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A SURVEY OF THE FREIGHT TRANSPORTATION DEMAND LITERATURE AND A COMPARISON OF ELASTICITY ESTIMATES

US Army Corps of Engineers®

IWR Report 05-NETS-R-01

Navigation Economic Technologies

The purpose of the Navigation Economic Technologies (NETS) research program is to develop a standardized and defensible suite of economic tools for navigation improvement evaluation. NETS addresses specific navigation economic evaluation and modeling issues that have been raised inside and outside the Corps and is responsive to our commitment to develop and use peer-reviewed tools, techniques and procedures as expressed in the Civil Works strategic plan. The new tools and techniques developed by the NETS research program are to be based on 1) reviews of economic theory, 2) current practices across the Corps (and elsewhere), 3) data needs and availability, and 4) peer recommendations.

The NETS research program has two focus points: expansion of the body of knowledge about the economics underlying uses of the waterways; and creation of a toolbox of practical planning models, methods and techniques that can be applied to a variety of situations.

Expanding the Body of Knowledge

NETS will strive to expand the available body of knowledge about core concepts underlying navigation economic models through the development of scientific papers and reports. For example, NETS will explore how the economic benefits of building new navigation projects are affected by market conditions and/or changes in shipper behaviors, particularly decisions to switch to non-water modes of transportation. The results of such studies will help Corps planners determine whether their economic models are based on realistic premises.

Creating a Planning Toolbox

The NETS research program will develop a series of practical tools and techniques that can be used by Corps navigation planners. The centerpiece of these efforts will be a suite of simulation models. The suite will include models for forecasting international and domestic traffic flows and how they may change with project improvements. It will also include a regional traffic routing model that identifies the annual quantities from each origin and the routes used to satisfy the forecasted demand at each destination. Finally, the suite will include a microscopic event model that generates and routes individual shipments through a system from commodity origin to destination to evaluate non-structural and reliability based measures.

This suite of economic models will enable Corps planners across the country to develop consistent, accurate, useful and comparable analyses regarding the likely impact of changes to navigation infrastructure or systems.

NETS research has been accomplished by a team of academicians, contractors and Corps employees in consultation with other Federal agencies, including the US DOT and USDA; and the Corps Planning Centers of Expertise for Inland and Deep Draft Navigation.

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EXECUTIVE SUMMARY

This survey provides a general overview of the methodology and results of several aggregate and disaggregate studies of freight transportation demand. The survey provides a detailed look at neoclassical “aggregate” models and disaggregate “choice” models based on McFadden’s random utility model. After presentation of these different methodologies to estimate freight demands, the study concludes with a comparison of elasticity estimates across modes and methods. The survey concludes with a discussion possible improvements to demand studies. This final discussion follows the suggestions of Oum et al. (1992) and leads to a recommendation of how these suggestions apply to modeling inland waterway transportation demand.

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I. INTRODUCTION

Transportation economics is "an applied area of economics that is concerned with the efficient use of society's scarce resources for the movement of people and goods from an origin to a destination" (McCarthy, 2001). Studies of transportation economics have been documented as early as 1840[1]. The first studies covered such topics as pricing of transportation infrastructure, congestion of roads, and optimal pricing of public transportation facilities (Winston, 1985). In his survey of developments in transportation economics, Winston (1985) discusses the ideas developed in these studies that are still widely used today in analyzing transportation problems. These ideas include Ramsey pricing (Dupuit, 1844), economies of scope and joint production (Wellington, 1877), and economies of scale (Lorenz, 1916). Since the appearance of these early transportation studies, countless others have analyzed issues in transportation economics. This paper focuses on the empirical transportation demand literature.

Transportation demand modeling is complicated by a number of characteristics that are central to the transportation industry. Small and Winston (1998) highlight some of these characteristics. These include: (1) the interrelated decisions of transportation, (2) the large number of distinct services differentiated by location or time (spatial and temporal aspects), and (3) the shipper's sensitivity to service quality (quality indicators include frequency, route coverage, reliability and comfort).

Empirical evaluations of these characteristics motivate many transportation demand studies. In particular, demand studies have based work on the mixed continuous discrete decisions of shippers (mode, location, and quantity) to evaluate relative import of factors

[1] Early studies of transportation economics include Ellis (1840), Dupuit (1844,1849), Wellington (1887),

important to choosing a transportation mode. Often there is a focus on the role of reliability and travel time in shippers' decisions and/or the influences of input or output price changes on firm's decisions (McCarthy, 2001). These estimates can be used to forecast the effect of various policy measures on transportation markets or individual firms and to evaluate the competitiveness of alternative modes of transportation.

In Section II we provide a general overview of the literature pertaining to estimation of transportation demand. Section III provides a comparison of the elasticity estimates from the studies discussed in Section II. Section IV concludes our study with a discussion of possible improvements to studies of transportation demand, and their application to inland waterway transportation demand studies.

II. LITERATURE REVIEW

Most of the studies of transportation demand from the last thirty years focus on estimation issues. While there is a wealth of passenger demand studies, the focus in this paper is on freight demand. This literature separates into two general categories: studies that employ aggregate data and those that employ disaggregate (shipper) data. We first turn to the aggregate models which played a key role in prompting the development of the more sophisticated disaggregate models. Most of the recent literature tends to use primarily disaggregate data and models based on shipper choices.

II.1. Aggregate Demand Models

Aggregate demand models use data that describe the behavioral aspects of a large group

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Pigou (1912), Lorenz (1916), and Knight (1924), to name a few.

of shippers (Small and Winston, 1998). There are two classes of aggregate demand models, modal split models and neoclassical aggregate demand models. The main difference between the two classes of models is the degree of behavioral assumptions embedded in each. The aggregate modal split models contain few behavioral aspects and hence are heavily criticized,[2] and this motivates the development of the neoclassical aggregate demand model.

The neoclassical aggregate demand models incorporate more of the behavioral aspects of groups of shippers. Small and Winston (1998) note that the neoclassical models based on standard microeconomic theory tend to be more satisfactory than the models not founded in theory. Another major benefit of the neoclassical models is the ability to use flexible functional forms in estimation. A very restrictive, linear, functional form is commonly used in modal split models. Examples of the neoclassical aggregate demand models are surveyed below.

Neoclassical Aggregate Demand Models

Oum (1979) identifies several weaknesses of existing demand models such as the use of restrictive functional forms, ad hoc[3] specifications of the model, the exclusion of service-quality attributes, and the use of highly aggregated data over heterogeneous commodities. He measures the price and quality responsiveness of demand using a derived demand model. Freight transportation demand is modeled as an input to a shipper's production and distribution activities.

[2] Winston (1985) identifies these articles as Perle (1964), McLynn and Watson (1967), Quant and Baumol (1966), Boyer (1997), and Levin (1978). These aggregate modal split models attempted to determine the number of trips or tonnage that were allocated between a given set of modes, over a cross section of city pairs, on the basis of relative travel times and costs among modes, or on the basis of characteristics of commodities that are transported (Winston, 1985).

[3] Ad hoc refers to the arbitrary specification of models without regard to the underlying production and

The formulation of the model is based on duality theory, or the relation between production and cost functions.[4] Thus, instead of imposing restrictions on the model by specifying a functional form, Oum derives a link-specific unit transport cost function for shippers as a function of freight rates, service quality attributes of various modes, and the distance of the link. A link is a section of a shipper's transportation network. The author specifies the cost function as a translog[5] and applies Sheppard's lemma[6] to the cost function to obtain the share-of-expenditure functions for rail and truck modes.

The data used include eight different commodity groups and consist of the distance of each link, total tons moved, average freight rate, transit time and its variability by mode on each link. All data employed were gathered for 1970 and taken from the Canadian Freight Transport Model database.

Oum develops three alternative models: (1) a general model, (2) a model with mode-specific hedonic aggregators and (3) a model with identical hedonic aggregators. The first model derives the cost function as a function of freight rates and quality attributes of various modes and the distance of the link. In the second model, a shipper bases his choice of mode on prices adjusted for quality variations. The last model assumes that the shipper chooses a mode using a comparison of the true contents of quality attributes. That is, the shipper views a mode not as a physical entity but rather as a set of attributes. Oum estimates the three models for each

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distribution technology of the shipper.

[4] Duality theory implies that if producers minimize input costs in producing given outputs, and if factor prices are exogenous, then the cost function contains the information needed to describe the corresponding production function, and vice versa.

[5] A translog function is a linear combination of all possible first and second order terms in the logarithms of independent variables.

