inventory theoretic approach in transportation selection models: A critical review. Logistics and Transportation Review, 27(4): 299-318.

U.S. Census Bureau: North American Industry Classification System (NAICS) (2010). Available at: www.census.gov/naics/, accessed February 2010.

U.S. Census Bureau: Statistics of U.S. Businesses (2009). Available at: http://www.census.gov/econ/susb/introduction.html, accessed February 2011.

U.S. Census Bureau: Economic Planning and Coordination Division (2008) County Business Patterns. Available at: http://www.census.gov/epcd/cbp/view/cbpview.html, accessed April 2008.

U.S. Census Bureau: Commodity Flow Survey (2007), available at http://www.bts.gov/programs/commodity_flow_survey/

U.S. Department of Transportation, Federal Highway Administration. Freight Facts and Figures, 2009.

U.S. House of Representatives (2009). The Surface Transportation Authorization Act of 2009. A Blue Print for Investment and Reform. Committee on Transportation and Infrastructure. http://transportation.house.gov/Media/file/Highways/HPP/Surface%20Transportation%20Blueprint%20Executive%20Summary.pdf

Vernimmen, B., and F. Witlox (2003) The Inventory-Theoretic Approach to Modal Choice in Freight Transport: Literature Review and Case Study. Brussels Economic Review, 46(2): 5-29.

Vleugel, J., and M. Janic (2004) Route choice and the impact of ‘logistic routes. In: Logistics Systems for Sustainable Cities (edited by E. Taniguchi, and R. Thompson). Elsevier.

Winston, C. 1983. The demand for freight transportation: Models and applications. *Transportation Research Part A*, Vol. 17, pp. 419–427.

Wisetjindawat, W., and K. Sano (2003) A Behavioral Modeling in Micro-Simulation for Urban Freight Transportation. Journal of the Eastern Asia Society for Transportation Studies, 5: 2193–2208.

Wisetjindawat, W., S. Matsumoto, and K. Sano (2005) Supply Chain Simulation for Modeling the Interactions in Freight Movement. Journal of the Eastern Asia Society for Transportation Studies, 6: 2991 – 3004.

Wisetjindawat, W., K. Sano, S. Matsumoto, and P. Raothanachonkun (2007) Microsimulation Model for Modeling Freight Agents Interactions in Urban Freight Movement. Proceedings, 86th Annual Meeting of the Transportation Research Board, Washington DC, 21–25 January 2007.

Yang, C. H., J. Y. J. Chow, and A. C. Regan (2009) State-of-the Art of Freight Forecasting Modeling: Lessons Learned and the Road Ahead. Proceedings, 88th Annual Meeting of the Transportation Research Board, Washington DC, 11–15 January 2009.

Yin Z., Y. Tang, and F. Sun (2006) Fuzzy Clustering with Novel Separable Criterion, *Tsinghua Science & Technology*, Volume 11, Issue 1, Pages 50-53.

Zadeh, L.A. (1965). Fuzzy sets. *Information and Control* 8 (3): 338-353.

Zhang, Y., R. O. Bowden, and A. J. Allen (2003) Intermodal Transportation Planning Using Commodity Flow Data. National Center for Intermodal Transportation and Mississippi Department of Transportation.

APPENDIX A. FUZZY EXPERT SYSTEM FOR SUPPLIER SELECTION MODEL

1. FUZZY VARIABLES

A review of the supplier choice literature revealed that the locations and financial positions of the companies are among the most important elements in the supplier selection decisions (Stadtler, 2005). Therefore, distance between buyer and potential suppliers was selected as one input variable. Number of employees is the other input variable that is used as a proxy for the financial position of the suppliers. In other words, suppliers with higher number of employees are considered to have a better financial position in a given industry. Although this assumption could be doubtful in a study with highly aggregate industry classification, this does seem reasonable for this study with a fairly disaggregate six-digit NORTH AMERICAN INDUSTRY CLASSIFICATION SYSTEM. The only output variable, however, is likelihood of partnership.

One distinctive characteristic of fuzzy rule-based systems that makes it lenient to imprecise data is use of fuzzy linguistic variables instead of crisp values. Any input variable (say distance) should be defined in the form of a categorical linguistic variable (say far, average, and close) in a procedure called fuzzification. Thus, a membership function has to be defined for each and every input variable to provide the degree by which the variable is associated to the linguistic categories. For example, if distance variable has a crisp value of 250 miles, fuzzified distance variable with three categories (far, average, and close) could have a membership value of 0.6 in the close category, 0.4 in the average category, and 0 in the far category. In other words, each membership value is the degree of truth of a statement (e.g. 250 miles distance is considered close in 60% of the situations). Similarly, any output variable needs to have a membership function to convert its fuzzy linguistic value to a crisp and clearly-defined value, in a procedure called defuzzification.

2. FUZZIFICATION METHOD

Fuzzification is a process through which crisp values of input variables are transformed into membership values for linguistic categories of a fuzzy set. Fuzzy C-Means (FCM) clustering method is used in this study to define membership functions. As understood from the name, this clustering method has a fuzzy nature and allows one data point to belong to more than one cluster with specific degrees of association to each cluster. This method was developed by Dunn (1973) and enhanced by Bezdek (1981) and has been commonly implemented in data analysis and pattern recognition (Yin et al., 2006). FCM sets the clusters' boundaries and membership values in a way that maximizes not only the compactness between data and cluster centers but also the separation between cluster centers.

