THE VALUE OF SERVICE IN FREIGHT TRANSPORTATION

by

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Submitted to the Department of Civil Engineering
in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

at the

Massachusetts Institute of Technology
June 1992

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ABSTRACT

There is an increasing interest in assessing the value of service in freight transportation. The growth of competition in the goods market and the increasing complexity of logistics has fostered the interests of shippers in transportation service as an important link in the supply chain. The ability of carriers to differentiate their services has then, become a strategic weapon rather than an operational tool in this new competitive environment. The objective of this thesis is to develop and implement a method to assess the value of service in freight transportation.

A critical element in the assessment of the value of service is a demand model sensitive to different dimensions of service. The underlying behavioral assumption is that shippers seek to minimize their logistic costs. However, the specification of the logistic cost function was extended to include shippers' perceptions of service, and non-traditional carriers' attributes, like responsiveness and level of effort required to deal with carriers.

In order to model the behavior of shippers in mode choice decisions, psychometric data was used to estimate the demand models. These data included shippers' perceptions of service, their attitudes or values towards different dimensions of service, and stated preferences (SP) in hypothetical transportation scenarios. Freight transportation demand (FTD) models have traditionally relied on revealed preference (RP) data, which are based on actual market choices made in observable situations. This has limited their usefulness in identifying service trade-offs in shippers' mode choice decisions.

In order to exploit the advantage of both RP and SP data, a methodology for combined estimation with RP and SP data is developed. Accuracy of the parameter estimates in the RP model can be gained by sharing some of its parameters with the SP model, while potential biases and errors specific to the SP data are explicitly considered in the SP model. The effectiveness and practicality of this methodology is demonstrated in the estimation of the FTD model using psychometric data.

A methodology for market segmentation using latent structure models is also developed. Among its advantages, it integrates attitudinal indicators with observable shippers' characteristics in the definition of the segments, while the classification model is implicitly derived in the clustering process. Demand elasticities were estimated for each segment, providing strategic information for service design and marketing. Lastly, shippers' perceptions of service are compared with carriers' observed performance. This provided the link between the shippers' behavior model with performance measures related to characteristics under carriers' control.

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Acknowledgments

This research was partially supported by the Brazilian Ministry of Education, through its agency for graduate studies fellowships (CAPES). It was also partially supported by the American Association of Railroads (AAR) grant to the MIT "Reliability Project".

I would like to express my gratitude to all people who have contributed towards the completion of this thesis.

Throughout my stay at MIT, I have been privileged to have Professor Moshe Ben-Akiva as my academic advisor and thesis supervisor. As the chairman of my doctoral committee he has provided me with valuable suggestions and insightful guidance. Professors Harris Koutsopolous, Anne Friedlaender and Daniel Mcfadden have also served as members of my committee and given me precious advice.

My special gratitude to Carl Martland, also a member of the committee, with his insightful suggestions from his experience in railroad research. His extensive comments on the draft copy significantly improved the clarity of this thesis. Above all, he was a dear friend during my research, with supporting words everytime.

Denis Bolduc helped me with the computation for Chapters 5 and 6. The support from the staff of the Sloan Computer Center and the CTS computer laboratory was also important in the empirical analysis.

I have learned many things, academic and non-academic, from my fellow graduate students and researchers in TSD, specially those working in the reliability project.

My sincere appreciation to the following people and organizations for providing me with the survey data which are essential to all empirical work presented in this thesis: Michael Smith at Burlington Northern Railroad, Carl Martland and Gerard McCullough at MIT, the American Association of Railroads, and the Interstate Commerce Commission.

Last, but never least, I would like to extend my sincere gratitude to my family. To my wife, Solange, with the extraordinary patience, love and care she has given me; to my parents, Ilza and Aluysio, with their continual support and encouragement, and to my daughter, Carolina, with her enjoyment and happiness in the last two years, I dedicate this accomplishment. Without them, this thesis would not exist.

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I - Introduction

Background

This research has been motivated by the increasing interest of carriers to determine the value of service quality in freight transportation. The ability of a carrier to differentiate its services has become a strategic weapon rather than an operational tool in the new competitive environment (Distribution[1988]). In fact, this trend towards emphasizing customer satisfaction in the transportation industry is expected to continue increasing as customer expectations rise and as carriers' ability to evaluate their performance improve.

The growth of competition in the goods market and the increasing complexity of logistics has also fostered shippers' interest in transportation service as an important link in the supply chain. With the emergence of a buyer's market , the performance of delivery firms is used both as an instrument of sales policy. Innovations in production and inventory control technologies also place additional challenges to the traffic manager trying to minimize the logistic costs of the firm.

In addition, transportation deregulation has changed the nature of business dealings between shippers and carriers. Through negotiations, a carrier and shipper develop the terms and conditions for a transportation contract. This contract may include not only prices, but also a detailed description of the service to be provided with penalties for not achieving the standards negotiated.

What is the value of service ? Clearly, once contracts are set, the penalties for not achieving the level of service required are a direct assessment of the value of service. But even this might be understated by the indirect consequences of poor service, like losing a customer and the reputation in the market place. The issue is even more critical in negotiations, where prior knowledge of shippers' needs provides carriers with a competitive edge.

To evaluate the consequences of changes in transportation service quantitatively, the proposed action is first translated into a set of changes in the level of service of the various transportation offerings. Then, a demand model is used to forecast the resulting changes in demand. Changes in demand will, in turn, result in changes in carriers' revenue. Carriers with the ability to predict the effect on demand of changes in the level-of-service can formulate strategies to design and market their services more effectively.

The Shippers' Behavior

Another motivation for this research comes from the theoretical side of estimating freight transportation demand models. Most studies in the literature have considered the shippers as an optimizing black box, relating the observed mode choices to the performance of the different modes available. The optimizing behavior is usually represented by shippers seeking to minimize their logistic costs when choosing a particular carrier. While the cost minimization assumption is reasonable under the increasing competition in the goods market, it is also important to consider different cognitive mechanisms acting upon individual shippers in their decision process.

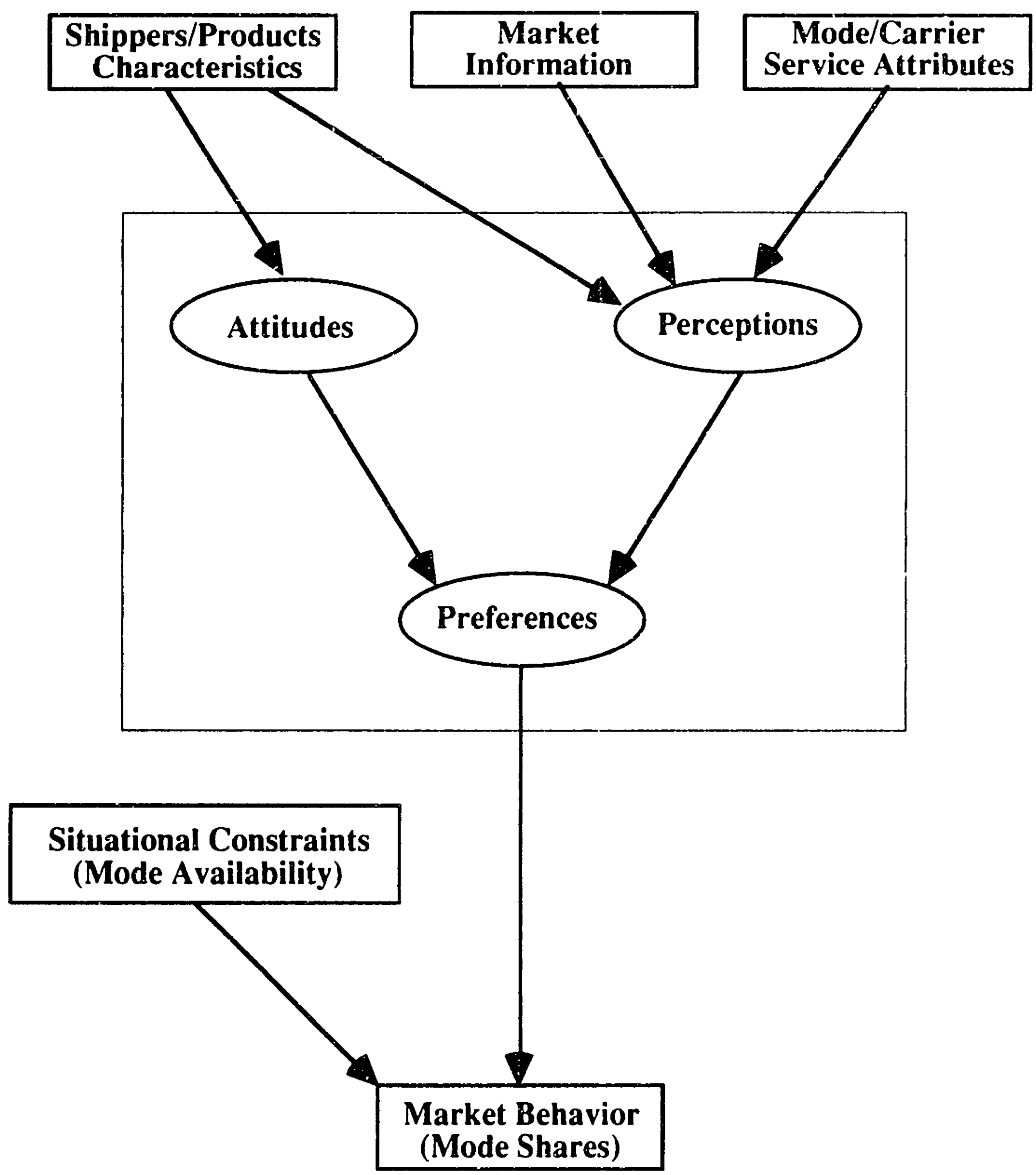
Several reviews and reformulations of consumer behavior analysis by econometricians and market researchers have appeared recently in the literature (see Hauser et al [1981], Ben-Akiva and Boccara [1987], McFadden [1988] and Morikawa [1989]). The underlying idea is that consumer behavior should be analyzed in more detail with attitudinal data if demand models with better predictive accuracy are to be obtained. This is particularly relevant to the assessment of the value of service in freight transportation, where a customer-oriented approach is a must to obtain relevant results.

Figure 1.1 presents a contemporary view of the consumer decision process, adapted to shippers' mode choice. In this diagram, ovals represent unobservable or latent variables, while rectangular boxes represent observable variables. The relationship between the actual attributes of alternatives and observed behavior is represented by three groups of intervening factors: perceptions, attitudes and preferences. While service attributes are interpreted by shippers in their perceptions, attitudes reflect their values or importance towards each attribute. Finally, mode preferences are derived from the interaction of attitudes and perceptions, representing the desirability of using each available alternative.

Market researchers have attempted to analyze explicitly the latent factors in the consumer decision process, and several methods to elicit information on perceptions, attitudes and preferences have been developed. Attitudinal and perceptual indicators are usually represented by the level of satisfaction or importance of attributes on a semantic

Figure 1.1

The Shippers' Behavior Model



scale. Stated preferences (SP) data are collected by presenting hypothetical scenarios to the respondents and asking for their preferences.

The Use of Stated Preferences Data

A critical element in the assessment of the value of service is then, a demand model sensitive to different dimensions of service quality. In particular, this demand model should represent the behavior of individual shippers in the market at the disaggregate level in order to be able to identify different strategies for service design and marketing. The estimated coefficients would reflect the service trade-offs that shippers consider in their mode choice decisions, and consequently, an implied assessment of the value of service.

Previous freight demand studies have used a discrete choice framework to model individual shippers' behavior (for example, see Winston [1981] and Chiang et al [1981]). Although this approach has better theoretical properties than conventional aggregate demand models, the observed predictive accuracy is not always satisfactory due to limitations of the available data. Moreover, the description of mode service is also limited to a set of observable service characteristics, like cost and transit time. Measurement errors and ambiguity in definition of these mode attributes and of the shippers' choice sets are other sources of limitations in the description of shippers' behavior.

Thus, a reasonable hypothesis is that data limitations have hindered disaggregate models from exhibiting their theoretical superiority. In this sense, SP data provide an excellent complementary source of information for estimating freight transportation demand models because it adds information on intangible attributes and contains more precise descriptions and greater variability of choice sets and explanatory variables.

The Objective of this Research

In disaggregate freight demand studies, the traditional view has been that valid choice data result only from revealed preferences (RP), i.e. from observing shippers actual mode choices in the market. Because of the uncertain reliability of SP data, they have rarely been used for quantitative analysis. At the other extreme, SP data have been used in marketing research without any consideration of potential biases in the data.

Thus, the research question is how to exploit the advantages of psychometric data to identify the service trade-offs that shippers consider in their mode choice decisions. The objective of this thesis is then to develop a framework to assess the value of service in freight transportation, which explicitly integrates different sources of psychometric data (stated preferences, attitudinal and perceptual indicators) while accounting for potential sources of biases specific to them. It draws upon state-of-the-art knowledge in consumer behavior and transportation demand theory, econometric methods, and marketing research.

Methodology and Major Contributions

Starting from the traditional cost minimization model, the logistic cost specification was extended to include shippers' perceptions of service and intangible service attributes. The relevancy of using shippers' perceptions of service is assessed through the comparison with data on observed mode performance. A new methodology for market segmentation, using latent structure models, is developed to explore differences in shippers' attitudes towards transportation service quality. RP and SP data are then combined in the estimation of the demand model, with explicit treatment of the potential biases that may be present in the SP data. Finally, the value of service is assessed from the behavioral interpretation of the coefficients in the demand model and the demand elasticities to different service attributes. Empirical estimation was conducted using survey data to demonstrate the applicability of the proposed framework and some implications in transportation service design and marketing.

The following contributions were obtained from applying the above methodology:

- Even though the comparisons between perceived service and observed performance were done only by commodity and by origin and destination regions, it shows that eliciting shippers' perceptions is an important alternative data source to estimate demand models. In addition, the information contained in shippers' perceptions have a strategic value to design and market transportation services, which has not been explored by carriers.

- By combining attitudinal indicators and observable characteristics in modelling shippers' latent attitudes towards service qualtity, the new market segmentation approach was able to identify well-defined groups of shippers that have needs and responses towards transportation service that are different from other shippers. Significant improvements over the definition of groups of shippers based only on attitudinal indicators were observed. In addition, the classification model was developed implicitly from the clustering process, allowing carriers to classify shippers in each segment based only on observable characteristics.

• Revealed and stated preferences data were combined in the freight transportation demand model. This allowed to accurately estimate most of the coefficients in the demand model, which embody the service trade-offs that shippers consider in their mode choice decisions. Even though stated preferences contained more random noise than the data on shippers' perceptions, they helped to identify trade-off among non-traditional service attributes, like the carriers' responsiveness to inquiries. Service design and marketing strategies for each segment are then derived from the demand elasticities.

Outline of the Thesis

This thesis is composed of nine chapters. Chapter 2 reviews the results of prior research relevant to assessing the value of service quality, especially with respect to freight transportation demand models and the use of SP data in transportation. The shippers' behavior model is developed in Chapter 3. Besides the conceptual model, the framework to combine RP and SP data is also discussed. Chapter 4 presents the data used to estimate the freight transportation demand models. Not only was a survey of shippers important to elicit attitudes, perceptions and preferences, but also were external data sources of observed carriers' performance used in this research. Chapter 5 provides a comparison between perceived service, used to calibrate the demand models, and the observed performance of different modes. Due to data availability, this analysis was restricted to rail carriers and to the cost, transit time and reliability dimensions of service. In Chapter 6, a new methodology for segmenting markets, based on a latent structure model, is developed and applied to the survey data. Chapter 7 presents the estimation results of the RP and SP demand models. A comparison between the estimated coefficients of the individual models justified the efforts to combine the data sources. Two estimation procedures were developed for the combined RP and SP model. The value of service is assessed from the final specification of the freight transportation demand model in Chapter 8. Shippers' responses and demand elasticities are then analyzed for each segment in order to obtain specific strategies for service design and marketing. Finally, Chapter 9 summarizes the thesis and presents the conclusions and future areas of research.

II - Freight Transportation Demand Models: a Review

The method to assess the value of service in freight transportation draws upon state-of-the-art knowledge in consumer behavior theory, marketing research, and transportation demand theory. While knowledge of consumer behavior helps to identify the basic process by which shippers evaluate and select among transportation alternatives, marketing research provides methods to measure the aspects of shippers' behavior identified as relevant to mode choice. Finally, transportation demand theory provides methods to forecast the impact of strategies designed to improve shippers' satisfaction with respect to service provided.

An extensive review of these areas would prove to be too long, yet fail to serve the purpose of highlighting the important issues addressed in this research. Instead, the following sections focus on specific work in freight transportation relevant to the assessment of the value of service. When necessary, references to the original study or to more extensive reviews are provided. Section 2.1 reviews the main freight transportation demand studies and the framework used to estimate the demand models. Section 2.2 focuses on using stated preferences to elicit shippers' behavior in mode choice decisions. Finally, section 2.3 assess the need for a marketing-oriented approach to estimate freight transportation demand models.

II.1 - Freight Transportation Demand (FTD) Models

An understanding of the demand for freight transportation is essential to the analysis of the value of service quality to shippers. Variations in the level of service or prices should affect the demand for a particular mode in large scale and more permanently than in passenger transportation. Not only are individual shippers responsible for large amounts of traffic, but also the time between mode choice decisions is increasing with the use of negotiated contracts between a carrier and shipper after deregulation.

Demand models attempt to explain the demand for transportation as a function of the rate charged and the level of service offered. In order to derive the specification it is usually assumed that shippers seek to minimize their logistic costs. Two alternative simplifying assumptions are commonly used in the literature. On one side, transportation is considered as a factor of production, separate from other inputs. Then, the demand for freight transportation is taken as the derivative of the cost function with respect to the transportation price (Shephard's Lemma). Besides the underlying assumption of competitive markets, this approach usually ignores that transportation rates are functions of shipment size, what makes prices endogenous (for a more detailed discussion, see Chiang et al [1981]).

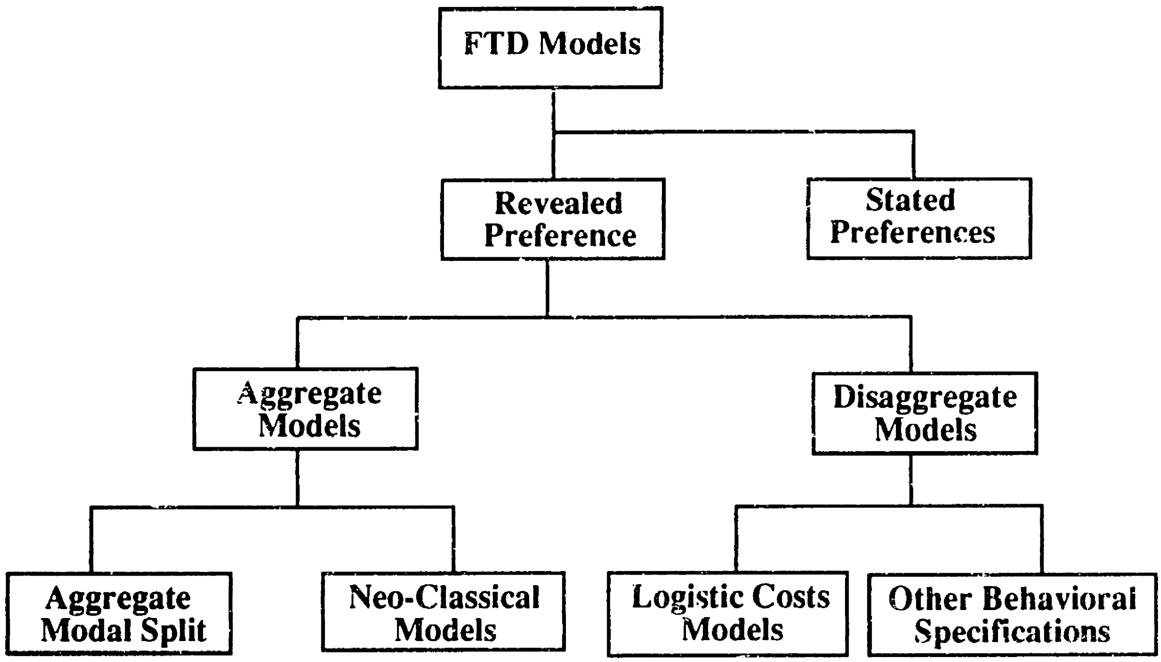
On the other hand, assuming factors demand fixed in a certain period of time, FTD models can be developed to address the choice of mode, shipment size and supplier to fulfill those demands. This implies that transportation costs have no effect on factor substitution. This approach is more amenable to short-run analysis, where firms can not adjust factor utilization easily. It can also be argued that in the methods used to elicit stated preferences, shippers are usually not given the possibility of substituting or adjusting input factors. Thus, the fixed factors demand model was adopted in this research.

Figure 2.1 presents the classification framework for freight transportation demand models used in this review. Traditionally, the estimation of FTD models have been classified in aggregate or disaggregate models (see Winston [1983]). The choice between aggregate an disaggregate models is usually heavily influenced by data availability. Both models are ultimately derived from the shippers' cost minimization, but the basic unit of observation is either an aggregate share of a particular mode at the regional or national level or the choice of mode/carrier for individual shipments, respectively.

Besides the traditional aggregate vs. disaggregate distinction, the FTD models were previously classified in terms of using revealed or stated preferences data. Even though most studies reviewed here have relied on revealed preferences, SP data recently came into the attention of transportation researchers as an important alternative source of information. In particular, incorporating SP data in freight transportation demand analysis was one of the motivations of this research. On the other hand, the classification framework also distinguished between neo-classical and aggregate modal split models within aggregate models and, between logistic cost and other behavioral specifications within disaggregate models. As described in Chapter 3, the logistic cost specification was used in this thesis.

Figure 2.1

Freight Transportation Demand FTD Models: A Classification Framework



- **Aggregate FTD Models**

Early FTD studies used aggregated data on mode shares and characteristics. Ad-hoc specifications were used in several studies prior to the introduction of the neoclassical economic theory in predicting aggregate demand for freight transportation. These models had no behavioral assumptions; they just tried to explain the mode shares in the transport between two regions with the characteristics of the transportation modes available and other characteristics of the regions and of the goods. For the neo-classical models though, several specifications were derived from the minimization of an aggregate firm's cost function, using flexible forms (e.g. translog and quadratic) to represent the production technology.

Two examples of using aggregate firms' costs to derive FTD models are the study of the Canadian surface transportation by Oun[1979] and the study of rail and truck shares for U.S. manufacturing firms, by Spady and Friedlaender[1980]. The use of aggregate data though, limited their sensitivity to changes in transportation rate structure and level of service. For example, aggregate studies typically constructed rates by dividing aggregate revenues by aggregate ton-miles or tons, without addressing the choice of shipment size.

- **Disaggregate FTD Models**

With the development of discrete choice theory in the 70's, the focus changed to disaggregate models using information on individual shipments. It has been argued that disaggregate FTD models provide more precise estimates of parameters and alleviate some measurement problems in aggregate studies. However, it is also true that data requirements increase significantly, making it difficult to construct a database to estimate FTD disaggregate models (see Chiang et al [1980]).

Within disaggregate models, two different specifications were used in freight transportation studies: the logistic cost models and other behavioral specifications. In the later, the emphasis is on the single mode choice decision, with the behavior of shippers derived from a random utility model accounting for the stochastic nature of levels of service provided by different modes and unobservable factors (see Allen [1977], Daughtey and Inaba[1978] and Winston [1981]).

In the logistic cost models, the mode choice decision is studied in connection with other decisions the firm has to take, specially within the framework of coordinating production and distribution decisions. Baumol and Vinod[1970] and Kulman [1974] were the first to analyze the demand for freight transportation as derived from the total logistic costs function of the firm, including explicitly the inventory carrying costs and safety-stock needs. Chiang et al[1981] further developed this approach, with the shipment size being simultaneously determined in the mode choice process. More recently, McFadden et al[1985] proposed a discrete-continuous FTD model, in which the mode, the shipment size and frequency are determined jointly.

More detailed reviews on freight transportation demand models can be found in Smith[1975], Winston[1983] and Zlatoper and Austrian[1989]. The latter provides an interesting emphasis on the data requirements of different demand studies. In particular, stated preferences (SP) data is discussed in the next section as an important alternative to elicit shippers' behavior. Finally, it is important to mention that the above discussion focused only on econometric models, without reference to the significant body of freight demand work in the area of network and spatial price equilibrium (see Harker[1985]).

II.2 - Analysis of Stated Preferences Data

In general, most of the FTD studies in the literature, aggregate or disaggregate, were based on revealed preferences (RP) data, i.e. actual market behavior of shippers and observed mode characteristics. Among the data difficulties encountered by these studies, at least three of them are relevant to elicit the need for alternative sources of information. First, some data on attributes are commercially confidential, specially at the individual shipment level. For example, freight rates actually paid may provide important information on the competitive advantage of shippers and carriers in the market after deregulation of U.S. surface transportation. It is also not obvious how some characteristics can be approximated as they are based on shippers' perceptions of service (e.g. reliability as the variability of transit time).

Second, many firms would perceive themselves as facing limited transportation alternatives, either for unavailability or lack of information on them. This creates a problem in estimating FTD models, where most of the information is derived from shippers that faces a trade-off between service characteristics. Finally, studies based on RP data can rarely be used to investigate the impact of new transportation technologies, unless some assumptions are introduced to extrapolate shippers' behavior.

On the other hand, since the early 70's, stated preferences (SP) data have being extremely useful in marketing research (e.g. Green and Rao[1971] and Green and Srinivasan[1978]) . Instead of considering the consumer as a black box, market analysts try to model explicitly the cognitive mechanisms governing their behavior and then, to simulate the response to innovative products and services. In Chapter 1, an example of shippers' decision path diagram was discussed as the base for the behavior model in this research.

One of the reasons the that SP data are frequently used in market research is that the experimenter can control the choice scenarios. As discussed in Morikawa [1989], it implies the following advantages over the traditional RP data:

- choice set can be specified;
- range of attribute can be extended;
- multicollinearity among attributes can be avoided;
- attributes that are not easily quantified, such as reliability, responsiveness and level of effort, can be incorporated; and
- attributes are free from measurement errors.

Not only is SP data able to elicit preferences with respect to new or non-existing options, but also different kinds of reasonable preference indicators, such as rankings and ratings, can be elicited. Table 2.1 summarizes the main characteristics of RP and SP data. The major issue on using SP data then, becomes its unknown reliability in terms of reproducing actual market behavior of shippers.

Table 2.1
Characteristics of RP and SP Data

Revealed Preference Data	**Stated Preference Data**
• Based on actual market behavior	• Based on hypothetical scenarios
• Choice set is ambiguous	• Choice set is specified
• attributes are subject to measurement errors	• attributes are free from measurement errors, but subject to perception errors
• Range of attribute level is limited	• range of attribute level can be extended
• Difficult to incorporate intangible attributes (e.g. responsiveness, and level of effort to deal with the carrier)	• can incorporate intangible attributes
• cannot provide direct information on new (non-existing) alternatives	• Can elicit preferences for new (non-existing) alternatives
• Preference indicator is "choice" (or mode shares)	• Can elicit any reasonable preference indicator (e.g. rank, rate, and choice)

Source: Morikawa [1989]

II.3 - The Use of Stated Preferences in Freight Transportation

In transportation research, the use of SP data has been held back due to the emphasis on forecasting transportation demand rather than on consumers' preferences or trade-offs. With the increasing applications of disaggregate behavioral models in the 80's, specially to analyze passenger travel behavior, the use of SP data has generated some interests among transportation researchers (see special issue "Stated Preference Methods in Transportation Research", Journal of Transport Economics and Policy[1988]). In addition, this emphasis on the consistency of SP data to forecast actual market behavior has fostered a body of research in combining RP and SP data in estimating demand models (see review in Morikawa [1989]). While SP data on trade-offs among attributes help to identify parameters of the RP model, these combined estimation methods also allows modeling explicitly response biases that may affect the validity of the SP data.

In the freight transportation demand area, the use of SP data is still very incipient. It is useful to distinguish between two types of studies that have tried to elicit the stated behavior of shippers. First, several researchers interviewed shippers from different industries and tried to identify the importance ranking of factors affecting mode choice. Seidenfus[1987] reviewed some studies done in Europe in order to identify common factors as well as shifts in shippers behavior over time.

It was observed that the importance of price or transportation rates reduced from first/second place in studies done between 1959 and 1972, to forth/sixth place in studies after 1983. While punctuality and speed maintained their importance, there was an increase in the significance of customer service and security. The overall conclusion was that less importance was being attached to price and more to the quality of service. The keener competition in the goods markets, the change to higher valued products in developed economies and the increase in the complexity of logistics were pointed out as reasons for the emergence of new service quality dimensions affecting mode choice. These studies are very useful in a qualitative assessment of the behavior of shippers and provide information to the specification of the demand models.

Second, very few FTD studies have tried to model the stated preferences or responses. In general, they have either used attitudes and perceptions as explanatory variables or modeled the preference indicator under a discrete choice framework. For example, Ortuzar and Palma [1988] used stated preferences in the analysis of exports of frozen fish and refrigerated vegetables from Chile. Shippers were asked to rank transportation profiles described by price, headway, lead time, shipment type and intermodal service. A logit model using ranking data was estimated (see Chapman and Staelin [1982]), whereas price was the dominant factor in shippers' stated preferences (10% increase in price could be offset by 86% decrease in travel time). Although the results were considered reasonable by the authors, they go against the trends of increasing importance being given to service quality.

Fowkes et al [1989] used SP data to analyze mode choice in Europe. The data set was formed by interviewing 50 shippers (which included ten commodity groups). They were asked to compare pairs of transportation profiles, described by cost, delivery time, percentage delivered on time, frequency of collection and number of transshipments necessary. Preference ratings were obtained from these comparisons and then, transformed into ad hoc probabilities used as the dependent variable in an aggregate logit model. The results confirmed the beliefs that high-value commodities are usually more sensitive to quality of service, while low-value commodities are more price-sensitive.

De Jong and Gommers [1992] used SP data to assess the value of time in freight transport in the Netherlands. All conjoint experiments were "within mode", i.e. the choice set consisted of alternatives referring to one particular mode; each alternative were described by the rate, transit time, travel time reliability, probability of damage and frequency of shipments. Logit models were then, estimated for previously defined market segments. On average, shippers were almost indifferent between some percentual change in transit time and the same percentual change in rates. In addition, raw materials had a higher value of time than the one for finished goods, which was related to the high costs of delays in the production process.

The studies by Ortuzar and Palma [1988], Fowkes et al [1989] and DeJong and Gommers [1992] noted an increased interest in determining the shippers' sensitivities to different service quality dimensions, as compared to previous demand forecasting emphasis. Two major weakness though, were identified in their estimation framework. First, the underlying logistic cost minimization behavior of shippers was not considered in the model specification. Both estimated models considered a linear combination of service attributes as the utility function, without relating the interdependency of shipment size and mode choice.

Second, SP data was used without an attempt to identify and correct for potential sources of biases affecting shippers responses in the conjoint experiment. For example, Ortuzar and Palma [1988] may have found price to dominate over other service attributes because shippers focused on differences in price to rank order the transportation alternatives, instead of considering the trade-offs among all service attributes.

II.4 - The Need for a Marketing-Oriented Approach to FTD Models

In order to assess the value of service in freight transportation, it is necessary to improve the understanding of the shippers' behavior in mode choice decisions. Even though previous demand models have attempted to model individual shippers in the market at the disaggregate level, data limitations have hindered their theoretical superiority. Not only was the description of service limited to a set of observable characteristics, but also measurement errors and ambiguous definitions of mode attributes restricted their use in evaluating shippers' sensitivities to improvements in the transportation service.

The main advantage of the marketing-oriented approach to FTD model is to use information on shippers' attitudes, perceptions and preferences to elicit their behavior in mode choice decisions (for example in passenger transportation, see Hauser and Koppelman [1981]) . Not only it attempts to model how shippers' perceptions of service influence their mode choices in the market, but also to identify the relative importance of service attributes and the situational constraints affecting the shippers' behavior. This approach would provide carriers with diagnostic information to design services that profitably meet the shippers' needs.

When a "better" transportation service is introduced, chances are that shippers will not immediately adopt it for much of their shipments. First, they need to become aware of the new service, they need to be convinced that it is a superior option for them, and they must determine that it satisfies their particular shipment needs. This is not a simple one-step process, but rather a series of stages in which shippers' perceptions are updated and their future behavior would depend on past experiences.

In particular, SP data provide an excellent complementary source of information for estimating freight transportation demand models because it adds information on intangible attributes and contains more precise descriptions of choice sets and explanatory variables. However, its use in freight transportation is still incipient, while lacking an explicit description of the underlying shippers' behavior model.

As reviewed above, the attempts to use SP data in freight mode choice models have ignored the logistic cost minimization process. Shippers are decision-makers imbedded in a profit maximizing organization. Different cognitive mechanisms may influence shippers' behavior, but their decision protocol should still be represented by the minimization of the logistic costs of the firm. It is, then, important to incorporate shippers' perceptions of service and intangible mode attributes in the logistic cost function to improve its ability to distinguish the service trade-offs that shippers consider in their mode choice decisions.

On the other hand, previous FTD models did not consider the potential sources of biases in the SP data. Most researchers realize that the critical issue in modeling with stated preferences is its consistency with respect to actual market behavior. Although some studies which compared SP and RP models quantitatively have supported the reliability of SP data in passenger transportation (see Morikawa [1989]), this evidence in freight transportation remains to be shown. It is then, critical to account for potential biases specific to the SP data in the specification of the FTD model, especially when combing RP and SP data sources.

III - The Conceptual Model

The conceptual model develops the relationship between freight modal split and shippers' perceptions of transportation modes service characteristics. It is hypothesized that shippers' perceptions of transportation service, as contrasted to actual performance, are relevant in the mode choice for individual shipments. A model of shippers' behavior should integrate the logistic cost criteria with decision-makers' perceptions of mode performance.

Starting from the shippers' behavior model in Chapter 1, the traditional logistic cost formulation is extended to include intangible dimensions of service. These dimensions help to identify differences among carriers that might influence shippers' market behavior, even if they are not directly quantifiable as a cost item in their operations. Demand models are then, estimated based on shippers' perceptions of service to determine their sensitivities to changes in different mode characteristics.

The following sections describe the shippers' behavior model, as well as its implementation framework. The use of attitudinal indicators and shippers' characteristics in market segmentation is discussed in section 3.3. Besides the extended logistic cost specification described in section 3.4, the RP and SP choice models are discussed in section 3.5. The framework to combine shippers' stated preferences with their current market behavior is then introduced in section 3.6. . Finally, different measures of the value of service in freight transportation are summarized in section 3.7.

III.1 - The Shippers' Behavior Model

Shippers represent the decision-maker in the mode choice for individual shipments. In a general sense, shippers can be the buyers or the sellers in the market transaction, seeking to overcome spatially separated production and consumption sites. The goal of the shippers' behavior model is to provide a framework to analyze how shippers process information about transportation services to decide on the mode/carrier for individual shipments.

The shippers' behavior model proposed in Figure 3.1 incorporates perceptions of service in mode choice by making explicit the cognitive mechanisms affecting the decision process[1]. In this diagram, ovals refer to unobservable or latent variables, while rectangular boxes represent variables that can be observed directly, or measured by suitable experiments. The relationship between mode service attributes and the current market shares is represented by four groups of intervening factors: attitudes, perceptions, preferences and the decision protocol.

While perceptions refer to shippers' perceived values for different mode attributes, attitudes are their own perspectives or importance of these attributes. Preferences are then, derived from attitudes and perceptions, representing the desirability of each mode. Finally, the decision protocol is defined by the assumption that shippers choose the mode that minimizes their annual logistic costs, calculated from the perceived service attributes.

Measurable inputs to the decision process are mode attributes, information from marketing programs and other sources, firms' demographic factors and transportation needs, past experience, and situational constraints, like mode availability. Mode attributes, such as transit time and rates, serve as cues in forming shippers' perceptions of service. Each system characteristic is a potential cause of some perceptual dimensions, but even in a one-to-one correspondence, it may not imply equivalence between perceptions and observed characteristics. An important service design tool for carriers wanting to influence shippers' behavior is the relationship between system characteristics and perceptions.

In addition, shippers/firms characteristics and market information also influence shippers' perceptions of service. Market information includes marketing programs, "word-of-mouth" advertising and other sources of information, while shippers' characteristics includes variables on the size of the firm (e.g. annual sales and number of employees), on product characteristics (e.g. average value and density) and on their transportation needs (e.g. length of haul and maximum acceptable delay). Shippers' characteristics are also used to determine attitudes regarding the importance of different service attributes and to make the decision protocol of minimizing logistic cost operational.

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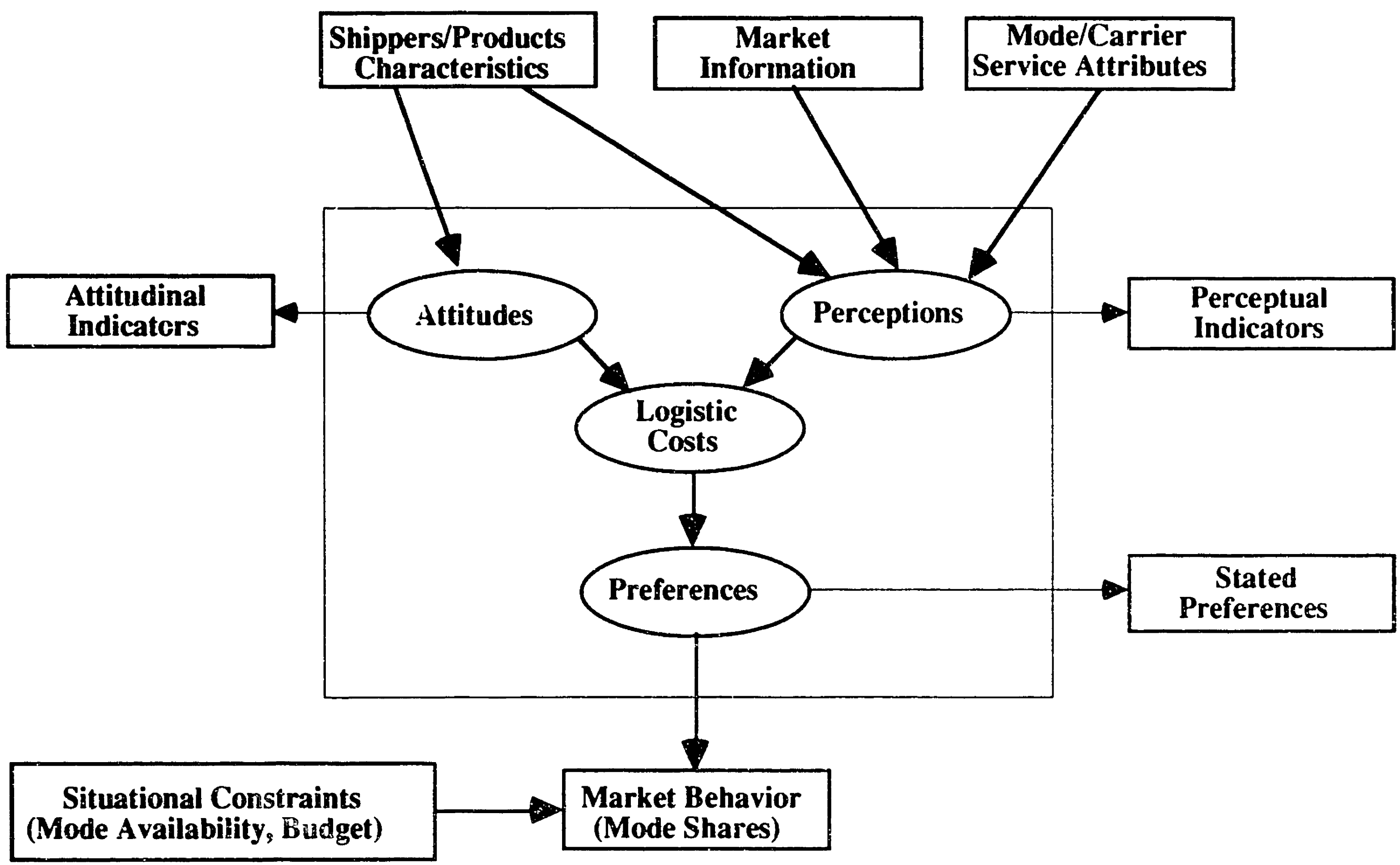
[1]This framework is adopted from earlier work by Ben-Akiva and Boccara [1987], McFadden [1988] and Morikawa [1989]

Figure 3.1

The Shippers' Behavior Model



The direct and measurable output of the decision process is the market behavior, in this case given by mode shares in freight transportation. For example, shippers may have perceptions of the reliability of transit time by different modes, attitudes regarding the importance of reliability in their operations, preferences among specific modes, and a protocol of minimizing their logistic costs. Given these behavioral intentions, market behavior is determined taking into account other situational constraints, like mode availability and transportation budget.