[6] Sheppard's lemma states that a small increase in the price of an input increases cost by an amount equal to the use of that input. For a greater detailed discussion of Sheppard's lemma see Sheppard (1953) or Oum (1979).

of the seven commodity groups. Then, he performs hypotheses tests to determine if speed and reliability variables are significant and chooses the best model for each commodity.

Using the estimates, elasticities of substitution between modes and the elasticity of demand for a mode with respect to its own or the other mode's freight rate and speed can be estimated. A summary of the estimated elasticities for rail and truck modes in Canada is presented in Table II.1.1. Oum finds that the elasticity of substitution between rail and truck is lowest for lumber, 1.04, while that for other commodities ranged between 1.40 and 1.57. These measures of elasticity indicate high substitutability between modes for most commodities; implying that a one percent increase (decrease) in rail freight rates would cause a more than one percent increase (increase) in the use of truck transportation and vice versa. The truck mode is less price elastic than rail mode for all commodities except for chemicals and fuel oils, and the price and quantity elasticities of demand vary substantially across commodities.

Table II.1.1

Comparison of Freight Elasticities for Canada[a]

Commodity Group/ Elasticities	Fruits, Vegetables & edible foods	Lumber, including flooring	Chemicals	Fuel oil except gasoline	Refined petroleum products	Metallic Products	Non-metallic products
Elasticity of rail-truck substitution	1.458	1.044	1.57	1.429	1.4	1.508	1.539
Compensated elasticity rail wrt rail freight rate	-1.006	-0.5324	-0.6282	-0.3858	-.9560	-1.176	-1.047
Compensated elasticity truck wrt truck freight rate	-0.4522	-0.5116	-0.942	-1.043	-0.4499	-0.3318	-0.4925
Ordinary elasticity rail wrt rail freight rate	-1.037	-0.5814	-0.6882	-0.4588	-0.988	-1.198	-1.079
Ordinary elasticity truck wrt truck freight rate	-0.5212	-0.5626	-0.982	-1.07	-0.5179	-0.4098	-0.5605
Compensated elasticity rail wrt rail speed	0.1348					0[b]	0.2693
Compensated elasticity rail wrt truck speed	-0.9016					-1.1491	-1.286
Compensated elasticity truck wrt rail speed	-.606					0[b]	-0.1267
Compensated elasticity truck wrt truck speed	0.4063					0.3232	0.6049
Compensated elasticity rail wrt reliability of rail speed	0.0342					0.1705	0.0868
Compensated elasticity rail wrt reliability of truck speed	-2.4354					-1.1454	-2.5350
Compensated elasticity truck wrt reliability of rail speed	-0.0154					-0.481	-.0408
Compensated elasticity truck wrt reliability of truck speed	1.0947					.3232	1.1924

Friedlaender and Spady (1980) follow a similar methodology. They present a

[a] *Source* Oum (1979b, table 3, p. 477)
[b] Values not significantly different from zero.

neoclassical aggregate demand model for freight transportation that uses Sheppard's lemma to derive an input demand equation from a firm's cost function. Their study yields the input share equations for truck and rail service, and the estimated input cost shares. The input share equations then provide own-price and cross-price elasticities of demand for truck and rail modes. Freidlaender and Spady use the year 1972 cross section of 96 manufacturing industries to estimate the input share equation for truck and rail service.

Table **II.1.2** displays the own-price and cross-price elasticities of demand by mode and commodity group. The own-price elasticities for rail vary from -1.681 for stone, clay, and glass to -3.547 for electrical machinery.[7] The own-price elasticities of demand for truck, however, vary considerably less and range from -1.001 for food products to -1.547 for wood products. The cross-elasticities are quite low and range between -0.129 and 0.025.

Notes: Elasticities evaluated at means of variables

[7] An elasticity with absolute value greater than one implies that a one percent change in the price results in a more than a one percent change in demand. The positive elasticity implies a change in the same direction while the negative sign implies changes in the opposite direction (if one increases the other decreases).

Table II.1.2

Elasticities of Demand for Freight Rail and Road Freight[a]

Elasticities/ Commodity Groups	Rail price elasticities	Truck price elasticities	Rail wrt truck rates elasticities	Truck wrt rail rates elasticieties
Food products	-2.583	-1.001	-0.023	0.004
Wood and wood products	-1.971	-1.547	-0.050	-0.129
Paper, plastic & rubber products	-1.847	-1.054	0.007	0.003
Stone, Clay &glass products	-1.681	-1.031	0.025	0.016
Iron & steel products	-2.542	-1.083	-0.053	-0.013
Fabr. metal products	-2.164	-1.364	-0.059	-0.099
Non-electrical machinery	-2.271	-1.085	-0.032	-0.010
Electrical machinery	-3.547	-1.230	-0.151	-0.061

Summary of Neoclassical Aggregate Demand Models

Although neoclassical aggregate demand models integrate behavioral aspects of shippers and use flexible functional forms, and they have a clear advantage over the early modal-split models, the neoclassical models are not without their shortcomings. One of the disadvantages of the neoclassical approach is the use of aggregate data, or averages, which can suppress a significant amount of fruitful information. These models make it difficult to capture variation in decision-maker's characteristics and may over or understate the sensitivity of demand to price

[a] *Source* Freidlaender Spady (1980, table 2, p. 439).
Notes Based on 5 regions in the USA over 1972.

and service qualities. This in turn may result in flawed inferences pertaining to policy variables and potentially lead to the adoption of sub optimal public policies.

II.2. Disaggregate Demand Models

Given the obstacles to using aggregate data, economists developed disaggregate approaches to estimating freight transportation demand. Using data on individual decision-makers allows for a richer empirical specification and may provide for the ability to use a large number of observations (Small and Winston, 1998). A disaggregate model uses the characteristics of the individual decision-makers and a complete set of service attributes of different modes. Therefore, they may yield more accurate elasticity measures, based on specific characteristics of the options available to shippers. Further, disaggregate approaches do not require the assumption that decision-makers are identical (and/or that the results apply to a "representative" shipper, and are explicit about the source of random disturbances.

Disaggregate demand models can be classified into two categories: inventory and behavioral models (Winton, 1983). Inventory-based models analyze freight demand from the perspective of an inventory manager who deals with a number of production decisions, while the behavioral models deal with only one decision, the choice of mode (Abdelwahab and Sargious, 1992).

There are only a few articles that use the inventory-based modeling approach; most of these are theoretical in nature. On the other hand, there exists a plethora of literature that uses the behavioral approach and is empirical in nature. This literature covers many topics including the mode choice of shippers, households, individual passengers, and vacationers.

Inventory-Based Demand Models

Inventory-based models analyze freight transport demand from the perspective of an inventory manager. These models differ from the behavioral models in that they attempt to integrate the mode choice decision with other production decisions (Abdelwahab and Sargious, 1992).[8]

In their seminal paper, Baumol and Vinod (1970) develop the inventory-based demand model. They analyze the transport mode decision made by shippers, and the total demand for transportation services. They develop two approaches to the model, an abstract mode approach[9] and standard inventory theory.[10]

In explaining freight shipment decisions, the authors include the following considerations: shipping cost per unit, mean shipping time, variance of shipping time and carrying cost per unit of time while in transit. In order to determine how a shipper chooses between modes, the shipper's indifference curve is specified. The authors use inventory theory

[8] Examples of literature containing inventory-based models are: Baumol and Vinod (1970), Das (1974), Roberts (1977), Constable and Whyback (1978), McFadden (1981), and Bevilacqua (1978). Abdelwahab and Sargious (1992) present a brief overview of this literature in their article.

[9] This is a technique that describes the type of carrier as a vector of values, which specify the attributes of that carrier offered to shippers.

[10] A mode is defined as the vector $m_i = (m_{i1}, \ldots, m_{in})$ where the element m_{ij} is the value of the j-th variable (e.g., speed or reliability) characterizing mode i. Under this type of framework, slow and fast trains make up two different modes because the vectors characterizing the two modes differ with respect to the value of speed. These two modes would likely be considered equivalent in other studies because they are both rail modes.

to investigate the tradeoff between two attributes. They note that "if one can describe exactly how transit time affects the inventory level (safety stock) and, hence, carrying costs, one can proceed to determine the pertinent indifference relationship" (Baumol and Vinod, 1970, p. 416). The abstract mode approach was originally created to analyze the demand for passenger travel, but is extended by Baumol and Vinod to apply to many modes and commodities.