MATLAB 7.9 was used to perform FCM clustering on two input variables in the supplier selection model, namely SIZE and DISTANCE. UIC National Freight Survey data was used to define the membership functions, illustrated in Figure A-1. Crisp vales of SIZE of the establishments are defined in eight categories, and the fuzzy values are determined in three linguistic categories: *small*, *medium*, and *large* (Table A-1). Crisp vales of DISTANCE between the supplier and buyer, on the other hand, are expressed in mile and the fuzzy values are again determined in three linguistic categories: *close*, *average*, and *far*. The only output variable is PARTNERSHIP, defined in three classes: *unlikely*, *average*, and *likely*. The goal of this fuzzy model is to estimate likelihood of partnership between a business establishment and a potential supplier according to a given set of rules.

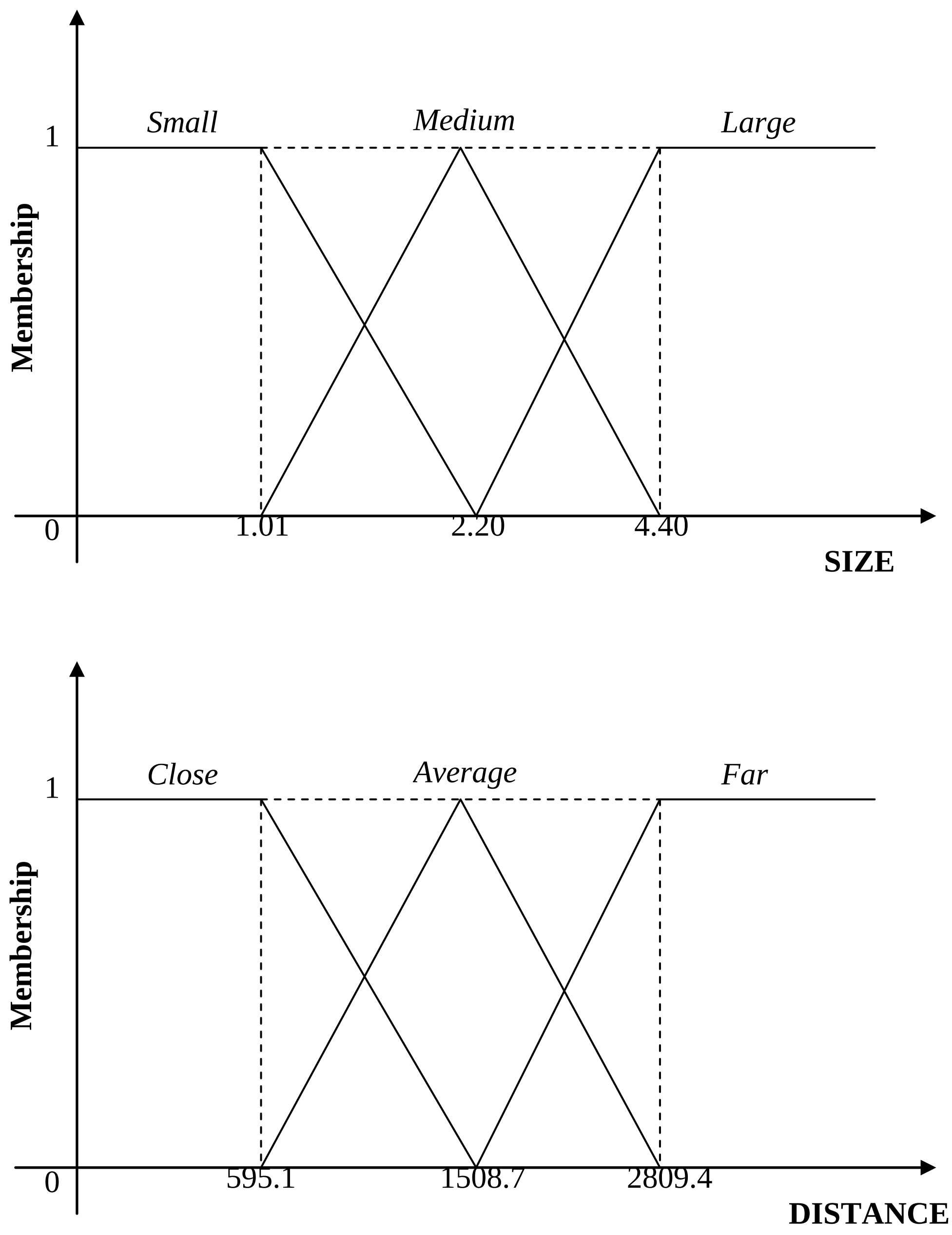

FIGURE A-1. MEMBERSHIP FUNCTIONS FOR INPUT VARIABLES IN THE SUPPLIER SELECTION MODEL

TABLE A-1. DEFINITION FOR ESTABLISHMENT SIZE CLASSIFICATION

Establishment size category	Range of number of employees
1	1 – 19
2	20 – 99
3	100 – 249
4	250 – 499
5	500 – 999
6	1000 – 2499
7	2500 – 4999
8	4999 <

3. INFERENCE METHOD

Inference engine is an essential component and core of a fuzzy logic system that processes fuzzified input variables and provides the fuzzy output variable(s). All the rules in this inference engine are simply expressed in linguistic form and are conceptually easy to apprehend. The rules, however, may be extracted from a set of observed data or from expert human experience. The latter is called fuzzy expert system and is very useful in the lack of appropriate data. Similar to other modeling efforts, some sort of validation is required either for the rules or the model outputs to assure the robustness of the model. Some rules were defined based on the findings of other researchers (Altinoz, 2008; Stadtler, 2005; Choi and Hartley, 1996; Spekman, 1988), and then all the rules were presented to more than 6,000 experts in the area of supply chain management in different industries for final evaluation. They were asked in an online poll with around 2 percent response rate to score the correctness of each rule on a scale of one to five. All the linguistic rules along with their correctness score are presented in Table A-2.