Besides the input characteristics and the output market behavior, the model also uses two intermediate types of behavioral information: attitudinal indicators or importance of different service attributes and stated preferences in hypothetical scenarios. While importance-ratings can be used to define market segments, stated preferences can be combined with current market behavior in the final demand model. Note that the decision protocol of logistic cost minimization is not elicited, but rather assumed as reasonable behavior of decision-makers' imbedded in a profit-maximizing organization. In addition, it is also assumed that the transportation need arises after the actual market transaction has been set between spatially separated buyers and sellers. This avoids further complexities regarding the bargaining process and long term relations between buyers and sellers in the market, while still proving a reasonable representation of shippers' mode choice decisions.

The modeling problem is to use psychometric data to quantify the theoretical or latent constructs in Figure 3.1, and then simulate the decision process to forecast market behavior. It is common in marketing research to present the results of experiments eliciting psychometric data as useful direct information on the decision-makers sensitivities and behavior. However, the data from these experiments can also be treated as additional information for the choice models traditionally used in the literature.

In fact, the objective of this research is to implement the shippers' behavior model using efficiently all available information. Through the estimated demand or mode choice models, the value of service in freight transportation can then, be assessed from simulating shippers behavior in the market after changing some input information to the decision process.

III.2 - Implementing the Shippers' Behavior Model

Modeling with psychometric data introduces two challenges. First, it is necessary to account for possible biases in the response of shippers regarding their preferences and trade-offs among service attributes. Second, to make the modeling effort of strategic interest to carriers, the link between shippers' perceptions and observed performance needs to be discussed. Given improvements in system characteristics, carriers want ultimately, to change shippers' perceptions and preferences.

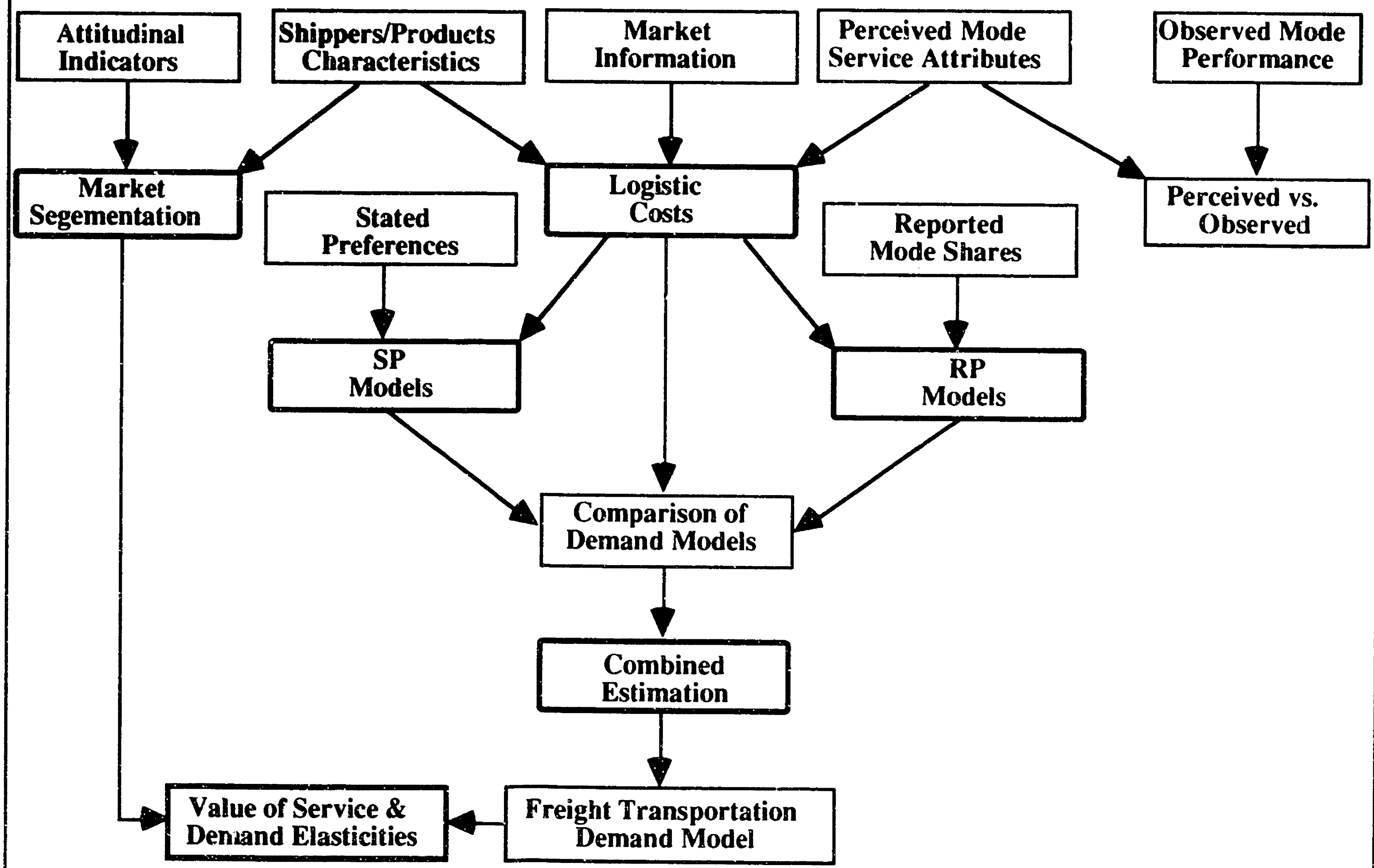
Figure 3.2 presents the implementation framework, including the input information and the underlying models in different stages of the decision process. The final outcome is to evaluate shippers' value of service and their sensitivities with respect to improvements in different dimensions of service. Note that the use of perceived mode service attributes in the logistic cost model is preceded by a comparison between shippers' perceptions and observed mode performance. This is important to assess the validity of using perception data elicited in surveys to model shippers' behavior. Moreover, it also provides the link between shippers' perceptions of service and attributes under carriers' control affecting their observed performance.

The identification of market segments from the attitudinal indicators provides the basis for differentiating the service offered to shippers. It is important not only to consider differences among shippers in the importance given to each service attribute, but also some observable shippers' characteristics in the identification and interpretation of the market segments. In particular, the later one helps to extend the service differentiation to new or current shippers that did not participate in the original survey, by classifying them into the previously defined segments. Section 3.3 describes a new approach to market segmentation based on shippers' latent attitudes towards service quality. Ideally, demand models should be estimated for each segment or at least, some coefficients be made segment-specific, in order to identify the differences underlying shippers' mode choice decisions.

The logistic cost function is the critical element in the specification of the demand models. It is important not only to determine the relevant cost components, but also to identify their relationship with shippers' perceptions of service. As described in section 3.4, the specification of the logistic cost was extended to include behavioral factors affecting shippers' mode choices.

Figure 3.2

Implementing the Shippers' Behavior Model



Two choice models serve as inputs in the final freight demand model. First, the RP model is used to explain current mode shares with shipper/firms characteristics and perceived service by the different transportation alternatives available. Second, the SP model is estimated from stated preferences under hypothetical scenarios of transportation service offerings. To some extent, these models are comparable when assuming that the same decision protocol affects shippers' behavior, i.e. shippers seek to minimize their logistic costs either in their current mode shares or in stating their preferences towards different hypothetical services. Section 3.5 describes the estimation framework for these revealed and stated preferences models.

Since the main interest is to model actual behavior in the market, the primary data source are shippers' revealed preferences (RP) in terms of mode shares and perceptions. However, the small number of observations and the possible lack of variation in perceived mode attributes in the RP data makes it desirable to incorporate stated preferences (SP) data in the choice model. Shippers' stated preferences in hypothetical transportation scenarios provide an indirect measurement on the sensitivities to the same service attributes, but may contain significant response bias.

The implementation framework, then, uses both choice models in a combined estimation of the final freight transportation demand model. The assumption is that stated preferences can help to identify or accurately estimate the service trade-offs embodied in the coefficients of the demand model. This is specially true for those dimensions that are not directly factored or quantified in a traditional logistic cost calculation, like the level of effort required to deal with carriers. The gain in efficiency of parameters estimates is possible since the choice models share the same logistic cost specification and potential sources of biases were accounted for when estimating the SP model. Section 3.6 describes in further detail, two estimation procedures for the combined model.

Finally, the freight transportation demand model is used to simulate shippers' market behavior for given improvements in the perceived service provided by different modes (section 3.7). Besides the behavioral interpretation of the coefficients in the demand model, elasticities derived from this market simulation provide another measurement on how shippers' value the transportation service and, a first assessment, on how much market share can be gained from improving perceived service quality. It is important to reemphasize that these demand elasticities are in the shippers' perceptions space. The comparison between perceived service and observed performance provides some insights in the validity of using these elasticities to measure the impact of changes in the system characteristics.

Thus, the proposed implementation of the shippers' behavior model allows the determination of the value of service that is consistent with shippers' stated preferences and actual market behavior. Segment-specific demand elasticities were derived as a tool to identify customer-oriented strategies in service design and marketing.

III.3 - Freight Transportation Market Segmentation

The managerial concept underlying market segmentation is the identification of groups of shippers who have needs and responses towards service quality that are different from other shippers. Even though service trade-offs are different for each shipper, it is reasonable to assume that groups of shippers may have similar sensitivities to service quality.

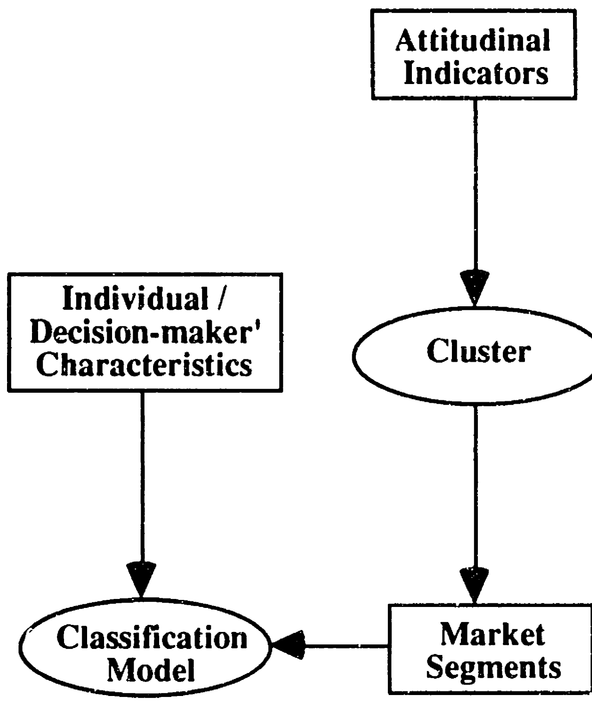
Equally important to defining segments, is the capability to classify current and potential shippers into those segments. In fact, market segmentation becomes operational only if there are identifiable and measurable characteristics of shippers strongly related to their attitudes towards different service attributes. Most studies though, neglect this topic or confuse it with designing strategies for each segment, due to the major difficulties in deriving a good classification model. Nevertheless, it is important to be able to assign shippers to different segments without a priori knowledge of their attitudes towards different attributes, in order to offer the service specific to their segment.

The input information for market segmentation are the attitudinal indicators and observable shippers' characteristics (see Figure 3.3). While attitudinal indicators provides information on the importance ratings of each service attribute, shippers' characteristics helped to identify reasons for their different attitudes towards service quality. Two approaches to freight transportation market segmentation are then developed, based on how the input information is used to identify the segments.

First, the traditional market segmentation approach recognizes that differences in the shippers attitudes towards service quality are the underlying motivation for defining market segments (see Figure 3.3). Using a cluster algorithm, segments are formed with shippers having similar attitudinal indicators across all service dimensions. Once segments are defined, strategies to design and market transportation services in each segment follows from the average importance ratings of each service dimension. For example, a market segment with high importance ratings attached to rates is formed by price-sensitive shippers, and a sensible strategy might be to offer them rate discounts even if at the expense of some service deterioration. Finally, using the discrete choice framework, the classification model identifies which of the observable set of shippers' characteristics were more relevant in assigning shippers to specific segments.

Figure 3.3

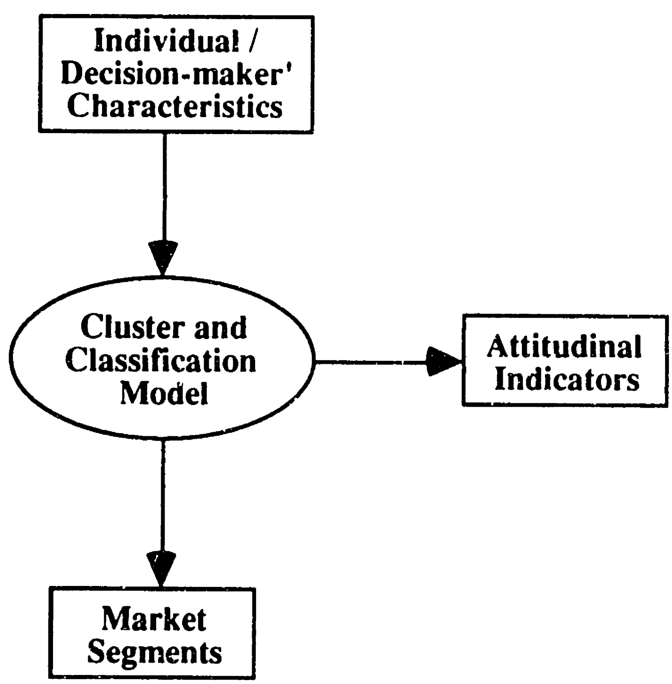
The Traditional Market Segmentation Approach



Second, a new approach for market segmentation analysis was developed based on latent structure models. The idea of the new approach is to combine the clustering and the classification model, by using the attitudes as indicators rather than causes of the latent dimensions on which shippers are to be grouped. The proposed latent structure model would therefore incorporate all information available to estimate the segmentation variables. This fact should potentially improve the identification of segments, especially when the attitudinal indicators are affected by response biases. Another advantage of the latent structure approach to market segmentation is that the classification model is derived implicitly from the clustering process.

Figure 3.4

The New Market Segmentation Approach



Chapter 6 describes in further detail the statistical framework used in both approaches. Considerable judgment is still necessary to define the best market segments and identify service design opportunities. In particular, differences in the value of service across segments can be used to develop strategies to design and market transportation services in each segment.

III.4 - Logistic Cost: Specification of the Decision Criteria

Firms purchase transportation service to move their inputs and outputs from and to markets that are spatially separated. If goods markets are competitive, it is reasonable to assume that mode/carrier choice decisions are governed by a cost minimization process. Shippers, or the firms they represent, should purchase the transportation service that provide the desired movements of goods with minimum annual logistic cost.

On the other hand, firms survive in the market with different levels of sophistication in their distribution activities. Large firms usually keep detailed records of costs and level of service provided in past shipments. Others, usually with small volumes shipped, rely on the reckoning of past experiences with different carriers or the "word-of-mouth" from different firms in the market place. Even though in both cases the cost minimization hypothesis is still valid, the information available for calculating the logistic costs is different. Moreover, firms choose carriers ex-ante to the actual realization of shipments, based on their "expectations" of the level of service to be provided by different modes.

The annual logistic cost includes all expenses incurred due to the storage and transportation of goods. Even though the perspective of the outbound traffic is taken for most of the formulation that follows, some cost components also reflect the logistics of buyers or receivers of goods due to their bargaining power[2] in the mode choice decisions. In addition, annual expenses were used instead of a by-shipment cost calculation to account for the increasing number of contracts between shippers and carriers after deregulation. These contracts are usually settled on a six-month to one-year volume basis, making the cycle of the firms' mode choice decisions longer and increasing the switching costs.

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[2]depending on the conditions of sale, the buyer may decide the transportation carrier or exercise pressure as to what are his/her needs in terms of transportation service (e.g. delivery time, loss and damage insurance).

The cost components are formulated in order to reflect shippers' perceptions of the service quality by different modes or carriers. These perceptions incorporate not only the uncertainties underlying ex-ante mode choice decisions, but also different levels of information availability on mode service attributes. Two extensions were incorporated to the traditional logistic cost calculations. First, it includes items usually not considered in previous freight transportation demand studies, like the unavailability of transportation equipment and the intangible service-related costs. Second, some mode attributes were formulated as how the shippers would probably perceive them, e.g. the reliability of transit time being measured as the fraction of shipments that arrive when wanted.

In addition, it is assumed that: (a) the market price of the goods shipped is fixed, (b) the goods shipped are not seasonal or perishable and, (c) daily shipment or receiving rate is quite stable. The following specification is then, derived for different components of the firms' logistic costs:

• order and handling costs (oc): include all administrative and handling costs related to receiving and shipping an order. Assuming a constant unit cost (o) per order, the annual order cost can be formulated as:

$$oc = o \cdot \frac{Q}{q} \tag{3.1}$$

where Q = annual tonnage shipped by the firm (ton/year) and
q = average shipment size (ton)

• transportation charges (tc): include all freight and special charges incurred during transportation. Assuming that any special charges were included in the reported rate per ton (r), the annual cost is given by:

$$tc = r \cdot Q \tag{3.2}$$

where r = average rate per ton (\$/ton)

• loss and damage costs (ldc): include the cost of capital tied-up with a loss or damage claim from the time of discovery of the damage until the claim is settled. Even though, in most cases, the direct loss and damage is paid by the carrier, the time to collect claims (m) adds to the shippers' logistic cost as follows:

$$ldc = i \,.\, d \,.\, m \,.\, p \,.\, Q \tag{3.3}$$

where i = discount rate (per year)
d = fraction of shipment lost or damaged
m = average period to collect a claim (years)
p = average price of product shipped (\$/ton)

• capital carrying cost in-transit (cct): includes the cost of capital tied up from the time an order is shipped until the shipment arrives, formulated as

$$cct = i \,.\, t \,\frac{p \,.\, Q}{365} \tag{3.4}$$

where t = typical transit time (days)

• inventory capital carrying costs (ic): includes the capital carrying cost tied up in inventory at the destination. Assuming constant shipment rates per day, the average inventory becomes one-half of the shipment size (q), and the following cost formulation is derived:

$$ic = i \,.\, p \,\frac{q}{2} \tag{3.5}$$

where q = average shipment size (tons)

• unavailability of equipment costs (uec): capital carrying costs due to the unavailability or late arrival of transportation equipment. The following cost formulation assumes an average number of days the equipment remained unavailable (n):

$$uec = i \, . \, (1 - u) \, . \, n \, . \, \frac{p \cdot Q}{365} \tag{3.6}$$

where u = fraction of times a sufficient quantity of acceptable equipment is received when wanted

• reliability costs (rec): include the cost of early arrivals, like the cost of providing extra storage space at the destination to unload vehicles that arrive early, and the cost of late arrivals, like the buyers' stock-out and safety-stock carrying costs. Even though shippers are usually not aware of inventory policies at the destination, they can evaluate the earliest and latest acceptable delivery time that would not compromise future sales. While the cost of early arrival is assumed to be negligible, the cost of late arrivals is developed assuming that the buyers balance their safety-stock carrying cost with the risk of reaching a stock-out situation. The reliability costs are then formulated as:

$$rec = i \, . \, L \, . \, \frac{p \cdot Q}{365} + (1 - \tau) \, . \, so \, . \, \frac{Q}{q} = i \, . \, (L + \frac{1 - \tau}{\Delta\tau}) \, . \, \frac{p \cdot Q}{365} \tag{3.7}$$

where L = latest acceptable delivery time (days)
$so = \frac{i}{\Delta\tau} \, . \, \frac{p \cdot q}{365}$, stock out cost (\$/stock-out, see Appendix A)
τ = fraction of shipments that arrive when wanted
$\Delta\tau$ = decrease in the probability of a stock-out from carrying an additional day of safety-stock (see Appendix A).

• intangible service-related costs (src): include costs associated to intangible dimensions of service quality, like carriers not offering EDI capabilities, unsatisfactory payment terms and billing, unsatisfactory responsiveness to inquiries and, the level of effort to deal with the carrier . Since these items are usually not considered in the logistic cost calculations, their formulation is postponed until the description of the shippers' survey in the next chapter.

Note that a great deal of information in the above specification of the logistic cost components are unknown or very hard to obtain. Besides the cost per order (o) and the implied discount rate (i), the number of days to collect loss and damage claims (m) and the average period the transportation remained unavailable (n) are difficult to elicit in a survey. A parametric logistic cost function is then, used in the specification of the demand models. The estimated parameters incorporate the information not available and thus, have a behavioral interpretation derived from the original formulation of the logistic cost components.

The logistic cost for mode j is given by:

$$W_j = o \cdot \left(\frac{Q}{q_j}\right) + r_j \cdot Q + i \cdot d_j \cdot m \cdot p \cdot Q + i \cdot t_j \cdot \left(\frac{p \cdot Q}{365}\right) + i \cdot p \cdot \left(\frac{q_j}{2}\right) + i \cdot \left(L + \frac{1 - \tau_j}{\Delta\tau_j}\right) \cdot \left(\frac{p \cdot Q}{365}\right) + i \cdot (1 - u_j) \cdot n \cdot \left(\frac{p \cdot Q}{365}\right) + src_j \tag{3.8}$$

Now, incorporating the unknown information on parameters β's to be estimated in the choice model:

$$W_j = r_j \cdot Q + \beta_1 \cdot \left[\left(t_j + L + \frac{1 - \tau_j}{\Delta\tau_j}\right) \cdot \left(\frac{p \cdot Q}{365}\right)\right] + \beta_2 \cdot d_j \cdot p \cdot Q + \beta_3 \cdot (1 - u_j) \cdot \left(\frac{p \cdot Q}{365}\right) + \beta_4 \cdot \left(\frac{Q}{q_j}\right) + \beta_5 \cdot p \cdot \left(\frac{q_j}{2}\right) + src_j \tag{3.9}$$

where

W_j = annual logistic cost using mode j ($ / year)

β_1 = i
β_2 = i . m
β_3 = i . n
β_4 = o
β_5 = i

Note that β_1 and β_5 are treated separately. It is assumed that the in-transit and in-hand inventory carrying costs are different, because, for example, the later includes the provision of storage space besides the capital tied-up in inventory.

III.5 - The Estimation of the RP and SP Models

Given the above logistic cost specification, mode choice could be predicted using it deterministically to find the mode with minimum cost. Besides having to enumerate all possible alternatives, this approach assumes that all information is available for different modes. In fact, it is usually not possible to predict the minimum logistic cost with certainty, either because of service variability from one shipment to another, or because not all information is available.

The random logistic cost specification then, assumes that the logistic cost contain an observable part $W(s_i, a_{ij})$ and an unobservable or random component ε_{ij}. The observable part is a function of shipper/firm characteristics s_i and mode j attributes a_{ij} perceived by shipper i, as specified by the logistic cost components.

The probability that shipper i chooses mode j is given by:

$$\begin{aligned} P_i(j) &= \Pr [\ W(s_i, a_{ij}) + \varepsilon_{ij} \leq W(s_i, a_{ik}) + \varepsilon_{ik}, \forall k\ ] = \\ &= \Pr [\ \varepsilon_{ij} - \varepsilon_{ik} \leq W(s_i, a_{ik}) - W(s_i, a_{ij}), \forall k\ ] \end{aligned} \tag{3.10}$$

Given the probability density function for ε_{ij}'s, the choice probabilities depend only on the observed logistic costs for different modes. In particular, assuming that ε_{ij}'s are independently and identically Gumbel distributed, the following multinomial logit can be derived (see Chiang et al [1980]):

$$P_i(j) = \frac{\exp(-\mu W(s_i, a_{ij}))}{\sum_{k \in M} \exp(-\mu W(s_i, a_{ik}))}, \tag{3.11}$$

where μ is a positive scale parameter; and

M is the set of available modes.

Both RP and SP choice models follows the same random logistic cost framework described by (3.9) and (3.10). The underlying statistical models though, varies with respect to the available information. While the RP model uses the actual behavior of shippers in terms of mode shares, the SP model uses the information elicited in the conjoint experiment . Chapter 7 describes the statistical models and the estimation results for each choice model.

In addition to the common parameters of the logistic cost function, RP and the SP-specific parameters are also included in each choice model. In particular, situational constraints are included in the specification of the RP model. Shippers, or the firms they represent, may have some characteristics that favor the use of one mode against the others. Besides the mode-specific constants that capture unobserved factors favoring their choice, other variables may influence a given mode share. For example, large annual tonnage may favor shipments by rail, short length of hauls usually rely on truck transportation, and high-value commodities are shipped by intermodal or by truck. Note that these variables do not vary across alternatives, and thus, are included only into the cost specification of the mode affected by them.

On the other hand, potential sources of biases in the SP data are accounted for by introducing additional dependent variables in the logistic cost specification to capture their effect. In the stated preference literature[3], the most common sources of biases are:

- justification bias, where responses are influenced by an attempt to consciously or unconsciously rationalize the shipper's behavior in actual market situations.

- unconstrained bias, because shippers' stated preferences may neglect actual situational constraints (e.g. mode availability, shipment size and frequency) influencing market behavior. The main effect of this bias is likely to be in opposite direction of the justification bias.

- prominence bias, because shippers may focus on a small set of attributes instead of the full description of the alternatives. This bias is less prominent when the attributes describing the alternatives vary with the scenario.

- protocol bias, which may arise from the survey settings and procedures. For example, it may arise from the order in which attributes are arranged in the description of alternatives, from learning during the exercise, and from the way respondents deal with the information presented to them (e.g. different interpretations of the response scale).

- hidden-motives bias, including shippers trying to influence policy or decisions believed to be derived from their answers, or shippers trying to answer in a way they think the interviewer expects them to, or shippers not fully understanding the exercise.

[3]see Ben-Akiva and Morikawa [1990] and Bradley and Kroes [1990]

For example, the actual mode shares can capture some inertia that shippers may have in answering the questions, related to their past behavior. If the estimated coefficients associated to mode shares are statistically significant, it may indicate the presence of justification biases in shippers. Other sources of biases may be assumed to have the expected effect of increasing the variance of the random terms or the mode-specific constants in the model, dismissing the need to account for them individually in the estimation process. More details on accounting for response biases can also be found in Chapter 7, where the estimation results for the SP model are presented.

III.6 - Combining RP and SP Models[4]

Combining RP and SP data sources may allow the identification or accurate estimation of model parameters, which is usually not possible using only the RP data. Since it uses all information available, the combined estimation usually improves the efficiency of the parameters. Each data set is associated to a likelihood-like function, where the data is considered a realization of the underlying probabilistic model used to estimate unknown parameters (see Chapter 7).

Let W_{ij} be the latent variable representing mode j's logistic cost for shipper n. The general set-up from using independently the data sources can be described by:

- the RP Logistic Cost Model:

$$W^{rp}_{nj} = - \beta' x^{rp}_{n} - \gamma' z^{rp}_{n} + \varepsilon_{nj} \tag{3.12}$$

where x^{rp}_{n} are the perceive mode attributes in the logistic cost specification;
z^{rp}_{n} are the variables associated to the situational constraints;
$(\beta,\ \gamma)$ is the vector of unknown parameters; and
ε_{nj} an unobserved random term.

[4]this section was adapted from Ben-Akiva and Morikawa [1991]

• the SP Logistic Cost Model:

$$W_{nj}^{sp} = - \beta' \mathbf{x}_n^{sp} - \delta' \mathbf{b}_n^{sp} + \nu_{nj} \tag{3.13}$$

where $\mathbf{x}_n^{sp}$ are the mode attributes used to describe the alternatives in a hypothetical scenario;

$\mathbf{b}_n^{sp}$ are the variables associated to bias correction terms;

$(\beta, \ \delta)$ is the vector of unknown parameters; and

ν_{nj} an unobserved random term.

In particular, situational constraints are represented by the vector of variables **z** with its corresponding coefficients γ in the RP model. On the other hand, the coefficients δ associated to bias factors (**b**) are specific to the SP model. The sharing of coefficients β by both models implies that trade-offs among mode attributes x's are expressed by the same logistic cost components in both market behavior and stated preferences.

The random components of the logistic cost specification, ε and ν, are assumed to be independently distributed with zero means. The level of noise in the two data sources are then represented by the variances of the disturbance terms, which are related by:

$$\mathrm{var}(\nu) = \mu^2 \ \mathrm{var}(\varepsilon) \tag{3.14}$$

Usually RP data contains more random noise than SP data, implying that μ should be between zero and one. It is possible to gain accuracy of parameter estimates by sharing data sources, because the bias and random errors specific to the SP data are captured by δ and μ, respectively.

Following the statistical framework in Ben-Akiva and Morikawa [1990], two procedures are designed to estimate the parameters (β, δ, γ, and μ): joint MLE, using RP and SP data simultaneously, and sequential MLE, using RP and SP data one after the other. In order to identify all parameters, the scale of the combined model was set by arbitrarily fixing the variance of the random term of the SP model to one.

Suppose that the observed choices in the RP and SP data are given by:

$d_{nj}^{rp} = 1$, if shipper n actual choice was mode j; 0, otherwise; and
$d_{nj}^{sp} = 1$, if shipper n stated choice was mode j; 0, otherwise.

Then, the underlying idea of the joint and the sequential estimation procedures can be summarized by:

- joint MLE: assuming that the RP and the SP observations are independent (i.e. ε and ν are independently distributed), the joint estimator of (β, δ, γ, and μ) is obtained by maximizing the joint log-likelihood function:

$$L(\alpha, \beta, \gamma, \delta, \mu) = \sum_{n=1}^{N^{rp}} \sum_{j=1}^{m} d_{nj}^{rp} \ln P_{nj}(\mathbf{x}_{nj}^{rp}, \mathbf{z}_n, \varepsilon_{nj}; \beta, \gamma, \mu) +$$

$$\sum_{n=1}^{N^{sp}} \sum_{j=1}^{m} d_{nj}^{sp} P_{nj}(\mathbf{x}_{nj}^{sp}, \mathbf{b}_n, \nu_{nj}; \beta, \delta) \tag{3.15}$$

where P_{nj} (.) is the probability that shipper n chooses mode j under the RP and the SP model

If ε and ν are not independent, the estimated coefficients are still consistent and asymptotically normal, but they are not fully efficient (see Amemiya [1985]). The covariance matrix of the joint maximum likelihood estimates, calculated as the inverse of the information matrix, will then be biased downwards.

- sequential MLE: the sequential estimator of (β, δ, γ, and μ) allows the use of ordinary logit estimation software, following the steps:

step 1: estimate the SP model and obtain $\hat{\alpha}$, $\hat{\beta}$ and $\hat{\delta}$.

Define $V_{nj}^{rp} = - \beta' \mathbf{x}_{nj}^{rp}$ and form the fitted values $\hat{V}_{nj}^{rp} = - \hat{\beta}' \mathbf{x}_{nj}^{rp}$.

step 2: estimate the RP model with the fitted value $\hat{V}_{nj}^{rp}$ included as explanatory variables $\mu \hat{V}_{nj}^{rp} + \mu \gamma \mathbf{z}_n^{rp}$ and obtain $\hat{\mu}$ and $\widehat{\mu\gamma}$.

step 3: Calculate $\widehat{\mu\beta} = \hat{\mu}.\hat{\beta}$.

Additional gains in the efficiency of the parameter estimates can be obtained from pooling the data sets by multiplying all the RP variables by $\hat{\mu}$, and re-estimating the parameters of the model.

III.7- Assessing the Value of Service in Freight Transportation

Given the estimated coefficients from the combined RP and SP demand model, the value of service can be assessed from their behavioral interpretation. For example, the coefficient associated to transit time and reliability can be interpreted as the implied in-transit capital carrying cost. Values in excess of the current market interest rates indicate that shippers attaches significant weight to these service dimensions in their mode choice decisions.

On the other hand, demand elasticities also provide information on the value of service in freight transportation. Instead of deriving them analytically and using a typical or average shipper to evaluate it, the sample enumeration approach was adopted. For a given percentage change in attribute x_{ik} of mode k, the freight transportation demand model is used to estimate the effect in each shipper's mode shares and aggregated over the sample.

Differences in the value of service across segments are also evaluated based only on these aggregate demand elasticities. Using the same combined RP and SP model, the percentage change in the demand for each mode due to improvements in the service provided is simulated for shippers in each segment.

If differences in the demand elasticities across segments are significant, it would confirm the hypothesis that a single marketing and service design is unlikely to satisfy all current and potential customers. Two general implications can be derived from the usefulness of the market segmentation to carriers in the market place. First, it is important for a carrier to "know its markets", providing service to meet profitably the shippers' needs. Not only should carriers differentiate their service in each segment, but also focus on those segments which do not have conflicting needs.

Second, carriers' competition will vary among market segments. For example, a motor carrier may find that its main competition is the railroads in the price-sensitive segment, while other truck owners may compete fiercely for the time and service quality sensitive shippers. Thus, marketing activities should emphasize carriers' advantages relative to the needs in each market segment and relative to the strengths and weakness of likely competitors in each market.

IV - The Database

Two sources of information were used in the implementation and tests of the conceptual and statistical framework described in Chapter 3. Freight transportation demand models were estimated based on a shippers' survey of current market practices and perceptions of mode services. This survey also elicited shippers' stated preferences in a conjoint exercise with respect to different dimensions of transportation service.

Auxiliary data sources were used to validate the information on shippers' perceptions of service elicited in the survey. A strong link between perceived service and observed performance should exist, which allows carriers to influence shippers' mode choice decisions. Due to data availability, this link was developed only for the cost and time dimensions of service, with special focus on the rail mode.

Both data sources are described in detail in the sections that follows. The shippers' survey is described in section 4.1 and 4.2, including some summary statistics along the main dimensions of service for each mode. Section 4.3 discusses some issues in designing a survey to elicit information on shippers' mode choice. The auxiliary data sources are described in section 4.4, with special attention to make them comparable to the shippers' survey.

IV.1 - Primary Data Source: The Shippers' Survey

In 1988, a major U.S. railroad (RR) was evaluating new information systems designed to improve operations control and service quality. As part of this effort, it was important to understand the benefits of introducing an information system, in particular to determine the effects of changes in service quality on market share and revenues.

A marketing research company, henceforth called company ABC, was retained to survey shippers and to determine their sensitivities to service and price. ABC's approach was based on service quality elasticities derived from a conjoint experiment on several dimensions of service. The elasticities estimates then, reflected what shippers say they would do, and not on choices actually made. In general, shippers' responsiveness exceeded the expectations and experience of some RR marketing officials, who questioned the validity of the information collected and the methodology used.

The methodology used by ABC lacked an underlying shippers' behavior model, specific to transportation mode choice, and did not address the issue of validity of the information elicited from shippers in the survey. However, ABC's database provided the opportunity to implement the proposed methodology and reflect on the issue of value of service from the shippers' perspective.

- **The study scope**

The primary focus of the ABC study was to determine the demand elasticities of service variables in the transport of five commodities:

- paper;
- aluminum;
- pet food;
- plastics; and
- tires.

In order to understand the service issues and competitive environment within each commodity area, ABC consultants held meetings with RR market managers. Based on these meetings, the following service variables were considered:

- freight rate ($ per ton);
- transit time (days);
- consistency of transit time (reliability in % of time shipments arrive when wanted)
- loss or damage (% of shipment value lost or damaged);
- initial useability of equipment (% of time sufficient equipment is available);
- EDI (1, if carrier offers EDI; 0, otherwise);
- payment terms and billings (% of times shippers are satisfied);
- responsiveness to inquiries (% of times shippers are satisfied);
- level of effort required to work with the carrier (easy, normal, difficult).

Decision-makers from companies manufacturing the selected commodities were screened for participation. Besides having the responsibility to select the mode or carrier in different shipments, the decision-maker should ship at least $ 1 Million of that commodity annually. Given 348 shipper meeting this criteria and agreeing to participate, the actual response rate was around 50%. Table 4.1 shows the breakdown of returned questionnaires by commodity.

Table 4.1
No of Questionnaires Returned

Product	**Number of Questionnaires Returned**
Paper	52
Aluminum	39
Pet Food	26
Plastics	29
Tires	20
TOTAL	**166**

Source: ABC Shippers' Survey.

The questionnaires were administered via the mail due to the geographic dispersion of selected shippers. As described below, revealed and stated preferences were collected together with perceptions of mode service.

- **Revealed preference data**

Revealed preference (RP) data describes the shippers' current practices regarding mode choice decisions. For each shipper, information was collected for two major corridors used in outbound shipments of the selected commodities. These corridors were defined by shippers in terms of the origin and destination region, as well as the percentage of their annual tonnage shipped in that corridor. Figure 4.1 shows the definition of the eleven regions in the U.S. domestic market used to define corridors.

Five modes were included in the questionnaire: truck only, single carrier rail, multiple carrier rail, transload (with at least one transshipment between truck and rail) and piggyback (TOFC or COFC). Besides the mode shares in each corridor, the shipper was also questioned about the truck and rail carrier most frequently used. Due to the small shares of some modes, the estimated demand models considered the choice among three modes: truck, rail (single and multiple carrier) and intermodal (transload, TOFC/ COFC).

In terms of service attributes, the shipper reported the typical rate per ton and the "dock-to-dock" transit time by truck and by rail in each corridor. For other attributes, the shipper informed his/her perceptions of the service provided by each mode available. The latter perceptions however, were not specific to the corridors.

Finally, questions about characteristics of shippers, or firms they represent, were also included in the survey. On one hand, information detailing the shipper's service requirements included acceptable early and late delivery times, and the most important factors affecting each service attribute. On the other hand, annual sales, number of employees and the decision-maker's experience in the position provided the demographics of shippers surveyed.

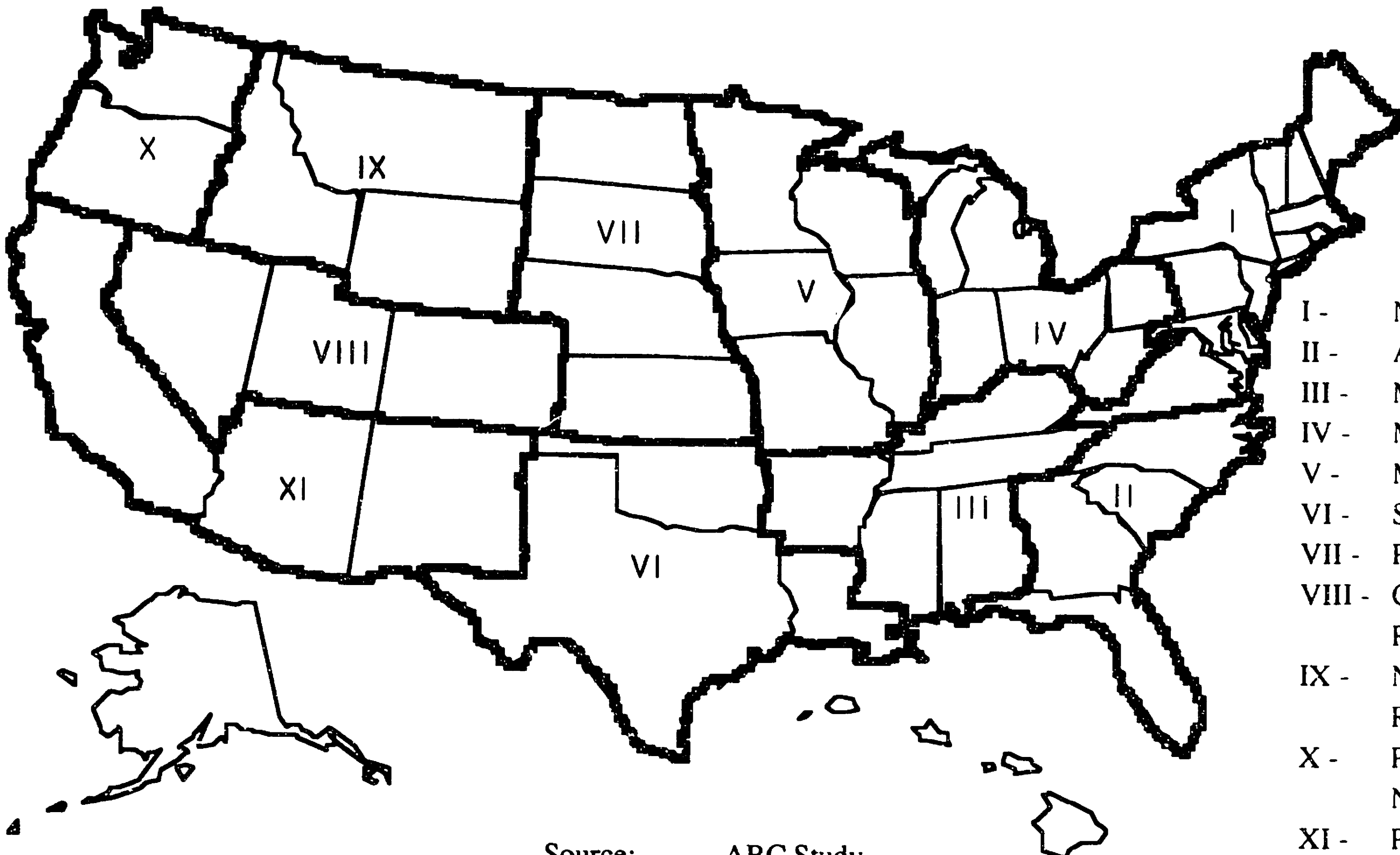
- **Stated preference data**

Stated preference (SP) data elicited shippers' behavior in hypothetical transportation scenarios. Shippers were presented with two offerings in terms of transportation service features, and asked to rate their preference relative to the right or the left profile on a 9-point Likert-scale. In this scale, one or nine meant strongly preference of one or the other profile, and five meant indifference between the two offerings. The scenarios did not refer to any particular corridor and, in fact, shippers were asked to think in general about their outbound shipments.