The authors develop three equations to produce the indifference curves. The first equation is a cost function derived under the assumption of perfect certainty, hence, making the safety stock (inventory level) equal to zero.[11] Although the safety stock is equal to zero, the authors use this as the base case in deriving the indifference curves from the cost functions.[12]

The next case introduces uncertainty to demand forecasts and delivery time and adds a term defining safety stock to the previous cost equation to examine the effect of uncertainty. The inclusion of this additional term makes it impossible to extract the indifference curves from the new equation.

Recognizing that firms maximize profit, Baumol and Vinod derive a total profit equation. From this equation, the optimal demand for transportation can be calculated using nonlinear estimation techniques. With a change in the original assumptions of the model the authors arrive at an equation that explicitly defines annual tonnage shipped, T:[13]

(Eq. II.2.1) $$\mathbf{T = (1/b)*[\Delta p - r - ut - ws/2 - wk - wk\,(s + t)^{1/2}\ ]}$$

where **Δp** is the price difference between origin and destination, **r** is the shipping cost per unit of

[11] In the case of perfect certainty, transit time and final consumer demand for the product can be predicted with perfect foresight.

[12] This is achieved by setting the cost function C equal to a constant K.

[13] This is achieved by defining safety stock as being proportional to the total volume of shipments, T,

commodity, **u** is the in transit carrying cost per unit, **t** is the average time required to complete a shipment, **w** is the warehouse carrying cost per unit per year, **k** is a constant, **s** is the average time between shipments and **b** is the slope of the demand curve.

Baumol and Vinod note three contributions of their theoretical model. First, their approach displays increased analytical power. For example, their approach enables one to infer what would happen to demand given a change in any of the attributes. These are the results from estimating demands for attributes rather than demands for modes themselves. Second, their approach allows incomplete data to be used; these data would otherwise have to be used in discrete batches.[14] Third, this approach provides the ability to internally test the results and accuracy of the demand estimates.[15]

The authors name two shortcomings to their approach. First, their approach would not be applicable to situations attempting to examine anything more than mode choice. Second, in order to derive the explicit equation defining annual tonnage shipped, **T**, the authors had to alter a major assumption. The original definition of safety stock was used in the first equations while it was redefined for the sole purpose of explicitly defining **T**, the annual tonnage shipped.

Behavioral Demand Models

The core of the literature pertaining to behavioral models is based on the notion that the

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instead of to its square root, as it was previously defined.

[14] This applies to a case where data on individual commodities and modes is sparse or incomplete, and thus cannot be used to estimate a demand function. They treat all modes as variants of a single mode, displaying different values for attributes. Hence, all of the data for the different modes and commodities can be combined to create a larger, more useful, data set.

[15] Baumol and Vinod provide the following example to illustrate this advantage. With data relating to four different modes, one can use the information about three modes to forecast the demand for the fourth mode as though it was a carrier that did not exist yet. By comparing the predicted demand for the fourth mode with the known demand, one would be able to test the performance and accuracy of the estimation method.

decision-maker maximizes utility with respect to the choice of mode. Although a number of disaggregate demand analyses preceded that of McFadden (1973), this work laid the foundation from which many other behavioral models are built (Winston 1985).[16]

Random Utility Models: Discrete Choice

The approach McFadden (1973) presents in his paper is that of utility maximization, where the utility function includes a random component. In this random utility approach the decision-maker makes a discrete choice by choosing among **J** alternative modes. The choice of the mode from the **J** available alternatives is assumed to maximize the decision-maker's utility. The utility function for the individual decision-maker is specified as follows:

(Eq. II.2.2) $$\mathbf{U_i = V(\beta; X_i, S) + \varepsilon\,(X_i, S)}$$

with $\mathbf{i = 1, \ldots\ldots J}$ and where $\mathbf{U_i}$ is the utility associated with transportation using mode **i**. The utility function is comprised of an observed and an unobserved, or random, component. The observable part of the utility function is $\mathbf{V(\beta; X_i, S)}$, where the vector function **V** consists of a vector of unknown parameters, $\boldsymbol{\beta}$, a set of modal attributes, $\mathbf{X_i}$, and the socioeconomic characteristics of the decision-maker, **S**.[17] **V** is systematic utility, that is, the same functional form applies to all shippers. The random portion of the utility function is $\boldsymbol{\varepsilon}\mathbf{(X_i, S)}$. This component of the utility reflects the unobserved tastes, preferences and characteristics of the individual decision-maker. Consequently, this term varies across decision makers.

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[16] Some of these early studies include Lisco (1967), Quarmby (1967), Domenrich et al. (1968), Lave (1969,70), Quant (1970), etc. See Winston (1985) for a more complete reference of early disaggregate work.

[17] The summary of McFadden (1973) relies, in part, on information provided in transportation demand surveys written by Winston (1985) and Small and Winston (1990). Both surveys contain excellent explanations and

According to the utility maximization assumption, the individual shipper chooses a particular mode **i** only if the utility realized from choosing mode **i** is greater than the utility realized from any other mode. Thus, the individual will choose mode **i** if $\mathbf{U_i > U_j}$ for all $\mathbf{i \neq j}$. In this model choices are predicted as probabilities, where the probability that the shipper chooses mode **i** is:

(Eq. II.2.3) $$\mathbf{P_i = Prob[U_i > U_j \text{ for all } i \neq j]}$$

Thus, the mode-choice probabilities depend, in part, on the random utility differences $(\boldsymbol{\varepsilon_i - \varepsilon_j})$, and their distribution (Small and Winston, 1998).

Using this framework, McFadden extends the mode-choice model to situations when the decision maker is confronted with more than two alternatives. He accomplishes this by assuming that the distribution of the random components follows the extreme value distribution.[18]

In a study by Daughety and Inaba (1978), the authors evaluate decisions confronting an elevator shipper that ships corn to various markets. The logit model is appropriate here because only one market and one mode are chosen to maximize the elevator's choice function (net-price or net-profit). It is assumed that the shipper is able to sell goods in various local markets, and that the market price is taken as given for the good and the transportation rates.

Different transportation modes are distinguished by their service attributes and by the costs induced by such attributes. These attributes include equipment availability, transit time and loading facilities. The varying level of reliability across modes introduces risk into the shipper's

details regarding the random utility model framework presented by McFadden (1973).

decision regarding mode and destination. Since elevator operators highly value equipment availability, Daughety and Inaba construct a measure for the availability attribute. Measured as the expected delay, the transport availability for a small shipper was 7.8 days and $0.0042/per bushel, and for a large shipper 13.5 days and $0.0072/per bushel.[21] Availability costs for truck transportation are assumed to be zero since trucks are readily available for small and large shippers.

Three exogenous variables in the observable portion of the model are the price at the j-th market, the transport rate of shipping to the j-th market by mode m and the availability cost associated with shipping by the m-th mode. The data used in the study are from a week in October of the 1975 harvest season. These data include price, quantity, transportation rate, destination, mode and distribution of delay times. The average regional prices from the database are used as proxies for the actual prices at the markets considered. The average price of corn is equal to $2.663 per bushel in the River region and $2.605 per bushel in the Local region[23]. Transportation rates for alternatives not chosen are estimated from data on shipment sizes, rates paid and distance shipped. River and Local regions are designated as the markets, while truck and single-car rail are designated as the mode choices.

The results of the study are displayed in Table II.2.1. Two logit models are estimated: (1) a net-price model determined by prices, rates and per unit cost, and (2) a net-profit model, where the prices were multiplied by the shipment size. The net-price model predicts the correct choice

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[18] For a more complete discussion see McFadden (1973) and Small and Winston (1990).

[21] A small shipper is defined as one using truck or single car rail transport, while a large shipper is defined as one using truck, single or multi-car rail transport.

[23] The River market covered Midwest/Mideast destination points on the Missouri, Mississippi, Illinois and Ohio Rivers and Chicago. The Local market refers to all other Midwest/Mideast traffic.

90 percent of the time, while the net-profit model predicts the correct choice 82 percent of the time. However, the parameters for the price variables are not statistically significant. Daughety and Inaba attribute this to the negotiating of bid prices and quantities between buyers and sellers. The coefficients for the revenue variables are significant at 1 percent level. This phenomenon is also explained by the bid negotiations. In light of such findings, Daughety and Inaba base their analysis and demand estimation for the remainder of the paper on the net-profit model.