TABLE A-2. LINGUISTIC RULES OF THE FUZZY RULE-BASED SUPPLIER SELECTION MODEL

Rule ID	Linguistic From	Score
1	If supplier and buyer are *small*, then partnership is *unlikely*.	2.4
2	If supplier is *medium* and *buyer* is *small*, then partnership is *unlikely*.	2.3
3	If supplier is *small* and buyer is *medium*, then partnership is *unlikely*.	2.3
4	If supplier is *small* and buyer is *large*, then partnership is *average*.	3.4
5	If supplier is *large* and buyer is *small*, then partnership is *average*.	3.4
6	If supplier and buyer are *medium*, then partnership is *average*.	3.8
7	If supplier is *large* and buyer is *medium*, then partnership is *likely*.	3.7
8	If supplier is *medium* and buyer is *large*, then partnership is *likely*.	3.7
9	If supplier is *large* and buyer is *large*, then partnership is *likely*.	3.5
10	If supplier and buyer are *close*, then partnership is *likely*.	3.9
11	If supplier and buyer are in *average* distance, then partnership is *average*.	3.7
12	If supplier and buyer are *far*, then partnership is *unlikely*.	3.0

In this case, the inference engine will evaluate all the rules for a given pair of supplier and buyer and find the minimum degree of membership in each antecedent. This value will be interpreted as the degree of membership in the consequent. Finally, fuzzy output could be obtained by finding the maximum degree of membership for each category (*unlikely*, *average*, and *likely*) of the output variable in the rule set. For example, four rules (1, 2, 3, and 12) suggest membership values for the *unlikely* category of the output variable, but the final membership value of the output variable would be the largest. Similar procedure should be carried out to obtain membership values of the other two categories (*likely* and *average*) of the output variable. Therefore, the output of this step of the model is a fuzzy value for PARTNERSHIP for a given pair of supplier and buyer.

4. DEFUZZIFICATION METHOD

The last step is to transform the fuzzy output variable into a crisp value in a procedure termed defuzzification. Several methods are introduced for defuzzification. The simplest approach is to select the category with the highest degree of membership and convert it to a real value in some way. Although this method is very easy to implement, information from the non-maximum categories would be lost in the defuzzification process. Centroid is a richer approach that finds a crisp output value using the membership values of all the categories. The area under the membership function will be determined, and a straight horizontal line at the membership value will chop off the top portion of the membership function area for each category of the fuzzy output variable. Center of mass of the remaining geometric shape should be determined and the x coordinate will be recognized as the crisp output value. Membership function for PARTNERSHIP is shown in Figure A-3.

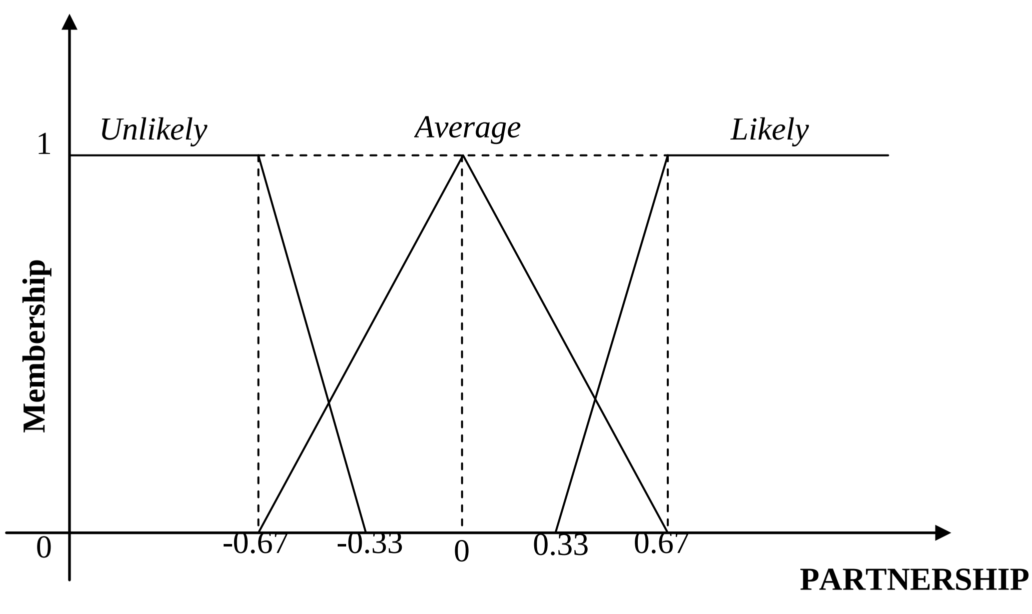

FIGURE A-3. MEMBERSHIP FUNCTIONS FOR THE OUTPUT VARIABLE IN THE SUPPLIER SELECTION MODEL

APPENDIX B. SHIPMENT SIZE MODEL

1. INITIALIZATION

For each class of commodity and shipping distance category a matrix should be specified with three columns (small, average, and large). Number of rows in each matrix, however, is equal to the total number of supplier and buyer pairs with matching commodity type and shipping distance category. Array of the total annual tonnage of a known commodity type that the supplier is sending for the buyer in a specific distance category is also known. The ultimate goal of this model is to break down this array and determine share of small, average, and large shipments. These matrices are defined and initialized at this stage as explained in following:

a. Define sets of commodity types (C), shipping distance classes (D), and shipment size clusters (S). In this case: C = {1, 2, 3, …, 43}; D = {<50 miles, 50-99, 100-249, 250-499, 500-749, 750-999, 1000-1499, 1500-2000, >2000}; S = {<1000 lbs., 1000-50000, >50000 lbs.}
b. For each commodity type $c \in C$ and shipping distance class $d \in D$, define matrix $A^{c,d}$ with three (number of shipment size clusters) columns and R rows, where R is the total number of supplier and buyer pairs that are trading commodity c and are at the distance of d.
c. For each row (r) in each $A^{c,d}$ that represents a specific pair of supplier and buyer, calculate:
   i. F = Supplier's establishment size
   ii. T = Buyer's establishment size
   iii. Ton = Annual tonnage of commodity c that is being traded between the supplier and buyer
   iv. FS = Degree of membership of F in small category
   v. FM = Degree of membership of F in medium category
   vi. FL = Degree of membership of F in large category
   vii. TS = Degree of membership of T in small category
   viii. TM = Degree of membership of T in medium category
   ix. TL = Degree of membership of T in large category
   x. Small = (FS + TS) / FS + FM + FL + TS + TM + TL.
   xi. Average = (FM + TM) / FS + FM + FL + TS + TM + TL.
   xii. Large = (FL + TL) / FS + FM + FL + TS + TM + TL.
   xiii. Set:
      - $A^{c,d}[r, 1] =$ Small * Ton,

- $A^{c,d}[r,2]$ = Average * Ton,
- $A^{c,d}[r,3]$ = Large * Ton.

2. MODIFIED ITERATIVE PROPORTIONAL FITTING (IPF)

Initial values that are set in the first step are iteratively adjusted at this stage to obtain a relatively close match to the observed shipment size distribution in the Commodity Flow Survey. Sum of each row in a given $A^{c,d}$ matrix is given and should not be changed after redistributing shipment sizes. Share of small, average, and large shipments for a given commodity type and shipping distance cluster is known from 2002 Commodity Flow Survey, and therefore desired sum of each column could be easily obtained. Each cell of a given $A^{c,d}$ matrix could be estimated by an iterative proportional fitting approach, when sum of each row and sum of each column is given. The only restriction that should be considered in this iteration is that all the cells should be within the limits that are defined for the shipment size clusters. For instance, all the cells in the last common should be larger than 50,000, according to the definition of large shipments in this study. Similarly, all the cells in the second column should be larger than 10,000 but not necessarily smaller than 50,000. The latter is because each cell shows total weight of shipments that are in a specific cluster of shipment size and are traded between two known business establishments in a year. Following procedure should be carried out for each $A^{c,d}$, after initialization to determine size of the shipments.

a. For each $s \in S$, set $CFS^{c,d}(s)$ = tonnage share of commodity c, shipped in size s at distance d, according to the Commodity Flow Survey data. For example $CFS^{34,1}(2)$ = % 48 means % 48 of total tonnage of machinery products (SCTG = 34) that was shipped less than 50 miles was medium size shipments, and the remaining 52% was either small of large, according to the Commodity Flow Survey data.

b. For each column (s), set Total_Column (s) = $CFS^{c,d}(s)$ * sum of all the cells.

c. For each row (r), set Total_Row (r) = sum of the r^{th} row.

d. $\varepsilon_1 = \varepsilon_2 = 0$.

e. While$|\varepsilon_1 - \varepsilon_2| > 1E-6$, repeat the following:

   i. Set $\varepsilon_2 = \varepsilon_1$,

ii. Adjust each column: cell values in each column (j) are proportionally adjusted so they sum up to Total_Column (s). Shipment size limits should be observed in this step. If a cell has a value below the minimum limit (e.g. less than 50,000 in the third column) it should be adjusted so the conditions are not violated. The adjustment procedure is a straight forward heuristic:
   - If a shipment is more than half but less than the minimum required weight of cluster definition, add the difference to it from the adjacent shipment size category.
   - Larger shipment categories are in priority of giving. For example, if an average size shipment is 950 lbs. and is 50 lbs. below the minimum required of 1000 lbs., this 50 lbs. difference should first be considered to be obtained from large shipment category of the same row. However, if large shipment has a value less than 50050, this transfer would not be possible by definition, and then the small shipment size should be checked to obtain the difference.
   - If a shipment is less than half of the required weight of cluster definition, this amount should be moved to the adjacent shipment size category.
   - Larger shipment categories are in priority of receiving.

iii. Adjust each row: cell values in each row (r) are proportionally adjusted so they sum up to Total_Row (r). Shipment size limits should be observed similar to ii.

iv. Calculate $\varepsilon_1 = \sqrt{\sum_r \left(\frac{\sum_j A^{c,d}(r,j)}{Total\_Row(r)} - 1\right)^2 + \sum_j \left(\frac{\sum_r A^{c,d}(r,j)}{Total\_Column(s)} - 1\right)^2}$

Although this approach is very straightforward and fully benefits from public data in the U.S., key information on shipment size determination is considered in this model. This includes establishment size of the supplier and buyer, shipping distance and commodity type. Since commodity type is defined at a considerably high resolution (2-digits Standard Classification of Transported Goods), this information embeds several characteristics of the commodity including value that significantly affects size of shipments. Contrary to the conventional iterative proportional fitting method with no control over the limits of the cell values, this approach could not exactly replicate the observed shipment size distribution in the Commodity Flow Survey data, because of the adjustments in steps ii and iii.