The transportation offerings or profiles in each scenario were described by the same attributes, but at different levels. In the ABC's study, each scenario used only two or three service attributes at a time to describe the profile, with the underlying assumption that the missing attributes were at the same level in both offerings. Since the mode was also

Figure 4.1

Origin-Destination Regions



I -	Northeast
II -	Atlantic
III -	Midsouth
IV -	Mideast
V -	Midwest
VI -	Southwest
VII -	Plains
VIII -	Central Rockies
IX -	Northern Rockies
X -	Pacific Northwest
XI -	Pacific Southwest

Source: ABC Study.

considered as an attribute, it was not always identified in the scenarios. Moreover, in order to retain the realism of these offerings, the rate and transit time attributes were formulated as increases or decreases from current levels. In Appendix B, a description of the levels of each service attribute is provided.

Figure 4.2 presents an example of such trade-off questions. Each shipper answered to forty trade-off questions, thinking about the choice of carriers for their outbound shipments of the selected commodity. The attributes and levels in each offering were chosen for each shipper based on his/her current perceptions of mode services to keep the realism of the question, while trying to better elicit the trade-offs among service attributes.

IV.2 - Current Market Environment

The shippers interviewed for the ABC's study represented companies ranging in size from less than \$ 10 million to more than \$ 5 billion in annual sales revenue earned from the selected commodities. In Figure 4.3, the distribution of company size in the overall sample is presented. The breakdown by commodity however, showed that paper and aluminum companies tend to be larger than companies for the other selected commodities, with 52% and 40%, respectively, having revenues greater than \$ 100 million (compared to 29% for the other commodities).

Overall, shippers reported that more than 70% of their shipments are made on their two major corridors. Among the different geographic definitions of corridors, within the Northeast region was the most frequently cited for paper, aluminum and pet food, accounting for more than 10% of all shipments of these commodities. Within the Mideast was reported as the major corridor by more than one quarter of plastic shippers. Even though tires shipments were reported to be geographically scattered, the Northwest-Midwest corridor accounted for 18% of their traffic.

In terms of mode usage, truck is reported as the predominant mode for each commodity studied, transporting 50% to 90% of total shipment volume. Rail shipments are important for paper and plastics, accounting for more than 40% of the volume shipped. The intermodal share is only significant for paper (6%), plastics (6%) and tires (8%). Table 4.2 presents the mode shares for each commodity in terms of annual tonnage shipped. The small sample size restricted further analysis of specific carrier usage for confidentiality and statistical significance reasons.

Figure 4.2

Example of Trade-off Question

Which service offering would you prefer ?

10%	**lower than average rate I pay now**
80%	**of shipments arrive when I want them to**

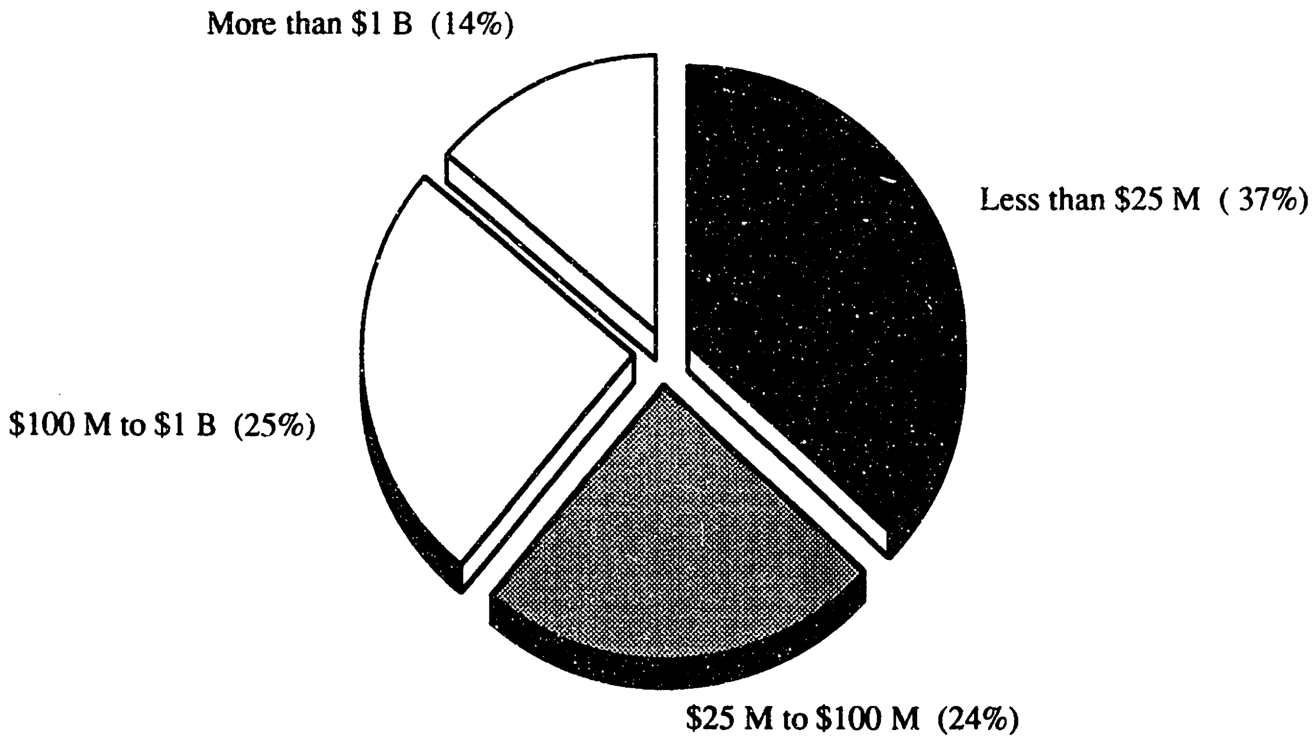
10%	**higher than average rate I pay now**
90%	**of shipments arrive when I want them to**

1	2	3	4	5	6	7	8	9
Strongly Prefer Left								Strongly Prefer Right

Source: ABC Study.

Figure 4.3

Company's Annual Sales in the ABC Study



Source: ABC Study.

Table 4.2
Mode Shares[1] for Selected Commodities

Product	Truck	Rail[2]	Intermodal[3]
Paper	50.3	43.4	6.3
Aluminum	88.5	9.6	1.9
Pet Food	93.0	4.8	2.2
Plastics	45.6	48.6	5.8
Tires	88.6	3.9	7.5
OVERALL	**71.9**	**23.9**	**4.2**

[1]In percentage of annual tonnage shipped.
[2]Includes single and multiple carriers movements.
[3]Includes transload and piggyback (TOFC or COFC) movements.
Source: ABC's Shippers' Survey.

Although truck usually costs more than rail, it is perceived to outperform rail in all major service dimensions. Furthermore, even with limited usage reported by shippers, intermodal is also perceived to perform better than rail on key elements of service, and to be at a similar level to truck in most areas. Table 4.3 presents the performance differences among modes as <u>perceived</u> by the shippers interviewed in the ABC's study.

It is important to observe that the differences in cost among modes is small relative to differences in other service dimensions, suggesting a significant advantage for the truck. While truck rates were about one third higher than rail, the most significant differences in service were observed for transit time and reliability dimensions. Truck is perceived to take roughly one-third the time of rail and to be about 10% more reliable than rail. Even though the perceived differences among modes are not so significant in other service dimensions, a similar pattern was observed - truck outperforms rail and intermodal is close to truck performance.

Table 4.3
Average Service Quality of Modes

Service Quality Dimension	Unit of Measurement	Truck	Rail[1]	Inter-modal[1]
Rate	$ / ton	62.07	44.27	53.17[2]
Transit Time	days	2.2	7.0	4.6[2]
Consistency of Transit Time	% of times shipments arrive when wanted	91.1	83.1	88.7
Loss or Damage	% of shipment value	0.3	0.6	0.6
Initial Useability of Equipment	% of times sufficient equipment is available	95.2	91.2	93.5
Offer EDI	1; if carrier offers EDI 0; otherwise	0.3	0.6	0.3
Payment Terms & Billings	% of times shipper is satisfied	84.4	76.6	84.2
Responsiveness to Inquiries	% of times shipper is satisfied	85.9	70.0	80.9
Level of Effort	1, easy ; 2, normal ; 3, difficult	1.2	1.7	1.3

[1]lowest level of service between single and multiple carriers for rail, and between transload and TOFC/COFC for intermodal.

[2]since intermodal rates and transit time were not elicited, the midpoint between rail and truck service is taken for illustrative purpose.

Source: ABC's Shippers' Survey.

IV.3 - Comments on Designing the Shippers' Survey

Most of the freight transportation demand studies reviewed in Chapter 2 relied on transportation databases, usually combining shippers' choice with carriers' observed performance. Among these databases, the waybill sample and car cycle analysis data, presented in the next section of this chapter, are good examples for the rail mode performance. The underlying assumptions are that shippers' have perfect information about available modes and that their perceptions of service are identical to carriers' observed performance. Not only is it difficult to identify all service dimensions relevant in the mode choice process, but also to observe them may turn out to be impossible. In addition, perceptions may vary across shippers independently of the observed average carriers' performance.

The concept of surveying shippers' perceptions of carriers' performance is critical to understand the mode choice process. However, surveys should be carefully designed to elicit shippers' behavior under different mode choice situations. Moreover, the analysis of survey data should incorporate potential source of biases affecting shippers answers to the questionnaire.

Even though, the shippers' survey was already completed by the time of this research, it is important to mention some strengths and weaknesses in the data collection process. It is true that the comments that follows have a hindsight vision of the problem, but they will prove to be useful in future designs of shippers' survey.

Surveys can usually be divided into two parts. First, trying to understand shippers current practice; second, trying to elicit their behavior under hypothetical scenarios. In both parts, it is important to have an underlying behavioral model in order to collect the relevant information and to present scenarios that are realistic descriptions of market situation.

One of the strengths of the ABC's study in collecting information about the shippers' current transportation practice was the identification of two major corridors. This allowed for a greater level of specificity in their information about mode shares. Unfortunately, perceptions of mode service were not specific to the corridors, except for rates and transit times. In addition, rate and transit time were informed only for the rail and truck modes, leaving the intermodal options without specific information regarding these attributes.

The choice of attributes to describe the transportation service was also very extensive, including dimensions not usually contemplated in demand analysis (e.g. satisfaction with payment terms and billings, responsiveness to inquiries and level of effort). However, the ABC's survey made no reference to the simultaneity between the shipment size and mode choice decisions. Not only are some mode attributes dependent on the shipment size (e.g. rates), but also the logistic cost is a function of the frequency of shipments. To correct this weakness, information about shipment size or frequency should be included in future surveys, preferably specific to corridors and modes used.

With respect to stated preference data, one of the strengths of the ABC's study was to adapt the trade-off questions depending on the information elicited for the current market practice. This approach, usually referred as adaptive conjoint analysis, recognizes the importance to formulate scenarios that are realistic under shippers perceptions of mode service.

On the other hand, the issue of presenting two or three attributes at a time to describe transportation services deserves some attention. Alternatively, the full profile approach could have been used, which includes all attributes in the description of each transportation offering. On of the advantages is that it is not necessary to rely on the assumption that missing attributes are equal between the profiles in a given scenario.

However, it is not recommended to use the full profile approach with a large number of attributes. In particular, the ABC's study selected ten attributes to describe transportation services. The benefits from the extensive description of transportation services have to be balanced with the ability of shippers to differentiate among all attributes in their stated preferences. Note that the mode used was also considered as an attribute, which was not always present in describing the alternative transportation offerings. This feature though, is not desirable when calibrating mode choice models.

IV.4 - Auxiliary Data Sources: The Waybill and Car Cycle Data

Auxiliary data sources were used to validate the information obtained from the shippers' survey, comparing perceived service with observed performance by different modes. Unfortunately, observed data for all service dimensions and modes contemplated in the ABC's study was not available. While some dimensions are not usually observed, e.g. satisfaction with payment terms and billings, responsiveness to inquiries and level of effort, other dimensions are not usually available in databases, e.g. useability of equipment and loss and damage. The auxiliary data sources described in this section focus on rail observed performance, and in particular rate, transit time and reliability measures of service.

- **Carload waybill statistics**

The Carload Waybill Statistics (CWS), collected under contract by the Association of American Railroads (AAR) for the Interstate Commerce Commission (ICC), is the most important database for railroad regulatory and public policy decision-making. With the introduction of electronic data reporting in mid-1981, railroad were required to provide additional information on the traffic sampled. With more than 90% of the sampled waybills being submitted in machine-readable input (MRI) format since 1985, a stratified sampling was adopted, allowing for an actual sample to population rate of over 2.6% (see Table 4.4).

The information reported in the waybill includes the shipment identification and mode-specific data. Under shipment identification, the origin-destination, the commodity being transported and the shipment size (weight and number of carloads) is reported. Under mode-specific data, the CWS include different components of freight revenue and estimated distance traveled in each railroad participating in the movement. Note that the CWS includes piggyback (TOFC/COFC) movements, whereas their identification is possible through the equipment type and data specific to intermodal carriers.

In order to use the CWS database to validate the shippers' survey information, it is important to aggregate the CWS to a comparable level of detail. Since shippers are not identified in the survey database, the validation can only be developed at the commodity level. Note that some selection biases may be introduced from the fact that the shippers' survey included only companies with annual revenues in excess to $1 million being derived from the selected commodities, while no such restriction is imposed in the CWS. Moreover, the CWS database has to be aggregated in terms of the origin-destination regions used to define the shipping corridors in the survey.

Table 4.4
The Stratified Sampling Procedure in the Waybill Statistics

No of Carloads Listed in Waybill	Sampling Rate
1 - 2	1 of 40
3 - 5	1 of 12
16 - 60	1 of 4
61-100	1 of 3
101 or more	1 of 2

Source: Wolfe, K. E., 1986, "The Carload Waybill Statistics", Transportation Research Forum.

After selecting the commodities from the waybill sample tape, 34,532 records were retained for further analysis. Table 4.5 presents the breakdown by commodity and car type used for the 1985 CWS (all railroads and origin-destination regions). Unfortunately, the 1989 CWS was not made available for this research, and the impact in the comparison with the shippers' survey data is addressed in Chapter 5. Even though the selected commodities represented 10% of the total waybill sample, more than 60% of the selected records involved movements of paper products. The car type dimension was important to identify intermodal movements specific to the selected commodities. Box cars were the most used rail car type for all commodities, except for plastics and pet food which had more than 60% of the waybill sample moving on covered hoppers. Intermodal movements were significant only for pet food and tires (above 10% of waybill records), which parallels the findings in the shippers' survey.

Table 4.5
Number of Records in CWS Database

Car Type	Paper	Aluminum	Pet Food	Plastic	Tires	Selected Product	Waybill Sample
Box Car[1]	21,151 (91%)	1,752 (51%)	446 (27%)	17 (1%)	897 (65%)	24,263 (70%)	59,695 (18%)
Hopper	7 (0%)	761 (22%)	1,001 (60%)	4,442 (93%)	-	6,211 (18%)	113,751 (34%)
Flat Car	63 (0%)	305 (9%)	-	9 (0%)	2 (0%)	379 (1%)	13,966 (4%)
Intermodal	1,821 (8%)	281 (8%)	221 (13%)	158 (3%)	480 (35%)	2,961 (9%)	93,876 (28%)
Others[2]	224 (1%)	339 (10%)	5 (0%)	150 (3%)	-	718 (2%)	52,536 (16%)
TOTAL	23,266	3,438	1,673	4,776	1,379	34,532	333,824
% WB Sample	7.0	1.0	0.5	1.4	0.4	10.3	100

[1]Includes tank cars.

[2]Includes gondolas, maintenance-of-way cars, passenger cars, cabooses and locomotives.

Source: Carload Waybill Statistics, 1985.

A sample of waybill statistics for the selected commodities is presented in Table 4.6. The distinction between rail and intermodal was done through the rail car type, assuming the car is used according to its type. Across all selected commodities, the average length of haul and rate (in $/ton) by rail are less than the ones observed by intermodal. Note that both modes were used, on average, by shipments over more than 1000 miles. On the other hand, intermodal shipment size was around 20 tons, being significantly smaller than the rail one.

Table 4.6
Waybill Sample Statistics for Selected Commodities

Product	Rail			Intermodal		
	Rate ($/ton)	Weight (ton)	Distance (miles)	Rate ($/ton)	Weight (ton)	Distance (miles)
Paper	42.21	59.00	916.14	48.33	21.47	1350.86
Aluminum	40.44	103.80	1118.54	44.64	25.10	1402.59
Pet Food	21.24	33.32	529.00	42.64	28.95	1233.70
Plastics	34.17	91.89	879.25	48.03	24.54	1473.89
Tires	61.97	23.96	922.96	71.89	15.79	1352.40

Source: Carload Waybill Statistics, 1985.

The ICC mandates that the Waybill Sample must contain less than one percent error, and that error must be of a non-repetitive or non-serial nature. According to the ICC, if one or more of the required data elements in the waybill is missing or illogical, the waybill is considered in error. However some issues on the interpretation and use of the CWS data still needs to be mentioned.

- reported revenues may be overstated to retain the confidentiality of contracts;
- differences between billed and actual weight (see Wolfe [1986]); and,
- transcontinental shipments are often billed as two or more separate waybills to receive quicker revenue settlements. In this case, the length of haul in the waybill may not represent the true movement.

• **Car Cycle Analysis System**

The Car Cycle Analysis System (CCAS) is a collection of computer software which processes car movement events reported to AAR Train II system in order to produce car utilization statistics. This data includes the basic car movement information necessary for creating and analyzing both loaded and empty car cycles. Figure 4.4 lists the major events which the Train II system has been designed to collect and store in its historical database. An individual car traveling in the U.S. rail network will often have reports from different railroads.

In order to effectively generate car utilization statistics, a sample of cars and a time period for which these statistics are needed is usually selected. Data processing costs are the main rationale for sampling freight cars. During the time of this research, the AAR Affiliated Laboratory at M.I.T. was developing an assessment of trip times and reliability of box car traffic using a 10% random sample of the CCAS data for that car type during the twelve-month period between November 1989 and November 1990.

This auxiliary data was then, derived from selecting the commodities of interest in the box car study database, reducing the data processing costs significantly. The appropriateness of the sample selection has to be evaluated in two dimensions. First, box cars were the most heavily used in the transportation of the selected commodities, except for plastics. Any validation of rail trip times and reliability are represented by box car movements. Second, ideally the time period contemplated in the box cars study should coincide with the one in the shippers' survey. Even though the time reference is one year later than the shippers' survey, one of the conclusions in the box car study was that the loaded trip times did not vary significantly between 1972 and 1990.

Due to variations in the reporting capabilities among railroads, the original box car database had some records with missing information. Table 4.8 shows the number of complete and partial records. Complete records have information on the different components of the car cycle, i.e. shipper, loaded, consignee and empty times. Since only the loaded trip times were analyzed further, the problem of different sample sizes due to partial records is minimized. All records containing information on the loaded trip time component of the car cycle were retained.

Figure 4.4

Car Movement Events in the CCAS Database

A - placement empty

B - released loaded

C - arrival loaded

D - interchange loaded

E - arrival loaded

F - placement loaded

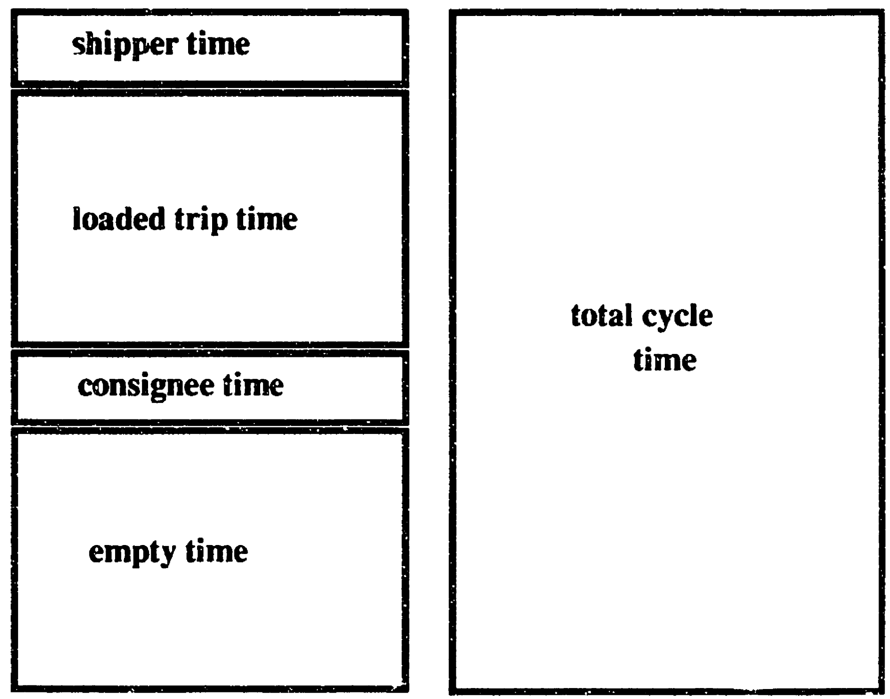
G - release empty

H - arrival empty

I - interchange empty

J - arrival empty

K - placement empty



Source: Little, P. et al (1991), "An assessment of Trip Times and Reliability of Box Car Traffic, CTS/MIT, Cambridge.

Table 4.8
Number of Records in the Box Car Cycle Database

Status	Shipper Time	Loaded Trip Time	Consignee Time	Empty Trip Time	Total Cycle
Complete	4,905	4,905	4,905	4,905	4,905
Partial	6,719	5,598	7,672	3,474	2,628
TOTAL	11,624	10,503	12,577	8,379	7,533

Source: Little, P. et al, 1991, "An Assessment of Trip Times and Reliability of Box Car Traffic", Center for Transportation Studies, M.I.T., Cambridge.

For the purpose of validating shippers' perceptions of service, car cycle statistics were aggregated in terms origin-destination regions and commodities. The auxiliary database with 28,445 records, contains information identifying the movements (origin, destination and commodity) and the components of the car cycle. Note that more than 92% of the records involved paper movements. Besides the comparison between perceived and observed trip times, several reliability measures are discussed in Chapter 5.

Table 4.9 presents some car cycle statistics for the selected commodities. The results derived for pet food and plastics may not represent adequately the rail performance, because of the importance of other than box cars in the rail transport of these products. On average, loaded trip time was around 9 days, representing more than 65% of the car cycle time without the empty trip component. Moreover, the time spent with the shipper was more than 2 days, being significantly larger than the time spent with the consignee. No significant differences across products is worth mentioning at this point.

Table 4.9
Box Car Cycle Components for Selected Commodities

(days)

Product	No. of Obs.	Shipper Time	Loaded Trip Time	Consignee Time
Paper	26,252	2.60	9.07	1.64
Aluminum	961	4.59	8.96	2.12
Pet Food	59	2.12	9.08	3.15
Plastics	40	3.97	12.61	6.03
Tires	1133	3.75	9.09	2.09
Overall	28,445	2.71	9.07	1.68

Source: Cycle Analysis System (Box Cars - Nov/89 to Nov/90).

• Other Auxiliary Information: Commodity and Mode Attributes

Besides the CWS and CCAS databases described above, other sources of information were used to complement the shippers' survey. However, the following information is not specific to the shippers surveyed, suffering from the same problems of aggregation regarding the commodity transported and the origin-destination regions.

Within each one of the selected commodities up to seven different products were specified in the shippers' survey. Prices and densities were obtained, at a product level of detail, from the Commodity Attribute Data File[1]. Values per pound quoted in the file are wholesale prices in 1972 dollars. These price were updated to 1989 dollars per ton using

[1] Samuelson, R. D. and Roberts, P. O. (1972), " A Commodity Attribute Data File for Use in Freight Transportation Studies", Center for Transportation Studies, M.I.T., Cambridge.

product-price indices and different industry reports specific to the commodities involved. Density figures were quoted for density loaded in a transport vehicle in pounds per cubic feet. Only conversion of units to the metric system (ton/m^3) was applied to the density data.

In terms of mode-specific information, distance by truck and by rail were estimated for each origin-destination region. Since specific locations were not specified for the transportation corridors in the shippers' survey, a typical city was chosen close to the center of each region, and the distance between regions determined through the shortest route in the modal networks. For movements within a region, two cities were chosen in order to span a significant part of the region. While for the rail network, only the main line railroad service between leading cities were considered, for the truck network, only the Interstate Highway System was included.

V- Comparing Perceived Service with Observed Performance

As hypothesized in Chapter 3, shippers are sensitive to changes in their perceptions of transportation services, and not directly to changes in the system characteristics. Nevertheless, a strong link between the perceived service and the observed performance should exist, allowing carriers to influence shippers' mode choice decisions through changes in system characteristics. In this chapter, this link is analyzed using information external to the shippers' survey. The purpose is to assess misperceptions on the shippers' behavior, and to discuss implications to the transportation service design and marketing.

The demand models used to determine the value of service in freight transportation (see Chapter 6) are calibrated based on shippers' perceptions of the service provided by different modes. It is then, important to understand the differences to the actual service provided and what mechanisms can be used to explain them. In addition, the following analysis was also used to validate the information in the shippers' survey, correcting for inconsistencies in their answers and supplying data for missing information.

These comparisons provide strategic information for carriers to evaluate the impact that changes in system characteristics have in shippers' perceptions of service and, ultimately, in their mode choice. Together with the demand elasticities for different service attributes, carriers can design better service to meet shippers' needs.

Even though the comparison could be developed for each service dimension considered in the survey, this analysis focused only on the cost of transportation and its transit time and reliability. The following section describes the scope of the analysis and discusses the limitations in the available data on carriers' performance. The perceived and observed rates are compared in section 5.2. Transit time and reliability are analyzed in section 5.3, including a discussion on reasons for misperceptions and strategies to influence shippers' perceptions along these dimensions. Intangible service dimensions that can not or are difficult to be observed, like responsiveness and level of satisfaction with payment terms and billings are analyzed in section 5.4. Finally, the information contained in shippers' perceptions of service is summarized in the last section.

V.1 - Scope of Analysis: Framework and Data Limitations

In order to develop a general framework to compare perceived service with observed performance, two issues with respect to its level of aggregation need to be addressed. First, perceptions are formed basically from shippers' past experience with different carriers or "word-of-mouth" in the market place, rather than based on average performance of the system. Ideally, the comparison should be developed with observed performance measured for shipments of a particular shipper whose perceptions of the service provided were also available. Second, the analysis should be carrier-specific in order to provide strategic information in the service design process.

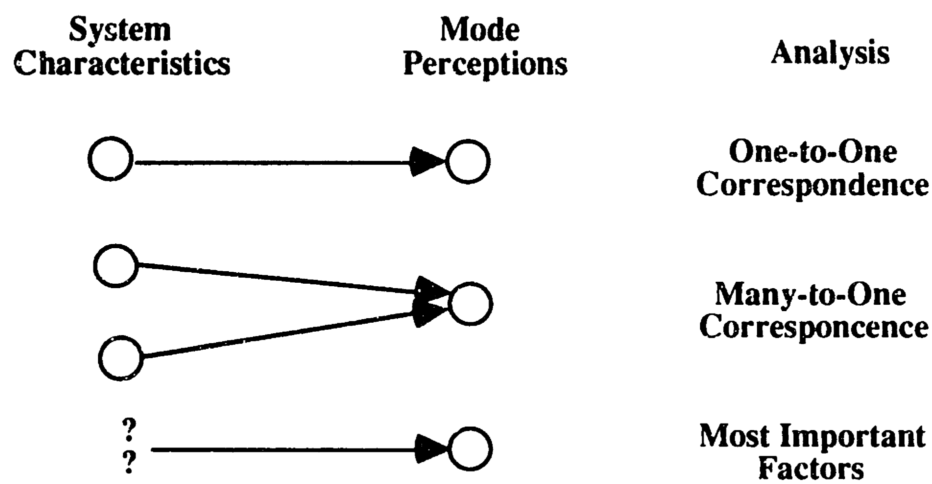
Unfortunately, it was not possible to develop shipper-specific comparisons. Not only were the shippers not identified in the survey data, but also the auxiliary databases did not have information on the owner of the cargo being transported (see Chapter 4). The maximum level of detail combining perceptions with observed performance data was commodity-specific comparisons, with some analysis also distinguishing the origin-destination regions for the movement.

In addition, due to confidentiality reasons and to lack of statistical significance of the small sample specific to different carriers, only mode-specific comparisons were made. In particular, the following analysis focused only on the rail mode, with brief comparisons with perceptions of truck and intermodal service when relevant. The purpose is not to analyze in detail the performance of different modes, but rather to provide some insights on how they compare with shippers' perceptions regarding cost, transit time and reliability.

Figure 5.1 presents a general framework for comparing perceived service and observed performance. For convenience, the comparisons were classified depending on the identification of system characteristics providing information to shippers' perceptions. Even though, this analysis was limited in scope, the framework can be applied to all service attributes in the survey. In addition, statistical models could be developed relating perceptions to changes in the system characteristics under the carriers control. These models would provide strategic tools for carriers to evaluate alternative service design strategies to better meet the shippers' needs. However, the level of aggregation in the available data and the limitations described in the following sections precluded the development of such models.

Figure 5.1

The Framework to Compare Perceived Service with Observed Performance



For perceptual dimensions that can be observed in the system, two types of comparisons can be developed: one-to-one and many-to-one correspondences. One-to-one correspondences refer to those perceptual dimensions that can be associated with a single observable system characteristic, e.g. rate and transit time. By changing the system characteristic under control of carriers, the statistical model would simulate the effect on shippers' perceptions of that service attribute. Many-to-one correspondences refer to perceptions for which there are different ways to measure them in the system, e.g. reliability of transit time. Now, carriers have different ways to affect shippers' perceptions, and they can choose the one with the highest impact at a minimum cost.

For perceptual dimensions that can not or are difficult to be observed in the system, shippers were asked to identify the most important factors affecting their perceptions of mode services. Among these perceptual dimensions, the level of effort to deal with carriers and the level of satisfaction with respect to payment terms and billings and to the responsiveness to inquiries are examples that can not be directly observed[1]. By correlating the perceptions of service provided with the number of times a given factor was appointed as being the most important one, carriers can identify areas of improvement along these dimensions.

V.2 - The Perception of Cost: Rail Rates

The cost of transportation includes all expenses incurred during the movement of shipments from the shippers' terminal to the consignees' dock. A strong link between carriers' revenue and shippers' perceptions of the rate per ton should exist, except for the latter one including special charges like terminal handling operations.

• Available Data and their Limitations

On the shippers' side, the perceived rate per ton by truck and by rail were elicited in the survey. These rates were elicited for two major corridors used by each shipper, defined by their origin-destination regions (see Chapter 4). Due to the regional level of aggregation, it was not possible to determine the actual length of haul in each corridor. Rather, the distance between centroids in the origin and destination regions was considered to be representative of the shipments surveyed. This issue was also of concern in the transit time and reliability analysis in the next section. Moreover, information on the shipment size was also not available in the survey, restricting the comparisons along this dimension.

On the carriers side, freight revenues were obtained from the waybill sample. Besides the inherent problems discussed in Chapter 4, this data source was available only for 1985. Even though significant changes did not take place between 1985 and 1989, this temporal mismatch with the shippers' survey poses additional problems in comparing observed vs. perceived rates. In particular, it would be difficult to identify if differences are related to an increase in rates or to cognitive mechanisms determining shippers' perceptions. Nevertheless, the waybill sample contains relevant information on the length of haul and the shipment size, not available in the shippers' survey.

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[1]unless a customer service department is operating with a detailed record of complaints.

With respect to the sample selection, only those shipments associated with the commodities in the shippers' survey, were selected from the 1985 waybill sample. In addition, rail movements were distinguished from intermodal ones through the car type used, as well as through some mode-specific variables available in the original database. No information was available on motor carriers' revenues. Table 5.1 presents the breakdown of the number of observations in each data source. In order to avoid biasing the analysis towards the large number of paper shipments, most of the analysis that follows was developed by commodity.

Table 5.1
Number of Observations in Database

Database	Mode	Paper	Aluminum	Pet Food	Plastics	Tires	Overall
Shippers' Survey	all	52	39	28	29	20	166
Waybill Sample	rail	19,088	1,808	1,022	4,412	859	27,190
	intermodal	1,687	235	218	157	480	2,777

- **Observed vs. Perceived Rates**

Given the origin and destination of shipments, rates are usually quoted on a per ton basis. Table 5.2 presents the rates per ton for each commodity in both data sources. While perceived rates were elicited in the survey, observed rates corresponds to the total freight line-haul revenues divided by the billed tonnage as reported in the waybill sample. Since there is not a direct correspondence between shippers in the survey and shipments in the waybill sample, the length of haul was used to evaluate any sample selection biases towards longer or shorter trips in anyone of the data sources.

Besides the similar average lengths of haul, observed and perceived rates per ton were also very close, where misperceptions can be attributed to random noise in the data. Also, the differences across commodities were consistent in both data sources, with plastics and pet food shipments being charged the lowest rates and tires shipments receiving the highest ones. The fact that the rate information were collected in different time periods did not play a major role in the comparisons, either because rates have not changed significantly between 1985 and 1989, or because the changes were offset by shippers perceiving a lower rate than they have been charged on average.

On the other hand, the comparison of rate across modes is presented in Table 5.3. While truck rates were, on average, perceived to be 30 to 35% more expensive than rail, intermodal revenues per ton were 20% higher than those observed in rail shipments. No significant variations on these percentages were observed across commodities.

Note that rates per ton were used instead of weighting them also by the length of haul (i.e. rate per ton-mile) for two main reasons. First, both data sources did not have information on the actual transportation distance. In the waybill sample, a network model was used to determine the distance between specific origin-destination locations. In the shippers' survey, these distances were estimated between centroids representing the origin-destination regions. Second, rate comparisons are meaningful only with shipment-specific data, i.e. rates by different modes available to a particular shipment. While in the shippers' survey, rates by truck and by rail referred to the same corridor, in the waybill sample, revenues referred only to the mode used and not to all available modes for a given shipment. Thus, introducing the length of haul dimension would potentially add random noise to the data, without enriching the already very aggregate comparisons of rates.

Since shippers' perceptions of rail rates were, on average, very close to the reported carriers' revenues in the waybill sample, statistical models relating them have limited use. In other words, it is reasonable to assume that shippers have accurate perceptions of the cost of transportation by different modes. To go beyond the comparison of mean rates, it is necessary to have shipper-specific data on observed rates by different modes.

Table 5.2
Perceived vs. Observed Rail Rates ($/ton)

Database		Paper	Aluminum	Pet Food	Plastics	Tires	Overall
Shippers' Survey	miles	930	910	770	830	1040	900
	$/ton	40.00	42.47	33.16	31.36	50.68	39.29
		(21.4)	(29.1)	(18.1)	(13.2)	(44.7)	(26.3)
Waybill Sample	miles	929	1131	652	890	965	927
	$/ton	42.52	40.68	25.79	34.46	63.79	41.13
		(34.0)	(26.8)	(19.7)	(23.8)	(35.4)	(32.3)

Obs.: Standard deviations in parenthesis

Table 5.3
Comparison of Average Rates ($/ton) by Different Modes

Database	Mode	Paper	Aluminum	Pet Food	Plastics	Tires	Overall
Shippers' Survey	truck	53.59	58.57	41.66	43.82	71.55	53.35
	rail	40.00	42.47	33.16	31.36	50.68	39.29
Waybill Sample	rail	42.52	40.68	25.79	34.46	63.79	41.13
	intermodal	48.38	44.54	43.10	48.18	71.89	51.70

In addition, rail and intermodal rate functions were calibrated using only the waybill sample. While increases in the shipment size was associated with rate discounting, longer lengths of hauls implied in higher rates per ton; both effects being statistically significant. Note that volume discounts were the highest for rail shipments of paper, and for intermodal shipments of aluminum and plastics. The specific results are not pertinent to the comparison of perceived vs. observed rates, since comparable data on shipment size was not available in the shippers' survey. Thus, they were omitted from this discussion.

VIII.3 - The Perception of Time: Rail Transit Time and Reliability

One of the most important dimensions of service quality in freight transportation are transit time and reliability. Even though motor carriers outperform the railroads in virtually all service dimensions, it is on transit time and reliability that lie their greatest advantages. On the demand side, shippers' logistic costs are influenced by the transportation lead time and its variability through the inventory carrying and stock-out costs. In fact, demand elasticities are perceived to be very high along these dimensions of service across all modes. Thus, it is very important to compare the perceived vs. the observed transit time and reliability and understand the causes of eventual misperceptions on shippers' behavior.

• Available Data and their Limitations

Besides the information on the shippers' survey, the car cycle data was used to obtain the observed rail performance with respect to transit time and reliability. The car cycle data refers to a sample of box cars movements in U.S. railroads, during 1990. As detailed in Chapter 4, box cars were the most used car type for all commodities, except for pet food and plastics which had more than 60% of the waybill sample moving in covered hoppers. Results for these products were then, omitted from the car cycle data analysis.

Table 5.4 presents the breakdown on the number of observations in both data sources. In order to avoid biasing the analysis of observed performance towards the significantly larger number of paper shipments, comparisons with shippers' perceptions were made at the commodity level.

Table 5.4
Number of Observations in Databases

Database		Paper	Alumi-num	Pet Food	Plas-tics	Tires	Over-all
Shippers' Survey	all	52	39	28	29	20	166
Car Cycle	% Box Cars[1]	90.1	47.6	16.6[2]	0.2[2]	65.1	15.6
	O/D with N >5	17,240	579	-	-	165	18,712
	Total	23,356	817	32	37	1,052	25,294

[1]from Waybill Sample, 1985.

[2]covered hoppers accounted for 93% of plastic movements and 60% of pet food movements

Two additional issues are relevant to the car cycle sample selection. First, for reliability measures, the thrust lies in the variability of transit time for the same product and origin-destination locations. Since car cycle data represented a 10% sample of all box car movements in 1990, only those O/D pairs with more than five movements were considered in the analysis. Assuming that each origin represents a different shipper, this selection corresponds to approximately those shippers with one or more shipments per week. Second, an outlier analysis was performed with the car cycle data. All movements with transit time below one day or above 21 days or three standard deviations from the mean transit time were excluded from the database.

For completeness, all information in the shippers' survey was included in the analysis, even if the equivalent observed data was not available or representative. Not only were the perceptions associated to all commodities analyzed, but also the perceptions of service by truck and by intermodal compared with those by rail.