Table II.2.1

Net-Price and Net-Profit Logit Models

	River (Price)	Local (Price)	River (Truck)	Local (Truck)	River (Rail)	Local (Rail)	Availability
Net-price %: 90 LRI: .6865	2.626 (1.046)	3.176 (1.193)	-33.21 (-3.889)	-64.63 (-4.491)	-16.74 (-3.547)	-25.29 (-3.410)	-457.5 (-2.394)
Net-profit %: 82 LRI: .4028	.00141 (3.412)	.00131 (2.945)	-.009604 (-3.925)	-.01282 (-3.297)	-.004848 (-3.635)	-.001574 (-3.060)	-.06695 (-1.951)

Daughety and Inaba also estimate rate functions by regressing freight rates on shipment data. These rate functions are then used to estimate demand functions. The results of two alternative demand functions are displayed in Table II.2.2 for four alternatives: (1) truck to the river, (2) truck-local, (3) single-car to the river and (4) single-car-local. The authors urge caution in the use and interpretation of the demand estimates they produce, however, as they state that the high linearity reflected in the estimates is a result of the linear functions used to derive the demand curves. Daughety and Inaba improve the approach by using industry supply curves based on cost analysis and by increasing the number of observations.

Table II.2.2

Alternative Demand Functions

Alternative	t_n	Constant	R^2
1	$-7.0341*10^8$	$1.1477*10^8$	.99
2	$-5.4795*10^8$	$5.8201*10^7$	.98
3	$-1.3673*10^8$	$2.526*10^7$	.99
4	$-3.3604*10^8$	$1.1122*10^8$	.93

Winston (1981) develops a model of freight demand based on the random utility model and uses disaggregate data for a much broader set of markets. His econometric model answers the following question: “What are the critical determinants of mode choice in freight transportation and what policy guidelines do these results have to offer?” (Winston, 1981, p. 982). This article examines a distribution center and its role in mode-choice decisions.

Winston takes the final choice of mode as being the responsibility of the regional physical distribution manager of either the shipping or receiving firm. Thus, two cases are considered: The case where the receiving firm makes the mode choice, and hence, pays the transportation costs; and the case where the shipping firm makes mode choice, and pays the transportation costs.[24]

Winston formulates a shipper and receiver behavior in the context of McFadden’s (1978)

[24]In the second case, where the shipper is making the choice of mode, it is assumed that the shipper does

random utility model. The formal theory of shipper behavior incorporates the Hicks-Zeuthen bargaining model. The formal theory of the receiver behavior, however, is developed in a Lancaster-type framework.[25] Different approaches are used because the modal attributes, such as speed, reliability, loss and damage, etc. may be more important to the receiver's utility as compared with the originator's utility. Winston note a set of problems confronted by each:

> <u>Case 1 (receiver makes the decision)</u>: Receiver maximizes expected utility with respect to the modal attributes of the i-th mode subject to a constraint on the quantity received.
>
> <u>Case 2 (shipper makes the decision)</u>: Shipper chooses the mode that maximizes the joint discounted value of expected utility of the receiver and him/herself.

An expected random utility model is derived for the case when the receiver is the decision maker and is then extended to include the case when the shipper is the decision maker. The random utility model for the k-th firm (shipping or receiving) is:

(Eq. II.2.4) $$\mathbf{EU_i^{\,k}(Z_i, S^k) = V(Z_i, S^k) + \varepsilon_i^k}$$

where the error term, $\boldsymbol{\varepsilon_i^k}$, contains unobserved variation of the firm's attitude toward risk and the expected value of unobserved modal, commodity and firm attributes. A multinomial probit model is chosen for estimation because, unlike the logit model, it allows for correlated error terms. In order to employ the single equation approach to estimating behavioral demand, Winston makes the assumption that shipment size and firm location are exogenous to the decision maker. Other variables include the value of the commodity, freight charges, mean and standard deviation of transit time, reliability and firm sales.

---

not have monopoly power or that the shipper and the receiver represent the same firm.

Winston uses two different data sets in his estimation. To estimate the receiving firm model, he uses data containing perishable agriculture commodities only. These data are gathered at the receiving firms' cities and include information on origin-destination pairs for freight carried by rail and exempt-motor freight throughout 1975 and 1976.

The shipper's model is estimated using data containing a wide variety of commodities. This data set contains information on a large number of shipments made by rail, regulated motor freight and private carriers for 1976 and 1977.

Table II.2.3 features the results for this study. The parameter estimates and statistical significance vary greatly across the commodity groups. The freight charge and location coefficients are statistically significant for all the models. But the coefficient estimates for service quality variables differ in their statistical significance. The authors find that the model with independently distributed errors cannot be rejected for the commodity groups that displayed statistically insignificant service quality parameters.

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[25] The Lancaster approach to consumer behavior claims that consumers derive utility from attributes of a good, not the good itself.

Table II.2.3

Shipper's Model Estimates

Commodity Group	Mode Considered	Point Estimates (Stand. Errors)			All Alternatives (Days)		
		Shipment Size (10,000 lbs.)	Commodity value ($/pound)	Freight charges ($1000)	Mean Transit Time Rail	Mean Transit Time Exempt	Mean Transit Time Common
Unregulated Agriculture	Rail exempt motor freight	-0.959 (0.090) (motor freight)	0.268 (0.063) (motor freight)	-2.026 (0.276)	-0.992 (0.166)	-0.646 (0.257)	
Regulated Agriculture	Rail common private	5.36 (1.34) (rail)	34.7 (25.2) (rail)	-3.09 (.60)		-2.44 (.81)	
Textiles and Fabricated Textiles	Rail common private	16.7 (3.28) (rail)	-44.2 (7.9) (rail)	-.69 (.31)		.57 (.51)	
Chemicals	Rail common private	5.04 (1.32) (rail)	-.35 (1.46) (rail)	-13.8 (.93)		-1.9 (1.01)	
Leather, Rubber, and Plastic Products	Rail common private	1.68 (.9) (rail)	4.35 (3.5) (rail)	-3.29 (.6)		-.04 (.94)	
Stone, Clay, and Glass Products	Rail common private	11.38 (3.13) (rail)	-.73 (.197) (rail)	-4.10 (1.49)		2.74 (2.01)	
Primary and Fabricated Metals	Rail common private	4.15 (1.96) (rail)	-13.82 (2.99) (rail)	-6.99 (.995)		8.28 (1.89)	
Machinery inc. Electric Machinery	Rail common private	19.94 (1.51) (rail)	-10.125 (1.49) (rail)	-6.242 (1.73)	3.46 (1.48)	.697 (.696)	1.63 (.97)
Transportation Equipment	Rail common private	.006 (.016) (rail)	4.66 (2.14) (rail)	-3.52 (1.10)		-1.41 (1.08)	
Paper, Printing and Publishing	Rail private	1.98 (3.11) (rail)	8.69 (15.7) (rail)	-14.08 (7.06)		-1.76 (.60)	
Petroleum, Petroleum Products	Rail private	1.73 (.671) (rail)	3.76 (2.95) (rail)	-2.98 (1.08)		-3.54 (1.07)	
Lumber, Wood and Furniture	Rail private	2.39 (2.75) (rail)	6.51 (5.11) (rail)	-24.14 (10.4)		-4.32 (3.33)	

Commodity Group	Standard Deviation Transit Time (days)	Reliability (σ/χ)	Location (miles from rail siding) Rail	Sales ($ billion) Private	Covariance Specification
Unregulated Agriculture	-0.819 (0.229)	0.626 (0.193)			Independent
Regulated Agriculture	-12.7 (4.04)	11.5 (5.84)	-35.4 (14.0)	-0.17 (.13)	Dependent
Textiles and Fabricated Textiles	.14 (1.61)	7.9 (8.83)	-25.1 (5.09)	5.4 (1.3)	Independent
Chemicals	2.3 (2.53)	-10.5 (2.54)	-20.5 (3.7)	.865 (.22)	Dependent
Leather, Rubber, and Plastic Products	1.18 (2.94)	1.03 (5.17)	-18.2 (8.94)	.88 (.85)	Independent
Stone, Clay, and Glass Products	-13.3 (2.16)	32.4 (5.01)	-39.34 (13.8)	5.57 (1.51)	Dependent
Primary and Fabricated Metals	-8.94 (1.91)	6.89 (2.1)	-85.05 (8.66)	.09 (.2)	Dependent
Machinery inc. Electric Machinery	10.05 (8.97)	-19.12 (1.51)	-69.78 (11.9)	1.96 (1.09)	Dependent
Transportation Equipment	-.985 (2.90)	-1.53 (4.84)	-12.08 (3.81)	-.04 (.063)	Independent
Paper, Printing and Publishing	-4.21 (1.05)	.413 (1.33)	-15.23 (10.3)	-4.52 (4.62)	Independent
Petroleum, Petroleum Products	-1.05 (1.94)	9.23 (3.28)	-25.78 (13.15)	-.950 (.571)	Independent
Lumber, Wood and Furniture	2.81 (1.83)	-5.39 (4.78)	-9.59 (5.67)	-6.86 (6.28)	Independent

Table II.2.4 from Winston identifies the commodity groups with service quality parameters significantly different from zero at the five percent level. Winston finds that the commodities most sensitive to service quality are those containing perishable items or inputs to perishable items (Regulated Agriculture, Primary and Fabricated Metals, and Paper, Printing and Publishing). The non-perishable commodities without inventory needs are least sensitive to service quality variables (Textiles and Fabricated Textiles, Leather, Rubbers and Plastic Products, and Transport Equipment).