APPENDIX C. UIC NATIONAL FREIGHT SURVEY

Freight data is such a valuable piece of information that some firms are in the business of collecting and analyzing it. Freight survey is always challenging because, as mentioned earlier, the target population is reluctant to participate, and also the information to be collected often include complex decisions that may be hierarchical and/or interdependent. Furthermore, each contact is made under a severe time constraint, since the respondents are typically surveyed while they are on the job. Thus, the survey structure and methodology are particularly crucial in carrying out successful freight surveys.

For this study, three survey methods were initially looked into, namely: mail-in mail-out, telephone interview, and web-based. Since this survey targets a vast number of business establishments across the U.S., in-person interview was rejected first. After evaluating the expected response rates, costs, and convenience factors of each approach, the web-based method was selected. Although a group of well-trained telephone interviewers could obtain a high response rate, web-based method could be generally performed in a more cost-effective manner and could take advantage of a variety of audio and visual stimuli to enhance the survey questions (Couper et al., 2001). Furthermore, web-based surveys can be completed at any time of the day by shipping managers who tend to be very busy during office hours. Since web-based surveys, while more economical than the telephone survey, tend to result in a low response rate that could make the results fallible, some information must be obtained from non-participants in order to assess the presence and the severity of the non-response bias (Heckman, 1990). This will be discussed in more detail in this chapter.

1. SURVEY DEVELOPMENT

The main objective of this survey was to facilitate the development of the proposed behavioral microsimulation of freight flow, Freight Activity Microsimulation

Estimator, in the U.S. Specifically, information on the modal selection process had to be collected since such information was not available. An initial review of the freight demand modeling studies, in addition to interviews with experts in the academia and industry sectors were undertaken before and during the questionnaire design. Five basic factors were found to have a significant impact on freight mode choice: accessibility, reliability, cost, haul time, and flexibility. A preliminary version of the survey was designed and later refined according to the inputs obtained from the knowledgeable informants in the field of freight transportation and web-based survey design.

The survey had three major sections: relevant characteristics of the establishments, information on five recent shipments, and contact information. Table C-1 summarizes the key questions in each section of the survey. A pilot survey was carried out on January and February of 2009. The pilot was sent to around 1,200 randomly selected business establishments and was followed by three follow-up emails, resulting in a 1.0% participation rate. Although the response rate of 1.0% was anticipated for this survey, some improvements in the final version of the survey caused a 20% increase in the response rate.

A marketing company was hired to send recruiting emails on behalf of our research team to randomly selected firms in the U.S. The responsibilities of the marketing company were to provide a list of shipping managers or a person with the knowledge of the shipping process in different industries; send an invitation email with an embedded link to the survey on our behalf, which was already designed by our team; send the reminders to the same population; and provide a follow up report when the survey was finished.

The main survey was carried out in April and May of 2009 followed by three email reminder that were sent 2, 7, and 14 days after the primary email contact, respectively. Figure C-1 presents the trend of receiving completed questionnaires over time. In total, 316 establishments participated in the survey providing information on 881 shipments across the country.

The follow up report contained some basic information about the firms in the sampling frame, including participant's name, phone number, address, company name, industry classification, and employment size of the establishment. Also, this report distinguished the persons who had opened the email and persons who had clicked on the survey link. According to this report, over 4,000 of the initial emails which totaled more than 30,000 bounced back. This made the number of successful email deliveries 25,997. However, some emails, even though they did not bounce back, were filtered in the spam folder of the recipients. The report revealed that, of the 25,997 establishments contacted, a total of 4,544 recipients had successfully opened the emails. Around 9.3% of those actually clicked on the survey link, but not all of them filled out the survey. To investigate the effect of the spam filters, we randomly selected firms from the sampling frame that was provided by the marketing company that carried out the recruiting, and contacted them by phone and asked whether they had received the email in their mail box or not. Roughly 40 persons were successfully contacted, of which less than half actually received the email.

TABLE C-1. AN OVERVIEW OF SOME QUESTIONS IN THE UIC NATIONAL FREIGHT SURVEY

Section	Question
I	Zip code of the establishment. Total gross floor area occupied by the establishment. Number of employees? Primary industry type of the establishment. Potential use of each mode of freight transportation by the firm. Access to rail-truck inter-modal facility. Warehousing situation in the company (owned / rented / outsourced).
II	Origin and destination. Mode(s) of transportation used for the shipment. Type, value, weight, and volume of the commodity. Cost and time of the entire shipping process. Whether the shipment was Inbound / Outbound / Import / Export / Containerized / Damaged / NOT delivered on time. Expected delivery time window at the destination. Use of consolidation center, distribution center, or warehouse for the shipment. Decision making unit (sending firm / receiving firm / a 3PL) Whether the same transportation mode was preferred TWO years ago for a similar shipment.
III	Company name, address, phone, and email.