• **Observed vs. Perceived Transit time**

In the shippers' survey, transit time was defined as the typical dock-to-dock trip time by truck and by rail. Two qualifications are then, necessary: first, it does not include the loading/unloading or any other terminal operations; second, the typical trip time might be interpreted as the time which occurs more often (mode) or just the average transit time in a given O/D pair. The equivalent concept in the car cycle data is the loaded trip time, averaged across all shipments of a given commodity in a particular O/D pair.

Tables 5.5 and 5.6 present the summary statistics for the observed and perceived transit time. It also includes the average length of haul, in order to assess the presence of biases towards short or long trips in either one of the data sources. In general though, the average length of haul were comparable in both data sources, with the largest differences being observed for paper shipments.

The observed transit time by rail was, on average, 8.5 days and did not present significant variations across commodities. In terms of car cycle components, the time spent on the shippers' terminal was usually higher than at the consignees' terminal, both representing about 35% of the car cycle without empty movements. The perceived time by rail was on average 7 days, with tires and plastic shipments usually taking longer than those of aluminum and pet food. Rail shipments was also perceived to take around five days more than the truck, across all commodities.

Besides differences in the sample selection, two reasons might account for shippers perceiving the transit time to take, on average, 1.5 days less than it actually does. First, shippers' perceptions might be related to the mode of the distribution, which under log-normality[2] is less than or equal to the mean transit time in a given O/D pair. Second, some shippers may not include weekends and holidays in their perceived transit time. In this case however, the observed transit time is heavily influenced by shippers or consignees that do not operate on part of the weekend, specially for long trips. If the rail car arrives on a weekend, it can not be released to the consignee's terminal until the next day of operation, which can add up to two days in the transit time. Compounding both effects, it is possible

[2]reasonable assumption where a minimum trip time exists and long trips are frequent due to possible delays.

Table 5.5
Observed Transit Time by Rail

(days)

	Paper	Aluminum	Tires	Overall
Distance	780	1150	1140	810
Shipper Time	2.6 (3.3)	4.5 (3.1)	3.5 (3.8)	2.7 (1.2)
Consignee Time	1.7 (1.5)	2.2 (1.7)	2.0 (1.9)	1.7 (1.6)
Loaded Trip Time	8.5 (3.3)	8.3 (2.8)	8.8 (2.7)	8.5 (3.2)

Obs.: Standard deviations in parenthesis.

Table 5.6
Perceived Transit Time by Truck and by Rail

(days)

	Mode	Paper	Alumi-num	Pet Food	Plas-tics	Tires	Over-all
Distance	**all**	930	910	770	830	1040	900
Transit Time	**rail**	2.2 (1.3)	2.3 (1.3)	2.0 (1.6)	2.1 (1.1)	2.7 (1.4)	2.2 (1.3)
	truck	6.9 (2.4)	6.7 (3.4)	6.3 (3.4)	7.4 (4.1)	7.9 (2.3)	7.0 (3.0)

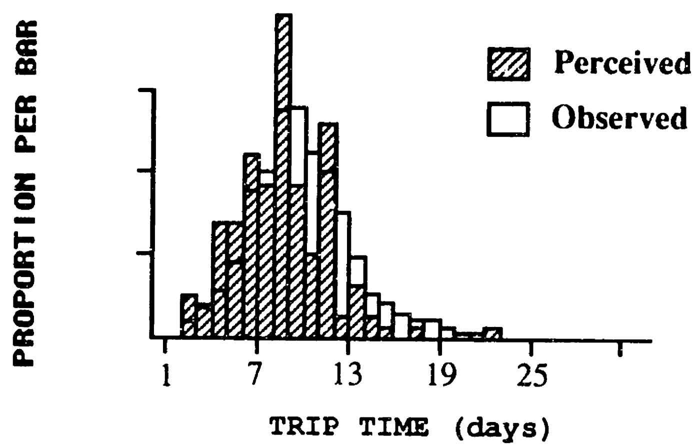
Obs.: Standard deviations in parenthesis.

to even reverse the relationship, i.e. shippers would be perceiving transit times to be longer than it actually is observed in the system.

Figure 5.2 shows the empirical distribution of perceived and observed transit times. Note that the perceived distribution corresponds to the frequency of typical transit time across all shippers in the survey, operating in the same corridor. All transit time distributions did exhibit the positive skewness characteristic of the log-normal distribution, with the perceptions being usually translated to the left of observed transit times. Besides the overall case, product and corridor-specific distributions followed the same pattern of those associated with the whole sample.

Figure 5.2

Empirical Distributions of Transit Time



Two additional analysis were then, developed. First, the correlation between transit time and length of haul was examined with a linear regression model for both data sources individually (see Table 5.7). Even though a poor fit was in general obtained, the constant of the perceived transit time by rail (6.17 days) was significantly higher than those in the truck model (0.9 days). This can be explained by the fact that most of the rail transit time is spent in yard operations without much correlation to distance, while truck has a much more stream-lined operation.

Table 5.7
Rail Transit Time Performance Models

transit time = a + b (distance)

		Constant	Distance	R^2
Observed	**Rail**	7.1105	0.00272	0.109
		(0.1313)	(0.00012)	
Perceived	**Truck**	0.8992	0.00153	0.355
		(0.1170)	(0.00012)	
	Rail	6.1724	0.00078	0.029
		(0.4714)	(0.00037)	

Obs.: Standard errors in parenthesis.

(observed / perceived) transit time

Paper	Aluminum	Pet Food	Plastics	Tires	Overall
0.684	0.684	0.615	0.799	0.739	0.729

In terms of comparing the perceived to the observed rail trip time models, both had very high constants, but the slope coefficient was much smaller in the perceived model. Aside from the fact that the later was not statistically significantly different from zero, this can be interpreted as shippers perceiving transit time not varying as much with distance. As expected, this puts railroads in extreme disadvantage with truck operations in short haul trips. Note that imprecision in the measure of distance in both data sources may have contributed to the poor fit of the model. Distances were calculated based on the origin-destination regions used in the shippers' survey, whereas the centroids in each region did not capture variations of specific locations within the regions.

Finally, the comparison between observed and perceived transit time was also done through the ratio of commodity-specific averages in both data sources. As shown in the bottom part of Table 5.7, perceptions were on average, 70% of the actual transit time. This result was reasonably stable across all commodities contemplated in the survey. Based on the reasons found to explain these differences, carriers should focus on reducing not the average transit time on the network, but rather the most often provided service to shippers that are sensitive to this dimension. This is correlated to the reliability of transit time discussed in the next section.

- **Observed vs. Perceived Reliability**

At some level, reliable service means moving cars from their origin to their destination so that they arrive within a time window that is acceptable to the customer. In the shippers' survey, reliability of transit time was defined as the percentage of time shipments arrive when they are wanted. In addition, shippers also reported the earliest and latest acceptable delivery time, which together defined the time window associated to shipments arriving when wanted.

With the observed car cycle data though, this concept is not entirely transferable, mainly because the acceptable time window is usually unknown. Traditionally, freight transportation demand studies have used the standard deviation of transit time or its coefficient of variation. On the other hand, to make comparisons with the perceived data more straight forward and to avoid distortions caused by extreme values, two additional measures were also analyzed:

- N-day-percent centered around the mean: percent of cars which arrive +/- $\frac{n}{2}$ days from the mean.

- Maximum n-day-percent: maximum percent of cars which arrive within a n-day period.

While the n-day percent measure is not so good for skewed distributions, the maximum n-day-percent is unrelated to the mean value and should be closely related to shippers' perceptions of compactness of the transit time distribution. Different values for n were used for both measures to avoid the unknown acceptable time-window in the car cycle data.

Tables 5.8 and 5.9 presents the summary statistics for the observed and perceived reliability of transit time by commodity. The maximum n-day percent was calculated for n varying from one to three days, which encompasses the average acceptable time windows in the survey. Given the skewness of the empirical transit time distributions, the n-day-percent centered around the mean was not included in the analysis.

The observed rail reliability varied from 36% with a one-day window to 66% with a three-day window, whereas tires shipments had the highest average reliability followed by aluminum and paper. Similar pattern was observed for the average coefficient of variation, which overall was 33% of the mean transit time. It is interesting to observe that the better service for tires was associated with higher rates per ton, what might indicate that rail carriers are already price differentiating their service.

On the perceived side though, rail reliability was 83% for an average acceptable time window of 1.4 days. Differences across products were not so significant, meaning that shippers do not have knowledge on any service-price differentiation. The comparison across modes always put truck as the most reliable mode (91%), followed closely by intermodal with 89% of shipments arriving when wanted.

Table 5.8
Observed Transit Time Reliability by Rail

	N	Paper	Aluminum	Tires	Overall
CV [1]		0.33	0.31	0.25	0.33
Maximum N-Day %	1	35.9 (13.2)	37.7 (11.5)	40.1 (11.8)	36.1 (13.1)
	2	52.8 (16.7)	56.3 (14.5)	59.5 (14.1)	53.1 (16.6)
	3	65.1 (17.5)	69.4 (14.0)	72.5 (14.3)	65.5 (17.4)

[1]coefficient of variation
Obs.: Standard deviations in parenthesis.

Table 5.9
Perceived Transit Time Reliability

	Mode	Paper	Alumi-num	Pet Food	Plas-tics	Tires	Over-all
TWD[1]	all	1.4 (1.4)	1.8 (1.6)	0.9 (1.2)	1.6 (1.5)	1.2 (1.5)	1.4 (1.5)
Reliability[2]	truck	93.1 (3.7)	89.6 (11.3)	91.4 (4.9)	92.2 (4.6)	87.0 (13.2)	91.1 (8.2)
	rail	84.3 (8.2)	83.6 (15.3)	82.5 (17.8)	83.8 (8.4)	75.0 (16.9)	83.1 (11.6)
	inter-modal	90.5 (4.7)	90.7 (4.2)	84.4 (13.8)	88.8 (12.4)	81.7 (20.8)	88.7 (11.6)

[1]acceptable time window (days) = latest - earliest acceptable delivery time
[2]in % of times shipments arrive when wanted
Obs.: Standard deviations in parenthesis.

Apart form differences in the sample selection, shippers seems to be perceiving reliability to be significantly higher than those levels actually observed in the system. One level of explanation deals with differences in the way reliability was measured in both data sources. Even if the maximum n-day percent is an adequate representation of shippers perceptions, the choice of n has a major implication in the comparison with the survey data.

The impact of variations in the acceptable time-window across shippers was not captured by assuming the same n-day period for all car movements. Shippers that have an acceptable time window bigger than n-days would tend to show a higher perceived reliability than the observed ones. In addition, shippers may have reported a much tighter acceptable time window than the one used to evaluate reliability in order to over-emphasize problems with having shipments delayed.

On another level, differences between observed and perceived reliability may be explained by the way railroads are selling their service. For example, if some slack is added to the schedule when negotiating the delivery time, shippers may be experiencing less delays and, consequently, perceiving a more reliable service. Figure 5.3 illustrates the effect of increasing shippers' expectations of transit time in their perceptions of service reliability.

By increasing the negotiated delivery time, carriers are more likely to meet it on several shipments than if the average transit time is used to sell the service. The perceived reliability gain is then, given by the area under the transit time distribution, between the expected and negotiated delivery time. The further apart are carriers able to negotiate these limits, the more reliable will the service be perceived. This analysis assumed that shippers perceptions of unreliable service is determined by the number of shipments that arrive later than the negotiated transit time, and thus, early arrivals have a minor impact on perceptions.

Of course, this assumes that the perceived transit time is longer than the observed mean time, which might be true after considering the weekend and mode effect explained before. Railroad experts[3] do recognize that "fattening the schedule" is not an unusual practice for marketing personnel trying to sell a more reliable service.

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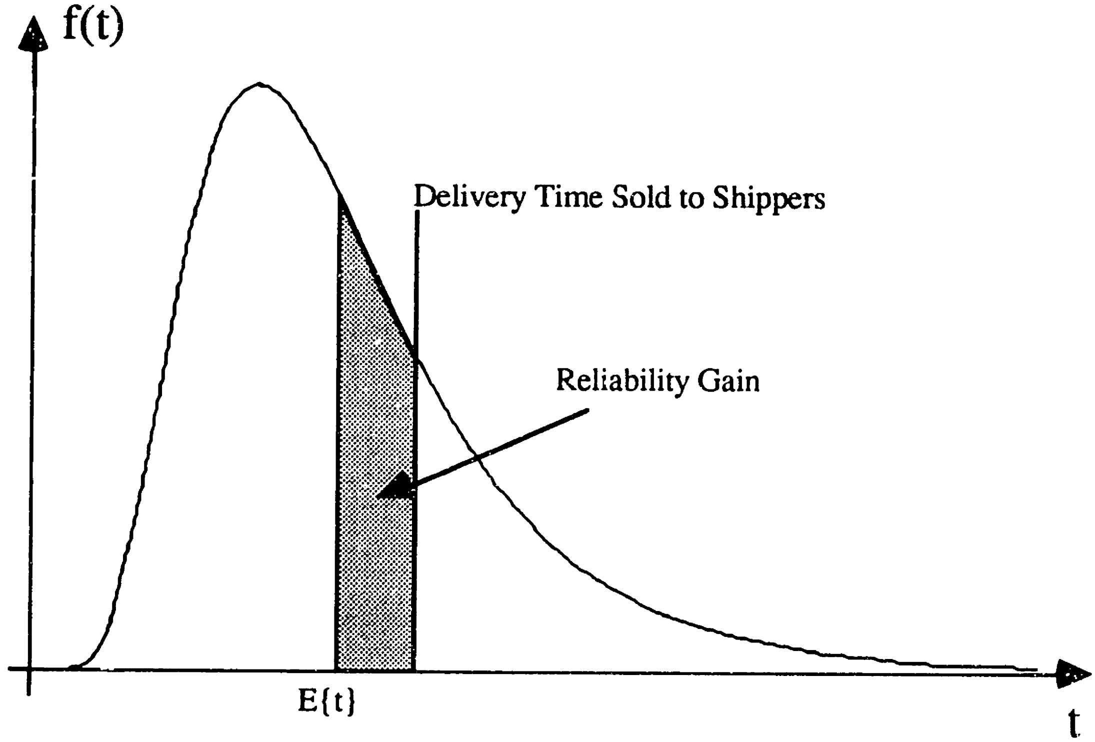
[3]from conversations with Carl Martland (MIT), and with Burlington Northern, CSX and CONRAIL officials.

Figure 5.3

The Effect of Increasing Transit Time in Service Reliability



Assuming that only delays are relevant to shippers' perception of reliability, reliability gain is the difference in the porobability of delays between the perceived and observed transit time

In terms of reliability performance models, two specifications were used. First, reliability was regressed on transit time for each data source individually. Even though a poor fit was obtained for most models, the effect of transit time was significantly estimated to be negative (see Table 5.10). Thus, the longer the trip, the less reliable it is; but the marginal effect of an extra day is extremely low compared to the average reliability given by the constant term.

Table 5.10
Rail Reliability Performance Models

reliability = a + b (transit time)

	N	Constant	Transit Time	R^2
	1	57.385	-0.632	0.022
		(0.725)	(0.068)	
Observed Max N-Day %	2	76.599	-1.158	0.067
		(0.741)	(0.070)	
	3	88.149	-1.366	0.099
		(0.704)	(0.066)	
Perceived	-	89.393	-0.766	0.026
		(1.882)	(0.259)	

Obs.: Standard errors in parenthesis.

(observed[1] / perceived) reliability

N	Paper	Aluminum	Pet Food	Plastics	Tires
1	1.58	1.60	1.57	1.54	1.52
2	1.26	1.28	1.25	1.24	1.24
3	1.11	1.13	1.10	1.11	1.09

[1]observed reliability in terms of maximum n-day %

Second, the perceived and observed reliability were correlated in the same model. Attempts to include more than one reliability measure resulted in a low R^2, whereas only the coefficients associated to transit time and the acceptable time window were significantly different from zero. This is justified by the high correlation among the observed reliability measures. Simple percentages calculations between the perceived reliability and the observed maximum n-day-percent can then, be used in the comparison of perceived and observed service. In particular, these percentages were very stable across commodities (see Table 5.10), independently of the time-window used in calculating the max n-day%.

- **Strategic Implications**

Despite the data limitations, it seems that shippers are perceiving rail service to be better than the observed performance with respect to transit time and reliability. By no means though, should this conclusion be used as an incentive for railroads to keep their status-quo operations. Significant differences among modes do exist and still endanger the railroad competitiveness in the transportation of the commodities analyzed.

Even though some factors act in the direction of reducing shippers' perceptions of transit time by rail, there is almost a five-day difference from the truck time. Since by the nature of railroad operations it would be very difficult to become competitive with the truck along this dimension, rail carriers should focus on reducing the variability of transit time. Note that intermodal operations constitute the best bet of railroads to compete with truck transit time in long haul trips.

On the reliability side, again shippers' perceptions seems to magnify improvements in the actual performance. This should provide incentives for rail carriers to stream line their yard operations, offering different priority services to satisfy shippers' needs. In addition, since differences in transit time are already so large, there is some room for rail carriers to pad their scheduled delivery time in order to get some improvements in perceived reliability without major efforts. Railroads have to some extent, not been aggressive in their marketing activities, whereas changes are required under the competitive pressures from motor carriers.

V.4 - The Unobserved Dimensions of Service: Level of Satisfaction with Payment Terms and Billings and with Responsiveness

By unobserved or intangible dimensions of service, are meant those perceptions of service that can not or are difficult to be associated with observable system characteristics. In order to improve service along these dimensions, carriers need to identify what are the key factors affecting shippers' perceptions of the service currently being provided. Moreover, it is necessary to distinguish between satisfied and unsatisfied customers to identify carriers' strengths and weaknesses with respect to these dimensions of service.

Three unobserved dimensions of transportation service were included in the shippers survey: responsiveness, satisfaction with payment terms and billing and level of effort to deal with carriers. Table 5.11 presents the average perceptions of service along these dimensions for each mode available. For the purpose of a quick assessment of differences in service, the discreteness of the scale of level of effort was neglected and simple averages computed.

In general rail carriers were perceived to provide an inferior service along these dimensions. Larger differences though, were observed for the responsiveness to inquiries than for the satisfaction with payment terms and billings. This indicates that there is more room for improvements on rail carriers responsiveness by perhaps enhancing their customer service department. It was also true that rail carriers were, on average, more difficult to deal with than their truck and intermodal counterparts. Note that intermodal operations are usually run as separate companies or departments from the traditional rail carriers, explaining the differences in shippers' perceptions of service.

The following analysis details the key factors determining shippers' perceptions with respect to responsiveness to inquiries and payment term and billings. Unfortunately, no information was available in the survey regarding the level of effort dimension. Nevertheless, the level of effort is important to shippers less sensitive to service quality or that keep less detailed records of their logistic costs to make an informed mode choice decision[4].

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[4]see market segmentation results in Chapter 8.

Table 5.11
The Unobserved Dimensions of Service
Average Perceptions

Dimension	Unit of Measurement	Truck	Rail	Inter-modal
payment terms & bills	% of times shipper is satisfied	84.4	76.6	84.2
responsiveness to inquiries	% of times shipper is satisfied	85.9	70.0	80.9
level of effort to deal with carriers	1= easy 2= normal 3= difficult	1.2	1.7	1.3

• Key Factors in Satisfaction with Payment Terms and Billings

In the survey, shippers were asked to rank the importance of nine key factors in determining their level of satisfaction towards payment terms and billings. These factors included from accurate fright bills to knowledge of late payment penalties. Table 5.12 presents the average rank of each factor, as well as the number of times it was ranked among the three most important factors.

Clearly, shippers are primarily concerned with accurate freight bills, being the most important factor for more than 90% of the shippers. As a second group of concerns, shippers want to receive bill timely and to be able to understand them. Factors associated with discounts, credit terms and penalties were among the least important ones.

Table 5.12
Key Factors in Payment Terms & Billings

Key Factors	Average Rank	Most Important[1]
(1) Accurate Freight Bills	1.24	156
(2) Discounts Properly Applied	4.23	72
(3) Timely Billing	4.51	65
(4) Understand Freight Bills	4.54	60
(5) Provides Support Documentation	4.77	68
(6) Early Payment Discounts	5.75	26
(7) Refunds or Rebates	6.17	25
(8) Credit Terms	6.18	15
(9) Knowledge of Late Payment Penalties	7.68	0

[1]number of shippers that ranked the factor among the three most important

In order to use these factors to improve service, it is necessary to distinguish between satisfied and unsatisfied shippers. Assuming that satisfied shippers are those that were satisfied 50% or more of the times they have used the carrier, Table 5.13 identifies the major strengths and weaknesses of each mode with respect to payment terms and billings. Unfortunately, the sets of strengths and weakness factors were not exclusive, indicating that while most shippers (111) perceive rail freight bill to be accurate most of the times, others (12) perceived this factor as the major source of dissatisfaction.

Thus, to gain competitiveness with truck and intermodal carriers, railroads need to identify the reasons for inaccuracies in the freight bills of some of their customers. It is not a generalized problem and it may be specific to a particular segment or product being transported. Due to the level of aggregation in the above information, this analysis was not pursued further. It is important to note that many of the other factors were identified by different shippers as main strengths in truck and intermodal payment terms and billings.

- **Key Factors in Responsiveness to Inquiries**

Under the responsiveness dimension, seven key factors were used to analyze shippers' level of satisfaction. These factors included from timely shipment tracing to a friendly and professional relation with carriers. Table 5.14 presents the average rank of each factor in the survey, as well as the number of times it was ranked among the three most important factors.

In contrast with the payment terms and billings analysis, no predominant factor was appointed to be the most important across all shippers for the responsiveness dimension. Instead, the key factors can be grouped in two sets, according to their importance in determining shippers' perceptions. First, the factors associated with a quick and easy access to information, being it shipment tracing or rates and schedules, had the lowest average ranks. Second, the factors associated with the carriers' customer service environment, including professionalism and flexibility to new ideas, were also among the most important factors for more than 30% of the shippers surveyed.

Table 5.13
Strengths and Weaknesses in Payment Terms and Billings

Weakeness[2]			Key	Strength[3]		
Rail	Inter-modal	Truck	Factor[1]	Truck	Inter-modal	Rail
12	2	5	**1**	135	83	111
-	-	-	**2**	1	2	-
-	-	-	**3**	1	-	-
-	-	-	**4**	-	-	-
-	-	-	**5**	2	3	3
-	-	-	**6**	-	-	-
1	-	-	**7**	5	3	5
-	-	-	**8**	6	3	7
1	-	-	**9**	4	2	1

[1] same order as in Table 8.14
[2] answers of unsatisfied shippers, i.e. those who are sometimes or seldom satisfied with payment terms and billings
[3] answers of satisfied shippers, i.e. those who are usually or always satisfied with payment terms and billings

Table 5.14
Key Factors in Responsiveness to Inquiries

Key Factors	Average Rank	Most Important[1]
(1) Timely Shipment Tracing	2.47	126
(2) Timely Answers to Information Inquiry	2.87	107
(3) Easy Access to Rates and Schedule	3.68	74
(4) Effective Handling of Billing System	4.17	61
(5) Easy Access to Appropriate Personnel	4.18	58
(6) Friendly and Professional Manner	4.74	45
(7) Listen to New Ideas	5.89	15

[1]number of shippers that ranked the factor among the three most important

In terms of strengths and weaknesses of each mode, again the key factors were not exclusive, i.e. there is no generalized problem in the responsiveness to inquiries dimension (see Table 5.15). For the rail mode, carriers should make available or improve their shipment tracing capabilities to more of their customers in order to gain competitiveness with the truck and intermodal. This does not necessarily imply in offering electronic data interchange (EDI), since some shippers do not have the capabilities to use it. In fact, most shippers which had timely shipment tracing as a weakness of rail carriers were small firms, without even plans to implement EDI.

Table 5.15
Strengths and Weaknesses in Responsiveness to Inquiries

Weakeness[2]			Key	Strength[3]		
Rail	Inter-modal	Truck	Factor[1]	Truck	Inter-modal	rail
15	3	-	1	54	36	30
6	2	3	2	31	14	24
3	-	-	3	9	4	5
2	-	-	4	9	7	8
4	-	-	5	34	19	27
1	-	-	6	3	5	3
2	-	-	7	16	8	11

[1] same order as in Table 8.16.

[2] answers of unsatisfied shippers, i.e. those who are sometimes or seldom satisfied with carriers' responsiveness to inquiries.

[3] answers of satisfied shippers, i.e. those who are usually or always satisfied with carriers' responsiveness to inquiries.

On the customer service factors, a much smaller number of shippers appointed them as a major weakness of rail carriers. However, a significant number of them identified these factors as the major strength for truck and intermodal carriers. Thus, relatively speaking, railroads should also improve their customer relation, specially regarding the access to their personnel.

V.5 - The Information in Shippers' Perceptions of Service

Understanding shippers' perceptions of service quality is critical in the process of service design and marketing. These perceptions are the base for the trade-offs among service attributes in the shippers' mode choice decisions. The above analysis showed a strong link between the perceived service and the observed performance for the rail mode. Nevertheless, there is also evidence that there is not a one-to-one correspondence between them, and some strategic value can be found in shippers' misperceptions.

Shippers' perceptions of the transportation costs seemed to be very accurate when compared to the actual rates charged. Not only are the rates a very tangible dimension of service, but also their influence is shown directly in the bottom line firms' profits. On the other hand, for transit time and reliability, the perceptions at first, were higher than the actual service provided. While for transit time, some measurement issues were relevant in explaining the differences, for reliability, some strategic value on shippers' misperceptions were discussed.

Given that railroads can compete with motor carriers on transit time only through their intermodal operations, management attention should be focused on reliability improvements. This is consistent with shippers' sensitivities to service attributes, discussed in Chapter 7. Reliability improvements though, is not only obtained through a more stream-lined yard operations, but also through a conscious effort in understanding shippers' needs when selling the service. It was shown that an increase in the delivery time expected by shippers, has a positive impact in the perceived reliability. In addition, since shippers are likely to be more reactive to improvements in reliability than to reductions in transit time, this might be translated into a net increase in the rail market share.

In general, the results from the key factors analysis of unobserved service dimensions were not as conclusive as the ones in the cost, transit time and reliability analysis. This might be related to the fuzziness of the concepts, which required much more interpretation of the answers in the shippers' survey. But also, the innovativeness of asking shippers' perceptions towards these dimensions might have biased their responses. Nevertheless, it is clear that railroads need to pay more attention on their customer service relations to compete with truck and intermodal operations.

VI - Freight Transportation Market Segmentation

The managerial concept underlying market segmentation is the identification of groups of shippers who have needs and responses towards service quality that are different from other shippers. Shippers are diverse and demand specialized service to meet their transportation needs. Not only they perceive the service provided differently, but also they value service differently in the mode choice process.

On the supply side, as competition intensifies, carriers enter the market with similar services and technology. It is then, necessary for carriers to find ways to identify and select among alternative market opportunities, and to tailor their service design strategies to these opportunities. Among the many ways to segment the freight market, it is important to select one that allows the matching of carriers' capabilities with shippers' unsatisfied needs.

In this chapter, a method to differentiate shippers according to their attitudes towards transportation service quality is developed. It includes not only the identification of market segments but also the estimation of a classification model. The later allows carriers to determine the segment that a given shipper is most likely to belong to, given his/her observable characteristics.

In the next section, previous studies are briefly reviewed to situate this research in the literature of market segmentation. The identification of market segments using attitudinal indicators and the development of the classification model from observable shippers' characteristics are presented in sections 6.2 and 6.3. An approach integrating the attitudinal indicators and shippers' characteristics in the definition of the segments is then, motivated using latent structure models in section 6.4. In this case, the classification model was derived implicitly from the definition of the segments. Finally, section 6.5 summarizes the findings.

VI.1 - Market Segmentation: Concepts and Data Requirements

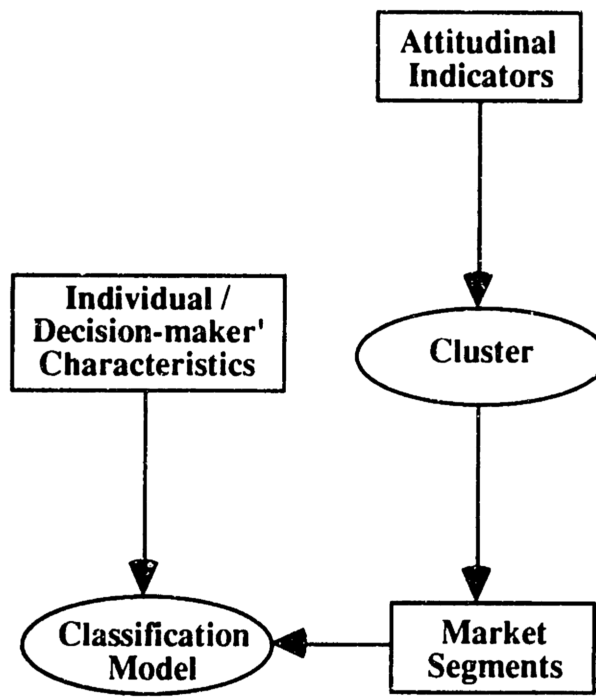
In the past, researchers have developed market segments based on attributes of the commodity being transported, like density and value, and on shippers or firms characteristics, like annual sales and volume of shipments. The variables used to find the segments should be measurable, relevant for a substantial group of shippers, and of operational value for service design strategies. However, the segments defined from product and firm characteristics alone did not recognize the cognitive mechanisms underlying the mode choice decisions, by which shippers value differently different dimensions of service. Moreover, these cognitive mechanisms were usually inferred after the segments were defined, based on average characteristics of shippers in each segment and the experience of the researcher in interpreting them.

More recently, market segmentation studies have tried to use attitudinal indicators to identify the main reasons for differences in shippers' mode choice behavior. These attitudinal indicators were usually elicited on surveys with attitudinal questions regarding how important are different dimensions of service to shippers. The segments then derived from these indicators, identify groups of shippers with similar attitudes towards service attributes. This approach to market segmentation is represented in Figure 6.1.

In particular, McGinns[1978] used 32 attitudinal questions regarding mode choice in an extensive survey of traffic executives in major U.S. firms. Besides the identification of market segments, service design strategies associated to each one were also discussed. Collision[1984] developed a similar study specific to marine services, while Cooper and Rose[1986] studied the benefits from market segmentation to a particular carrier. All studies argued about being not possible to design a single marketing and service design that will satisfy all current and potential customers. Carriers can either focus their efforts on a carefully defined segment (e.g. UPS and Federal Express in the small packages segments), or effectively differentiate their service in different market segments.

Figure 6.1

The Traditional Market Segmentation Approach



In most studies though, the classification model was not formally derived. The comparison with average characteristics of shippers in each segment is usually proposed as a mean to identify the segment that a new shipper belongs to. Since for these shippers, attitudinal indicators are not available, it is important to identify observable characteristics that are strongly correlated with their attitudes towards service. For example, shippers of high-valued commodities should rate the importance of transit time and reliability very high, due to the implication in their inventory carrying costs.

On the other hand, several approaches in the marketing literature have tried to improve the definition of market segments by combining attitudinal indicators and shippers' characteristics (see Wind and Cardozo[1974] and Bonoma and Shapiro[1978]). They usually rely on dividing the process into a macro-segmentation stage, based on product's and firms' characteristics, and in a micro-segmentation stage, based on the attitudinal indicators. Even though there are advantages in terms of the incremental data collection efforts, the major drawback of these approaches is the nested definition of segments. For example, within a group of shippers of high-valued commodities, it may be identified one segment for which transit time and reliability is important, and another, for which rates is the most important dimension of service.

The objective of the following analysis is to identify groups of shippers who have needs and responses towards service quality different from other shippers in the survey. Besides characteristics of shippers, or the firms they represent, the basic source of information was the importance ratings given to each transportation service attribute. These ratings were self-stated on a five-point scale, i.e. shippers rated each service attribute from essential (1) to not important at all (5) in their mode choice decisions. Table 6.1 presents some descriptive statistics for these ratings across shippers in the survey. On average, reliability was the most important service dimension.

The major problem in using this information is that shippers may overstate their importance ratings, appearing that all service attributes are very important to all shippers. This makes it difficult to discriminate shippers based on their attitudes towards service quality, and the results from market segmentation become less meaningful. A new methodology for combining attitudinal indicators with observable shippers characteristics was developed to improve the definition of the market segments (see section 6.4). To some extent, the proposed latent structure model account for response biases in self-stated ratings, by relying mostly in observed characteristics to define the segments.

Equally important to defining segments, is the capability to classify current and potential shippers into those segments. In fact, the market segmentation based only on attitudinal indicators becomes operational only if there are identifiable and measurable characteristics of shippers strongly related to their attitudes towards each service attribute. It is important to be able to assign shippers to different segments without a priori knowledge of their importance ratings to different attributes, in order to offer the service specific to their segment.

Table 6.1
Importance Ratings for Different Service Dimensions

Service Attribute	Average	Frequency Distribution[1] 1	2	3	4	5
Rate	1.57	93	56	14	1	2
Transit Time	1.50	99	53	12	2	-
Reliability	1.28	125	37	3	1	-
Loss and Damage	1.33	116	45	5	-	-
Useability of Equip.	1.42	116	38	7	3	2
Payment Terms & Bills	1.65	82	66	15	1	2
Responsiveness	1.45	99	61	5	1	-
Level of Effort	1.55	88	65	11	1	1

[1] 1=essential; 2=very important; 3=somewhat important;
4=not very important; 5=not important at all

Obs.: The total number of responses for each service attribute is equal to the number of shippers in the survey. (i.e. a total of 166 shippers).

Among the observed characteristics used in the classification model, three groups of variables can be defined: product attributes, like value and density; firms' characteristics, like number of employees and annual sales, and shippers' transportation needs, like annual tonnage shipped, average distance and acceptable delivery time windows. Given the segments based only on the attitudinal indicators, these variables interacted in a probabilistic framework to explain the market segments shippers were assigned to, which can then be used to classify shippers that did not participate in the original survey (see section 6.3). For the approach combining shippers' characteristics and attitudinal indicators in the definition of the segments, the classification model can be derived implicitly from the latent structure model coefficients.

The following sections describe the statistical methods used in the market segmentation analysis, as well as the results obtained with the shippers' survey data.

VI.2 - Identification of Market Segments: The Cluster Algorithm

The primary method of segmentation is to use analytical clustering techniques to identify groups of shippers that are homogeneous to the criteria selected to represent similarity. In these techniques, groups of similar shippers are usually defined by their proximity on the measured characteristics space. However, considerable judgment is still necessary to define the best market segments and identify service design opportunities.

• The Method

Given a set of importance ratings **w**, cluster analysis determines groups of shippers that minimizes the variation within groups, while maximizing the variations between them. For a set S of shippers and a set of m importance ratings $\mathbf{w}=\{\mathbf{w}_1,\mathbf{w}_2,\ldots\ \mathbf{w}_m\}$ associated to each shippers and to each service dimension, the objective is to partition S into p disjoint segments $(s_1, s_2,\ldots\ s_p)$.

Most efforts to derive a simple group structure from a complex data set require a measure of "closeness" or "similarity". There is often a great deal of subjectivity involved in the choice of a similarity measure. For the purpose of clustering shippers, the proximity between them was indicated by the square of the Euclidean distance in the m-dimensional space of the importance ratings of service attributes, i.e.

$$d_{kl} = \sum_{i=1}^{m} (w_{ik} - w_{il})^2 \tag{6.1}$$

As proposed by Kaufman and Rousseuw [1990] the importance ratings were used as interval measures, to avoid losing information contained on the fact that the further apart the ratings are, the more dissimilar are the shippers.

Non-hierarchical clustering procedures only find a solution that is locally optimal, i.e. the between-group variation would increase if any shipper is assigned to a different segment. These methods start form either (1) an initial partition of items into groups or (2) an initial set of seed points, which will form the nuclei of clusters. Good choice of starting configurations is important to the performance of the algorithm. One way to start is to randomly select seed points from among the observations or to randomly partition the observations into initial groups.

The standard K-means procedure was used to identify the freight transportation market segments. It can be described by the following steps:

step 1: select initial seeds

step 2: form clusters assigning each shipper to the nearest seed.

step 3: update cluster seeds to cluster means, where the latter is defined by the mean vector of all importance ratings, considering only the shippers that are currently assigned to each cluster.

Steps 2 and 3 are repeated until changes in the clusters are very small or the maximum number of iterations is achieved. Note that the final assignment of shippers to clusters is dependent on the choice for initial seeds.

In particular, the SAS[1] implementation of the K-means algorithm was used. Initial seeds are selected from observations that satisfy a minimum distance from all other seeds already identified (for the first seed, no minimum distance restriction applies). Note that,

[1]Statistical Analysis System, SAS Institute.

importance ratings on each service attribute must be available for the shipper in order to consider him/her an initial seed. In addition, to avoid biases related to the order in which the observations are examined, the SAS implementation allows replacing the already identified seeds as new observations are considered, provided that the overall spread of seeds on the clustering variables space is improved (see details in SAS Users' Manual[1989]). The convergence of the algorithm is defined based on the maximum distance by which any seed has changed being less than or equal to the minimum distance between initial seeds times a constant (usually 0.01). This algorithm has shown to be empirically efficient for large data sets (more than 100 observations).

A problem common to most clustering techniques is to decide, a priori, on the number p of clusters present in the data set. Of course, not all p lead to "natural" clusterings, and it is usually necessary to experiment with different values to select the one that gives the most meaningful interpretation. In addition, several analytical criteria to determine the best p were proposed in the cluster methods literature, but the problem remains essentially unresolved (see Everitt[1980]). Two major reasons contribute to the complexity of deriving a formal significance test for p: the lack of a suitable null hypothesis and the complex nature of the multivariate sampling distributions.

- **The Results**

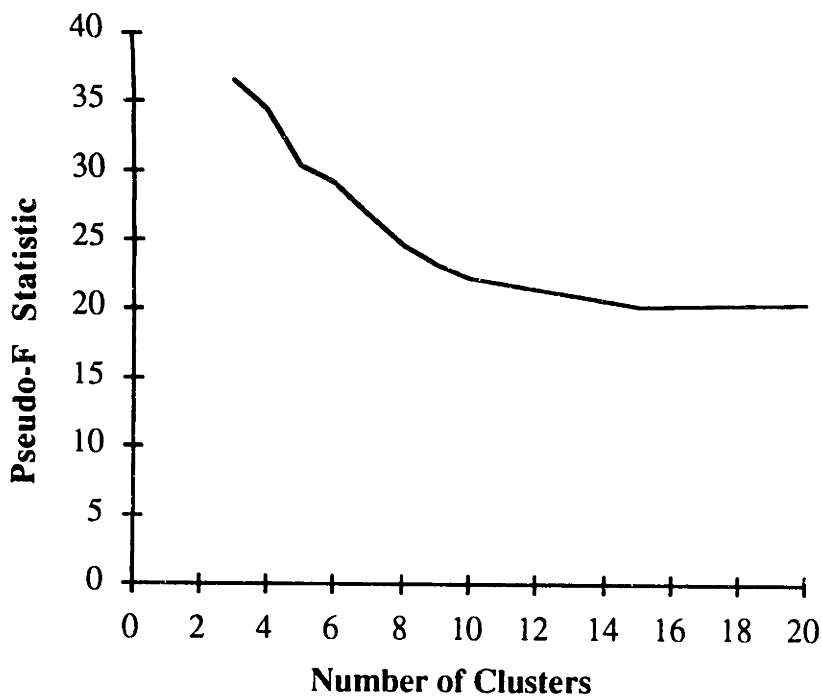
In the exploratory analysis, the number of clusters varied from three to twenty in order to identify the most meaningful partition. Besides the interpretation of the segments generated, the pseudo-F statistic was also used to identify the best p, i.e.

$$\text{pseudo-F} = \frac{R^2 / (c - 1)}{(1 - R^2) / (n - c)} \tag{6.2}$$

where R^2 is the mean square deviation from cluster means in the sample
n is the number of observations;
c is the number of cluster

Since it is a monotonically decreasing function of the number of clusters, a smaller jump in its value tends to indicate that two similar cluster were separated in that iteration. The main difficulty in using this criteria is that several jumps in the pseudo-F statistic may be observed. Figure 6.2 shows the pseudo-F statistic for different values of p, with the major jump observed for the six-cluster solution.