Table II.2.5

Service Quality Parameters Significantly Different from Zero at the Five Percent Level[a]

Zero	One	Two
Textiles and Fabricated Textiles	Chemicals	Regulated Agriculture
Leather, Rubber and Plastic Products	Stone, Clay and Glass Products	Primary and Fabricated Metals
Transport Equipment	Machinery, including Electrical Machinery	Paper, Printing and Publishing

[a]In order to avoid confounding structural and sample size effects, the table only includes commodity groups whose sample sizes were relatively similar.

Winston concludes his study by calculating the market elasticities of demand for various modal attributes using probit estimates of his model. These elasticities are provided and discussed in Section III. One of the shortcomings of Winston's study is the averaging out of seasonal effects. Thus, the author states that his approach failed "to completely control for the volume of a given firm's shipping activity over its normal production cycle" (Winston, 1981, p. 998), and that the future estimation should consider examining mode choice over a longer time horizon. He also stresses the advantages of the disaggregate behavioral demand model, such as richer econometric specification, more precise estimates of market elasticities, and the foundation in behavioral theory.

Random Utility Models: Joint Choice and Simultaneous Equations

Like the early aggregate models, the disaggregate discrete mode choice models came under scrutiny. Much of the scrutiny stemmed from the inability to account for the simultaneous decisions frequently made with the choice of mode. For example, Winston (1981) makes the assumption that both shipment size and location are exogenous to the choice of mode. In response, a new generation of transportation demand models have emerged that recognize the simultaneous decisions made with the choice of mode, such as shipment size and destination.

The basic discrete choice model is extended to allow for joint choices.[26] The early models define a joint choice by combining discrete choices; choice of mode is combined with choice of destination. McFadden (1978) developed the nested logit model that accounted for the preferences over a class of outcomes by allowing the random utilities to be correlated within groups, but not across groups (Small and Winston, 1998). Thus, the joint choice process is categorized by groups of possible outcomes, and the discrete choices are made simultaneously.

Mixed continuous/discrete choice models provide another way of analyzing joint choices. These models define a joint choice as a continuous choice made in conjunction with a discrete choice. This approach has recently been applied to estimating freight transport demand.

Inaba and Wallace (1989) implement a switching regression model or self-selectivity model, to estimate the demand for freight transportation. They address two issues: 1. The simultaneity between the mode choice and the shipment size decisions; and 2. the effects of spatial competition on the demand for freight transportation. The switching regression model is used to account for the possible endogeneity of the shipment size with respect to the mode choice.

Equations for shipment size and profit, conditional on the mode choice, are derived. The shipment size for a given mode and firm is defined as a function of distance between a supplier and the firm, the firm's storage capacity, and a *subset* of the mode-specific characteristics. The firm's profits are defined as a function of distance between a supplier and the firm, the firm's

[26]For a detailed discussion of joint choice literature see Small and Winston (1990).

storage capacity and the *entire* set of characteristics of mode-specific characteristics. The profit function determines the optimum mode choice and the optimum shipment size.

To control for correlated errors in the shipment size and profit equations, Inaba and Wallace use a two-stage method developed by Lee (1982) to estimate their model. In the first stage, a conditional logit model is used to produce the coefficient estimates for the distance and mode characteristics variables. In the second stage, these coefficients are used in the shipment size equation to form selectivity corrections, and the shipment size equation is estimated using weighted least squares. The conditional logit model and the shipment size model containing the selectivity correction are then combined to form the unconditional expected transportation demand for a given mode.

The authors use survey data of grain elevators with federal or state licenses in Idaho, Oregon, Montana and Washington for the year 1984. The survey included questions about capacity, loading facilities, service and handling charges, costs, loading times, service characteristics, destination prices for wheat, and shipment costs. The data collected are not only the costs and characteristics of the mode used, but also those of the alternative modes.

The estimated results indicate that higher service costs for a given mode lower the probability of the mode being chosen. The coefficient estimates of the dummy variables for unit trains and barge indicate that these modes are preferred if they are available. A test for misspecification bias reveals that there is simultaneity between shipment size and mode choice. The authors also estimate a set of demand elasticities. Table II.2.6 presents the unconditional average demand flows and average rate elasticities per contract destination. The demand functions are relatively rate inelastic due to the short-run nature of the mode decisions studied.

Table II.2.6

Unconditional Average Demand Flows (Bushels) and Average Rate Elasticities Per Contract Destinations

Region	Destinations						
	Seattle	Portland	River	California	Great Falls	Ogden	Minneapolis
Montana							
Barge Flow	NF	NF	NF	NF	NF	NF	NF
Barge Elast.							
Truck Flow	2,236	2,277	4,311	1,463	4,698	4,728	2,310
Truck Elast.	-.733	-.615	-.346	-.690	-.445	-.603	-.459
Single Flow	1,470	1,572	3,085	1,042	2,718	3,847	1,027
Single Elast.	-.224	-.127	-.123	-.499	-.077	-.077	-.233
Mult. Flow	1,382	1,732	2,441	995	3,337	5,287	571
Mult. Elast.	-.275	-.103	-.180	-.05	-.08	-.06	-.823
Unit Flow	12,885	73,452	NF	NF	NF	NF	NF
Unit Elast.	-.087	-.045	NF	NF	NF	NF	NF
Truck/B Flow	NF	2,116	NF	NF	NF	NF	NF
Truck/B Elast.	-.148	NF	NF	NF	NF	NF	NF
Truck/M Flow	1,076	1,298	2,432	618	1,072	2,811	380
Truck/M Elast.	-.233	-.154	-.075	-.421	-.192	-.121	-.153
Eastern Washington							
Barge Flow	NF	57,294	NF	NF	NF	NF	NF
Barge Elast.	NF	-.007	NF	NF	NF	NF	NF
Truck Flow	839	1,287	2,173	694	NF	NF	NF
Truck Elast.	-.607	-.433	-.253	-.921	NF	NF	NF
Single Flow	669	862	1,678	516	NF	NF	NF
Single Elast.	-.912	-.243	-.048	-1.05	NF	NF	NF
Mult. Flow	598	908	1,281	547	NF	NF	NF
Mult. Elast.	-.985	-.242	-.179	-1.04	NF	NF	NF
Unit Flow	13,648	66,636	NF	NF	NF	NF	NF
Unit Elast.	-.069	-.043	NF	NF	NF	NF	NF
Truck/B Flow	NF	8,210	NF	NF	NF	NF	NF
Truck/B Elast.	NF	-.058	NF	NF	NF	NF	NF
Truck/M Flow	734	881	1,097	613	NF	NF	NF
Truck/M Elast.	-.599	-.283	-.101	-.897	NF	NF	NF

The authors identify three advantages of their study. First, their theoretical model demonstrates the conditions under which shipment size and mode choices are generated from the same optimization problem. Second, their model fills a gap between the spatial econometric models and the highly spatial but less behaviorally complete models. Third, the authors' research hypotheses are largely validated in the empirical results. Drawbacks of the model include omission of the farmer's reservation prices and distributional assumptions of the error terms (Inaba and Wallace, 1989, p. 624).

Abdelwahab and Sargious (1992) present an alternative approach to analyze the joint choices of mode and shipment size. The authors introduce a third equation to the general structure of the switching simultaneous equations model derived by Lee (1980) and used by Inaba and Wallace (1989). This third equation eliminates the problems associated with modeling two choices, one of which is discrete and the other continuous.

The first equation of the model specifies the unobserved index determining the mode choice. The second and third equations define shipment size for rail and truck modes as a function of exogenous variables. The exogenous variables include modal, commodity and market attributes. The data come from the Commodity Transportation Survey. The authors begin by estimating a reduced form probit model of the unobserved index of choice. The estimates from the probit model are then used in the two stage least squares estimation of the shipment size equations.