	Respondent's position in the company. Survey evaluation (Friendly / Neutral / Unfriendly) Willingness to participate in another online / telephonic / mail-in mail-out / in-person survey.

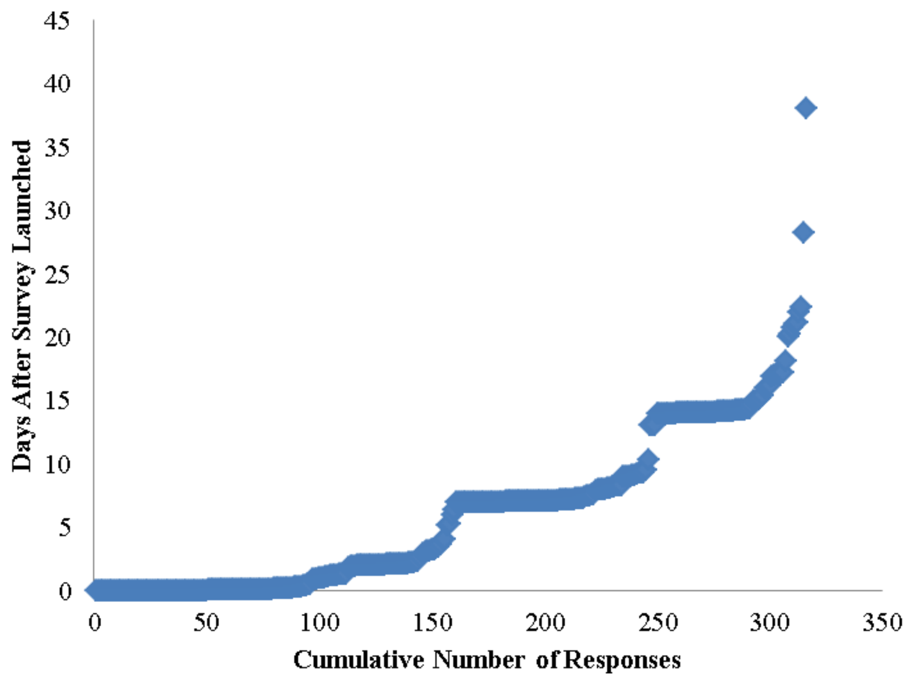

FIGURE C-1. TOTAL NUMBER OF PARTICIPANTS IN THE SURVEY OVER TIME

2. DESCRIPTIVE STATISTICS

Once the survey was completed, the answers were downloaded from the survey host site and cleaned. Respondents from a diverse range of industry type participated in this survey. In terms of the geographical coverage, however, the survey collected inputs from all the States except for Alaska, North Dakota, Utah, and Wyoming. On the other hand, Illinois, Wisconsin, Montana, New Mexico, Nevada, New Hampshire, Pennsylvania, and Nebraska had the highest participation rate. Since different industry groups were invited to participate in the survey, information of a diverse range of commodities was obtained. As illustrated in Figure C-2, mixed freight has the highest share of 20%, while coal and minerals have a share of only 1%. With the data coverage over a wide variety of commodity types, the demand model could be able to account for commodity heterogeneity, which is an essential issue especially for a behavioral model. Also, a rich dataset should cover a wide spectrum of shippers in terms of size. Fifty two percent of the participants were from a company with an employee size of between 50 and 1,000, while 34% reported an employee size of less than 49, and the rest were large firms with more than 1,000 employees.

Table C-2 shows the dollar value and weight of commodities that are shipped by each mode of transportation. This table also compares the figures from this survey against the 2002 Commodity Flow Survey (U.S. Department of Transportation, 2006). Share of rail and truck are reasonably close in terms of value and weight of transported commodities. However, air and water modes of transportation are somewhat skewed in this survey and should be properly addressed in any analysis. Weighting the shipments in a way that a decent match with the Commodity Flow Survey mode shares could be obtained between aggregate shares of each mode is a simple solution. However, for the ultimate objective of this study, which is the development of a behavioral mode choice model, the data on air and water modes are not as critical as those for truck, rail, and intermodal, because the mode choice for those two modes can be predicted rather accurately based on the value and type of commodity being shipped. Also the behavioral modal split model that is discussed in the following chapters has only focused on truck, rail, and truck-rail intermodal.

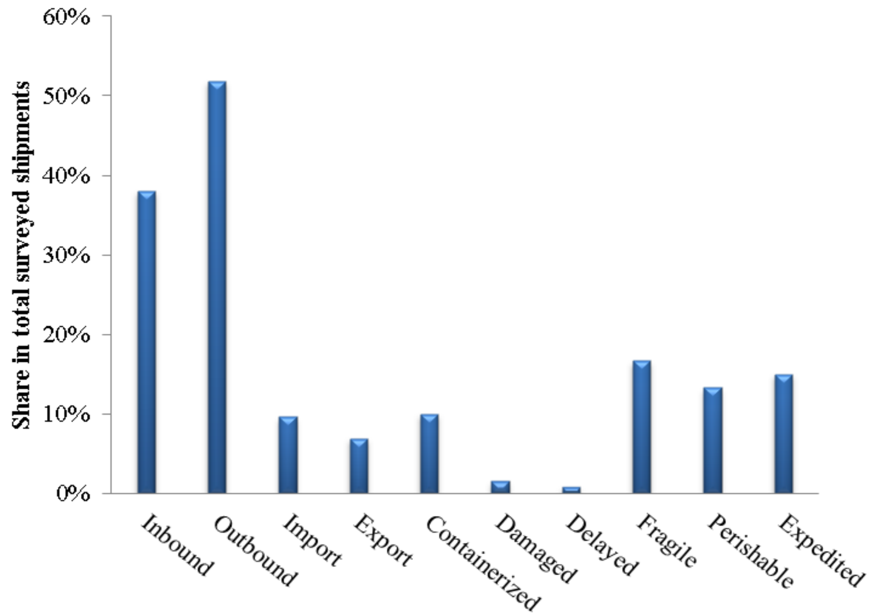

FIGURE C-2. COMMODITY TYPES IN THE SURVEY.