Figure 6.2
Choosing the Number of Clusters



The major problem with using this six-cluster solution lies on the unbalanced number of shippers in each cluster. Small-size clusters are usually associated with the presence of outliers in the data set, instead of natural groupings of shippers. In particular, one cluster, representing those shippers sensitive to all service quality attributes, accounted for more than 60% of all shippers in the sample. This result can also be associated with the fact that shippers tend to overstate their importance ratings, making all service dimensions look very important. Nevertheless, two other segments had a significant number of shippers: the reliability-sensitive shippers, with 34 members, and the price-sensitive shippers, with 10 members.

In order to avoid solutions with small-size clusters, the implementation in SAS allows the user to specify the minimum number of shippers in all clusters.

Table 6.2 presents the best segmentation result, when the minimum cluster size was set to three. Besides showing the average and standard deviations of the importance ratings in each cluster, the ratio of the between to the within (B/W) variances was used as a measure of goodness of fit. Values greater than one for the B/W ratio are good indication of well-defined clusters along each dimension and overall. The higher the B/W ratio the more homogeneous is each group of shippers compared to all other shippers in the survey.

The solution obtained though, did not perform well under this criteria, re-emphasizing that the importance ratings alone may not be sufficient to distinguish groups of shippers. Among the dimensions of service that contributed the most to identify the clusters, the useability of equipment and the level of effort had the highest B/W ratio.

Based on the average importance weights given to each service dimension, the following interpretation of each cluster was developed:

- segment 1 : shippers less sensitive to all service attributes;
- segment 2 : cost-sensitive shippers;
- segment 3 : shippers sensitive to the responsiveness of carriers, including the supply of equipment;
- segment 4 : time-sensitive shippers;
- segment 5 : shippers sensitive to loss and damage and, to payment terms and billings;
- segment 6 : shippers sensitive to all service attributes; and
- segment 7 : shippers sensitive to the level of effort required to deal with carriers.

For example, cluster 4 has the lowest importance weight for transit time and reliability, indicating that time-sensitive shippers were included in this segment. Again, the biggest segment, with more than 50% of shippers surveyed, was characterized as being composed of shippers sensitive to all service dimensions.

Table 6.2
Cluster Means of Importance-Ratings[1] on Service Dimensions

Cluster	N	rate	tt	rel	lod	ueq	ptb	rsp	lef
1	18	1.61 (0.5)	2.44 (0.6)	2.28 (0.6)	1.61 (0.5)	2.00 (0.8)	2.06 (0.5)	1.72 (0.6)	2.00 (0.5)
2	10	1.40 (0.5)	2.10 (0.7)	1.40 (0.5)	2.30 (0.5)	2.00 (0.9)	2.00 (0.7)	2.00 (0.5)	2.70 (1.1)
3	19	2.95 (0.7)	1.53 (0.5)	1.26 (0.5)	1.68 (0.6)	1.32 (0.5)	2.05 (1.0)	1.42 (0.5)	1.68 (0.5)
4	23	1.57 (0.6)	1.22 (0.4)	1.09 (0.3)	1.13 (0.3)	1.39 (0.5)	1.61 (0.5)	1.96 (0.6)	2.22 (0.5)
5	6	1.50 (0.6)	1.17 (0.4)	1.17 (0.4)	1 (0)	3.50 (0.8)	1 (0)	1.50 (0.5)	1.67 (0.5)
6	86	1.23 (0.4)	1.24 (0.4)	1.12 (0.3)	1.14 (0.4)	1.06 (0.2)	1.31 (0.5)	1.16 (0.4)	1.13 (0.3)
7	4	2.75 (1.5)	3.25 (0.5)	1.25 (0.5)	1.75 (1.0)	2.50 (1.7)	3.50 (1.0)	2.25 (1.9)	1.25 (0.5)
B/W Ratio	0.9	1.1	1.1	0.9	0.7	1.2	0.8	0.5	1.2

[1] 1=essential; 2=very important; 3=somewhat important; 4=not very important; 5=not important at all

Obs.: tt = transit time; rel = reliability; lod = loss & damage; ueq = useability of equipment;
ptb = payment terms & billings ; lef = level of effort to deal with carriers. Standard deviations in parenthesis.

In order to use this market segmentation results to develop the classification model in the next section, the small-size clusters were joined with their nearest cluster. As such, cluster 5 was combined with cluster 4, defining shippers that are sensitive to the dependability of the transportation service (i.e. transit time, reliability and loss and damage); and cluster 7 was combined with cluster 1, defining a segment of shippers less sensitive to service quality. The latter group includes shippers that usually take the minimum effort alternative. Besides being intuitively acceptable, these aggregations reduced eventual numerical instabilities in the estimation of the classification models.

VI.3 - Classification of Shippers: the Multinomial Logit Model

The usefulness of the market segments defined in the previous section depends on the identification of observable characteristics of shippers that are strongly related to their importance-ratings on each service dimension. These characteristics involve product attributes, firm's demographics, and operating variables reflecting shippers' transportation needs. The classification model then, estimates the probability of a shipper belonging to a particular segment, given his/her characteristics.

• The Method

Cluster-specific means of shippers' characteristics can be used in a first attempt to classify them, i.e. shippers are assigned to the segment which has the mean values closer to their own characteristics. This approach though, becomes subjective and difficult to apply as the number of shippers' characteristics increases, unless a common metric is defined for the comparison between a new shipper and those already assigned to a market segment.

The statistical framework for finding characteristics that are good descriptors of market segments is called discriminant analysis. Let $x = \{ x_1, x_2, \ldots x_n \}$ be the vector of shippers' characteristics and p_j be the prior probability[2] that a given shipper belongs to cluster j. Then, using Bayes' theorem, the conditional probability of that shipper belonging to cluster j is given by:

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[2]in the case of complete ignorance, the shipper is equally likely to belong to any segment.

$$P(j \mid \mathbf{x}) = \frac{p_j \, f_j(\mathbf{x})}{\sum_{i=1}^{m} p_i \, f_i(\mathbf{x})} \text{, where } f_j(\mathbf{x}) \text{ is the density of } \mathbf{x} \text{ in segment } j \tag{6.3}$$

If densities $f_j(\mathbf{x})$ were assumed to be multivariate normal, with mean μ_j and common covariance matrix Σ, then:

$$f_j(\mathbf{x}) = (2\pi)^{-k/2} \Sigma^{-1/2} \exp\left[-\frac{1}{2}(\mathbf{x} - \mu_j)' \Sigma^{-1} (\mathbf{x} - \mu_j)\right] \quad \text{and}$$

$$P(j \mid \mathbf{x}) = \frac{\exp(\alpha_j + \beta_j' \mathbf{x})}{\sum_{i=1}^{m} \exp(\alpha_i + \beta_i' \mathbf{x})},$$

$$\text{where } \alpha_j = \log(p_j) - \frac{1}{2}(\mu_j' \Sigma^{-1} \mu_j) \text{ and } \beta_j = \Sigma^{-1} \mu_j \tag{6.4}$$

The procedure then, minimizes the total probability of misclassification by assigning each shipper to the segment j with the highest $P(j \mid \mathbf{x})$, or equivalently, with maximum scores $(\alpha_j + \beta_j' \mathbf{x})$.

In order to make the discriminant analysis operational, it is assumed that the prior probabilities p_j, means μ_j and covariance matrix Σ are estimated by their sample values, i.e.

$$\hat{p}_j = \frac{n_j}{n}; \; \hat{\mu}_j = \bar{\mathbf{x}}_j; \text{ and } \hat{\Sigma} = \frac{1}{n - m} \sum_{j=1}^{m} \sum_{i=1}^{n_j} (x_{ji} - \bar{x}_j)(x_{ji} - \bar{x}_j)' \tag{6.5}$$

where n_j is the number of shippers in segment j;

n is the number of shippers in the survey;

m is the number of clusters; and

$\bar{x}_j$ is the mean of observations in the jth group.

Alternatively, the maximum likelihood estimators for (α_j, β_j) can be derived from maximizing the following likelihood function:

$$L = \prod_{i=1}^{n} \prod_{j=1}^{m} [P(j \mid x)]^{y_{ij}}, \tag{6.6}$$

where $y_{ij} = 1$, if shipper i belongs to cluster j; 0, otherwise.

For the specification of $P(j \mid \mathbf{x})$ in (6.4), this is equivalent to the multinomial logit, with all coefficients being alternative or segment-specific. Not all coefficients (α_j, β_j) though, are estimable, and the normalization $\alpha_m = \beta_m = 0$ is usually imposed in practice.

The MLE estimator is more robust than those obtained with the discriminant analysis. Cox[1966], Day and Kerridge[1967] and McFadden[1976] noted that this model holds for a variety of situations, including multivariate independent dichotomous variable and a combination of multivariate normal and dichotomous variables. Then, while under non-normality inconsistent estimators are obtained with the discriminant analysis procedure, the loss of efficiency from using the MLE is small in large samples. In addition, the multinomial logit model has the desirable property that the expected number of cases is equal to the observed number in each segment.

• The Results

As a first attempt to develop the classification model, Table 6.3 presents the mean values of shippers' characteristics in each cluster. Among the shippers' characteristics, the following were used on the classification model:

- product attributes: price ($/ton) and density (ton/$m^3$);

- firms' demographics: annual sales and number of employees;

- shippers' transportation needs: annual tonnage shipped, % of shipments in two major corridors, average length of haul, earliest and latest acceptable delivery time, and the use of EDI.

Note that the average importance ratings for each segment were presented in Table 6.2, considering the original seven-cluster solution.

Even though the interpretation is not decisive, it is worth mentioning some relevant factors in the classification of shippers in those segments. Cost-sensitive shippers (cluster 2) presented the lowest commodity value, and shippers less sensitive to all service attributes (cluster 1) had the maximum acceptable delay. On the other hand, variables like the commodity density and the average transportation distance presented small variations across segments and should have a minimum impact in the classification of shippers.

Table 6.3
Average Shippers' Characteristics in Each Market Segment

Cluster	N	Annual Tonnage (10^3 t)	Annual Sales (10^6 \$)	Price (\$/t)	Density (t/m^3)	Maximum Delay (days)	% in 2 Main Corridors	Average Distance (miles)
1	22	202	558	2.06	0.60	0.96	73	815
2	10	76	602	1.52	0.61	0.54	78	895
3	19	86	321	2.10	0.58	0.42	66	796
4	29	140	803	1.75	0.60	0.63	81	969
5	86	224	1180	2.06	0.65	0.48	71	916

The estimation results for the MNL classification model confirmed the expectations regarding the most significant variables, but had a poor goodness of fit. Table 6.4 presents these results for the full model, i.e. considering all shippers' characteristics in the specification. Note that cluster 5 was used as the base alternative for the normalization of the coefficients in the model.

Even though the increase in the likelihood function was sufficient to reject the null hypothesis of all coefficients being zero, a very limited number of coefficients were statistically significant at 5% level of significance. In addition, the percent predicted correct, a relevant measure when using the model to classify new shippers, was around 60%, whereas the naive model of assigning every shipper cluster 5 would have predicted 50% of the times correctly.

Among the estimated coefficients, those associated with the size of the firm and the maximum acceptable delay were significant for cluster 1. Thus, the smaller the firm's annual sales and the larger the acceptable delay, the more likely is the shipper to be less sensitive to transportation service. The coefficient associated with the commodity value was significant for cost-sensitive shippers (cluster 4), and as expected with a negative sign. No variable was particularly significant to identify shippers in other clusters.

Thus, a good classification model could not be developed for the market segments identified from shippers' importance ratings of different service dimensions. To some extent, the poor fit is associated to the fact that the clusters, in the first place, were not well-defined (low B/W ratio). In the next section, a method is developed to account for differences in shippers' characteristics together with their importance ratings in the definition of the segments.

Table 6.4

The Estimated Coefficients in the Classification Model

Variable \ Cluster	1	2	3	4
constant	-0.958 (1.49)	-1.34 (1.80)	0.945 (1.54)	-0.343 (1.08)
annual tonnage	-0.00126 (0.0011)	-0.00507 (0.00411)	-0.00285 (0.00241)	-0.00152 (0.00111)
annual sales	-0.000600 (0.000403)	0.0000821 (0.000411)	-0.000174 (0.000311)	-0.000134 (0.000213)
number of employees	-0.000250 (0.000112)	0.0000318 (0.000233)	-0.0000241 (0.000212)	0.000122 (0.000113)
price	0.102 (0.310)	-0.616 (0.381)	0.00814 (0.293)	-0.424 (0.252)
density	-1.02 (0.972)	-0.554 (1.271)	-0.656 (0.981)	-0.944 (0.761)
distance	-0.00059 (0.000715)	-0.00003 (0.000814)	0.00096 (0.000737)	0.000241 (0.000512)
earliest acc. delivery	0.251 (0.312)	-0.235 (0.482)	-0.536 (0.444)	0.262 (0.261)
maximum accept. delay	0.958 (0.364)	0.426 (0.521)	0.265 (0.501)	0.340 (0.331)
% shipped in 2 corridors	-0.0147 (0.0141)	0.0121 (0.018)	-0.0194 (0.0152)	0.0022 (0.0113)
use EDI	0.912 (0.611)	1.16 (0.741)	1.03 (0.601)	0.261 (0.492)
L(0) = -254.3	(N = 166)	L* = -186.7	$\rho^2 = 0.267$	% predicted correct = 57.6

Obs.: Standard errors in parenthesis.

Cluster 5 was used as the base alternative in the MNL estimation.

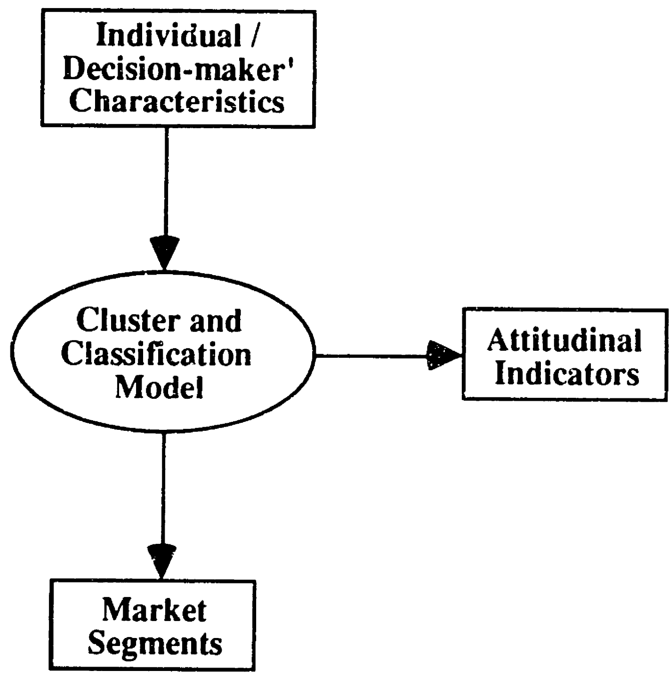
VI.4 - Combining Importance-Weights and Shippers' Characteristics: The Latent Structure Model

In the market segmentation literature, several studies tried to consider both information, attitudinal indicators and observable characteristics, in the definition of market segments. They all relied on using the information sequentially, whereas segments are first derived from observable characteristics and then, within these segments, attitudinal indicators are used when the need for more precise tailoring of strategies strategies (see Wind and Cardozo[1974] and Bonoma and Shapiro [1984]). One of the major advantages of using the information sequentially is that the data collection effort can be structured in an incremental way, i.e. attitudinal indicators are collected only when additional detail is made necessary to design and market transportation services in each of the segments

Given that attitudinal indicators and shippers' observable characteristics were available in the survey, a new approach for market segmentation analysis was developed based on latent structure models (see Figure 6.3). The idea of the new approach is to combine the clustering and the classification model, by using the attitudes as indicators rather than causes of the latent dimensions on which shippers are to be grouped. The proposed latent structure model would therefore incorporate all information available to estimate the segmentation variables. This fact should potentially improve the identification of segments, especially when the attitudinal indicators are affected by response biases.

Figure 6.3

The New Market Segmentation Approach



- **The Method**

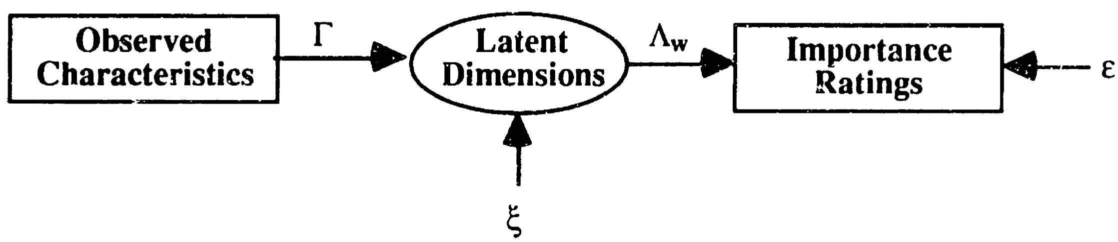
The proposed framework assumes that shippers' attitudes towards service quality (η) are latent or not observable. In order to use them in the definition of the market segments, a latent structure model is adopted to hypothesize the relationships between these latent attitudes and shippers' observable characteristics and attitudinal indicators. In particular the path diagram in Figure 6.4 describes these relationships using the multiple-indicators multiple-causes (MIMC) model. The mathematical formulation of the MIMC model is then, given by:

$$\eta = \Gamma \mathbf{x} + \xi \qquad (6.7)$$

$$\mathbf{w} = \Lambda_{\mathbf{w}} \eta + \varepsilon \qquad (6.8)$$

Thus, latent attitudes η are determined by the observable characteristics **x** in the structural equations (6.7), and the importance ratings **w** are used as indicators of the same latent variables in the measurement model (6.8). The disturbance terms ξ are assumed to be uncorrelated with **x** and with measurement errors ε, where $E[\xi] = 0$ and $E[\varepsilon] = 0$.

Figure 6.4
The Path Diagram for the Latent Structure Model



Depending on the specification of the non-zero (or free) elements in Γ and Λ_w, different interactions between importance-ratings and observed characteristics can be represented with the above MIMC model. In particular, one should start by hypothesizing about what latent dimensions (η) are important in differentiating shippers' behavior in mode choice decisions. Then, the MIMC model is identified by selecting the indicators that influence each dimension, not necessarily exclusively, and which observed characteristics determine these latent segmentation variables.

Typically, the dimensionality of η is less than the original number of dimensions in **w** and **x**, implying in a desirable reduction of the clustering space. Several empirical settings seem to be appropriately modeled with the MIMC model. Not only are the importance-ratings usually elicited for several attributes, but also are several observed characteristics potential causes for market segmentation. In practice, clusters derived from more than five variables makes the interpretation of segments complex. Moreover, correlated variables tend to mask the cluster structure present in the data.

In particular, previous market segmentation using attitudinal indicators have also used a latent variables to reduce the dimensionality of the clustering space. McGinns[1978] used five latent dimensions defined from an exploratory factor analysis of the information elicited in 32 attitudinal variables elicited in the survey of traffic managers. The advantage of the MIMC model though, is that it combines prior beliefs on which attitudinal indicators influence each latent variable in a confirmatory factor analysis model (measurement equations), with observable characteristics that are likely to determine shippers' attitudes towards service quality (structural equations).

The estimates of $(\Gamma,\ \Lambda_w)$ were obtained from maximizing the following log-likelihood function:

$$L = \log|\,\Sigma(\theta)\,| + \mathrm{tr}\{\ S\ \Sigma^{-1}(\theta)\ \} - \log|\ S\ | - p + q \tag{6.9}$$

where $\mathbf{S}$ is the sample covariance matrix of $(\mathbf{w},\mathbf{x})$; and
$\Sigma(\theta)$ is the parametric covariance matrix derived from (6.7) and (6.8).

In Chapter 4 of Bollen[1989], the implied specification of $\Sigma(\theta)$ is derived and the conditions for the identification of the MIMC model are discussed.

Given $\widehat{\Gamma}$, fitted values for the latent segmentation variables $\widehat{\eta}$ are formed for each shipper using the structural equations. This does not imply that importance ratings are not relevant, since the measurement model is estimated jointly with the structural equations.

In the clustering process, the objective is to minimize the sum of squared distances to cluster means. Then, the following relationship should hold in the latent variable space for each shipper:

$$\sum_{j=1}^{n} (\widehat{\eta}_{ij} - s_{c_i j})^2 \leq \sum_{j=1}^{n} (\widehat{\eta}_{ij} - s_{cj})^2 \tag{6.10}$$

where s_{cj} is the cluster-mean for observed characteristic j in cluster c

Otherwise, shipper i would not have been assigned to cluster c_i.

Moreover, the sum of squared distances in the latent variable space is proportional to the following linear form in the observed characteristic space (see details in Appendix C):

$$\sum_{j=1}^{n} (\hat{\eta}_{ij} - s_{cij})^2 = \hat{\alpha}_c - \sum_{k=1}^{q} \hat{\beta}_{ck}\, x_{ik}$$

where $\hat{\alpha}_c = 2 \sum_{j=1}^{m} s_{cj} \left(\sum_{k=1}^{q} \hat{\gamma}_{jk}\, \mu_k \right) - \sum_{j=1}^{m} s_{cj}^2$;

$\hat{\beta}_{ck} = 2 \sum_{j=1}^{m} \hat{\gamma}_{jk}\, s_{cj}$;

and μ_k is the mean of observed characteristic k (6.11)

Assuming that observed characteristics (**x**) in the structural equations are the same variables used in the classification of shippers, $\hat{\alpha}_c$ and $\hat{\beta}_{ck}$ above are equivalent to those obtained from estimating the MNL model. While the classification model assigns shippers to the segments with the maximum discriminant score $\hat{\alpha}_c - \sum_{k=1}^{q} \hat{\beta}_{ck}\, x_{ik}$, in the clustering process, each shipper is assigned to the segment that minimizes the same linear form. Since the classification model should also explain the cluster membership of the shippers surveyed, the equivalence of coefficients follows[3].

The fact that ($\hat{\alpha}_c$, $\hat{\beta}_c$) can be derived implicitly from the clustering process eliminates any misclassification error for the shippers surveyed. Nevertheless, this error free statement should not necessarily hold for a new shipper. The performance of the classification model ultimately depends on the goodness of fit of the structural equations in the MIMC model. While a poor fit may still lead to good definitions of market segments, the use of the classification model to forecast segment membership is limited. In fact, this would again be a manifestation of the difficulties to associate the shippers' importance-ratings to their observable characteristics.

[3]except for reversing the signs, since the clustering method minimizes the squared distances and the classification model is estimated by maximizing the likelihood function.

- **The Results**

In order to apply the latent structure model to the shippers' survey data, the first step was to specify and estimate the MIMC model. Three latent dimensions were defined: cost, time and service quality. These dimensions should capture differences in shippers' behavior towards transportation service and are indicated by the importance-ratings elicited in the survey. While cost and time captures the importance of rates and transit time, respectively, service quality encompass other dimensions of service included in the survey, like level of effort and responsiveness. Note that by assuming that these latent dimensions are sufficient, they represent a reduction on the clustering space from the original ten service attributes to three dimensions.

However, to identify and estimate the MIMC model, some restrictions have to be imposed in the $\widehat{\Gamma}$ and $\widehat{\Lambda}_w$ matrices. In particular, it is necessary to hypothesize which importance ratings indicate each latent dimension, and which observable characteristics are causing them.

On the measurement equations (6.8), some attitudinal indicators were assumed to influence more than one latent dimension. For example, the importance of loss and damage influenced shippers' attitudes towards cost and service quality. In addition, a cluster analysis on the attitudinal indicators showed that more than 70% of the sample variance of these ratings could be explained by three-groups of variables. Moreover, these groups of attitudinal indicators were the same as those importance ratings used as indicators of each one of the latent constructs, i.e.

- cost includes rate and payment terms and billings;

- time includes transit time and reliability;

- service quality includes loss and damage, useability of equipment, responsiveness to inquiries and level of effort.

On the structural equations (6.7), the specification of Γ was less clear, with several observable characteristics being potential causes of each latent dimension. Using a full specification, i.e. all the observable characteristics affecting all the latent dimensions, several structural coefficients were not statistically significant. Then, some restrictions were applied to Γ and their impact on the goodness of fit of the model assessed. For example, the earliest delivery time was hypothesized to influence only the attitude of shippers towards the time dimension, while annual tonnage and average length of haul were causes to the cost dimension. On the other hand, some observable characteristics were kept as in the full specification, i.e. as causes of all latent dimensions. The path diagram in Figure 6.5 details the best specification of the structural equations.

Tables 6.5 and 6.6 presents the estimated coefficients and standard errors for the structural and measurement equations, respectively. While all coefficients in Λ_w were significant at 5% level of significance, some structural coefficients were kept in the model even if not statistically significant to aid in the classification stage.

In the final specification of Λ_w, satisfaction with payment terms and billings influencing time and cost dimensions, and loss and damage, influencing cost and service quality. Besides having the highest impact in the goodness of fit, these overlapping added flexibility to the definition of the latent dimensions. For example, loss and damage adds to the shippers' logistic costs, besides being a key factor in determining the quality of service provided by different carriers. Note that the coefficients set to one in Λ_w constitute an arbitrary choice of scale for the latent dimensions.

For the structural equations, the squared multiple correlation coefficients were less than 0.2. Even though this does not represent a very good fit, the model did have some degree of success in relating importance-ratings and observable characteristics to model shippers' latent attitudes towards service quality. In addition, the signs of the coefficients were coherent and provided some insights as to how shippers will be grouped into market segments. For example, the coefficient associated to the maximum acceptable delay had a negative sign in the determining the cost dimension, indicating that shippers allowing more delays are also more sensitive to cost[4]. Similarly, the positive coefficients observed in the time and service quality equations, indicate that those shippers with high acceptable delays, value these dimensions less importantly.

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[4]since importance-weights were used to set the scale of latent dimensions, the smaller its value, the more important is that dimension to shippers.

Figure 6.5
The Estimation of the MIMC Model

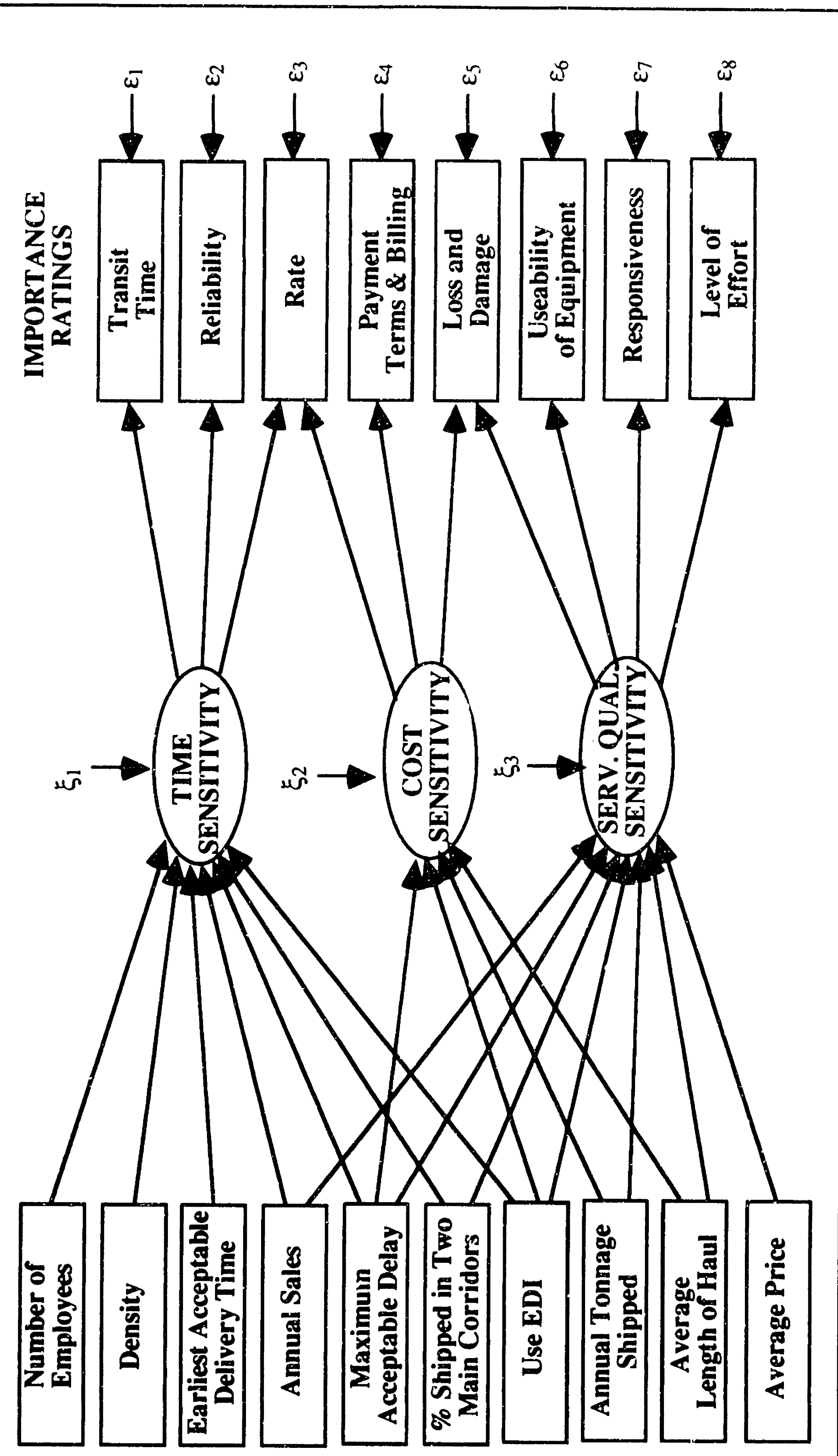


Table 6.5

The Structural Equations Coefficients

Observable Characteristic	Latent Variable		
	Cost Sensitivity	Time Sensitivity	Service Quality Sensitivity
annual tonnage	-0.0531 (0.0514)	-	-0.153 (0.0552)
annual sales	-	-0.312 (0.0811)	-0.0851 (0.0553)
number of employees	-	0.0142 (0.0791)	-
price	-	-	-0.0973 (0.0491)
density	-	-0.0731 (0.0581)	-
distance	-0.109 (0.0542)	-	-0.0944 (0.0493)
earliest accept. delivery time	-	-0.101 (0.0643)	-
maximum accept. delay	-0.191 (0.0612)	0.196 (0.0734)	0.135 (0.0551)
% shipped in 2 corridors	-	0.0991 (0.0602)	-
use EDI	0.126 (0.0603)	0.109 (0.0674)	0.120 (0.0562)
squared multiple correlation	0.197	0.162	0.197

Obs.: Standard errors in parenthesis.

Table 6.6
The Measurement Equations Coefficients

Importance-Ratings	Latent Variables			Squared Multiple Correlation
	Cost Sensitivity	Time Sensitivity	Service Quality Sensitivity	
rate	0.935 (0.209)	-	-	0.301
transit time	-	1.08 (0.115)	-	0.735
reliability	-	1.00 (-)	-	0.636
loss and damage	0.800 (0.199)	-	0.637 (0.166)	0.561
useability of equipment	-	-	1.00 (-)	0.389
payment terms and billings	1.00 (-)	0.308 (0.126)	-	0.542
responsiveness	-	-	1.07 (0.166)	0.442
level of effort	-	-	1.24 (0.177)	0.595

Obs.: Standard errors in parenthesis.
The scale of the latent variables were set by fixing one coefficient to one in each measurement equation.

After extracting the fitted values of each latent variable associated to each shipper from the structural equations, the clustering algorithm was applied to identify market segments. Five clusters were formed with a better balance in size and a better overall B/W ratio (above 2.5) than those defined only from the importance-ratings. Tables 6.7 and 6.8 present the cluster means for each latent variable and the corresponding means of importance-ratings associated to each original service attribute.

The interpretation of the segments represented in each cluster became less complex when dealing with only three dimensions (see Table 6.7). Since the scale of the latent variables were set by one of the importance-weights, the smaller the value of a given latent variable, the more important are those attributes associated to it in the MIMIC model for the

Table 6.7
Cluster Means for Latent Variables

Cluster	N	Latent Dimension			Segment Interpretation
		Cost Sensitivity	Time Sensitivity	Service Quality Sensitivity	
1	42	0.189 (0.262)	0.149 (0.202)	0.354 (0.122)	less sensitive to service
2	53	0.965 (0.201)	0.132 (0.104)	0.580 (0.0911)	less sensitive to cost
3	34	-0.676 (0.414)	0.0922 (0.332)	0.0161 (0.331)	cost -sensitive
4	16	-1.96 (0.810)	0.871 (1.23)	-0.717 (0.861)	cost and service quality sensitive
5	13	-0.362 (0.81)	-2.33 (1.91)	-2.67 (1.21)	time and service quality sensitive
B/W Ratio		4.77	1.175	2.551	overall = 2.6

Obs.: standard deviations in parenthesis

Table 6.8

Cluster Means of Importance-Ratings[1] on Service Dimensions

(The Latent Structure Approach)

Cluster	N	rate	tt	rel	lod	ueq	ptb	rsp	lef
1	42	1.643 (0.85)	1.667 (0.72)	1.286 (0.55)	1.381 (0.49)	1.310 (0.56)	1.714 (0.74)	1.476 (0.55)	1.619 (0.58)
2	53	1.530 (0.78)	1.450 (0.67)	1.360 (0.59)	1.360 (0.59)	1.490 (0.67)	1.660 (0.76)	1.510 (0.58)	1.550 (0.64)
3	34	1.500 (0.06)	1.382 (0.55)	1.147 (0.36)	1.294 (0.52)	1.265 (0.67)	1.647 (0.73)	1.441 (0.56)	1.706 (0.94)
4	16	1.444 (0.51)	1.560 (0.73)	1.440 (0.63)	1.190 (0.40)	1.630 (1.10)	1.440 (0.63)	1.250 (0.45)	1.500 (0.73)
5	13	1.460 (0.66)	1.080 (0.28)	1 (0)	1.231 (0.44)	1.231 (0.60)	1.460 (0.66)	1.154 (0.56)	1.231 (0.44)

[1]1=essential; 2=very important; 3=somewhat important; 4=not very important; 5=not important at all.

Obs.: tt = transit time; rel = reliability; lod = loss & damage; ueq = useability of equipment;
ptb = payment terms & billings ; lef = level of effort to deal with carriers.
Standard errors in parenthesis.

shippers in a given market segment. While clusters 1 and 2 included shippers less sensitive to one or more dimensions of service, in cluster 3, 4 and 5 shippers were significantly more sensitive to service. Note that the service quality dimension was usually associated to cost or time-sensitive shippers. In the next section, shippers' responses to changes in service is analyzed by segment, including some indications on the main factors in designing segment-specific services.

The differences in cluster means of the original importance-weights were less pronounced than when the clusters were based on them alone. This is explained by the interaction of observed characteristics in forming the latent dimensions. In fact, the differences in the cluster means of these characteristics (see Table 6.9) also allowed the development of the classification model coefficients deterministically, as described above. Since by definition, all shippers surveyed are perfectly classified into one cluster, the analysis of observed characteristics focused only on understanding the market segments.

The commodity value was higher for time-sensitive shippers than those in the cost-sensitive segment, reflecting the importance of inventory carrying costs. Note that even though the shippers in cluster 1 were less sensitive to service quality, they also presented a high commodity value. This can be explained by the small size of the firms in cluster 1, whereas the low volume of annual sales would be translated in less bargaining power and poor service levels provided by carriers. On the other hand, large shippers were very sensitive to time and service quality, while cost-sensitive shippers were usually associated with long length of hauls. Finally, the maximum acceptable delay also helped to differentiate cost and time sensitive shippers, being higher for the former ones.

Thus, the latent structure approach improved significantly the market segmentation results, specially when associated to classifying shippers according to their observed characteristics. Combining the information has also the advantage of reaching good results even if some response biases are present in the self-stated importance-ratings. On the traditional market segmentation approach, if the behavioral variables were biased, the whole process is compromised, specially the classification model based on ill-defined clusters. On the other hand, the latent structure model would discount the relevance of the importance-ratings, relying mostly on the observed characteristics to define the segments.

Table 6.9
Average Shippers' Characteristics in Each Market Segment
(The Latent Structure Approach)

Cluster	N	Annual Tonnage (10^3 t)	Annual Sales (10^6 \$)	Price (\$/t)	Density (t/m^3)	Maximum Delay (days)	% in 2 Main Corridors	Average Distance (miles)
1	42	94.0	169.5	2.25	0.61	0.58	74.5	963
2	53	38.1	62.3	1.88	0.62	0.63	81.9	498
3	34	183.4	493.1	1.88	0.63	0.60	65.9	1254
4	16	661.6	1165.0	1.70	0.70	0.95	64.1	1669
5	13	460.7	7596.0	2.34	0.59	0.44	65.8	961

VI.5 - Summary

From the above market segmentation analysis, it is apparent that shippers attitudes towards service quality vary significantly. Even within the selected group of commodities in the survey, it was possible to identify groups of shippers who have needs and responses towards service quality that are different from other shippers. Thus, there is a potential for carriers to differentiate their service to meet shippers' unsatisfied needs. It is unlikely that one service design and marketing strategy will satisfy all the current and potential shippers for a given carrier. Chapter 8 explores different strategies specific to each market segment defined above.

In addition, better market segments were defined when considering not only shippers' attitudes towards service quality, but also observable characteristics of shippers. The use of a MIMC model to explore the latency of shippers' attitudes improved significantly the definition of the market segments. Also, the classification model was developed implicitly and deterministically from its coefficients, without any misclassification errors for shippers in the survey.

VII - The Estimation of Freight Transportation Demand Models

Freight transportation demand (FTD) models were estimated using the information available in the shippers' survey. Revealed preferences (RP) models related the current market behavior in terms of mode shares to shippers' perceptions of the service provided. Stated preferences (SP) models then used the information elicited in the conjoint experiment, i.e. shippers' preferences under different hypothetical scenarios of transportation service offerings. The same cost minimizing behavior was assumed in both models, whereas shippers choose the mode that minimizes their annual logistic cost.

Since the main interest is to model actual behavior in the market, the primary data source are shippers' revealed preferences (RP). However, the small number of observations and the possible lack of variation in mode attributes in the RP data makes it desirable to incorporate stated preferences in the demand models. This chapter then, presents two estimation procedures and results used to combine the RP and SP models, while still accounting for potential biases and situational constraints specific to each data source. The purpose is to use all information available to accurately estimate the coefficients in the demand model. These coefficients embody the service trade-offs that shippers consider in their mode choice decisions, and are the basis for assessing the value of service in freight transportation (see Chapter 8).

Section 7.1 reviews the logistic cost specification, with some additional derivations necessary to use the information available in the shippers' survey. Sections 7.2 and 7.3 present the statistical framework and the estimation results for the RP and SP models, including the interpretation of the coefficients with respect to shippers' sensitivities to service quality. A comparison of the estimated coefficients in both models is discussed in section 7.4. Two estimation procedures for the combined RP and SP model are then used: the joint estimation (section 7.5) provides asymptotically efficient estimators for independent data sources, and the sequential estimation (section 7.6) provides an interesting alternative for using ordinary estimation software to get consistent estimators. Section 7.7 summarizes the findings from the estimation of the demand models.

VII.1 - The Logistic Cost Specification Revisited

As described in Chapter 3, the logistic cost for mode j is given by:

$$W_j = r_j\,Q + \beta_1\,[(\,t_j + L + \frac{(1 - \tau_j)}{\Delta\tau_j}\,)\,(\frac{p\,Q}{365})\,] + \beta_2\,d_j\,p\,Q + \beta_3\,[(1 - u_j)\,(\frac{p\,Q}{365})\,] + \beta_4\,\frac{Q}{q_j} + \beta_5\,p\,\frac{q_j}{2} + src_j \qquad (7.1)$$

where r_j = rate (\$ / ton);

- t_j = transit time (days);
- τ_j = fraction of times shipments arrive when wanted;
- d_j = fraction of shipment value lost or damaged;
- u_j = fraction of times a sufficient quantity of equipment is available;
- Q = annual tonnage shipped (10^3 tons);
- p = average value of the commodity being shipped (\$ / ton);
- L = maximum acceptable delay (days);
- $\Delta\tau_j$ = marginal decrease in the probability of stock-out due to an additional day of safety-stock (see Appendix A);
- q_j = average shipment size (tons); and
- src_j = intangible service-related attributes.