Table II.2.7 presents the results to the equation of mode choice. The estimated coefficients of the service variables in the mode-choice equation have the correct signs and are statistically significant. The results to this equation suggest that trucks are favored for transporting lighter and higher valued commodities.

Table II.2.7

ML Estimates of the Reduced Rail Truck/Rail Choice Equation

Variable	Parameter	ML Estimate	"t" statistic
CONSTANT	π_0	2.4795	18.4*
TON	π_1	-0.0100	-3.8*
DEN	π_2	-0.0030	-5.0*
VAL	π_3	0.1014	3.0*
LIQ	π_4	0.0462	0.5
GAS	π_5	-0.2916	-1.0
PART	π_6	-0.0584	-0.6
TMP	π_7	-0.2092	-1.2
SHK	π_8	-0.5912	-2.7*
RD2	π_9	0.4905	6.1*
RD4	π_{10}	0.2718	2.2*
TTIME	π_{11}	-1.6943	-17.0*
TCOST	π_{12}	-0.1183	-13.7*
TLD	π_{13}	-0.0149	-9.1*
RCOST	π_{14}	0.0160	20.4*
P^2		0.4086	
$L(\beta)$		-682.7	
% Truck		0.6324	
Mean Prob.		0.6306	
N. Obs.		1586	

* Significant at the 5% level.

Table II.2.8 presents the results from the equations for the shipment size of rail and truck service. All of the estimated coefficients in the shipment size equations are significant. This is not surprising because the authors ran a series of regressions using all or a combination of the 27 exogenous variables and then chose the one with the best overall fit. Denser, gaseous, and temperature controlled commodities tend to be moved in larger quantities using trucks. Denser and gaseous commodities are moved in larger quantities using rail as well. Traffic density is positively related with shipment sizes of trucks and negatively with shipment sizes of rail transportation. The results show that shipment size varies significantly across different geographical regions.[27] The authors test and find evidence of interdependence between the decisions of mode and shipment size.

Table II.2.8

ML Estimates of the Truck Shipment Size Equation, ST

Variable	Parameter	ML Estimate	"t"-statistic
CONSTANT	α_0	13.9352	45.9*
TON	α_1	0.0336	5.3*
DEN	α_2	0.0084	6.7*
GAS	α_3	2.3496	3.3*
PART	α_4	0.5734	3.4*
TMP	α_5	1.0467	3.6*
SHK	α_6	-1.0597	-2.2*
RD1	α_7	-0.6262	-3.8*
RD2	α_8	-4.4183	-19.7*
RD4	α_9	-4.8770	-14.4*
TTIME	α_{10}	16.6232	76.5*
TCOST	α_{11}	0.0149	6.2*
TLD	α_{12}	0.2630	10.0*
RCOST	α_{13}	-0.0935	-46.8
R^2		0.8249	
$L(\beta)$		-2293.7	
σ_1		2.3827	
$P_{1\varepsilon}$		-0.1936 (t=-1.65**)	
N. Obs.		1003	

* Significant at 5% level. **Significant at 10% level.

[27] The authors compare shipment sizes in two regions using the Interstate Commerce Committee classification of the regions; shipment sizes in Official, Southern, and Southwestern Territories are compared with those in Mountain Pacific Territory.

ML Estimates of the Rail Shipment Size Equation, SR

CONSTANT	β_0	83.2765	6.1*
TON	β_1	0.2594	10.7*
DEN	β_2	0.0894	9.8*
VAL	β_3	-1.7730	-3.4*
LIQ	β_4	4.8161	3.3*
GAS	β_5	29.8602	9.0*
PART	β_6	5.9057	4.6*
RD2	β_7	-11.7037	-11.2*
RD4	β_8	-9.4014	-6.9*
RTIME	β_9	9.8227	10.7*
TCOST	β_{10}	0.1601	10.4*
TLD	β_{11}	2.2626	5.6*
TREL	β_{12}	-51.7894	-6.7*
RLD	β_{13}	-0.4760	-4.6*
RCOST	β_{14}	-0.2703	-33.0*
R^2		0.7238	
$L(\beta)$		-2356.3	
σ_2		13.7720	
$P_{2\varepsilon}$		0.4868 (t=2.66*)	
N. Obs.		583	

* Significant at 5% level.

Abdelwahab (1998) extends the study of Abdelwahab and Sargious (1992) to include estimates of elasticities of mode choice probabilities and market elasticities of demand. The author reports both aggregate and disaggregate elasticities. The disaggregate elasticity is defined as the change in a shipper’s probability of choosing a mode in response to a change in the values of the mode’s attributes. The aggregate elasticity is a weighted average of these disaggregate elasticity measurements with the weights being the mode choice probabilities. Abdelwahab uses the coefficient estimates from the joint choice model to generate values for the market elasticities of demand. Four different price elasticities are calculated, one for each market segment, as defined by Abdelwahab. The elasticity estimates derived in this study are discussed in greater detail in Section III.

Summary of Random Utility Models: Joint Choice and Simultaneous Equations

Many advantages stem from extending the basic discrete choice model to the simultaneous equation model for estimating joint choices of mode and shipment size. The simultaneous equation models are used to analyze spatial policy issues, identify interaction between mode and shipment decisions, examine modal choice behavior and generate various elasticity estimates. However, the data requirements are extensive for estimating such a model, and the inability to obtain the required data may limit the explanatory power of this model. Also, a key assumption of the simultaneous equation model is the independence of the error terms across alternative modes, and a violation of this assumption would likely decrease the validity of the estimated results.

Shortcomings of Disaggregate Demand Models

Although disaggregate models are an improvement over the aggregate models, there are deficiencies. First, some of the models are very difficult to estimate if more than two alternatives (for example truck, rail and barge) are allowed. Second, the data required for the estimation of disaggregate models is usually difficult to obtain. In addition to detailed information regarding mode and shipment characteristics, shipper attributes are essential and can be difficult to obtain.

III. ELASTICITY ESTIMATES

In this section, we provide a more detailed discussion of the elasticity estimates derived in the studies discussed in Section II. The discussion centers on differences in estimates, functional forms, previous surveys, and our own comparisons of elasticities from different approaches and studies.

III.1. Functional Forms and Elasticity Estimates

One set of studies focuses on how the specification of functional form affects the estimated values of elasticities. Oum (1989) explores how changes in the specification of the model affect the elasticity estimates. He compares elasticity estimates for models that use four different functional forms: (1) Linear demand model; (2) Log-linear demand model; (3) Logit model; and (4) Translog demand model. He finds that changes in the estimated elasticities are a direct result of changes in the functional form of the model.

Oum first estimates a demand model for aggregate freight using the four different functional forms. Then, he compares the estimates obtained from each model and performs likelihood ratio tests for model selection. Oum finds that the Translog demand system is the best model for aggregate freight.

He then compares demand elasticities evaluated at mean values of the variables generated by the four models described above and a model using the Box-Cox specification. These elasticities are presented in Table III.1.1. The author points to three notable findings. First, the cross-price elasticities from the logit model are negative; a counterintuitive result. Second, the own-price and own-quality elasticity estimates from both the Box-Cox and Log-linear forms are higher than expected, while the Translog and Linear forms generate demand elasticities that are closer to the expected value. Third, the author suggests that the Translog model is not only robust but produces the most favorable elasticity estimates.

Oum repeats the process described above using a subset of the original data. These data include only one commodity, fruits, vegetables and other edible foods. The results are similar to those obtained from the aggregated commodity study and points to robustness of results. That is, the Translog model produced the most reasonable results (Table III.1.1).