TABLE C-2. VALUE AND WEIGHT SHARE OF EACH MODE IN THE SURVEYED DATA

Mode	Dollar Value		Weight		Shipments
	COMMODITY FLOW	UIC[2]	COMMODITY FLOW	UIC	UIC
Truck	68%	67%	60%	49%	69%
Rail	3%	4%	10%	12%	5%
Water	1%	8%	4%	8%	5%
Air, air & truck	5%	9%	0%	1%	11%
Intermodal[3]	15%	12%	7%	30%	11%
Pipeline & unknown	9%	-	20%	-	-

[1] Commodity Flow Survey (2002) data do not include imports and exports that pass through the United States from a foreign origin to a foreign destination by any mode.

[2] UIC National Freight Survey.

[3] Intermodal includes U.S. Postal Service and courier shipments and all intermodal combinations, except air and truck.

3. LESSONS LEARNED

The survey was successful in general and around 7% of the persons who opened the recruiting email, filled out the questionnaire. However, following lessons could be enlightening for future establishment surveys:

- Some critical characteristics must be known for all the businesses in the sampling frame to conduct the selection bias analysis. Otherwise collected data could be useless. Fortunately, such information can be obtained from various commercial sources at a reasonable price.
- Companies have to trust the survey team; otherwise they will not share their business information. Renowned and trustable logos could boost the response rate, while unrelated or infamous logos could have negative effects. According to the reviews that we got from some experts after the pilot, logo of a university research center was replaced by the logo of the University of Wisconsin at Madison, and a better response rate was obtained in the main survey.
- When conducting an online survey, spammed emails could be a very critical issue. A rough estimate of the number of spammed emails should be obtained in the pilot to make sure massive spamming problem will not occur in the main survey.
- Survey questions must be reviewed by experts, before and after the pilot. Categorical choices promote the respondents to answer a question, since the exact figures will not be revealed. In some cases, aggregation level could be left up to the respondents, by providing some options. This was practiced in this survey, when asking about the firm's location and giving two choices of zip code and city.
- Some questions cannot be answered by the selected population and should be removed after the pilot to minimize the survey burden.

4. NON-RESPONSE BIAS ANALYSIS

Statistical analyses on a nonrandom sample can lead to questionable conclusions and poor policies. If a survey is designed in a way that a group of population with specific characteristics is more likely to be included in the sampling frame or participate, collected data will obviously be biased and all the modeling results will be open to discussion. The latter type of selection bias, which is caused by a nonrandom pattern in participating in the survey, is often referred to as non-response bias. Heckman (1990) proposed a two-step correction method to detect and address this issue. In the first step, the probability of responding to the survey should be modeled, resulting in a dichotomous logit or probit model. The estimated parameters are then used to generate an additional explanatory variable, which should be added to the final model in the second step. In fact, Heckman accounted for non-randomly selected samples as a form of omitted-variables bias.

There is always a concern in business establishment surveys that size, location, or industry type of the firms affects the probability of participation (Roorda et al., 2010). This section investigates such trends in our survey and presents some binary models that might be implemented in the second step of the Heckman correction method in future statistical analyses. However, probability of participation is defined as the chance of clicking on the survey link. Number of employees was used to approximate establishment size, which turned out to be insignificant in all the models. Industry type and location of the establishment, however, had slightly significant effect on probability of participation. This correlation was minor and revealed after testing different grouping criteria for industry type and location of the establishments. Industry type was defined in four categories based on Standard Industrial Classification (SIC) codes (Table C-3). Geographical location of each firm was also defined by a 4-category variable, using the state in which the establishment is located (Table C-3).

TABLE C-3

VARIABLE CLASSIFICATION FOR SELECTION BIAS ANALYSIS

Variable	Category	Description
Location (State)	I	AK, ND, UT, WY
	II	OR, VA, HI, AL, MS, AZ, CT, MA, WA, CA
	III	NY, OK, ME, NC, WV, AR, MO, ID, RI, MD, OH, SD, GA, TX, MI, CO, MN, FL, KS, LA, SC

	IV	TN, IN, NJ, VT, IA, DC, DE, KY, WI, PA, NE, NH, NV, IL, NM, MT
Industry Type (SIC)	I	8, 9, 10, 12, 21, 29, 31, 43, 44, 53, 60, 61, 62, 63, 64, 76, 82, 83, 84, 86, 89
	II	7, 13, 15, 16, 17, 20, 23, 25, 26, 32, 33, 37, 38, 41, 47, 48, 49, 50, 51, 52, 54, 55, 56, 65, 72, 73, 78, 79, 81
	III	22, 24, 27, 28, 30, 34, 35, 36, 39, 45, 46, 57, 58, 59, 70, 80, 87
	IV	1, 2, 14, 40, 42, 67, 75