This formulation adequately represent the logistic cost for the shipments of the five commodities contemplated in the shippers' survey. Not only are these commodities non seasonal and non perishable, but also there is no a priori reason to invalidate the assumptions of fixed product prices and stable shipment rates used in the derivation of the cost components.

The implementation of the random cost model then, depends on the choice variables available. In particular, mode shares are used in the RP model (section 7.2) and stated preferences in hypothetical scenarios in the SP model (section 7.3). Even though most of the data requirements are directly available in the shippers' survey, some cost components required additional transformations on the data or the use of information in the auxiliary data sources.

• **Shipment Size**

The shipment size decision is intertwined with the mode choice, affecting the logistic cost by different modes. The joint decision process is described by the probability that shipper n chooses mode j and shipment size q, i.e.

$$P_n(j,q) = P_n(j \mid q) \cdot P_n(q) \tag{7.2}$$

where $P_n(j \mid q)$ is the probability of choosing mode j, given the shipment size q;
$P_n(q)$ is the probability of choosing shipment size q.

The unconditional probability of shipper n choosing mode j is then, given by:

$$P_n(j) = \sum_q P_n(j \mid q) \cdot P_n(q) \tag{7.3}$$

Note that (7.3) recognizes that shipment size is usually characterized in a discrete manner, e.g. carloads and the block-structure of freight rates.

In order to proceed from (7.3), a functional form for $P_n(q)$ has to be assumed or shipment size blocks have to be specified a priori with the associated probabilities of choosing them. Studies have shown limited success in relating observations of shipment size to theoretical distributions (see Hall [1985]). On the other hand, discretizing the shipment size in blocks is not an option since the actual shipment size was not elicited in the shippers' survey.

In the Waybill Sample, information on the shipment size by rail and by intermodal was available in terms of the tonnage billed and the number of carloads used. The typical shipment size was one rail car or one container across all commodities surveyed (see Table 7.1). This also indicated that the tonnage shipped by rail was almost double the one by intermodal due to differences in the car capacity. For example, paper shipments were on average of 55 tons by rail and 20 tons by intermodal carriers. The economies of scale then, seems to be limited to the full carload shipment, with shippers adjusting their needs through the frequency of shipments.

Given the evidence in the Waybill Sample for the same commodities in the survey, a carload shipment specific to each mode and products shipped was assumed in the logistic cost calculations. Even though information on actual shipment sizes by truck was not available, the truckload assumption is reasonable when the interest lies on traffic with truck-rail competition. The order cost (oc_j) then, becomes a function of the number of carloads shipped per year, while the storage cost at the destination (sc_j) reflect a half-carload inventory carried, on average, across the year. The formulation of these cost components is given by:

$$oc_j = \beta_4 \frac{Q}{cap_j} \quad \text{and} \quad sc_j = \beta_5 \, p \, \frac{cap_j}{2} \tag{7.4}$$

where cap_j = vehicle capacity of mode j.

Besides the full carload assumption, minimizing the logistic cost function specified in (7.1) with respect to the shipment size q provided additional insights (see Appendix C for details). The objective then, was to find which additional variables might capture the effect of shipment size on the logistic costs. These variables would be introduced in the logistic cost specification as situational constraints specific to some modes. In particular, while increases in the shipment ton-miles tend to reduce the overall logistic cost per ton by rail, short length of hauls provide an intrinsic advantage to truck carriers.

Table 7.1
Shipment Size by Commodity in the Waybill Sample

Mode		Paper	Alumi-num	Pet Food	Plastics	Tires	Overall
rail	tons	56.31 (20.07)	78.26 (18.08)	59.47 (22.53)	87.73 (10.46)	24.24 (14.29)	62.04 (23.30)
	carloads	1.004 (0.101)	1.018 (0.157)	1.028 (0.503)	1.002 (0.050)	1.055 (0.443)	1.077 (0.157)
inter-modal	tons	20.51 (9.32)	21.66 (9.18)	24.41 (14.13)	23.06 (12.43)	15.79 (11.68)	20.24 (10.54)
	carloads	1.107 (0.633)	1.072 (0.452)	1.115 (0.552)	1.204 (0.732)	1.179 (0.981)	1.123 (0.694)

Obs.: standard deviations in parenthesis

- **Intangible Service-Related Attributes (src)**

In addition, the logistic cost specification was extended to include intangible service-related attributes available in the survey. In other words, the benefits associated to offering EDI, and the costs associated to the level of satisfaction with payment terms and billings, with the responsiveness to inquiries and, and with the effort required to deal with carriers were incorporated in the logistic cost function. Since these attributes are usually not considered in the logistic cost calculations, a constant unit cost was associated to each one in (7.1) i.e.:

$$src_j = \beta_7 EDI_j + \beta_8 ptb_j + \beta_9 rsp_j + \beta_{10} def_j \qquad (7.5)$$

where EDI_j = 1, if carriers offer EDI capabilities; 0, otherwise
ptb_j = fraction of times shipper is satisfied with payment terms & billings
rsp_j = fraction of times shipper is satisfied with carriers' responsiveness
def_j = 1, if carrier is difficult to work with; 0, otherwise.

Alternatively, it might be hypothesized that the effect of these attributes in mode choice decisions vary with the size of the firm, in which case the level of service provided by each mode should be weighted by the annual tonnage shipped. In the next section, both specification are discussed for the RP model.

- **Rates and Transit Time by Intermodal**

As discussed in Chapter 4, shippers reported the typical rate and transit time by rail and by truck in two major corridors. Since intermodal rates and transit time were not reported, external data sources were used to calibrate some relationships between intermodal and other modes service. In particular, the waybill sample was used for rates, and the car cycle data for transit time, both comparing intermodal to rail service.

The comparability between the external data sources and the shippers' survey was guaranteed at the commodity and origin-destination region levels. In other words, only shipments relating the commodities in the survey and only the origin and destination locations within the regions for which rate and transit time are available in the survey were used in developing the relationship between intermodal and rail service.

Besides differences in the sample selection, another disadvantage of using external data is that they refer to observed mode performance, while the survey elicited shippers' perceptions of the service provided by different modes. Nevertheless, as discussed in Chapter 5, shippers usually have fairly accurate perceptions of the cost and transit time by different modes available to them.

A simple ratio between rail and intermodal performance was then, proposed for rates and transit time. On average, intermodal rates were 30% higher than those by rail, for car movements matching the same origin and destination regions. For the transit time, intermodal took on average, 30% of the time by rail, which represented an absolute difference of around four days in their lead times. Note that one day was added to the intermodal transit time to account for container pick-up and delivery not included in the loaded trip time of the car cycle data (see Little et al [1991]). In addition, these relations were only used when the result was less than the perceived truck rate or higher than the perceived truck time, otherwise the intermodal performance was set equal to the truck mode.

- **Reliability Costs**

In the logistic cost specification, reliability costs included basically the cost of late arrivals (cla), like the buyers stock-out and safety stock carrying costs. In Appendix A, the following specification was derived:

$$\text{cla} = i \cdot \left(\frac{p\,Q}{365}\right) \cdot \left(L + \frac{1 - \tau_j}{\Delta\tau_j} \right) \tag{7.6}$$

where $i =$ discount rate (per year)

$Q =$ annual tonnage shipped (tons)

$p =$ average price of the commodity shipped ($ / ton)

$L =$ maximum acceptable delay (days)

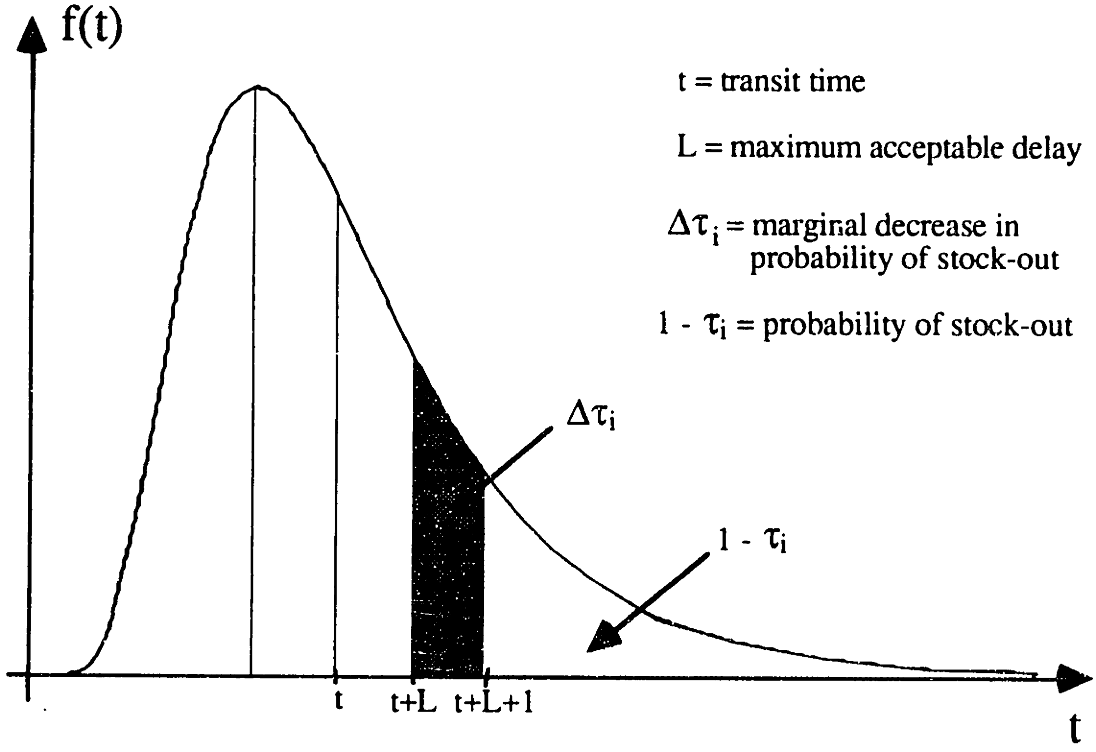
$1 - \tau_j =$ probability that shipment by mode i is delayed by more than L days

$\Delta\tau_j =$ marginal decrease in the probability of a stock-out occurring when using mode i with an additional day of safety-stock

In order to incorporate these costs in the shippers' logistic cost function, it was necessary to assume that their perceptions (L^*) do reflect the safety-stock carried at the destination. However, to adjust for the stock-out risks, the ratio $(1 - \tau_j) / \Delta\tau_j$ needs to be evaluated for the different modes available. In fact, since the perceived reliability τ_j^* was measured as the percentage of times shipments by mode i arrived when shipper wanted, its complement $(1 - \tau_j^*)$ was considered to be the probability of a stock-out situation at the destination due to delays above the maximum acceptable L^*.

The issue then, is the derivation of the marginal decrease in the probability of a stock-out due to an additional day of safety stock ($\Delta\tau_j$). Alternative assumptions for the transit time distribution provide different values for $\Delta\tau_j$ (see Figure 7.1). However, only the typical transit time (t_j^*) and the probability of arriving later than (t_j^* + L^*) when using mode i were elicited in the survey. The approach then, was to use this information to fully characterize a theoretical distribution for transit time.

Figure 7.1
Transit Time Distribution



Transit times are generally skewed to the right as a result of minimum trip time and frequent long trip times due to possible delays (for the rail mode, see discussion in Little et al [1991]). Appendix A describes the empirical estimation of using the log-normal distribution and the negative exponential curve to characterize the right tail of the perceived transit time distribution for each mode. In fact, the latter approach provided more reasonable results, which are summarized in Table 7.2 in terms of the marginal decrease in the probability of stock-out and the risk-adjusted safety-stock averaged for each mode.

Table 7.2
Average Risk-Adjusted Safety Stock
(using the negative exponential approximation[1])

Safety-Stock	Attributes	Truck	Rail	Intermodal
marginal probability of stock-out[2]	$\Delta\tau_i$	0.052 (0.035)	0.050 (0.013)	0.043 (0.024)
risk-adjusted safety stock (days)	$L + \frac{(1 - \tau_i)}{\Delta\tau_i}$	1.64 (0.50)	3.07 (0.84)	1.92 (0.43)

[1]for details, see Appendix A.
[2]marginal decrease in the probability of a stock-out occurring, given an additional day of safety-stock.
Standard deviations in parenthesis.

Truck was usually perceived as the fastest an most reliable mode. Buyers should then, carry small amounts of safety-stock when using it, and as observed, have the highest benefits from adding an additional day of safety-stock. On the other hand, rail being perceived as more unreliable, needs more safety-stock to adjust for the risks of stock-out, which was translated into having the highest ratio $(1 - \tau_i) / \Delta\tau_i$ among all modes. Intermodal was, on average, in-between the truck and rail mode, but closer to truck users' safety-stock.

Besides the information on reliability, the derivations above made use of the typical transit time by different modes, making it difficult to isolate their effects in the model. In other words, the correlation between the in-transit carrying cost and the reliability cost coefficients should allow them to be estimated jointly as the same in-transit capital carrying cost without major differences in the goodness of fit of the demand model.

VII.2 - The Estimation of the RP Model

Revealed preferences (RP) models attempts to explain the current use of different modes with shippers' perceptions of the service provided by them. This definition of RP models departs from its traditional use in the literature, since it includes perceptions of service as independent variables instead of the observed performance of different modes. Nevertheless, it was shown in Chapter 5 that shippers' perceptions of service are relevant to their mode choice decisions, and that a strong link with carriers' observed performance exists. Note that the actual market behavior was represented in terms of reported mode shares.

- **Statistical Framework**

The statistical framework for the RP model was influenced by the fact that mode choice for individual shipments were not observed directly, but rather the mode shares on all the firm's shipments in a given corridor. When only grouped data, like shares and proportions, are available, the traditional discrete choice models are not directly applicable. These models were developed when the independent variable is discrete or categorical, without any particular order among the alternatives in the choice set. Nevertheless, shares and proportions are derived from individual choices regarding these alternatives, where the number of times a given alternative was chosen is averaged across all observations.

In the case of repeated observations for the same value of independent variables, minimum chi-square methods are shown to be consistent and asymptotically normal (see Judge et al [1982]). For example, the logit model can be conveniently expressed as a linear functional form using the logarithm of the odds ratio (P_{nj}/P_{nk}) given by:

$$\log\left[\frac{P_{nj}}{P_{nk}}\right] = \beta'(x_{nj} - x_{nk}) + u_n \tag{7.7}$$

where P_{nj} = probability that shipper n chooses mode j

x_{nj} = vector of mode j attributes perceived by shipper n;

β = vector of parameters in the logistic cost function; and

u_n = random error term

The minimum chi-square methods then, assume $P_{nj} = s_{nj}$ in large samples, where s_{nj} is the observed share of mode j for shipper n.

Two drawbacks in using (7.7) or other inverse transformations should be discussed. First, the residual are not homocedastic, i.e. their variance depends on the number of observations used to determine the share of a given mode. This can be easily shown by expanding the logarithm of the odds ratio in Taylor series around the values of the true probabilities P_{nj} (see Amemiya [1985]). The estimation procedure should then, use weighted least squares, with the weights given by some estimate of $var(u_n)$[1].

Second, the logarithm of the odds ratio or other inverse transformations are usually not defined for the extreme cases, where $P_{nj} = 0$ or 1. This constraint is not very attractive for mode choice, since shippers may in fact use exclusively one mode/carrier for all shipments in a corridor. For the binary logit, Cox [1970] suggested a perturbation based on the number of observations used to derive each mode share, which does not affect the asymptotic properties of the estimates of β.

Note that both approaches to circumvent the drawbacks in the minimum chi-square methods depends on the prior knowledge of the number of observations generating the mode shares. Unfortunately, this information was not available in the shippers' survey. Alternatively to minimum chi-square methods, a maximum likelihood-like procedure was used to estimate the coefficients β.

The log-likelihood function for the discrete choice model is given by:

[1] e.g. obtained from estimating the model initially with ordinary least squares.

$$L(\beta) = \sum_{n=1}^{N} \sum_{j=1}^{J} d_{nj} \log(P_{nj}) \tag{7.8}$$

where $d_{nj} =$ 1 if shipper n chose mode j; 0 otherwise.

$$P_{nj} = \frac{\exp(\beta' x_{nj})}{\sum_{k=1}^{J} \exp(\beta' x_{nk})}$$ in the logit model with J alternatives

It is assumed that mode shares were derived from repeated observations of mode choices, where shippers' perceptions of mode service are the same across observations. However, as mentioned above, the underlying number of observations in which mode j was chosen is unknown, and only the mode share s_{nj} for each shipper n was reported in the survey.

The following log-likelihood-like function was then specified:

$$\tilde{L}(\beta) = \sum_{n=1}^{N} \sum_{j=1}^{J} s_{nj} \log(P_{nj}) =$$

$$= \sum_{n=1}^{N} \sum_{j=1}^{J} s_{nj} \log[(\sum_{k=1}^{J} \exp(-\beta' x_{nk}))^{-1} \exp(-\beta' x_{nj}) \tag{7.9}$$

Note that the intuition behind (7.9) was obtained from taking the expected value of (7.8) with respect to the index function d_{nj} and, substituting the reported mode shares as a consistent estimator of $E[d_{nj}]$.

By maximizing (7.9) with actual data on explanatory variables x_n's and mode shares s_{nj}'s, consistent and asymptotically normal coefficients β are estimated (see extremum estimators in Ameniya[1985]). Since the shares are used in place of the actual number of observations choosing each alternative, these estimates are not as efficient as the MLE with repeated observations.

Note that (7.9) is globally concave and conventional numerical optimization routines can be used. In particular, the estimation procedure was developed using the non-linear optimization routine in GAUSS [1988]. The implementation used quasi-Newton updates, where the hessian matrix was approximated by the inner product of the first derivatives of (7.9). In addition, robust standard errors were estimated using the asymptotic normality results for extremum operators in Ameniya [1985].

- **The specification of utility functions**

Two specifications of the cost function for different modes were tested within the RP model. First, as it is commonly hypothesized in the discrete choice literature, a simple linear combination of perceived service attributes was used to explain the mode shares. Second, it was assumed that shippers seek to minimize their logistic costs as specified in (7.1). In both cases, the assumption of carload shipments was reflected in the order costs being proportional to the number of carloads shipped per year and in the half-carload inventory carried, on average, across the year. The utility of each mode is then given by the negative of the cost function, whereas the parameters included in its specification are estimated using the maximum-likelihood-like procedure described above.

Besides the logistic cost formulation, additional structure in the shippers' behavior was provided by including situational constraints in the utility function. These constraints attempt to explain intrinsic advantages of particular modes in the choice process, which are not reflected in the logistic costs. In addition to the mode-specific constants, two types of variables were included in the cost functions:

- product attributes, whereas shippers may use a particular carrier for reasons not captured in the logistic cost specification, but related to the product being shipped (e.g. packaging). Besides adding product-specific constants to the utility specification, an abstract formulation was attempted using the commodity value and density of the product.

- shippers' transportation needs, whereas shipments with high ton-miles are more likely to be shipped by rail, and short length of hauls are usually captive to truck carriers. Note that ton-miles and length of haul were also considered important factors to represent the effect of shipment size in the logistic costs (see Appendix C).

Table 7.3 presents the specification table for the RP models, including not only the cost function, but also mode-specific constants and situational constraints. The coeffient associated to the rates charged (β_0) corresponds to a scaling factor for all logistic cost components. Note that, in the linear combination of perceived service attributes, the transit time and the reliability were associated to two separate coefficients (β_1, β_{10}) since they

Table 7.3
Specification Table for the RP Model

• cost function

Coefficient	**(Generic)**[1]	**Linear Combination**	**Logistic Cost**
β_0 **(scale)**	rate	r_j	$r_j Q$
β_1	transit time & reliability	t_j	$(t_j + L + \frac{(1 - \tau_j)}{\Delta\tau_j})\ x$
β_2	loss or damage	d_j	$d_j\, p\, Q$
β_3	useability of equip.	u_j	$(1 - u_j)\ x$
β_4	order cost	$\frac{Q}{cap_j}$	$\frac{Q}{cap_j}$
β_5	storage cost	$p\,\frac{cap_j}{2}$	$p\,\frac{cap_j}{2}$
β_6	offer EDI	EDI_j	EDI_j
β_7	paym. terms & bills	ptb_j	ptb_j
β_8	responsiveness	rsp_j	rsp_j
β_9	level of effort-difficult	def_j	def_j
β_{10}	reliability	τ_j	-

[1]All variables were previously defined in (7.1), except for $x = p \cdot Q / 365$.

Table 7.3 (Cont.)
Specification Table for the RP Model

- **mode-specific constants, firms' size and shippers' transportation needs**

Mode	γ_1	γ_2	γ_3	γ_4
truck	1	0	0	length of haul (10^3mile)
rail	0	0	annual ton-miles (10^6mile)	0
intermodal	0	1	0	0

- **product-specific characteristics and dummy variables**

Mode	γ_5	γ_6	γ_7	γ_8	γ_9	γ_{10}
truck	1 if paper 0 ow.	1 if alum. 0 ow.	1 if pet f. 0 ow.	1 if plast. 0 ow.	average price (\$ / ton)	0
rail	0	0	0	0	0	density (t / m^3)
intermodal	1 if paper 0 ow.	1 if alum. 0 ow.	1 if pet f. 0 ow.	1 if plast. 0 ow.	average price (\$ / ton)	0

were measured in different units in the survey. The comparison between the estimation results for the two specifications of the cost function are discussed in the next section.

Not all situational constraints had a significant effect in explaining shippers' mode choice behavior. The non-significant coefficients associated to situational constraints were omitted from the final specification of the RP model. In addition the specification of situational constraints in Table 7.3 also incorporates some restrictions on the parameters, which reflects the results from several specification tests. For example, annual ton-miles being included only on the rail utility function was better than including it also in another mode utility function. Also, the motivation behind considering the rail mode as the base alternative for most situational constraints (e.g. product-specific constants) is related to the small number of shippers using intermodal.

- **The results**

Table 7.4 presents the estimated coefficients for both specifications of the utility functions. In general, adding structure to the shippers' mode choice decision process improved the goodness of fit for the RP models. More of the coefficients associated to the logistic cost components were significant and with the expected signs, than those based in a linear combination of original service attributes. In addition, some situational constraints did in fact improve the explanatory power of the model.

The overall gain in the log-likelihood function from using the logistic cost specification was of two likelihood units. The improvements in the significance level of the estimated coefficients were more noticeable for those associated with the traditional logistic cost components, i.e. rate, transit time, reliability, loss and damage, and useability of equipment. This come at no surprise, since for the other service attributes the specification was the same in both models, i.e. just a linear combination of perceived service levels.

This improvement from considering the logistic cost specification has to be weighted by the fact that one less coefficient is estimated in that specification. In particular, the coefficients associated with transit time and reliability were combined in the same logistic cost parameter without a significant loss in the goodness of fit (less than 0.5% in the log-likelihood value at optimality). This was expected due to the use of transit time in the calculations of the reliability costs in section 7.1. In the next section, this parameter was

Table 7.4
The RP Model

Attributes[1]		linear combination service attributes		logistic cost specification	
		coefficient	std error	coefficient	std error
situational	truck	1.53	0.499	1.93	0.420
constraints	intermodal	-1.41	0.656	-1.29	0.514
	price	0.395	0.205	0.515	0.221
	distance	-0.523	0.338	-0.502	0.314
	ton-miles	0.296	0.125	0.310	0.136
rate		-0.00716	0.00616	-0.112	0.0656
transit time &reliability		-0.0446[2]	0.0553[2]	-0.137	0.0862
loss and damage		-0.190	0.157	-0.195	0.0852
useability of equipment		-5.24	2.01	-7.80	4.26
order costs		-0.235	0.201	-0.211	0.316
storage costs		-0.00332	0.0103	-0.00972	0.0107
offer EDI		0.460	0.475	0.446	0.471
payment terms & bills		1.34	0.975	1.05	0.930
responsiveness		0.810	0.794	0.677	0.785
level of effort-difficult		0.160	0.617	0.330	0.589
reliability		0.00402	0.0148	-	-

$L(0) = -364.7$	$L^* = -188.1$	$L^* = -186.0$
$(N = 332)$	$\bar{\rho}^2 = 0.440$	$\bar{\rho}^2 = 0.449$

[1]see definitions in Table 7.3.

[2]includes only the effect of transit time.

interpreted as a common in-transit inventory carrying cost, reflecting the transit time and its variability for different modes.

Note that the coefficients associated to storage and order costs were not statistically significant. Also, as shown in Table 7.5, the effect of intangible service-related attributes were not significantly different from zero in both specifications. Despite the non-significant coefficients, these variables were kept in the model because of the stated preferences analysis.

Table 7.5
T-statistics for Coefficients Associated to Intangible Service Attributes

Intangible Service-Related Attributes	Linear Combination	Logistic Costs
offer EDI	0.968	0.947
payment terms & bills	1.37	1.13
responsiveness	1.02	0.862
level of effort - diff.	0.259	0.560

Obs.: the critical value for 5% level of significance is 1.645

Alternative specifications to include intangible service attributes in the logistic cost function were tried without improvements from the constant unit cost specification shown in (7.5). In particular, weighting the level of these service attributes by the number of shipments or the annual tonnage shipped in each mode decreased the value of the log-likelihood at optimality. Even though no significant effect was captured with these variables, they were kept in the model for the stated preferences analysis.

In terms of the situational constraints, the effect of both, product attributes and shippers' transportation needs, were significantly estimated in the RP model. While the total ton-miles had a positive impact in the rail utility function, the negative coefficient associated to the average length of haul reflects the advantages of motor carriers in short distances. No significant effect associated to annual sales or to number of employees in the firm could be estimated.

For the product attributes, the abstract formulation was preferred over using product-specific constants. Besides not having a major difference in the final log-likelihood value (less than 3 likelihood units for an increase of three parameters in the specification), the coefficients associated to product-specific constants were highly correlated among themselves and with the other coefficients in the logistic cost specification. In addition, the coefficient associated to the density of the product was not significant in the rail utility function. Thus, only the value of the commodity being shipped was used to capture preferences towards truck and intermodal carriers. Note that making other coefficients product-specific, like the effect of price or storage costs, also did not improve significantly over the results in Table 7.3.

Even though the results described above considered generic coefficients associated to the logistic cost components, alternative-specific coefficients were also tried. In the latter case, several coefficients were not statistically significant , making it hard to use the model to evaluate the value of service. Nevertheless, the alternative-specific formulation provided some insights as to what service attributes are significant in using a particular mode. While the rate charged had a significant negative impact on the truck and intermodal utility, transit time, reliability and loss and damage were important for rail carriers. Note that useability of equipment had a negative and significant effect in both truck and rail utilities, indicating that car availability is an important issue across all modes. Finally, the responsiveness dimension was significant only for truck carriers, with a positive impact in their utility function.

Thus, the logistic cost formulation was selected as the best specification for the RP model, and used in the following analysis. Even though not all the estimated coefficients were statistically significant, they were kept in the specification for the combined estimation in section 7.5 and 7.6. As expected, the overall goodness of fit of the final RP model was not high, indicating the presence of random noise in the data on shippers' perceptions of the service provided by different modes.

An outlier analysis on the final model was also performed based on differences between the predicted and observed mode shares for each shipper. The largest differences were obtained for shippers using predominantly intermodal carriers, for whom truck was usually predicted as the most used mode. This indicates that the model does not differentiate well between truck and intermodal services. Nevertheless, only a small number of shippers in the sample were using intermodal predominantly, and the impact from excluding them in the estimated coefficients and in the overall goodness of fit of the RP models was not significant.

- **The interpretation of the coefficients**

Among the validity tests for the RP model, the reasonableness of the estimated behavioral coefficients is particularly important to the assessment of the value of service in freight transportation. The coefficients associated to the logistic cost components embody the trade-offs among different dimensions of service implied by the shippers' mode choice decisions. Not only are the sign of coefficients restricted logically, but also their magnitude have logical bounds.

Since all the significant coefficients in the final RP model had the expected signs, the issue then is to verify if their magnitudes are reasonable. Most of the coefficients associated to the logistic cost components have an implied behavioral interpretation, which is derived from the information they incorporated in the original formulation of the cost components (see Chapter 3). For example, the coefficient associated to loss and damage incorporates information on the discount rate (per year) and the average number of days to collect a claim. On the other hand, the one associated with useability of equipment includes the discount rate and the average number of days the transportation equipment remained unavailable.

However, only the relative magnitude of the coefficients should be interpreted. This is because the coefficients in the logit model are estimated within a multiplicative scale parameter, not identified in the model. Thus, in order to draw economic inferences the coefficients of all cost variables were normalized by the rate coefficient. These results for the significant coefficients in the RP model are shown in Table 7.6.

Table 7.6
The Normalized Coefficients of the RP Model

Parameter	Service Attribute	Normalized Coefficient	Interpretation
β_1	**transit time & reliability**	1.23 (0.693)	implied discount rate (per year)
β_2	**loss and damage**	1.74 (1.42)	implied discount rate (per year) times the average number of days to collect a claim
β_3	**useability of equipment**	69.6 (54.7)	implied discount rate (per year) times the average number of days the equipment is unavailable
β_4	**order cost**	1.88 (2.94)	order cost ($/carload)
β_5	**storage costs**	0.0868 (0.106)	implied discount rate (per year)

Obs.: Other coefficients were not estimated to be significantly different from zero.
Standard errors in parenthesis were estimated using the delta method (see Appendix D)

The normalized coefficient of transit time and reliability (1.22) gives the implied discount rate for the capital tied-up with goods in-transit. The result of 123% is significantly higher than the normal market cost of capital, indicating that shippers in the real world may overemphasize the importance of transit time. This might also be explained by the importance of uncertainties in the transit time and the associated stock-out consequences. Note that this implied cost of capital translates into a transit time value of 0.3% per day, which is very close to those obtained in Chiang et al [1980].

For the discount rates implied by the loss and damage coefficient, the average number of days to collect a claim is also factored in its estimated value. Thus, for a one-month collection period, the implied interest rate is around 6% per year, which is consistent with the market rates. On the other hand, the discount rate implied by the coefficient associated with useability of equipment includes the average number of days the transportation equipment remained unavailable. However, assuming a reasonable one-week waiting time, this result still gives a very high implied discount rate. This indicates that shippers incur extra costs due to the unavailability of equipment above those explained by the cost of capital related to the shipment retention in the origin. Perhaps the eventual loss of sales is an important consideration in this cost component.

Unfortunately, the coefficients associated to the order and storage costs were not significant at 5% level. This explains the very low unit order cost implied by the coefficient associated with the number of carloads. However, the implied discount rate of 8.7% per year on inventory carrying cost was reasonable. Note that these results are also influenced by the underlying assumption of carload shipment size for all shippers.

For the other coefficients no logical bounds can be argued a priori, specially those related to non-traditional service quality dimensions in transportation, like the responsiveness to inquiries. They represent a unit cost associated to the service provided along each dimension.

VII.3 - The Estimation of the SP Model

Stated preferences (SP) models used the information elicited in the conjoint experiment to model shippers' mode choice decisions. In this experiment, shippers rated their preferences towards hypothetical transportation service offerings. Aside from potential response biases in the conjoint experiment, shippers' stated preferences should be similar to their current market behavior. In other words, the trade-offs among service attributes should be motivated by the same logistic cost minimization process used in explaining the current mode shares.

- **Statistical Framework**

As described in Chapter 4, the conjoint experiment used a nine point Likert-scale, where 1 or 9 meant to strongly prefer one or the other service in the scenario and 5 meant indifference between them. The scenarios were based on ten service attributes, where the transportation alternatives were described by two or three attributes at a time at different levels.

The statistical framework should then, consider the discrete and ordinal nature of the response scale. While multinomial choice models fail to account for the ordinal nature, linear regression analysis consider the differences between consecutive points to be the same across the scale, when only the ranking is relevant. Ordered response models (ORM) provides a convenient framework to handle interval data which for some reason were grouped together in categories (see Maddala [1983]).

Since there are nine categories in the response scale, it is possible to identify eight threshold values in the utility scale such that (see Figure 7.2):

$$
\begin{aligned}
&P(y = 9) = P(\alpha_8 \leq U) \\
&P(y = 8) = P(\alpha_7 \leq U \leq \alpha_8) \\
&P(y = 7) = P(\alpha_6 \leq U \leq \alpha_7) \\
&\vdots \\
&P(y = 1) = P(U < \alpha_1)
\end{aligned}
\tag{7.10}
$$

where $U = \beta' x + u$;

x = vector of differences in logistic cost components of the alternatives;

β = vector of unknown parameters; and

u = random error term.

In a given scenario, the probability that shipper n rates their preferences at j can be formulated as:

$$\Pr[\, y_n = j \,] = \Lambda(\alpha_j - \beta' x_n) - \Lambda(\alpha_{j-1} - \beta' x_n) \quad \text{, for } j=1,\ldots m \text{ categories} \tag{7.11}$$

where $\Lambda(.)$ is the logistic cumulative distribution[2]; and

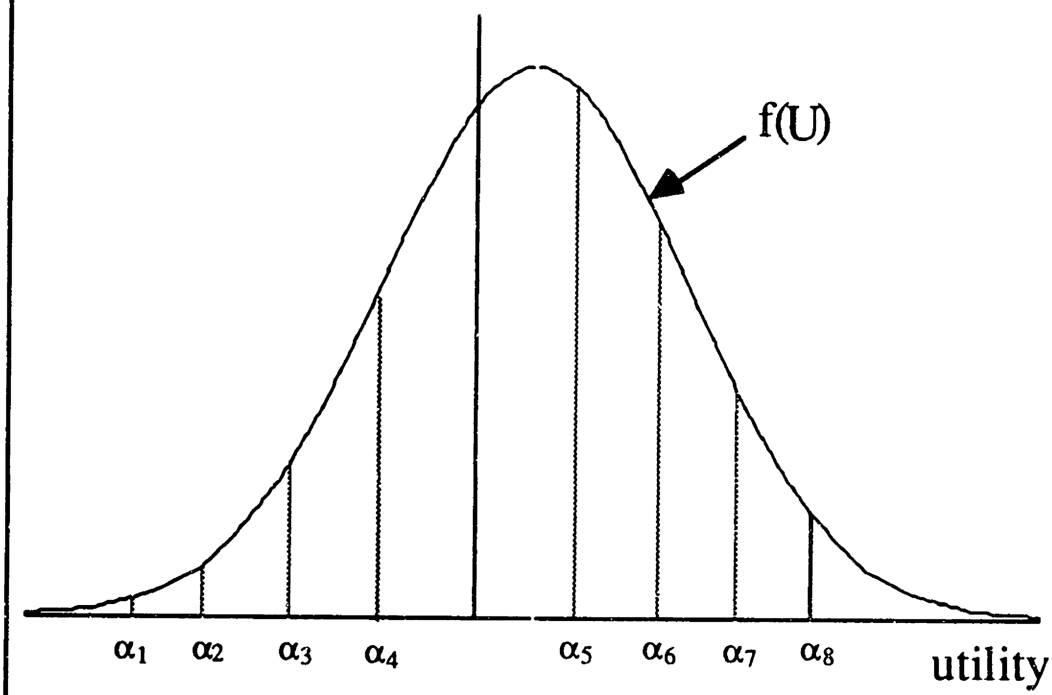
$-\infty = \alpha_0 \leq \alpha_1 \leq \ldots \leq \alpha_{m-1} \leq \alpha_m = \infty$, are the thresholds.

---

[2]derived from the assumption that u_n are iid Gumbel distributed

Figure 7.2

Utility Function and Threshold Parameters
(nine-point symmetric response scale)



Define $d_{nj} = 1$, if y_n falls in category j; 0, otherwise. Then, to estimate (α, β), the following log-likelihood is maximized:

$$L(\alpha, \beta) = \sum_{n=1}^{N} \sum_{j=1}^{m} d_{nj} \log [\Lambda(\alpha_j - \beta' x_n) - \Lambda(\alpha_j - \beta' x_n)] \tag{7.12}$$

In particular, the estimation procedure was developed using the non-linear optimization routine in GAUSS [1988]. The implementation used quasi-Newton updates, where the hessian matrix was approximated by the inner product of the first derivatives of (7.12). In addition, since each shipper responded to forty trade-off questions, the observations in the SP data set are likely to be correlated. To avoid underestimating the standard errors of the parameters, robust statistics were calculated using the asymptotic normality results in Amemiya [1985].

It is important to observe that there is little interest in determining elasticities with respect to the arbitrary response scale in the conjoint experiment. In practice, if demand elasticities were to be derived from stated preferences, the response scale would be converted to a binary choice between transportation alternatives in each scenario, which then, has a meaningful interpretation. Unfortunately, the transportation modes were not always identified in a given scenario, making the conversion to a binary choice without purpose. Thus, demand elasticities to service attributes were only derived for the model combining the RP and SP data sources (see Chapter 8), where the conjoint experiment was used to help to identify service trade-offs in mode choice decisions.

- **The specification of the utility functions**

Shippers' stated preferences are elicited from comparing pairs of transportation services, described by the same attributes used in the RP model. However, their values were established a priori to cover a significant range of service offerings, while retaining the realism of the scenarios.

Given the same parametric logistic cost specification used in the RP model, the differences between the cost components implied by the hypothetical alternatives in each scenario were computed and used as independent variables **x** in the utility function $\beta' \mathbf{x}$ (see Table 7.7). For example, loss and damage costs were formulated as $\beta_3 \,.\, d \,.\, p.\, Q$ where $d = d^L - d^R$ is the difference between the loss and damage levels describing the two transportation offerings in a given scenario. The average price and annual tonnage shipped is obtained from data on shippers' demographics, and is invariant during the conjoint experiment for each shipper.

Table 7.7
Specification Table for the SP Model

Coefficient	**(Generic)**	**Logistic Cost**
β_0**(scale)**	rate	$(r^L - r^R) . Q$
β_1	transit time & reliability	$[(t^L - t^R) + (\frac{(1 - \tau^L)}{\Delta\tau^L} - \frac{(1 - \tau^R)}{\Delta\tau^R})] x$
β_2	loss and damage	$(d^L - d^R) p Q$
β_3	useability of equip.	$(u^R - u^L) x$
β_6	offer EDI	$(EDI^L - EDI^R)$
β_7	paym. terms & bills	$(ptb^L - ptb^R)$
β_8	responsiveness	$(rsp^L - rap^R)$
β_9	level of effort-diff.	$(def^L - def^R)$
γ_0	truck constant	$(tr^L - tr^R)$
γ_1	intermodal constant	$(in^L - in^R)$

All variables were defined in (7.1), except for $x = p . Q / 365$;
$tr^i = 1$, if alternative i was described as truck mode; 0, otherwise; and
$in^i = 1$, if alternative i was described as intermodal mode; 0, otherwise.
(L, R) are the indices of the alternatives in a given scenario

Whenever an attribute was not included in a given scenario, it was assumed that it was at the same level in both offerings and that they refer to the same mode when not explicitly identified in the scenario. This is equivalent to have the logistic cost components associated to missing attributes not influencing shippers' stated preferences.

Since the mode was not always present in the description of the alternatives, it was difficult to identify or accurately estimate mode-specific coefficients in the SP models (including situational constraints). In addition, order and storage costs were derived from the carload shipment size assumption, which was not used in describing the hypothetical alternatives. It is reasonable then, to assume that they are equal for the alternatives in a given scenario (coefficients β_4 and β_5 were omitted in Table 7.7). Thus, only the mode-specific constants were included in the utility function to reflect shippers intrinsic preferences towards one mode that are not justified by differences in the underlying logistic costs.

On the other hand, it is very difficult to determine the risk-adjusted safety stock for each hypothetical scenario used in the conjoint experiment. First, not all mode attributes were used to describe the alternatives in a given scenario. For example, the trade-off might be between two alternatives with different levels of reliability, but without specifying the transit times involved. Second, the mode was not always defined in the scenarios. Thus, even if the perceived mode attributes were to be used in the conjoint experiment, it would still be necessary to identify the modes in the trade-off questions. The solution was then, to consider the average $\Delta\tau$ for each shipper when the mode was not defined, or the mode-specific $\Delta\tau_j$ calculated from shippers' perceptions of service, in the SP model.

Finally, potential sources of response biases in the conjoint experiment were considered in the specification of the utility functions. In particular, two modifications were introduced in the logistic cost specification of the SP models. First, the observed mode shares were included as independent variables in the utility function, when the modes were identified in a given scenario. Conceptually, the mode shares would capture any significant justification bias, by which shippers would attempt to consciously or unconsciously rationalize their actual market behavior when stating their preferences in hypothetical scenarios.