Table III.1.1

Elasticity of Demand for Freight for all Commodities, Canada 1979

Elasticities	Model Type				
	Translog	Log-linear	Linear	Box-Cox	Logit
Elasticity of rail-truck substitution	1.19				
Own price elasticity					
-rail	-0.598	-1.517	-0.638	-1.384	-0.830
-truck	-0.692	-1.341	-0.048	-1.140	-0.928
Cross price elasticity					
-rail wrt truck price	0.498		0.059		-0.175
-truck wrt rail price	0.592	0.453	0.838	0.403	-0.616

Source Oum (1989, table 9, p. 181)

Table III.1.2

Elasticities for Commodity 14 (Fruits, Vegetables and Other Edible Foods)
(Evaluated at Means of Variables: t-statistics in Parentheses)

Elasticities	Translog	Log-linear	Linear	Box-Cox	Logit
SRH	1.147 (16.3)				
ERR	-0.688 (16.0)				
EHH	-0.459 (12.7)				
FRR	-0.796 (18.9)	-0.795 (2.8)	-0.391	-0.795	-0.484
FRH	0.495 (45.0)				-0.466
FHH	-0.652 (18.6)	-1.542 (9.0)	-0.318	-1.248	-0.970
FHR	0.351 (39.0)				-0.262
ERR^1	15.914 (2.1)				
ERH^1	-2.285 (6.0)				
EHH^1	1.523 (2.3)				
HER^1	-10.607 (5.9)				
FRR^1	18.413 (2.3)	26.559 (2.3)		26.561	2.52*
FRH^1	-1.644 (5.8)	-8.795 (1.9)		-8.776	-4.15*
FHH^1	2.166 (2.8)	3.892 (1.8)		2.808	2.34*
FHR^1	-8.119 (6.2)				-1.41*
ERR^2	44.589 (1.9)				
ERH^2	-4.127 (6.4)				
EHH^2	2.751 (2.4)				
HER^2	-29.720 (5.1)				
FRR^2	51.592 (2.0)	243.388 (2.2)		243.41	
FRH^2	-2.969 (6.2)				
FHH^2	3.911 (3.0)		-30.269		
FHR^2	-22.750 (5.2)	-48.563 (5.4)		-40.324	

* Since the modal speed variables are not statistically significant in the total volume (rail and truck combined) equation, these ordinary demand elasticities for speed variables are in fact the same as the share elasticities.

Westbrook and Buckley (1990) specify a cost function with transportation demands through Shepherd's lemma. While they focus on determining a specification that satisfies regularity conditions, they also analyze how the alternative specifications of the cost function and transformed data affect elasticity estimates. The three functional forms reviewed in this study are Translog (TL), CES-Translog (CESTL), and the Barnett Translog (BTL). This study examines the fruit and vegetable commodity class as well.

Table III.1.3 provides the substitution elasticities and the cross- and own-price elasticities for rail and truck modes. The elasticities generated by the TL and BTL specifications are consistent with each other but quite different from those generated by CESTL. However, none of the specifications meet regularity conditions, and the authors proceed to find technologies that do.

Table III.1.3

Elasticities of Substitution and Demand for Rail and Truck Transportation Between Chicago and New York

Functional Form	Destination	Subs. Elast.	Own-price demand elast.		Cross-price demand elast.	
		Rail, Truck	Rail	Truck	Rail, Truck	Truck, Rail
TL	Chicago	5.43	-0.36	-0.41	0.32	0.45
	New York	2.70	-0.55	-0.53	0.22	0.42
CESTL	Chicago	1.55	-0.10	-0.12	0.09	0.10
	New York	0.55	-0.06	-0.11	0.04	0.09
BTL	Chicago	5.61	-0.39	-0.46	0.28	0.43
	New York	2.44	-0.09	-0.59	0.18	0.41

Source Westbrook & Buckley (1990, table 2, p. 627)

Substitution Elasticities and Demand Elasticities for the minimum Concavity Violation Cases

	Destination	σ_{12}	(s.e.)	ε_{11}	ε_{22}	ε_{12}	ε_{21}
TL	CHI	5.55	(0.53)	-0.84	-0.90	0.30	0.44
	NY	2.36	(0.16)	-0.80	-0.89	0.15	0.38
BTL	CHI	6.23	(0.57)	-1.10	-1.80	0.30	0.41
	NY	2.24	(0.13)	-0.07	-1.30	0.14	0.38

Westbrook and Buckley proceed by using *prior affine transformation* on BTL and TL to improve the concavity and hence minimize the number of concavity violations. The estimated elasticities of the transformed TL and BTL models are also provided in Table III.1.3. Although the estimates for the elasticities of substitution do not change much from those disclosed earlier, the authors find that the standard errors for the estimates decrease dramatically. Also, evidence of strong competition between rail and truck emerges as the estimates for the own-price elasticities of demand increase from those previously observed.

III.2. Surveys of Elasticity Estimates

There are a variety of survey articles in the literature. Some of these surveys and the studies involve comparisons of the estimates reported in different studies with different data sets, approaches, etc. Goodwin (1992) provides a thorough review of travel demand elasticities. In his paper, Goodwin surveys recent travel demand studies and provides a discussion of the relevance to policymaking. Goodwin believes that policymakers should be aware of how sensitive travel demand is to changes in travel prices. This review arrives at the intuitive conclusion that long-term elasticities are higher than short-term elasticities and suggests a dynamic component to travel demand responses and the effects of price changes over time.

Perhaps more relevant to freight transportation demand is the survey of Oum, Waters, and Yong (1992). This survey provides a detailed summary of the own-price elasticity studies. The literature analyzed by Oum et al. covers both passenger and freight demand and includes a wide range of modal alternatives. They first describe the various demand elasticity measures and review different demand models. Table III.2.1 shows the demand elasticity estimates of rail, truck and airfreight for various commodities and functional forms. They, as one might expect, find that elasticities range widely across both commodities and functional forms.

Table III.2.1

Elasticities of Demand for Freight Transport

Mode	Range surveyed	Most likely range	# of studies
Rail			
Aggregate commodities	-1.52 to –0.60 (-1.79 to –0.09)	-1.20 to –0.40	4
Assembled automobiles	-1.08 to –0.65	-1.10 to –0.70	2
Chemicals	-2.25 to –0.39 (-0.66)	-0.70 to –0.40	3
Coal	-1.04 to –0.02	-0.40 to –0.10	2
Corn, wheat, etc.	-1.18 to –0.52	-1.20 to –0.50	3
Fertilizer	-1.04 to –0.02	-1.00 to 0.10	1
Foods	-2.58 to –0.02 (-1.36)	-1.00 to –0.30	9
Lumber, pulp, paper, etc.	-1.97 to –0.05 (-0.87 to –0.76)	-0.70 to –0.10	7
Machinery	-3.55 to –0.61	-2.30 to –0.60	3
Paper, plastic and rubber products	-1.85 to –0.17	-1.00 to –0.20	4
Primary metals and metallic products	-2.54 to –0.02 (-1.57)	-2.20 to –1.00	5
Refined petroleum products	-0.99 to –0.53	-1.00 to –0.50	3
Stone, clay and glass products	-1.62 to –0.82 (-0.69)	-1.70 to –0.80	4
Truck			
Aggregate commodities	-1.34 to –0.05	-1.10 to –0.70	1
Assembled automobiles	-0.67 to –0.52	-0.70 to -0.50	1
Chemicals	-2.31 to –0.98	-1.90 to –1.00	2
Corn, wheat, etc.	-0.99 to –0.73	-1.00 to –0.70	2
Foods	-1.54 to –0.32	-1.30 to –0.50	3
Lumber, wood, etc.	-1.55 to –0.14	-0.60 to –0.10	3
Machinery	-1.23 to –0.04	-1.20 to –0.10	3
Primary metals and metallic products	-1.36 to –0.18	-1.10 to –0.30	3
Paper, plastic and rubber products	-2.97 to –1.05	-3.00 to –1.10	2
Refined petroleum products	-0.66 to –0.52	-0.70 to –0.50	3
Stone, clay and glass products	-2.17 to –1.03	-2.20 to –1.00	2
Textiles	-0.77 to –0.43	-0.80 to –0.40	1
Air			
Aggregate commodities	-1.60 to –0.82	-1.60 to –0.80	3

III.3. Our Comparison of the Price Elasticity Estimates

We constructed Table III.3.1 to allow comparisons between elasticity estimates from the literature reviewed in this paper. Table III.3.1 contains the own-price elasticity estimates for rail and truck modes and the cross-price elasticities for rail and truck. The estimates are from the following studies: Oum (1979), Friedlaender and Spady (1980), Winston (1981) and Abdelwahab (1998)[28]. Table III.3.1 also presents the characteristics of these studies. Elasticity estimates are presented for seven commodity groups: Food Products, Lumber/Wood Products, Chemicals, Primary and Fabricated Metal Products, Rubber & Plastic Products, Stone, Clay & Glass Products, and Electrical Machinery.

[28] Please note that the elasticity estimates reported by Winston (1981) are mode choice elasticities. The elasticities from Friedlaender and Spady (1980) are calculated for both the 'all region' and the 'Interstate Commerce Committee official region'. Also, the estimates from Abdelwahab (1998) are for the 'Interstate Commerce Committee official region' and the estimates from Oum (1979) for Canada.