Location, establishment size, and industry type of the recipients were inputted to Limdep Econometric Software (Greene, 2002) to estimate the probability of participation in the survey with logit and probit models. Newey and McFadden (1994) have more details on discrete choice models. Final models are reported in Table C-4, with standard t-values in the parentheses below each coefficient. Except for employment size, which does not have any significant correlation with probability of participation, all other coefficients are statistically significant with a 99 percent confidence interval. Neyman-Pearson tests (Wald, Likelihood Ratio, and Lagrange Multiplier) were also performed to see whether or not each model has a statistically significant explanatory power (Greene, 2002). Coefficient estimates and some model fit measures are summarized in Table C-4. Model 1 estimates probability of participation among 4,544 recipients, who had opened the email. However, the second set of models (Model 2) estimates such probability for the entire population. A brief comparison between the first and second sets of models does not show large fluctuations in coefficients of similar variables. Nonetheless, the first set of models has a superior overall fit, which was expected. This is because the first set of models are predicting a rare event with almost 9.3% chance of occurrence, while the other set has only a chance of 1.6%.

The next stage is to choose between the logit and probit models. According to most standard econometric textbooks, there is not a robust theoretical reason for preferring logit over probit or vice-versa (Gujarati, 2003). However, very different probabilities could be estimated by two binary choice models when modeling a rare event

(Jin et al., 2005). In our case, Model 1 and 2 are predicting rare events with only a 9.3% and 1.6% chance of responding to the survey, respectively. Thus, the choice of which model to use could have a fundamental impact on the predicted probabilities and eventually on the final models and policies. Silva (2001) has

TABLE C-4

FINAL MODELS FOR SELECTION BIAS ANALYSIS

Item		Model 1[1]		Model 2[2]	
		Probit	Logit	Probit	Logit
Coefficients	Constant	-1.312 * (-25.394)	-2.258 * (-22.608)	-2.295 * (-64.076)	-4.508 * (-48.264)
	Industry type (III)	0.314 * (4.972)	0.586 * (4.989)	0.215 * (5.008)	0.550 * (5.055)
	Industry type (IV)	0.506 * (5.722)	0.931 * (5.972)	0.474 * (7.863)	1.163 * (8.277)
	Location (I)	-0.255 * (-3.336)	-0.498 * (-3.282)	-0.213 * (-3.947)	-0.569 * (-3.940)
	Location (III)	0.329 * (4.986)	0.599 * (5.068)	0.255 * (5.726)	0.625 * (5.798)
Fit Measures	Log likelihood	-1176.882	-1176.482	-2077.139	-2076.288
	Model Chi-squared	112.269 *	113.069 *	152.487 *	154.191 *
	Akaike I.C.	0.76005	0.75980	0.16019	0.16012
	Pseudo R-squared	0.04553	0.04585	0.03541	0.03580

[1] This model predicts participation chance among those who *opened* the recruiting email.

[2] This model predicts participation chance among *all* the persons who were in the email list.

[*] Significant with a P-value less than 0.01.

developed an econometric procedure by which researchers can choose between a variety of discrete choice models including probit and logit. In this procedure, a combination of the competing models is defined in the form of an artificial variable, $z(\rho)$. This variable should be calculated by Equation (1) and then added to the basic model to re-estimate the coefficients. If this variable does not have a significant coefficient, the basic model will be preferred. In this case, logit model is set as the basic model, and $z(\rho)$ is calculated for three different values of ρ, according to Silva's suggestion.

$$z(\rho) = \left[\frac{(P_p/P_l)^\rho}{\rho} - \frac{((1-P_p)/(1-P_l))^\rho}{\rho}\right]\frac{P_l[1-P_l]}{P_l'} \tag{1}$$

In the equation above, P_l and P_p are predicted probabilities by logit (basic model) and probit models, respectively. P_l' is the derivative of the logistic function in the logit model with respect to its utility function. An over-rejection trend of the null hypothesis was revealed in a simulation analysis, which leads to a slight modification. Silva (2001) suggested a weighted version of z, computed as in Equation (2).

$$z^*(\rho) = z(\rho)\sqrt{P_l[1-P_l]} \tag{2}$$

As presented in Table VII, both weighted and non-weighted tests rejected the null hypothesis with a more than 99 percent confidence interval, for all levels of ρ. Thus the logit model is preferred to the probit. This model is could be used in the first stage of Heckman correction (Heckman, 1990) for any further modeling effort on the surveyed data. However, as pointed earlier in Table C-4, this model has a pseudo R-squared of only four percent which is comparatively low and shows a very slight selection bias. In the second stage, however, a transformation of these predicted probabilities (Heckman, 1990) should be added to each model as an extra explanatory variable to correct for this slight bias.

TABLE C-5. SILVA TEST RESULTS FOR SELECTION BIAS ANALYSIS: LOGIT VERSUS PROBIT

Item	Model 1[1]		Model 2[2]	
	Non-weighted	Weighted	Non-weighted	Weighted
ρ = 0	1.27 (0.26)	1.77 (0.18)	3.21 (0.07)	3.47 (0.06)
ρ = 0.5	1.27 (0.26)	1.77 (0.18)	3.23 (0.07)	3.49 (0.06)
ρ = 1	1.27 (0.26)	1.78 (0.18)	3.24 (0.07)	3.50 (0.06)

[1] This model predicts participation chance among those who opened the recruiting email.

[2] This model predicts participation chance among all the persons who were in the email list.
Note: P-values are reported in the parentheses.