Second, the survey settings and procedures were considered to identify potential sources of biases. Under the traditional ordered response models framework, the estimated thresholds are considered invariant across all observations. However, non-random differences in the way shippers interpret the response scale may introduce biases in the estimated coefficients in the SP model. These non-random differences may reflect efforts of shippers in the survey to adhere to recognized norms or may be rooted in some other socially conditioned response bias. Similar to Bolduc and Poole [1989], the constants thresholds were then replaced by some linear functional form with a random error term and, estimated jointly with the other coefficients. This formulation is discussed in further details at the end of this section.

Note also that a symmetry restriction was imposed in the estimation of the thresholds. This reflected the nature of the response scale; for example, there is no reason to assume that strongly preferring one transportation offering is different from strongly preferring the other one since the order in which the alternatives are presented is arbitrary. Thus, the number of thresholds estimated in the final specification is reduced by half from the traditional ordered response models, helping to balance the effect of introducing a linear functional form associated to each threshold.

- **The results**

Table 7.8 presents the results for the SP models for all shippers surveyed. In general, most coefficients in the ordered logit models using stated preferences data were estimated significantly different from zero. These models were specially able to isolate the trade-offs involving non-traditional dimensions of service quality, like the level of satisfaction with payment terms and billings and with responsiveness to inquiries. However, the coefficient associated to rates was not significant at 5% level. Besides being an indication that shippers were not to sensitive to rates when expressing their stated preferences, the design of the conjoint experiment may also have affected this result.

Since shippers rated their preferences in forty different scenarios, it was possible to estimate commodity-specific SP models. However, the results showed several coefficients not significant, making the comparison across commodities very difficult. To some extent, this is explained by the correlation among responses for the same shipper in conjoint experiment, whereas each scenario represented trade-offs between only two or three attributes at a time. This issue is further explored in the market segmentation analysis in

Table 7.8
The SP Model

Logistic Cost Specification		coefficient	standard errors
Thresholds[1]	constant (α_1)	0.397	0.0216
	constant (α_2)	0.851	0.0510
	constant (α_3)	1.39	0.0932
	constant (α_4)	2.19	0.180
Mode-Specific Constants	truck	-0.306	0.118
	intermodal	0.0137	0.103
rate		-0.00556	0.0144
transit time & reliability		-0.0211	0.0106
loss and damage		-0.0297	0.00861
useability of equipment		-0.881	0.351
offr EDI		1.40	0.0953
payment terms & billings		0.209	0.145
responsiveness		0.252	0.158
level of effort - difficult		-0.596	0.0982

$L(0) = -18{,}801.1$ ($N = 6640$) $L^* = -13{,}899.5$ $\bar{\rho}^2 = 0.260$

[1]refers to the right most bounds. By the symmetry restriction, the other bounds are just the negative of these values.

Chapter 8, with the demand elasticities to service quality being calculated for different market segments.

In terms of response biases, the improvement in the log-likelihood value from including the mode shares in the utility function specification was not significant. In addition, the estimated coefficients associated to the mode shares were also not significant at 5% level. This result was expected since the modes were not always identified in the description of the transportation alternatives in each scenario. Unless the level of some attributes could be directly associated to a particular mode, there is no reason to believe that shippers' stated preferences would be influenced by any justification or inertia behavior towards their current mode usage.

For the symmetry restriction on the estimated bounds, the increase in the log-likelihood value was not enough to reject it at 5% level. If there is no explicit order in which each transportation offering is presented in each scenario, there is no reason to believe that the response scale is not symmetric around its indifference point. A shipper that strongly prefer the first alternative should also strongly prefer the second one, if the order in which the alternatives are presented is reversed.

• **The estimation of variable thresholds in ordered logit models**

So far, the SP models have been estimated using thresholds or bounds constant across all shippers. In this section, this assumption is relaxed by specifying individual specific random bounds, which slide on the real continuum of the underlying or latent dependent variable so as to accommodate differences in the interpretation of the response scale. Similar to Bolduc and Poole [1989], the individualized bounds were assumed to be linear functions of variables that explain the cognitive or other processes influencing the position of shippers' discrete responses (see derivation in Appendix F).

$$\alpha_{n,j} = \theta_j' \mathbf{z}_n + \varepsilon_{n,j} \tag{7.12}$$

Two types of variables $\mathbf{z}_n$ were included in the linear functional form for the bounds. First, variables related to the survey protocol and shippers' responses tried to capture the individual interpretation of the response scale. In particular, the average deviation from the indifference point in the scale for each shipper and a dummy variable indicating if two or three attributes were used to describe the alternatives in a given scenario, were introduced in the bounds. While the average deviation captures if the shipper is more likely to have extreme opinions or preferences about transportation service, the dummy variable captures the effect of having more attributes to trade-off in each scenario.

Second, socioeconomic variables were included to capture the shipper-specific effects in the location of the bounds. The firm's annual sales and the shipper's experience as a decision-maker were used. The hypothesis was that larger firms and more experienced shippers should be more conservative in expressing their opinions towards transportation service. Thus, less responses on the extreme of the scale should be observed for these shippers in the conjoint experiment. Note that the parsimony in the variables included in the bounds is justified by the increase in the total number of parameters to be estimated in the model. For example, for a nine-category response scale, two additional variables would introduce twenty-four parameters related to the bounds[3].

Even though the value of the log-likelihood improved significantly with the variable bounds model, the coefficients associated to the logistic cost components were very close to those in the constant bounds model. The maximum difference between the logistic cost coefficients was less than 5%. Table 7.9 presents the estimated coefficients associated to the bounds, considering the two type of variables described above.

From the signs of the coefficients, the average deviations variable had an opposite effect in the location of the bounds than that of the number of attributes dummy. While the more extreme are the responses, the closer are the middle bounds, the more attributes in the scenario, the further apart are the middle bounds.

On the other hand, the firm's annual sales and the shipper's experience as a decision-maker tended to make the middle bounds further apart. To some extent, this confirms the hypothesis that large firms and experienced shippers are more conservative in expressing their opinions. In this case though, the improvement in the log-likelihood value is much smaller than when using the variables related to the survey protocol and the shippers' responses.

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[3]in this model, eight bounds would be estimated, with a total of 8 x 3 = 24 parameters, including a constant in the bounds' functional form.

Table 7.9
The SP Model:
Symmetric Variable Bounds

Bound	Constant	Deviations from Indifference	Three-Attributes Dummy	L* ($\bar{\rho}^2$)
1	0.445	-0.154	0.0602	
	(0.0160)	(0.0176)	(0.0260)	
2	0.968	-0.347	0.164	
	(0.0229)	(0.0264)	(0.0264)	13314.3
3	1.61	-0.598	0.274	(0.290)
	(0.0306)	(0.0407)	(0.0469)	
4	2.60	-1.01	0.389	
	(0.0411)	(0.0498)	(0.0662)	

Bound	Constant	Annual Sales ($ Billion)	Shippers' Experience (years)	L* ($\bar{\rho}^2$)
1	0.314	0.00272	0.0141	
	(0.0252)	(0.00268)	(0.00446)	
2	0.742	0.00925	0.0188	
	(0.0362)	(0.00387)	(0.00628)	13469.9
3	1.29	0.0193	0.0167	(0.282)
	(0.0463)	(0.00517)	(0.00795)	
4	1.93	0.0237	0.0463	
	(0.0595)	(0.00711)	(0.0104)	

Obs: The above coefficients refers to the right most bounds. By the symmetry restriction, the coefficients for the other bounds are just the negative value of these coefficients.

Even though the variable bounds model provided interesting insights as to how shippers' perceive the response scale differently, its usefulness in determining the value of service in transportation is limited. Since the coefficients associated to the logistic cost components did not vary significantly with variable bounds, there is no major advantages in considering this formulation in further analysis. Note that the combined RP and SP model used the constant bounds specification in order to make its estimation less complex.

VII.3 - Comparing RP and SP Model

Given that the RP and SP models are based on the same logistic cost specification, it is important to compare the estimated coefficients in both models. Such comparison would permit an assessment of the validity of the different data sources used in explaining the same phenomenon. In addition, the following analysis provided some insights into the estimation of a model combining the RP and SP information, developed in sections 7.4 and 7.5.

Two issues precluded the direct comparison of the estimated coefficients. First, both models were estimated with an implicit multiplier scale μ, not necessarily equal between the RP and SP data. Thus, only the relative magnitude of the coefficients should be compared. Second, the comparison of coefficients is only relevant for those that were estimated to be significantly different from zero.

The coefficients were then, normalized by the coefficient associated to time and reliability. This choice of the normalization coefficient was justified based on it being significantly different from zero in both models. Table 7.10 presents the normalized coefficients that are common in both models.

Besides transit time and reliability, only the coefficients associated to useability of equipment and loss and damage were significant in both models. For these coefficients, the differences were not large, indicating that the RP and SP data are capturing similar behavior of shippers. Unfortunately, the coefficient associated to rate was only significant on the RP model, not allowing further comparisons.

Table 7.10
Comparing the Normalized Coefficients:
the RP and the SP Model

Parameters	RP Model	SP Model	Test Statistic for Equality of Parameters
rate	0.814 (0.460)	0.264 (0.692)	0.662
transit time + reliability	1.0	1.0	-
loss and damage	1.44 (1.10)	1.41 (0.775)	0.0223
useability of equipment	57.1 (45.8)	41.8 (25.9)	0.291
offer EDI	-3.28 (3.98)	-66.5 (33.4)	1.880
payment terms and billings	-7.81 (8.86)	-9.89 (8.74)	0.167
responsiveness to inquiries	-5.13 (6.92)	-11.9 (9.87)	0.562
level of effort - difficult	-2.56 (4.87)	28.3 (15.0)	1.957

Obs.: Standard errors in parenthesis were estimated using the delta method (Appendix D).

$$\frac{\hat{\beta}_k^{rp} - \hat{\beta}_k^{sp}}{\sqrt{\operatorname{var}(\hat{\beta}_k^{rp}) + \operatorname{var}(\hat{\beta}_k^{sp})}}, \tag{7.13}$$

where β_k is the coefficient of the kth logistic cost component;

$\hat{\beta}_k^{rp}$ is the estimate of β_k from the RP model; and

$\hat{\beta}_k^{sp}$ is the estimation of β_k from the SP model.

Note that (7.13) assumes that both RP and SP data sets are independent. The results are also presented in Table 7.10, which shows that none of the coefficients were statistically different in both data sets at 5% level of significance The coefficients associated to offering EDI and level of effort had the highest test statistic, but they were not significantly different from zero in the RP model. Again, this provides additional evidence that both models are explaining similar mode choice behavior.

In fact, one of the advantages in combining both models is to capture the effects that were not significant in the RP data source. This is particularly important for the non-traditional cost components in the utility functions, i.e. offering EDI, satisfaction with payment terms and billings, responsiveness to inquiries and the level of effort to deal with carriers. Since the value of service are based on the elasticities derived from the FTD model, it is important to be able to estimate significant coefficients associated to every service attribute used in the survey.

VII.4 The Joint Estimation of the RP and SP Models

In the joint estimation, both data sets are used simultaneously in determining the parameters of the RP and SP models. Conceptually, it was assumed that shippers seek to minimize their annual logistic costs, either in their current market behavior, or in their stated preferences towards hypothetical service offerings. Thus, the same logistic cost formulation described in (7.1), was used in the specification of the utility functions in the combined model.

- **The estimation procedure**

As discussed in chapter 3, the joint estimation procedure was based on maximizing the following log-likelihood-like function:

$$L = \sum_{n=1}^{N^{rp}} \sum_{j=1}^{J} s_{nj} \ln \left[\left(\sum_{k=1}^{J} \exp(\mu(-\beta' x_{kn}^{rp} + \gamma' y_n^{rp})) \right)^{-1} \exp(\mu(-\beta' x_{jn}^{rp} + \gamma' y_n^{rp})) \right] +$$

$$\sum_{n=1}^{N^{rp}} \sum_{i=1}^{I} d_{ni} \ln \left[\Lambda(\alpha_i - \beta' x_n^{sp} - \delta' z_n) - \Lambda(\alpha_{i-1} - \beta' x_n^{sp} - \delta' z_n) \right] \tag{7.14}$$

where $n =$ 1, 2, ... N or N^{sp}) observations in each data set;

$j =$ 1, 2, ... J alternatives or modes in the RP choice set;

$i =$ 1, 2, ... I categories in the SP response scale;

$s_{nj} =$ mode j share for shipper n;

$d_{ni} =$ 1, if stated preference of observation n fell in category i; 0, o.w.;

$\beta =$ parameters associated to the logistic cost specification;

$x_{kn}^{rp} =$ shipper n perceptions of service attributes by mode k;

$\gamma =$ parameters associated to the situational constraints in the RP model;

$y_n^{rp} =$ variables representing the situational constraints for individual n;

$\delta =$ parameters associated to response bias terms in the SP model;

$z_n^{sp} =$ variables in to bias terms and mode-specific constants;

$x_n^{sp} =$ differences in the service attributes of the alternatives in scenario n;

$\Lambda(.)$ is the logistic cumulative distribution function.

Note that the RP and SP model share the same parameters β associated to the logistic cost components. In addition, the situational constraints y_n^{rp} are specific to the RP model, and the thresholds α and bias correction variables z_n^{sp} are included only in the SP model. The variables s_{nj} and d_{ni} serve as weights or choice indicators for the modes available and the SP-scale category, respectively.

The principal motivation of the joint estimation is the possible gain in accuracy of parameters estimates by sharing some parameters (β) between the RP and SP models. This is feasible because the biases and random errors specific to the SP data are captured by the threshold variables z_n^{sp} (if any) and by the scale parameter μ. In particular, it was expected that the SP data would help to identify the trade-offs involving those intangible dimensions of service not significant in the RP model, i.e. offering EDI capabilities, satisfaction with payment terms and billings, responsiveness to inquiries and level of effort to deal with carrier.

Again the general non-linear optimization procedure in GAUSS [1988] was used to estimate the parameters (β, γ, α, δ, μ) given the available RP and SP information. The estimators obtained belongs to the general class of extremum estimators, which are proven to be consistent and asymptotically normal (see Amemiya [1985]). Even though the likely dependency between the RP and SP data sources makes these estimates not fully efficient, they are still consistent. Note that robust estimators for the standard errors were used to assess the significance of the parameters estimated in the combined model.

- **The estimated coefficients**

Table 7.11 presents the estimated parameters for the joint RP and SP model. In general, most of the coefficients associated with the logistic cost components were estimated to be significantly different from zero. This allowed meaningful derivations of the value of service, as well as of the demand elasticities presented in Chapter 8. As expected, the major advantage over the RP model was the identification of significant effects for the non-traditional dimensions of service in the combined model. Note that different mode-specific constants for the RP and SP data were included in the combined models, also helping to identify biases and constraints specific to each data set.

An important exception to the improvements in the accuracy of the estimated coefficients, was the non-significant coefficient associated to the rate charged. While the underlying interpretation would be that shippers of the commodities surveyed are less sensitive to rates, it is also true that, on the RP model, this coefficient was close to be significant at 5% level. Thus, in order to capture its effect appropriately, a RP-specific rate coefficient was introduced in the second specification presented also in Table 7.11. Besides not improving significantly the goodness of fit of the model, the rate coefficients were still not statistically significant under the new specification. Note that in fact, this is not inconsistent with the increasing number of contract rates with severe discounts after deregulation of U.S. surface transportation. Shippers feel that there is little more to be gained in terms of the rates currently being charged.

Table 7.11
The Joint RP and SP models
The Common Coefficients

Logistic Cost Parameters	Model 1		Model 2	
	coefficient	std error	coefficient	std error
rate	-0.00850	0.0171	-0.00674	0.0168
transit time & reliability	-0.0205	0.00958	-0.0217	0.0107
loss and damage	-0.0304	0.00736	-0.0309	0.00748
useability of equipment	-0.897	0.271	-0.909	0.311
offer EDI	1.40	0.0347	1.40	0.0348
payment terms & billings	0.213	0.0832	0.211	0.0834
responsive-ness	0.255	0.0981	0.253	0.0992
level of effort -difficult	-0.592	0.0637	-0.593	0.0639
RP - scale (μ)	0.394	0.318	0.321	0.317
L(0) = -19,165.8 (N = 6640)	L* = -14,091 $\bar{\rho}^2 = 0.263$		L* = -14,090 $\bar{\rho}^2 = 0.264$	

Table 7.11 (cont.)
The Joint RP and SP models
Situational Constraints and Thresholds

RP Parameters	Model 1	Model 2	SP Parameters	Model 1	Model 2
truck constant	4.76 (3.96)	6.40 (6.39)	**truck constant**	-0.307 (0.0779)	-0.308 (0.0779)
intermodal constant	-3.30 (3.24)	-3.22 (3.89)	**intermodal constant**	0.0135 (0.0775)	0.0128 (0.0769)
average price	1.01 (1.14)	1.34 (1.64)	**threshold** (α_1)	0.397 (0.00461)	0.397 (0.00462)
length of haul	-1.10 (1.27)	-1.33 (1.73)	**threshold** (α_2)	0.851 (0.00708)	0.852 (0.00713)
annual ton-miles	0.780 (0.760)	1.12 (1.26)	**threshold** (α_3)	1.390 (0.00911)	1.390 (0.00911)
number of carloads	-0.753 (1.041)	-0.561 (1.10)	**threshold** (α_4)	2.192 (0.00993)	2.192 (0.0100)
storage costs	-0.0169 (0.0468)	0.0352 (0.0648)			
rate	-	-0.444 (0.678)			

Obs.: Standard errors in parenthesis.

Another specification with RP-specific coefficients for all the logistic cost components was also estimated without a significant improvement in the goodness of fit of the model. In particular, the RP-specific coefficient associated to offering EDI and level of effort - difficult, which were the two attributes most likely to be different in both models (see individual comparison in Table 7.10), were not significantly different from zero. This re-confirms that the RP and SP data are capturing similar mode choice behavior, except for a difference in scale.

Before proceeding in the analysis of the estimated coefficients, the joint RP and SP models were tested against those estimated using each data set separately. In section 7.4, the test of the equality of individual parameters from the two data sets showed that only two coefficients, loss and damage and offering EDI, were significantly different a 5% level.

On the other hand, the test for equality of the coefficient vectors across two or more data sets can usually be performed by comparing the likelihood value of the joint model with that of the separate models. In fact, the joint model can be considered as a restriction of the individual RP and SP models, in which the logistic cost coefficients are restricted to be the same in both data sources. The likelihood ratio test statistic is given by

$$- 2(L_R - L_U), \tag{7.15}$$

where L_R = log-likelihood for the restricted model; and
L_U = log-likelihood for the unrestricted model.

This test statistic is χ^2-distributed with K_U - K_R degrees of freedom, where K_U and K_R are the number of estimated parameters in the unrestricted and restricted models, respectively. The log-likelihood for the unrestricted model is given by the sum of log-likelihood of the models estimated separately from the RP and SP data sets. The restricted model corresponds to the joint estimation results in Table 7.11.

In the likelihood ratio tests shown in Table 7.12, there is not enough evidence to reject the null hypothesis that the coefficients are equal for both specifications of the joint RP and SP model. Thus, combining the data sources under either specification is desirable, since most coefficient common to the RP and the SP models are similar, except for a multiplicative scale. Note that, as described in Chapter 3, the likely dependence between the RP and the SP data sets may have influenced the results of the likelihood ratio tests. At

Table 7.12
Testing the Equality of Parameters
Between the RP and SP Data Sets

Model	Specification	L*	No of Parameters
RP	logistic cost	-186.0	16
SP	logistic cost	-13,899.5	15
unrestricted model		14,085.5	31
restricted models (joint RP & SP)	Model 1	-14,090.5	23
	Model 2 (RP-specific rate)	-14,089.9	24

- **test of equality of parameters between the RP and SP data sources**

Model	test statistic	degrees of freedom	p-value	$\chi^2_{0.05}$
common logistic cost components	10.0	8	0.2650	15.51
with RP-specific rate coefficient	8.80	7	0.2673	14.07

best, they can be considered an approximation to the generalized Wald test proposed in Amemiya [1985].

The interpretation of the scale parameter μ is related to the amount of random noise in each data set. Let ε and ν be the random error term associated to the RP and SP utility functions, respectively. In the specification of the joint likelihood-like function as the sum of the RP and SP models, they were assumed to be independently distributed with zero means. The level of noise in the data sets is then, represented by the variance of ε and ν, and related to each other in the following expression:

$$\text{var}(\varepsilon) = \mu^2 \text{var}(\nu) \tag{7.16}$$

Thus, an estimated value of μ less than one can be interpreted as the SP data having more random noise than its RP counterparts. Note that the scale parameter was associated to the RP model, as opposed to the scale of stated preferences, for convenience in the development of the computer programs.

In fact, the scale parameter was estimated to be between 0.3 and 0.4 for all the combined model specifications. This indicates that the SP data set contains more random noise than the information elicited in shippers' perceptions of service. As expected, shippers may have being less careful in expressing their stated preferences than when evaluating the service actually provided by different modes. Not only are some dimensions of service not made explicit in their market behavior, but also missing information on describing the alternatives in the hypothetical scenario (only two attributes at a time were used) may have contributed to noise in the SP data.

The other coefficients not associated to the logistic cost specification had a mixed performance in the combined model. While the thresholds were still very significant, the coefficients associated to the RP situational constraints were, in general, not estimated to be significantly different from zero. Note that linear functions for the thresholds were also tried without major effect in the other coefficients.

• The unbalanced number of observations in each data set

The lack of significance of some RP-specific coefficients should not be interpreted as their effect not being important in the combined model. Rather, since the number of SP observations was almost 20 times larger than the available RP data, the effect of these coefficients may have been underestimated in the above optimization problem. Moreover, comparing the estimates obtained from the RP data set alone with those from the combined model, very small differences between the coefficients associated with the situational constraints and mode-specific constants were observed. Note that the estimates from the joint model had to be scaled by the parameter μ to make this comparison meaningful.

In order to address this issue of loss of efficiency in the joint model estimates, several simulations with different weights assigned to the RP observations were performed. These weights varied from one, which represents giving the same weight for both RP and SP observations, to twenty, which is the ratio between the number of responses per shipper in both data sets. The upper limit was derived based on the fact that additional information provided by the same shipper are not independent, and should have less impact in the estimation procedure.

Even though no theory was developed for these weights, the simulation results provided some interesting insights in the issue of combining data sets with unbalanced number of observations. Multiplying the RP observations by a number greater than one is equivalent to pretending that there are more observations in the RP data set. While the value of the coefficients were very stable (less than 5% change) across all simulations, the standard errors decreased significantly. On the other hand, multiplying the SP data by a weight less than one increased the standard errors of the parameters, but with a lower impact on those specific to the RP model. Note that it was not possible to estimate the joint model for weights less than 0.2 due to numerical instabilities in the model estimation.

The evidence from the simulation results suggested that the standard errors may be relatively underestimated by the fact that the RP data set contributes only small amounts to improve the objective function, and thus, the accuracy of coefficients specific to that data set is less important in the optimization process. Thus, the coefficients associated to the situational constraints in the RP model were kept in the combined model. In addition, since after scaling, the estimated coefficients were very close to those estimated using the RP data set alone, it collaborates to the fact that they are capturing similar effects in both estimation procedures.

VII.5 - The Sequential Estimation of RP and SP Models

An alternative sequential estimation method for combing RP and SP data sources was also described in Chapter 3. The advantage of this method is that one can use ordinary logit or probit estimation software. The drawback though, is that the estimators are still consistent but less efficient than those obtained with the joint estimation.

- **The estimation procedure**

The sequential estimation procedure can be described by the following steps:

step 1: use the estimated SP model to obtain $\hat{\beta}$, which are the coefficients associated to the logistic costs (and common to both RP and SP models)

step 2: define $V^{rp} = \beta' x^{rp}$, and form the fitted values $\widehat{V^{rp}} = \hat{\beta}' x^{rp}$ using the RP data set.

step 3: estimate the RP model with the fitted values $\widehat{V^{rp}}$ included in the utility function specification, i.e.

$$U^{rp}_{i,n} = \mu \widehat{V^{rp}_{i,n}} + \mu\gamma' y^{rp}_n + \varepsilon \tag{7.16}$$

step 4: calculate

$$\widehat{\mu\beta} = \hat{\mu}\,\hat{\beta} \tag{7.17}$$

which are the RP logistic cost coefficients.

Note that in the sequential estimation μ was also associated to the RP model, make the comparison with the scale parameter in the joint estimation direct. Its interpretation then, is that values less than one would indicate that the SP data has more random noise than the information elicited in the conjoint experiment.

- **The estimated coefficients**

Table 7.13 presents the coefficients estimated using the sequential procedure. Similar to the joint estimation, two specifications were used: one sharing all the logistic cost coefficients between the RP and the SP model, and another including a RP-specific coefficient associated to the rates charged. Note that the SP coefficients in step 1 were obtained from Table 7.3, in which the demand model was estimated using only the SP data set.

Table 7.13
The Sequential RP and SP model

Parameters	Model 1		Model 2	
	coefficient	std error	coefficient	std error
fitted logistic cost	0.378	0.216	0.318	0.222
truck constant	1.86	0.393	2.049	0.408
intermodal constant	-1.31	0.450	-1.03	0.469
average price	0.396	0.195	0.428	0.203
annual ton-miles	0.305	0.126	0.359	0.134
average length of haul	-0.434	0.302	-0.425	0.308
number of carloads	-0.299	0.214	-0.0169	0.250
storage costs	-0.00664	0.00991	-0.0112	0.0103
RP-specific rate	-	-	-0.146	0.0811
L(0) = -19,166 (N = 332)	L* = -14,091[1] $\bar{\rho}^2 = 0.263$		L* = -14,090[1] $\bar{\rho}^2 = 0.264$	

[1]refers to the sum of the log-likelihood for the SP model alone and the new RP model with the fitted logistic cost component.

The scale parameter in the sequential estimation was estimated to be between 0.3 and 0.4, which is very close to the scale obtained in the joint estimation. First, this reconfirms that more random noise is present in the SP data set than in the information contained in the conjoint experiment. Second, this provides evidence contributing to the similar results between the joint and sequential estimation procedure. The issue then, is the loss of efficiency when using the information sequentially.

The similarity among the other estimated coefficients can be verified by comparing the original estimates in the SP model with those obtained in the joint estimation (see Table 7.14). The value of the coefficients were again very close between the joint and sequential estimation procedures. However, as expected, the standard errors were higher in the sequential estimator, showing the loss of efficiency from using the information one after the other instead of jointly. Note that these conclusions are also valid for the model including the RP-specific rate coefficient.

The losses in efficiency were larger among the non-traditional dimensions of service. This is explained by the presence of random noise in the RP data, which is used to form the fitted logistic costs in the sequential estimation. In particular, a reverse situation was observed for the coefficient associated to the rates charged, which was not significant when using the SP data alone. Finally, the reduction in the standard error of the scale parameter μ obtained with the sequential estimator should not be stressed since it is likely to be underestimated. This is because the sequential estimation assumes that the SP model coefficients are deterministic in forming the fitted logistic cost, neglecting the random error embodied in the coefficient estimates.

It is important to observe that the issue of unbalanced number of observations between the RP and SP data set is not relevant in the sequential estimation. Since the SP model coefficients were assumed as external information and used deterministically to form the fitted values V^{rp}, the number of observations in the SP data set does not enter in the combined estimation. The consequence was that the coefficients associated to the RP situational constraints are, in general, significantly different from zero.

Table 7.14
Comparing the Joint and Sequential Estimation Procedures

Logistic Cost Parameters	Joint Estimation	Sequential Estimation
rate	-0.00850	-0.00556
	(0.0171)	(0.0144)
transit time and	-0.0205	-0.0211
reliability	(0.0096)	(0.0106)
loss and	-0.0304	-0.0297
damage	(0.00736)	(0.00861)
useability of	-0.897	-0.881
equipment	(0.271)	(0.351)
offer	1.40	1.40
EDI capabilities	(0.0347)	(0.0953)
payment	0.213	0.209
terms and billings	(0.0832)	(0.145)
responsiveness to	0.255	0.252
inquiries	(0.0981)	(0.158)
level of effort -	-0.592	0.596
difficult	(0.0637)	(0.0982)
RP - scale	0.394	0.378
(μ)	(0.318)	(0.216)[1]

[1]standard error is underestimated, since it assumed that the SP coefficients are deterministic.

• **The number of scale parameters in the utility function**

Another specification for the utility function was also explored in the sequential estimation, in which more than on scale parameter was used. In particular, it was assumed that the scale affecting the traditional logistic cost components may be different from the one related to the other service attributes, like level of effort to deal with carriers. The specification of the utility function in step 3 is then, given by:

$$U_{i,n}^{rp} = \mu_1 \widehat{V_{i,n}^{rp,1}} + \mu_2 \widehat{V_{i,n}^{rp,2}} + \gamma' y_n^{rp} + \varepsilon \tag{7.18}$$

where $\widehat{V_{i,n}^{rp,1}}$ related to the traditional logistic cost components (rate, transit time, reliability, loss and damage and useability of equipment), and

$\widehat{V_{i,n}^{rp,2}}$ refers to the other service attributes (offering EDI capabilities, satisfaction with payment terms and billings, responsiveness to inquiries and level of effort to deal with carriers)

The same four-step estimation procedure was applied using (7.18), whereas the two fitted values $\widehat{V_{i,n}^{rp,1}}$ and $\widehat{V_{i,n}^{rp,2}}$ were estimated using the SP model coefficients with the RP data set. Table 7.15 shows the estimated scale parameters λ_1 and λ_2, as well as the associated goodness of fit measures for the combined model. Even though the improvement in the model fit was significant, the interpretation of λ_1 and λ_2 as the relationship between the variances of the disturbance terms is no longer valid.

Table 7.15
Multiple vs. Single Scale Parameters
in the Sequential Estimation Procedure

	μ_1	μ_2	L* ($\bar{\rho}^2$)
Single Scale	0.318 (0.222)	-	-14,094 (0.263)
Multiple Scale	6.81 (2.32)	0.298 (0.224)	-14,091 (0.264)

However, the evidence in the estimated parameters does contribute to the fact that the scale between the two sets of service attributes are different. It may be argued that $\mu_1 > 1$ implies that shippers were able to distinguish the current service provided by carriers along these dimensions, while $0 < \mu_2 < 1$ indicates that only in the conjoint experiment were shippers able to isolate the effect of other service-related attributes in their preferences.

On one hand, this evidence was also confirmatory of the initial expectations that the SP data set would help to identify the effect of non-traditional service attributes in the combined model. Moreover, the much smaller coefficients associated to the traditional logistic cost components in the SP model than those in the RP model, may indicate the presence of more random noise and thus, less benefits should be derived along these dimensions in the combined estimation.

This idea of incorporating multiple scale was not used in the joint estimation due to the difficulties in interpreting them in terms of more or less random noise in one data set. Instead, only RP-specific coefficients associated to logistic cost components were introduced in the joint estimation to capture differences in the multiplicative scale associated to them. Note that by having a full set of logistic cost coefficients specific to the RP model did not improve the goodness of fit of the joint model significantly from considering only a RP-specific rate coefficient in the joint model specification. This indicates that one scale parameter μ may be sufficient to capture the differences in both models, except for the coefficient associated with rates.

VII.6 - Summary

The estimation of the freight transportation demand model incorporated shippers' perceptions of service attributes in a logistic cost specification. Adding structure to the shippers' behavior model improved significantly the results from the model using only a linear combination of service attributes. Nevertheless, it was not possible to identify or accurately estimate all coefficients in the RP model.

In particular the service trade-offs involving intangible dimensions of service, like the level of satisfaction with payment terms and billings and the responsiveness, were not significant in explaining the current mode shares. On the other hand, these coefficients were significant in the SP model. Except for the coefficient associated to rates charged, all other were estimated to be significant at a 5% level.

Moreover, a comparison between coefficients in the RP and in the SP model showed that similar phenomenon is explained by both data sources. The efforts to combine the RP and SP data then, improved the accuracy of the estimated coefficients in the freight transportation demand model. While the joint estimation results are more efficient, the sequential estimation procedure allowed the use of ordinary statistical software. For the available information in the shippers' survey, the loss of efficiency from estimating sequentially was not enough to discard its convenience. Note that being able to estimate significant coefficients in the demand model is critical to assess the value of service in freight transportation (see Chapter 8), since these coefficients embody the service trade-offs that shippers consider in their mode choice decisions.

VIII - The Value of Service in Freight Transportation

The value of service in freight transportation can be assessed from the coefficients in the demand models. These coefficients embody the trade-offs among service attributes implied by shippers' mode choice decisions. In particular, normalizing all the coefficients by the one associated with the rates charged provides a dollar unit for the benefits derived from improving different dimensions of service.

Given the same parametric logistic cost function used in the specification of the RP and the SP model, each coefficient has a behavioral interpretation which restricts logically its sign and magnitude. For example, the coefficient associated to loss and damage can be interpreted as the implied discount rate times the number of days necessary to collect a claim. Alternatively, demand elasticities provide a measure of shippers' sensitivities to different service dimensions. For a set of changes in the level of service provided, the demand model can be used to forecast the resulting changes in demand and consequently, in carriers' revenues.

Carriers with the ability to predict the effect on demand of changes in the level-of-service can formulate strategies to design and market their service more effectively. In particular, these strategies should be specific to each market segment, since different shippers have different needs and responses towards service quality (see Chapter 6). Demand elasticities were also evaluated based on simulations of changes in different transportation service attributes for shippers in each market segment.

From the joint RP and SP demand model in Chapter 7, the value of service is then determined in section 8.1, through the behavioral interpretation of its coefficients and the demand elasticities across all shippers in the survey. In section 8.2 market responses and demand elasticities to service attributes are compared across market segments. Finally, section 8.3 summarizes the findings, including the strategic implications of marketing and designing transportation services in each segment.

VIII.1- The Value of Service

In this section, the value of service in freight transportation is determined from the coefficients in the joint RP and SP models. First, their behavioral interpretation provides information on how shippers evaluate their logistic cost in mode choice decisions. Second, demand elasticities with respect to each service dimension are determined based on the simulated impact of changes in the service provided by different modes. The objective was to evaluate shippers' sensitivities to service quality as a tool to be used in designing and marketing transportation services.

• The behavioral interpretation of coefficients

The behavioral interpretation of the coefficients in the joint model was similar to those discussed for the RP model in Chapter 7. Under the joint estimation though, the multiplicative scale associated to the utility function was explicitly estimated in the model. Nevertheless, all coefficients were still normalized using the coefficient associated to the rates charged, providing a convenient dollar unit in the analysis.

Table 8.1 presents the normalized coefficients and their behavioral interpretation. While the implied discount rate of 12% per year was reasonable for a thirty-day period to collect a loss and damage claim, the implied discount rate associated with in-transit inventory and equipment availability were excessively high. The coefficient associated to transit time and reliability may have been overestimated due to the emphasis shippers place on these dimensions of service, specially the variability of transit time.

On the other hand, the cost associated to the useability of equipment may include more than just the capital carrying cost due to shipments retention at the origin, i.e. shippers could be factoring in their perceptions, the cost of loss sales. In addition, the assumption of an average seven-day period for equipment unavailability may not be adequate for the commodities surveyed. The fact that the rate coefficients were not significant in the combined model should also inflate some of these normalized coefficients and their final interpretation.

Table 8.1
Behavioral Interpretation of Coefficients

Service Attribute	Coefficient	Behavioral Interpretation
rate	1	scaling factor
transit time & reliability	2.41	implied discount rate associated to in-transit inventory of 240% per year[2]
loss and damage	3.58	implied discount rate associated to loss and damage claims of 12% per year
useability of equipment	106	implied discount rate associated to equipment unavailability of 1500% per year[3]
order costs	88.6	cost of $ 89 per shipment
storage costs	1.99	implied discount rate associated to inventory of 200% per year
offering EDI capabilities	165	benefit of $165 per year derived from carriers offering EDI capabilities
payment terms and billings	25.0	benefit of $25 per year from improving the satisfaction with payment terms and billings
responsiveness to inquiries	30.0	benefit of $ 30 per year from improving the carriers' responsiveness to inquiries
level of effort - difficult	69.7	cost of $70 per year from using carriers that are difficult to work with

[1]after normalizing by the rate coefficient.

[2]it was assumed that it takes an average of 30 days to collect loss and damage claims, i.e. implied discount rate = 2.41 / 30.

[3]it was assumed that on average, transportation equipment remains unavailable for 7-days, i.e. implied discount rate = 106 / 7.

The coefficients associated to order and storage costs in the joint RP and SP model were not significant at 5% level. The implied cost per shipment and the implied discount rate associated to inventory were above reasonable market values. In both cases though, the implied behavioral interpretation is not accurate due to the presence of excessive random noise in the estimated coefficients. The assumption of carload shipment for all shippers might also be influencing these results.

For the other service-related attributes, the coefficients were, in general, lower than expected, indicating that the dollar benefits derived from improving service along these dimensions are small. For example, providing EDI capabilities was translated into a 164-dollar benefit per year for shippers, which seems small comparable to its use to provide timely and accurate information about shipments. In relative terms, the benefits from improving payment terms and billings were smaller than those associated with improving carriers' responsiveness. In addition, the coefficient associated to carriers being difficult to work with captured the effect from improving customers relations in transportation firms. Only for those shippers less sensitive to other more traditional service attributes, and for which mode choice decisions might be governed by the minimum effort to get things shipped, is this dimension of service relevant.

• **The demand elasticities with respect to service quality**

Apart from the above behavioral interpretation of coefficients, demand elasticities also provides useful information to determine the value of service in freight transportation. The basic idea was to use the joint RP and SP model to simulate shippers responses to changes in the current service provided by each mode. The sensitivity measure derived, i.e. the percent change in mode shares, has the advantage to be unit-free and thus, invariant with respect to scaling and normalization factors.

The demand elasticity for mode j due to a 1% change in attribute k of mode i (x_i^k) was defined by the following arc elasticity:

$$E_{ij}^k = \frac{\left(\frac{\tilde{S}_j - S_j}{S_j}\right)}{\left(\frac{\tilde{x}_i^k - x_i^k}{x_i^k}\right)} \tag{8.1}$$

where $S_j = \frac{1}{N} \sum_{n=1}^{N} \widehat{P}_n(j\,;x)$

$\tilde{S}_j = \frac{1}{N} \sum_{n=1}^{N} \widehat{P}_n(j\,;\tilde{x})$

$\widehat{P}_n(j\,;x)$ is the fitted probability of choosing mode j given attributes x

$\mathbf{x}_i = \{x_i^1, x_i^2, ..., \; x_i^k, ... \; x_i^K\}$ is the vector of perceived service by mode i.

Note that by definition, demand elasticities are based on changing one attribute at a time, while maintaining the perceived service along the other dimensions. Moreover, these changes are simulated on the perception space, which may not be translated fully from changes in the system characteristics. This issue of comparing perceived service with observed performance was addressed in Chapter 5.

Table 8.2 presents the demand elasticities for each mode due to changes in the perceived service attributes. They were obtained by simulating a 1% increase in each attribute. Note that the elasticity estimates may vary significantly outside the ranges on which the attributes were simulated.

For the dimensions of service associated with offering EDI capabilities and with the level of effort, shippers' sensitivities were simulated by making EDI available to every shipper and by making the carriers within each mode easy to work with. These sensitivities then represent the percent change in mode shares only for those shippers which would perceive an improvement in the service provided (see Table 8.3).