Table III.3.1

Elasticity Estimates According to Author

Author	Oum	Friedlander & Spady		Winston		Abdelwahab
Model	Aggregate translog function	Aggregate translog function		Multinomial probit mode choice		Simultaneous equations
Data Type	Aggregate	Aggregate		Disaggregate		Disaggregate
Data Year	1970	1972		1975-1977		-
Market	Canada	All regions	ICC official	USA		ICC official regions
Type of Elasticity	**Commodity Groups Used for the Elasticity Estimation**					
	Fruits and Vegetables	**Food Products**		**Unreg. Agriculture**	**Reg. Agriculture**	**Food Products**
Cross-price (rail-truck)	-1.006	-.023	-.033	-	-	1.4888
Cross-price (truck-rail)	-.4522	.004	-.002	-	-	1.2612
Own-price (rail)	-1.037	-2.583	-2.680	-1.11	-.29	-1.499
Own-price (truck)	-.5212	-1.001	-1.010	-.99	-.27/-.32	-1.1963
Lumber, Wood, and Wood Products						
Cross-price (rail-truck)	-.5324	-.050	-.672	-		1.293
Cross-price (truck-rail)	-.5116	-.129	-.186	-		1.1125
Own-price (rail)	-.5814	-1.971	-2.106	-.08		-1.2816
Own-price (truck)	-.5626	-1.547	-1.719	-.14		-1.0591
Chemicals						
Cross-price (rail-truck)	-.6282	-		-		1.0421
Cross-price (truck-rail)	-.942	-		-		1.0786
Own-price	-.6882	-		-2.25		-1.0534

(rail)						
Own-price (truck)	-.982	-		-2.31	-1.87	-.927
Primary and Fabricated Metal Products						
Cross-price (rail-truck)	-1.176	-.059	-.545	-		.9042
Cross-price (truck-rail)	-.3318	-.099	-.164	-		.9326
Own-price (rail)	-1.198	-2.164	-8.656	-.019		-.9084
Own-price (truck)	-.4098	-1.364	-1.581	-.18	-.28	-.7972
Rubber and Plastic Products						
Cross-price (rail-truck)	-	.007	-.009	-		1.2592
Cross-price (truck-rail)	-	.003	-.004	-		1.2812
Own-price (rail)	-	-1.847	-1.897	-1.03		-1.2348
Own-price (truck)	-	-1.054	-1.083	-2.01	-2.97	-1.1358
Stone, Clay, and Glass Products						
Cross-price (rail-truck)	-	.025	.008	-		.9525
Cross-price (truck-rail)	-	.016	.005	-		.9818
Own-price (rail)	-	-1.681	-1.757	-.82		-.9558
Own-price (truck)	-	-1.031	-1.061	-2.04	-2.17	-.7494
Electrical Machinery						
Cross-price (rail-truck)	-	-.151	-.177	-		1.1672
Cross-price (truck-rail)	-	-.061	-.089	-		1.1991
Own-price (rail)	-	-3.547	-3.816	-.61		-1.1644
Own-price (truck)	-	-1.230	-1.312	-.78	-.04	-1.1938

As in previous surveys, this table shows there is substantial variation in elasticity estimates across commodities and between studies. The variation in elasticities over commodity groups and estimation methods is intuitive. Demand for transportation should not respond to changes in prices identically for all commodities. Similarly, one would not expect the responsiveness to price changes to be the same for all firms shipping the commodity, as the size, location, and characteristics of the firms vary. Different studies analyze behavior in different markets. Markets compared here range from Canada, to the entire US, to regions within the US, hence the variations in elasticities.

A closer look at Table III.3.1 yields other important information. The own-price elasticity estimates for rail service in Table III.3.1 vary from -0.019 (Winston, Fabricated Metal) to -8.656 (Friedlaender and Spady, Fabricated Metal). However, the majority of the estimates exceed unity in absolute value, and all of the estimates display a negative sign. This is an indication of rail service being elastic with respect to its own price. Food products, metals, and electric machinery are particularly elastic. For every commodity, the absolute value of the own-price elasticity estimates for rail derived by Friedlaender and Spady (1980) exceed estimates derived by the other studies.

For nearly all commodities and models, the absolute value of the own-price elasticities for truck service, also presented in Table III.3.1, are lower than those reported for rail. According to expectations, these estimates display negative signs. The own-price elasticities for truck vary from -0.04 to -2.97. This interval is a lot smaller than it for rail service. In fact, the majority of the own-price elasticity estimates for truck service are relatively close to unity. This indicates that the demand for truck service is less sensitive than the demand for rail service to own-price changes. The own-price elasticity estimates for truck from Abdelwahab (1998), for example, vary only slightly across commodities, staying between -0.7494 and -1.1938.

The cross-price elasticities in the table range between -0.674 and 1.489. The aggregate studies of Oum, and Friedlaender and Spady produce generally negative cross-price elasticities with low absolute values. These negative values suggest that shippers view the two modes as complements, while the low elasticity values suggest the demand for rail and truck service to be independent. Abdelwahab, using disaggregate data, produces elasticities which are not only positive but also much higher than those estimated by the aggregate studies. Abdelwahab's results, then, suggest that rail and truck service are substitutes.

Friedlaender and Spady justify their counterintuitive results by discrepancies in their data. Namely, most of the truck service in their data is associated with small shipment sizes, while rail service is associated with large shipment sizes. An alternative explanation may be the regulation of the rail industry.

Overall, aggregate and disaggregate models tend to produce noticeably different elasticity estimates. Another factor in explaining the differences in estimated values may be the time period under study. All studies except for Abdelwahab's use data from a time period in which rail rates were regulated; Abdelwahab uses data that are post-deregulation. Hence, variations in policy measures and regulation of transportation industries may influence the elasticity estimates.

IV. CONCLUSION

IV.1. Possibilities for Improving Future Research

As suggested by Oum et al. (1992), there are many aspects of the previously described studies that can be improved or extended in future research. First, previous studies ignore the presence of competition between modes and, hence, the own price elasticity estimates may be understated (Oum et al., 1992). Second, as is discussed in section III.3, the type of data used has an effect on the values of the elasticity estimates. Using disaggregate data is likely be more precise in estimating price elasticity of demand.

As suggested by this and other studies, there is a need to develop the relationship between short and long run estimation. As noted by Oum et al., even though demand becomes more elastic in the long run due to the ability to adjust to price changes, there is a need for “more carefully structured long-run studies” (Oum et al., 1992, p. 36). This could be achieved by including variables for choice of location and asset ownership, which reflect long-run decisions and affect elasticity estimates.

Oum et al. also urge researchers to carefully consider the underlying reasons in specifying a functional form for their estimation. As demonstrated in Section III, alternative specifications and functional forms may affect estimation results. It is also suggested that great care be taken in identifying possible interactions between demand and supply side variables in the analysis.

IV.2. Estimating Inland Waterway Transportation Demand the Improved Way

The improvements suggested in the previous section may also benefit studies of barge transportation demand. First, note that only a few studies attempt to estimate the demand for inland waterway transportation. Most freight transportation literature concentrates on rail and truck service, while failing to include barge service as a competing transportation mode.

In structuring a data set to estimate the demand for inland waterway transportation, it is helpful to consider the suggested improvements in Section IV.1. First, the prices and service quality attributes of modes competing with barge service ought to be included. This allows for competition between modes to have effects on the price elasticity estimates that would otherwise be distorted.

Second, researchers should consider carefully the use disaggregate data; these data should capture attributes of both the shipper and the shipment. Potential attributes of the shipper could include location, the stated preferences of carrier, destination, route choice, alternative modes, and the revealed preferences of carrier, route, or alternative locations or modes. Attributes of the shipment could include size, weight, destination and frequency as well as, of course, rates.

Third, a study of the barge transportation demand should incorporate the spatial nature of the transportation modes and the commodities. In doing this, the researcher may be able to decipher the sensitivity of demand with respect to the distance from competing modes.

VI.3. Final Remarks

The purpose of this paper is to review the freight transportation demand literature. We provide a summary of the methodology and the main results of aggregate and disaggregate demand studies. We follow the development of the empirical work through time. The comparison of elasticity estimates provides an illustration of how results may differ due to varying methodologies. We summarize the areas for improvement in estimating transportation demand suggested by Oum et al. (1992). Using these suggestions, we provide a guideline to estimating the inland waterway transportation demand. Although the suggested improvements provide only a general overview of the necessary components for a tractable analysis, they can be coupled with the existing methods of analyzing inland waterway transportation demand.

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