For motor carriers, higher benefits can be derived from decreases in their rates than any other improvements in the service provided. In fact, after deregulation, rate discounting has been a common practice in the truck industry with significant gains in the market share for some commodities. However, truck carriers are currently working on very small margins and competition among themselves has driven rates really down to allow further reductions. For other service attributes, useability of equipment was the most important. Even with the proliferation of independently-owned carriers in the

Table 8.2

Demand Elasticities to Service Quality

Service Attribute	Change in	Truck	Rail	Intermodal
rate	typical rates per ton	-1.150	-0.448	-0.324
transit time	typical transit time	-0.059	-0.865	-0.291
reliability	fraction of time shipments arrive when wanted	0.576	2.985	2.284
loss and damage	fraction of shipment lost or damaged	-0.057	-0.286	-0.279
useability of equipment	fraction of time equipment is available	0.977	0.502	3.737
payment terms and billings	fraction of time shipper is satisfied	0.117	0.529	0.699
responsiveness to inquiries	fraction of time shipper is satisfied	0.142	0.599	0.836

Table 8.3

Shippers' Sensitivities[1] to EDI and Level of Effort Dimensions of Service

Service Attribute	Truck	Rail	Intermodal
offering EDI capabilities	0.374	2.312	5.091
level of effort - difficult	0.016	0.174	0.042

[1]percentage change in demand from making EDI available to all shippers and from making carriers not difficult to work with.

truckload segment, the availability of equipment is still a major issue for truck users. Note that the low elasticities for most service dimensions should not be interpreted as truck users not being sensitive to them. Rather, the service offered trucks is usually much better than those by other modes, that improvements have little impact in their market share.

For rail carriers, transit time and reliability were the most elastic dimensions of service. In particular, a 1% increase in shippers' perceptions of rail reliability may be translated into almost a 3% increase in its current market share. The elasticity of transit time though, was below one, indicating that carriers may improve reliability by adding slack in the perceived transit time with a net benefit on their market share. This is emphasized by the fact that the elasticities refer to the perceived service, and considerable effort should be spent on how to affect shippers' perceptions through changes in the system performance or through better marketing of the rail service.

For intermodal carriers, one of the highest elasticity was also obtained for improvements in the reliability dimension of service. However, the useability of equipment was the most elastic dimension, reflecting the importance of container availability in intermodal operations.

Two additional issues remains to be discussed with respect to these demand elasticities to service quality. First, a comparison with recent studies provided additional evidence on the reasonableness of the estimates described above. In particular, one of the problems with the original study using the shippers' survey was that the demand elasticities to service were very high compared to prior expectations of marketing officials in the RR railroad. ABC Company estimated the elasticity with respect to reliability to be on averages 5.3 for all commodities in the survey, while in this research this value was around 3.0. Similar differences can be found with respect to other service attributes. This can be explained by the different specification of the demand model and by the use of both, revealed and stated preferences data in its estimation.

Other recent studies in freight transportation did not have the same level of detail or the same definition for the service attributes, making it difficult to compare results. In particular, the Kansas State University study (see Smith [1991]) estimated price elasticities to be between -1.3 and -3.0 for different commodities based on actual mode choices in the 1970's. Also in that study, service was defined as car-miles per car-year on the assumption that if railroads provide better service, cars would turn faster. This aggregate service elasticity was then, estimated to be between 0.6 and 4.3, which encompasses all the service related elasticities presented in Table 8.2. Thus, in general, the demand elasticities obtained from combining RP and SP data seem to be reflecting accurately shippers' sensitivity, with the advantage of distinguishing among different dimensions of service.

Second, the cross elasticities between modes can be defined as the percentage change in the share of mode j due to changes in the perceived service by mode i. In particular, the cross-elasticities between rail and the other modes allow one to evaluate the impact of improvements in different dimensions of rail service on truck and intermodal shares (see Table 8.4). As expected, it is likely that an improvement in the reliability of rail services will generate some retaliation from intermodal and motor carriers due to its high impact on their current mode shares. This retaliation though, is not restricted to improvements in truck or intermodal reliability, and should include different strategies to differentiate their service in the market. On the other hand, the effect of rail rates increases in truck and intermodal shares is negligible. Other cross-elasticities were also significantly below the one for reliability.

Finally, it is important to mention that both, the behavioral interpretation of coefficients and the demand elasticities, provided similar assessments of the value of service in freight transportation. However, the latter approach was able to differentiate across modes and market segments (see next section). In general, shippers place a high value on the reliability of transit time observed either from the high implied in-transit capital carrying cost, or from the high demand elasticities to changes in that service attribute. Equally important was the provision of sufficient and acceptable transportation equipment when shippers want.

Table 8.4
Cross-Elasticities Between Rail and Other Modes

Service Attribute	Rail - Truck	Rail - Intermodal
Rate	0.077	0.055
Transit Time	0.15	0.098
Reliability	-4.92	-3.50
Useability of Equipment	-0.854	0.57

VIII.2 - Market Responses and Elasticities Across Segments

Given the market segments defined in Chapter 6, it is important to assess the response of shippers in each segment given the current level of service provided by truck, rail and intermodal carriers. Two types of responses were analyzed: which products are being shipped and what modes are being used in each segment. Table 8.5 presents the average mode shares and the percentages of shippers of each commodity in the different market segments.

In terms of commodities, there is a reasonable spread across all segments. This indicates that current marketing department organization around groups of products may be insufficient to capture shippers' transportation needs. It is important to recognize that, for example, within paper shippers, some are very cost-sensitive (like those shipping scrap paper) and others are very sensitive to time and service quality (like those shipping newsprint). A unique marketing and design strategy is unlikely to satisfy both groups of shippers. Note that most aluminum and plastic shippers are less sensitive to service quality, while a significant group of tires shippers are cost-sensitive (30% of the sample).

Table 8.5

Market Response Across Segments

Cluster	Product Shipped[1]					Average Mode Shares		
	Paper	Aluminum	Pet Food	Plastics	Tires	Truck	Rail	Inter-modal
1	0.38	0.19	0.04	0.36	0.25	0.70	0.25	0.05
2	0.16	0.40	0.52	0.42	0.30	0.86	0.09	0.05
3	0.16	0.22	0.35	0.14	0.30	0.73	0.18	0.08
4	0.18	0.08	0.09	0.04	0.05	0.56	0.33	0.11
5	0.12	0.11	-	0.04	0.10	0.63	0.28	0.08

[1]Values represent fractions of the total number of shippers in the survey.

In terms of current mode shares, shippers that are less sensitive to service quality or those that are cost-sensitive tend to use more rail than other shippers in the survey. Cluster 5 though, is an exception, whereas time and service-quality were also important for rail users. One explanation is offered by the size of the firms in cluster 5, i.e. large shippers have bargaining power with rail carriers to get premium service. Intermodal shares were high on the cost and service quality sensitive segment, representing shippers demanding high service standards but at a lower than truck rates. It is important to qualify these observations under the sample of commodities surveyed, which biased towards shippers with high truck shares.

In order to evaluate differences in the elasticities to service attributes across market segments, two alternatives were available. First, one can calibrate the segment-specific demand models. The small sample of shippers assigned to some segments though, makes it difficult to use the estimation procedures described in Chapter 7. Instead, some coefficients could still be made segment-specific in the overall model. In particular, the coefficient associated to time and reliability was made segment-specific in the combined RP and SP estimation. Unfortunately, this model did not show a significant improvement over the restricted model with the same coefficients across market segments.

Second, segment-specific demand elasticities were obtained by simulating the effect of changes in service attributes in the mode shares of those shippers in a given segment. The joint RP and SP demand model estimated in Chapter 7 was used to determine the mode shares after the service improvements. This assumes, for example, that even though the rate coefficient is the same across segments, the effect of increasing it depends on the current rates charged and the shippers' annual tonnage shipped in each segment. Tables 8.6 to 8.8 present the demand elasticities with respect to different service attributes, by segment of the market and by mode of transportation.

The results were, in general, very consistent with the definitions of the market segments. For example, shippers in segment 5 presented the highest elasticities to transit time and reliability for all modes, conforming to its interpretation as time and service quality sensitive segment. This is specially important to show the validity of the information elicited in the survey and of the demand models estimated from them. Note

Table 8.6
Truck Demand Elasticities by Segment

Service Attribute	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5
rate	-0.653	-0.283	-1.583	-3.121	-3.180
transit time	-0.033	-0.067	-0.085	-0.097	0.021
reliability	0.461	0.101	0.777	-1.543	-1.619
loss and damage	-0.025	-0.061	-0.051	-0.066	-0.371
useability of equipment	0.786	0.205	1.385	2.173	2.826
payment terms & bills	0.112	0.102	0.149	0.147	0.088
responsiveness	0.139	0.125	0.171	0.189	0.109

Table 8.7
Rail Demand Elasticities by Segment

Service Attribute	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5
rate	-0.286	-0.151	-0.511	-0.716	-1.385
transit time	-0.793	-0.196	-0.885	-0.971	-3.875
reliability	2.671	0.673	2.677	3.968	11.566
loss and damage	-0.326	-0.081	-0.268	-0.314	-1.207
useability of equipment	0.433	0.125	0.510	0.596	2.146
payment terms & bills	0.579	0.604	0.519	0.349	0.526
responsiveness	0.617	0.720	0.581	0.421	0.543

Table 8.8
Intermodal Demand Elasticities by Segment

Service Attribute	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5
rate	-0.265	-0.131	-0.428	-0.488	-1.118
transit time	-0.281	-0.085	-0.364	-0.385	-1.249
reliability	2.310	0.691	2.657	2.974	10.286
loss and damage	-0.140	-0.069	-0.422	-0.553	-1.129
useability of equipment	3.714	1.208	4.475	4.681	1.576
payment terms & bills	0.717	0.732	0.660	0.654	0.672
responsiveness	0.836	0.875	0.793	0.807	0.818

that shippers' perceptions of current mode services and stated preferences in hypothetical scenarios were not used in the above market segmentation analysis.

On the other hand, the differences in the demand elasticities across segments were significant. This confirms the hypothesis that a single marketing and service design is unlikely to satisfy all current and potential customers, even within the restricted group of commodities in the survey. Two general implications can be derived from the usefulness of the market segmentation to carriers in the market place. First, it is important for a carrier to "know its markets", providing service to meet profitably the shippers' needs. Not only should carriers differentiate their service in each segment, but also focus on those segments which do not have conflicting needs.

Second, carriers' competition will vary among market segments. For example, a motor carrier may find that its main competition is the railroads in the cost-sensitive segment, while other truck owners may compete fiercely for the time and service quality sensitive shippers. Thus, marketing activities should emphasize carriers' advantages relative to the needs in each market segment and relative to the strengths and weakness of likely competitors in each market.

VIII.3 - Strategic Implications to Service Design and Marketing

In order to combine the interpretation of market segments with the associated shippers' responses and elasticities, some implications for service design and marketing is further discussed. Similar to McGinnis[1978], the market segments can be defined in a more operational way as follows:

• **Segment 1: The Minimum Effort Shipper** (N = 42 or 25% of total)

Shippers that are less sensitive to service quality, usually choose the minimum effort alternative. This is confirmed by the high importance-weight given to the level of effort to deal with carriers, while the demand elasticities associated to these shippers were usually very low across the traditional dimensions of service, like rate and transit time. Note that the elasticities to the level of satisfaction with payment terms and billings and to the responsiveness dimension were at comparable levels with other segments, but still below one.

In marketing to this segment, improving customer relations should be targeted. Not only should carriers representative be accessible, but also should they provide a courteous and friendly environment to work with. Traditionally, transportation firms tend to pay less attention to this strategy, specially with small firms.

• **Segment 2: The Service Oriented Shipper** (N = 53 or 32% of total)

In this segment shippers were equally sensitive to most dimensions of service, with a somewhat inelastic behavior towards the rate charged. They were mainly composed of small firms with short transportation distance needs. As expected, truck is the most used mode, combining the pick-up and delivery efficiency with the small shipment size requirements.

Here, the carriers' marketing efforts should emphasize their past records in terms of reliability, dependability and availability of service. Railroads have a major disadvantage in this segment, including in its piggyback operations. Motor carriers, on the other hand, should have a more intensive than extensive marketing activity, in which regions might be targeted as opposed to individual customers.

• **Segment 3: The Price Oriented Shipper** (N = 34 or 20% of total)

The members in this market did not differ significantly from other shippers in the survey. However, the estimated demand elasticities with respect to changes in the rates charged were among the highest ones across all segments. Note that the average share of rail carriers in this segment was around 18%, which is below the expected for price oriented shippers.

To gain market share, carriers should stress the competitive rates in this segment, even if that means severe discounting for truck rates. It is in this segment that lies the highest potential of increasing the rail participation, with reasonable service at very low rates. Possibly, service can be kept at a lower level to allow bigger concessions on rates. Note that this segment is particularly attractive to contract carriers, where the total transportation package can be negotiated with greater flexibility.

• **Segment 4: The Competitive Shipper** (N = 16 or 10% of total)

Besides being relatively sensitive to transit time and reliability, shippers in this segment had also high demand elasticities with respect to rates charged. They also were characterized by low value commodity and long length of haul shipments, obtaining the highest usage of rail carriers (on average, 33%).

In this segment, shippers are looking to "get the best out of his dollar". Carriers can not afford to increase rates and provide a better service, or to discount rates and provide a lousier service. Efficiency is the underlying marketing focus, where carriers should balance good performance in all areas. Competition is likely to be intense between truck and rail carriers in this segment, whereas a middle ground between low cost and quality service is reached.

• **Segment 5: Inventory Oriented Shipper** (N = 13 or 8% of total)

In this segment, the commodity value was the highest across all segments. Shippers were significantly more elastic to transit time and reliability. The fact that rail shares were high among shippers in this segment can be explained by the inclusion of the most large firms in the survey. Large shippers have considerable bargaining power over rail carriers to get a premium service.

Carriers marketing in this segment should maintain transit time and reliability under tight control, so that shippers can efficiently manage their high inventory costs. This is the market where intermodal operations have the highest growth potential, emphasizing their reliability records at a reasonable price.

VIII.4 - Summary

From the above market segmentation analysis, it is apparent that shippers needs vary significantly. This variability, in general, cross the boundaries of product characteristics, mode usage and traffic patterns. In the definition of market segments it is necessary to consider not only observable characteristics of shippers, but also their attitudes towards service quality.

It is fundamental to assess the differences in the value of service across segments in order to profitably design and market transportation services. The understanding of the segments enables carriers to compete more effectively in different markets. Note that the above definitions of the market segments and marketing strategies is completely dependent on the commodities surveyed. Other segments may not be represented in the survey of shippers presented in Chapter 4. For example, McGinnis[1978] found a segment related to the importance of loss and damage to shippers, contemplating mostly shipments of chemicals an electrical machinery. In this survey though, the loss and damage dimension had a minor effect in shippers mode choice decisions.

IX - Conclusions and Recommendations

Shippers' are becoming increasingly sensitive to transportation service quality. Not only has the relative importance of rates decreased, but also different dimensions of service are under consideration in mode choice decisions. This thesis developed and applied a method to assess the value of service in freight transportation as a strategic tool for designing and marketing services.

• The Method: Summary and Major Findings

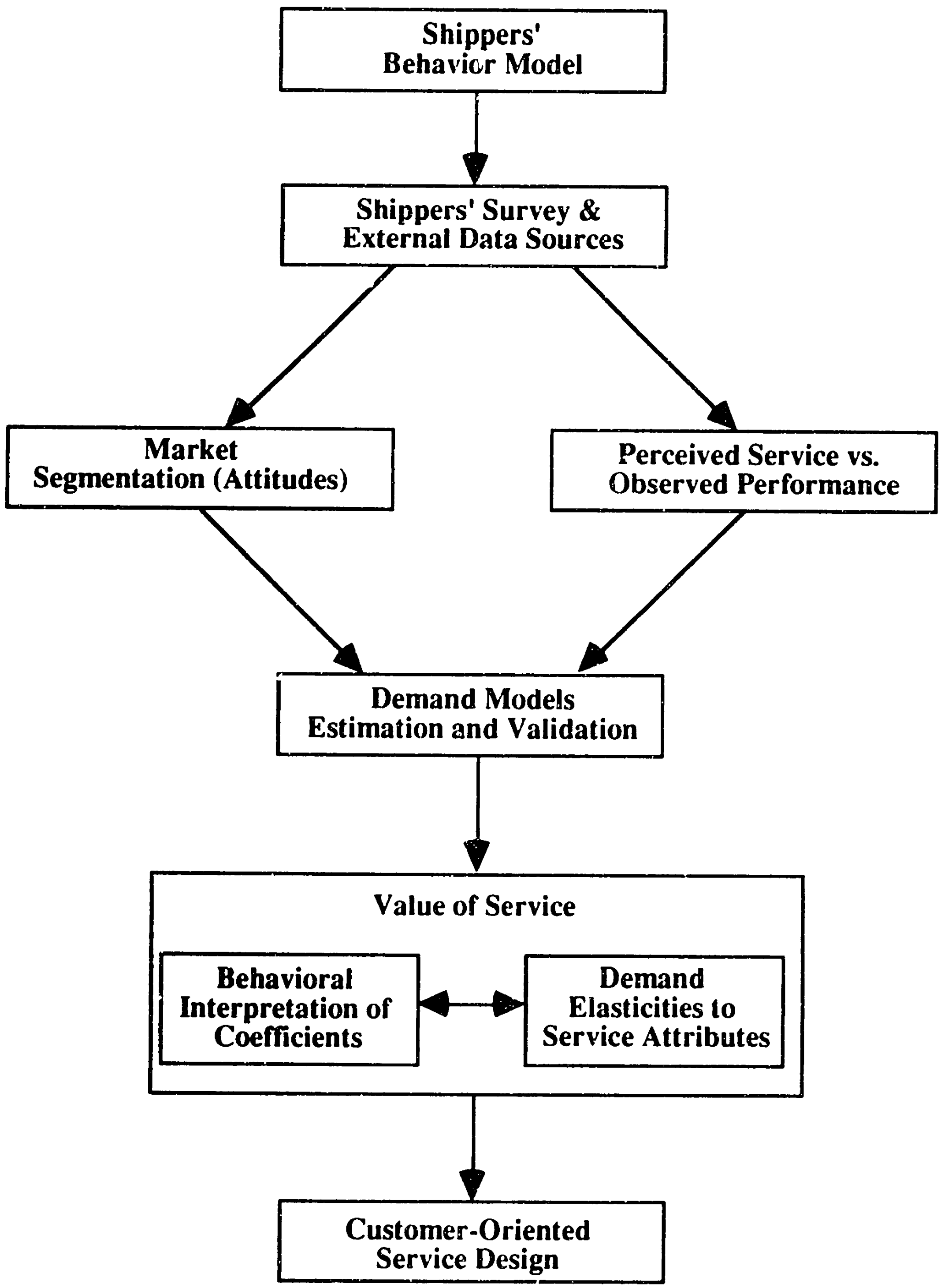
Figure 9.1 summarizes the method to assess the value of service in freight transportation. The following comments highlights the major conceptual and statistical modeling contributions in implementing each stage. The objective was to provide carriers with shippers' sensitivities to changes in different dimensions of service and how to relate them to objective and measurable system performance.

(1) Shippers' Behavior Model

In assessing the value of service, it is important to understand the decision process of shippers. The behavior model hypothesized how attitudes, perceptions and preferences interact to determine the mode choice. The underlying decision protocol assumed that shippers seek to minimize their logistic costs. However, the specification of the logistic cost function considered perceptions of service provided by different modes as the basic input information. Not only need the service attributes to be measured in a way reflecting shippers' perceptions, but also the specification of the logistic cost components was extended to include non-traditional service dimensions, like responsiveness and level of effort.

Figure 9.1

The Method to Assess
the Value of Service in Freight Transportation



The important contribution was that by adding structure to the shippers' behavior, it was possible to identify the service trade-offs they consider in their mode choice decisions. Besides the specification of the demand models, the behavior model should also guide the design of the shippers' survey. Shippers are imbedded in a profit maximizing organization, and their mode choice behavior should reflect the effects on the annual logistic costs of the firm.

(2) Shippers' Survey

The shippers' survey was the primary source of information to estimate the demand models. It had been previously designed and applied by a marketing consulting company, retained by a major U.S. railroad (see Chapter 4). Two types of information were elicited in the survey. The major strengths and weaknesses are highlighted in the following discussion:

- shippers' behavior

First, current market behavior was elicited in terms of mode/carriers usage and the perceptions of the service provided by them. It is important to be as specific as possible in eliciting these information in order to capture variations in the behavior of shippers in the market. In the survey, shippers were asked about their two major corridors.

Second, attitudes were elicited by asking shippers about the value or the importance of each service dimension in their mode choice decisions. This allowed differentiating market segments in the assessment of the value of service. However, the survey settings seem not to have avoided response biases, i.e. most of the service attributes were very important to most shippers. Other attitudinal indicators, like ranking and indifference point lotteries could also have been used to help to identify the importance of each service dimension to each shipper.

Third, stated preferences were elicited using a conjoint experiment with hypothetical transportation service scenarios. This source of information can help to identify or accurately estimate the coefficients in the demand models. Response biases are also of a major consideration in modeling with this information. The survey did not use the full profile approach, making it more difficult to associate these stated preferences with the actual market behavior in the market. Not only was it necessary to assume that omitted attributes were the same across the alternatives, but also the mode was not always identified in the scenario.

- shippers' and firms demographics

The survey also elicited demographic and socio-economic information on shippers and on the firms they represent. This information was necessary to calculate the different logistic cost components in the demand model specification. Again it is critical to have a shippers' behavior model to guide the design of the questions. In particular, one of the missing information in the available survey was the shipment size used by different shippers, which is intertwined with their mode choice decisions.

It is important to mention that besides the survey, external sources of information were also used to complement the shippers' survey. For example, information on observed performance by different carriers and possibly, specific to each shipper surveyed, is critical to validate the perceptions and to provide the link with carriers' operations. The waybill sample and the car cycle data are good examples, but do not exhaust these data requirements.

Finally, the definition of the shippers willing to participate in the survey as well as the service dimensions to be analyzed is very important to get meaningful results from the process. The shippers' surveyed should be representativ of all traffic, or at least, of a well defined segment on which carriers want to act upon. The service dimensions should be carefully defined in order to elicit the relevant information for mode choice decisions with minimum amount of measurement error.

(3) Perceived Service vs. Observed Performance

Another important step in the assessment of the value of service in freight transportation was the comparison between perceived service and observed performance. This provided the link between the shippers' behavior model with performance measures related to characteristics under carriers' control. Unfortunately, the available data on carriers' performance limited the analysis to the rail mode and to the cost, transit time and reliability dimensions.

Given the level of aggregation of the external data sources, no models were calibrated in this stage. Misperceptions of the service provided were evaluated only based on average values of shippers' perceptions and mode performance for each commodity in the survey. In general, shippers have very good recollection of typical rates per ton in different corridors, with observed rates being very close to the perceived ones. On the other hand, shippers seem to be perceiving transit time and reliability better than the average service being provided.

The major contribution was to identify causes for eventual misperceptions that provide strategic value to transportation service design and marketing. Besides measurement and sample selection issues, the misperceptions in transit time and reliability indicated that rail carriers are already increasing the negotiated transit times with shippers to improve the perceptions of the reliability of the service provided. This is consistent with the fact that shippers are more sensitive to changes in reliability than to increases in transit time.

(4) Market Segmentation and Classification Model

Even though the group of commodities in the survey already corresponds to a segment of the freight transportation market, additional efforts was spent to identify groups of homogeneous shippers with respect to their behavior towards service quality. Besides the traditional market segmentation approach, a new method based on latent structure models was developed. Among its advantages, this method allows the use of attitudinal indicators (like the importance-weights given to each dimension of service) jointly with the shippers' characteristics (like annual sales and maximum acceptable delays). This not only improved the definition of the segments, but also made it possible to implicitly derive the classification model for current or new shippers, whose attitudinal indicators were not elicited in the survey. As reported in Chapter 6, the improvements over the traditional benefit market segmentation approach was significant.

Among the findings, five segments could be identified within the shippers' who participated in the survey. The interpretation of these segments offers substantial information for carriers to differentiate their service. For example, there is a segment of shippers which were inventory-oriented, i.e. significantly more elastic to transit time and reliability than to other dimension of service.

(5) Demand Model Estimation and Validation

Given the shippers' behavior model, demand models were specified to reflect the service trade-offs in the logistic cost function. Discrete choice models provided a convenient statistical framework to model shippers' decisions on modes and carriers. In particular, the minimization of the logistic cost function was incorporated in the utility functions of different modes, as a means of reflecting the decision protocol.

Two choice models were estimated with the information elicited in the survey. The revealed preferences (RP) model relating the current market behavior in terms of mode shares to shippers' perceptions of service. The major finding was that putting structure on the shippers' behavior helped to accurately estimate the service trade-offs in their current mode usage, i.e. using the logistic cost function to specify the model improved significantly its goodness of fit measures and the significance of the coefficients. Nevertheless, random noise was still a major factor in the elicited perceptions of service, indicating that shippers were not able to distinguish the service provided by different modes/carriers across all dimensions.

Stated preferences (SP) model was then, estimated using the information contained in the conjoint experiment. Using the same logistic cost specification, most of the coefficients were significantly estimated. This constituted an advantage over the RP model, specially for the non-traditional dimensions of service, like responsiveness and level of effort. The major contribution in this area was to account for potential source of response biases in the specification of the SP model. Besides the method commonly used in the literature to introduce independent variables related to specific biases in the utility function, the ordered response model with variable thresholds was developed and implemented. As explained in Chapter 7, this model considers variations in the way that shippers might interpret the arbitrary preference scale in the conjoint experiment, by introducing a linear functional form associated to each threshold. Even though the improvement in the goodness of fit of the SP model was significant, the impact on the coefficients associated to the logistic cost was not significant. Thus, the variable threshold model was not considered further in the assessment of the value of service.

Given the same decision protocol in the RP and SP model, a combined estimation was developed using all the information available in the shippers' survey. Besides the contribution of implementing a similar framework to that developed in Morikawa [1989], the major findings from the combined estimation were.

- the SP data had more random noise than the information elicited in the shippers' perceptions of the service currently being provided.

- the SP data though, helped to identify or accurately estimate the service trade-offs in the logistic cost function. This was specially true for the non-traditional dimensions of service, like level of satisfaction with payment terms & bills and carriers' responsiveness.

Overall, there was a gain in the efficiency of the parameters estimates in the combined demand model. This is particularly important since these coefficients are the base for the assessment of the value of service in freight transportation.

(6) Value of Service: Behavioral Interpretation of Coefficients and Demand Elasticities

Given the freight transportation demand model, the value of service was assessed in two different ways. First, the behavioral interpretation of the coefficients provided important information on how shippers' evaluate their logistic costs in mode choice decisions. For example, the coefficient associated to transit time and reliability corresponds to the implied in-transit capital carrying cost.

Another way to assess the value of service was through the demand elasticities to changes in the perceived service provided by different modes. These elasticities provided an indication to carriers of how much market share can be gained due through improvements in different dimensions of service. They were calculated by simulating the effect that improving one dimension of service has on each shippers' mode shares given by the demand model.

The major findings were that reliability and transit time are among the most sensitive dimensions of service, especially for rail and intermodal carriers. Not only were the implied in-transit capital carrying cost excessively high, but also the demand elasticities were greater than one. Other important dimensions of service are price for truck users and, equipment availability for intermodal users.

(7) Service Design: Strategic Implications of the Value of Service

The assessment of the value of service in freight transportation has major implications on service design and marketing. Carriers are able to identify market opportunities, where they can match their capabilities with shippers' unsatisfied needs, and profitably increase their market share.

Reliability of transit time is the main factor affecting shippers' mode choice decisions. Substantial gains in market share can be obtained by improving the perceived service along this dimension. Note that these gains were quantified based on changes in shippers' perceptions, which is not directly translated to changes in system characteristics. Not only it assumes shippers' full awareness of the improvements in reliability, but also their acceptance that the new service meets their transportation needs.

On the other hand, carriers can differentiate their service across market segments. Even though the demand elasticity with respect to changes in reliability was on average, the highest among all service dimensions, significant differences in shippers' sensitivities were observed across segments. Table 9.1 presents a summary of the market segments identified, with their major implications to service design.

These design strategies were based on identifying the more important service dimensions in each segment and the shippers' characteristics that distinguish each segment from the others. In particular, a segment of price-sensitive shippers was identified in the survey, for which the rates charged were much more important than other dimensions of service. A strategy of rate discounting is appropriate to this segment, even if it implies in some service deterioration. In another segment, customer relations were emphasized for the minimum effort shippers. Not only is the accessibility of carriers representatives important, but also the provision of a courteous and friendly environment to work with is relevant to shippers' decisions. Traditionally, transportation firms have not been able to work beyond the price differentiation, specially regarding customer relations.

Table 9.1

Service Design and Marketing Strategies in Each Segment

Market Segment	Service Design and Marketing Strategy
Minimum - Effort	emphasis in customer relations, making the interaction with shippers professional and courteous
Service - Oriented	emphasis on reliability, dependability, and availability of the service provided
Price - Oriented	emphasis on competitive rates, even if it implies in some service deterioration
Competitive	balance good performance in all service dimension with reasonable rates charged
Inventory - Oriented	tight control over transit time and reliability records, while managing efficiently shippers' expectations

Finally, a wider set of strategies are available to achieve changes in shippers' perceptions than those related only to modifications in operational characteristics. Besides investments in transportation capacity and rationalizations of their operations, carriers should pay close attention to the marketing of the service in itself. For example, one way for rail carriers to improve reliability is to reduce the time spent in yards for priority movements. On the other hand, carries can negotiate delivery time higher than those in schedules and operating plans in order to gain in the perceived reliability of the service provided. This strategy of adding slack to the schedule is by no means new to the transportation industry. In fact, some airlines are now selling and heavily advertising on-time performance, even though their trip times are longer than during the regulatory period.

In general, the message was that shippers are becoming increasingly more sophisticated in terms of their transportation service requirements. Not only the traditional dimensions of service, like transit time and reliability, continue to be important, but also other service-related attributes, like responsiveness and level of effort, are influencing some shippers' mode choice decisions. Carriers, on the other hand, should understand their customers and their different transportation needs. Then, they should explore different strategies to differentiate their service, including improvements in customer relations. The conventional operational/investment focus should give way to a customer-oriented service design and marketing approach, by which carriers would profitably meet shippers' needs.

- **Future Research**

This thesis explored an effective method to assess the value of service in freight transportation. The principal contribution was on the development of a combined estimator for freight transportation demand models, which incorporates non-traditional data on shippers' trade-offs among service attributes. In the theoretical side, the assumption of independence among the random components in the RP and SP data is likely not to hold, and its impact on the loss of efficiency of the parameter estimates should be further investigated. In the implementation side, the unbalanced number of observations in both data sets is also likely to affect the estimated standard errors of the parameters, although the effect on their value was empirically tested to be negligible.

Another extension to the methodology developed in this thesis would be to incorporate latent perceptions and attitudes in the demand model. Even though perceptual indicators were used in the logistic cost specification, considering the latency of perceptions would allow the investigation of measurement errors on the survey. On the other hand, attitudinal indicators were used only on the market segmentation analysis. Incorporating these information in the demand model would allow the estimation of taste variation parameters reflecting shippers' attitudes towards service quality.

Even though the results for the five commodities in the shippers' survey demonstrated the effectiveness and practicality of the methodology, more empirical analysis are necessary to justify the methodology for a wider variety of applications. In particular, a survey including shippers of other commodities is also desirable to validate the results and strategic implications discussed above.

Figure 9.2 provides some guidelines to improve the design the shippers' survey used, if additional data collection efforts are undertaken. Given the shippers' behavior model, the survey should be designed to elicit different information related to each stage of the decision process. The decision protocol should also be kept in mind, i.e. the survey should identify the service trade-offs in the logistic cost specification including information on the shippers' shipment size decision. In addition, researchers should try to use the full profile approach, or at least, always identify the mode in each scenario. Even though restrictions might apply to using the full profile approach due to the likely large number of service dimensions considered, the identification of the mode is important when combining stated and revealed preferences.

Note that extending the shippers' survey to more commodities has also the benefits of verifying the usefulness of the new market segmentation approach to a wider set of shippers. So far, the latent structure approach was applied to an already selected set of shippers, with the empirical results being encouraging for further investigation in more general settings.

Finally, the comparison between observed performance and perceived service is an interesting and promising area for future research. It was shown that carriers can arbitrage over shippers' misperceptions of service to gain market share. Nevertheless, a more structured analysis of how shippers form their perceptions of service can be of significant strategic value to transportation firms.

The final word of this thesis would be that understanding the shippers behavior is critical to the freight transportation industry. Any step taken in this direction represents a competitive advantage over other carriers in the market, by allowing firms to differentiate the service provided and profitably meet the shippers' needs.

Figure 9.2

Some Guidelines to the Shippers' Survey Design

- **Market Behavior**

  - elicit infomation on mode / carrier usage and availability to each shippers

  - be specific in terms of transportation corridors or shipments to be considered in the answers

  - elicit shippers' perceptions of service by each mode available

- **Stated Preferences and Attitudes**

  - use different attitudinal indicators: importance scale, ranking, and indifference point lotteries.

  - use the full-profile in describing the alternatives or at least, identify the modes in each scenario

  - avoid response biases with a realistic description of the alternatives, by adptating the experimental design to each shipper, and by using validation questions.

- **Shippers' and Firms' Characteristics**

  - elicit informations relevant to describe the decision process and the external factors influencing shippers' behavior.

  - include information on firms' characteristics (annual sales, number of employees), commodity attributes (packaging, density, price) and transportation needs (shipment size and frequency, length of haul).

References

Allen, W. B. (1977). The Demand for Freight Transportation: a Micro Approach. Transportation Research - B. 11: p. 9-14.

Allen, W. B., Mahmoud, M. M. and McNeil, D. (1985). The Importance of Time in Transit and Reliability of Transit Time for Shippers, Receivers and Carriers. Transportation Research - B. 19B(5): p. 447-456.

Amemiya, T. (1981). Qualitative Response Models. Journal of Economic Literature. XIX: p. 1483-1536.

Amemiya, T. (1985). Advanced Econometrics. Cambridge: Harvard University Press.

Aptech Systems. (1988). Gauss System Version 2.2. Kent: Aptech Systems Inc.

Bagozzi, R. P. (1980). Causal Models in Marketing. New York: John Wiley & Sons, Inc.

Ballou, R. H. (1985). Business Logistics Management: Planning and Control. Englewood Cliffs, N. J.: Prentice-Hall, Inc.

Bates, J. (1988). Econometric Issues in Stated Preferences Analysis. Journal of Transport Economics and Policy. XXII(1): p. 59 to 69.

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

Bayliss, B. (1988). The Measurement of Supply and Demand in Freight Transport. Hants, England: Avebury Grower Publishing Company Ltd.

Ben-Akiva, M. and Lerman, S. (1985). Discrete Choice Analysis. Cambridge: MIT Press.

Ben-Akiva, M. (1988). Applications of Disaggregate Modelling Method to Intercity Freight, in Jornada sobre Ultimas Tendencias Mundiales en el Studio de la Demanda de Transporte de Mercancias. Madrid, Spain: Ministerio de Transportes, Turismo Y Comunicaciones - Secretaria General Tecnica.

Ben-Akiva, M. and Morikawa, T. (1990). Estimation of Travel Demand Models from Multiple Data Sources, in The 11th International Symposium on Transportation and Traffic Theory. Yokohama, Japan:

Bolduc, D. and Poole, E. (1989). Ordinal Probit Model with Random Bounds. 8911: Department of Economics, University of Laval.

Bollen, K. A. (1989). Structural Equations with Latent Variables. Wiley Series in Probability and Mathematical Statistics. New York: John Wiley & Sons, Inc.

Bookbinder, J. H. and Fraser, N. M. (1989). The Role of Game Theory in Shipper-Carrier Negotiations. Transportation Research Forum.

Boyer, K. D. (1977). Minimun Rate Regulation, Modal Split Sensitivities, and the Railroad Problem. Journal of Political Economy. 85(3): p. 493-512.

Bradley, M. (1988). Realism and Adaptation in Designing Hypothetical Travel Choice Concepts. Journal of Transport Economics and Policy. : p. 121-141.

Bradley, M. A. and Kroes, E. P. (1990). Simlutaneous Analysis of Stated Preference and Revealed Preference Information, in PTRC 18th Summer Annual Meeting. University of Sussex, England:

Chiang, Y., Roberts, P. O. and Ben-Akiva, M. (1981). Develoment of a Policy Sensiive Model for Forecasting Demand. Massachusetts Institute of Technology.

Christenberry, W. S. (1975). The Relationship of Freight Modal Split to Shippers' Perceptions of Transporta. Transprtation Reserch Forum.

Constable, G. K. and Whybark, D. C. (1978). The Interaction of Transportation and Inventory Decisions. Decision Science. 9: p. 688-699.

Cox, D. R. (1977). Analysis of Binary Data. Monographs on Statistics and Applied Probability. New York: Chapman and Hall.

Dagenais, M. G. (1973). The Use of Incomplete Observations in Multiple Regression Analysis. Journal of Econometrics. 1: p. 317-328.

Daughety, A. F. (1979). Freight Transport Demand Revisited: a Microeconomic View of Multimodal, Multicharacteristics Service Uncertainty and the Demand for Freight Transport. Transportation Research - B. 13: p. 281-288.

Davis, L. J. (1985). Consistency and Asymptotic Normality of the Minimum Logit Chi-Squared Estimator When the Number of Design Points is Large. The Annals of Statistics. 13 No. 3: p. 947-957.

DeGroot, M. H. (1986). Probability and Statistics. New York: Addison-Wesley Publishing Company.

DeJong, G., Gommers, M. (1992). Value-of-Time in Freight Transport in the Netherlands from Stated Preferences. The Netherlands: Hague Consulting Group.

Everitt, B. S. (1984). An Introduction to Latent Variables Models. London: Capman and Hall Ltd.

Fernandez, L., Enrique, J. and Friesz, T. L. (1983). Equilibrium Predictions in Transportation Markets: the State of the Art. Transportation Research - B. 17(2): p. 155-172.

Fisk, C. S. (1984). Game Theory and Transportation Systems Modeling. Transportation Research - B. 18(4/5): p. 310-313.

Florian, M. and Gaugry, M. (1983). Transportation Systems Analysis: Illustrations and Extensions of a Conceptual Framework. Transportation Research - B. 17(2): p. 147-153.

Fowkes, T. and Waderman, M. (1988). The Design of Stated Preference Travel Choice Experiments. Journal Transport Economics and Policy. XXII No. 1(January): p. 27-44.

Fowkes, A. S., Nash, C. A. and Tweddle, G. (1989). Valuing the Attributes of Freight Transport Quality: Results of the Stated Preference Survey. Instute for Transport Studies. : p. 1-23.

Fowkes, A. S. and Tweedle, G. (1989). A Computer Guided Stated Preference Experiment for freight Mode Choice. University of Leeds, ITS.

Friedlaender, A. F. and Spady, R. H. (1979). A Derived Demand Function for Freight Transportation. Review of Economic and Statistics. 62: p. 423-441.

Friesz, T. L., Tobin, R. L. and Harker, P. T. (1983). Predictive Freight Network Models: the State of the Art. Transpotation Research - A. 17(6): p. 409-417.

Goudge, D. and Strasser, S. (1989). A Transportation Industry Scale for the Measurement of the Customer Service Orientation of Carrier Salespeople. Tranportation Research Forum.

Green, P. E. and Srinivasan, V. (1978). Conjoint Analysis in Consumer Research: Issues and Outlook. Journal of Consumer Research. 5: p. 103-123.

Green, P. E., Carroll, J. D. and Goldberg, S. M. (1981). A General Approach to Product Design Optimization via Conjoint Analysis. Journal of Marketing. 45(Summer): p. 17-37.

Hagerty, M. R. (1985). Improving the Predicitive Power of Conjoint Analysis: the Use of Factor Analysis and Cluster Analysis. Journal of Marketing Research. XXII(May): p. 168-184.

Hall, R. W. (1985). Dependence Between Shipment Size and Mode in Freight Transportation. Transportation Science. 19(4): p. 437-444.

Harker, P. T. (1985). The State of the Art in the Predictive Analysis of Freight Transport Systems. Transport Reviews. 5(2): p. 143-164.

Harker, P. T. and Friesz, T. L. (1986). Prediction of Intercity Freight Flows, I: Theory. Transportation Research - A. 20(2): p. 139-153.

Harker, P. T. and Friesz, T. L. (1986). Prediction of Intercity Freight Flows, II: Mathematical Formulations. Transportation Research - B. 20(2): p. 155-174.

Hauser, J. R. and Koppelman, F. S. (1975). Designing Transportation Services: a Marketing Approach. Transportation Reseach Forum.

Hauser, J. R., Tybout, A. M. and Koppleman, F. S. (1981). Consumer-Oriented Transportation Service Planning. Applications of Management Science. 1: p. 91 to 138.

Hauser, J. R. and Simmie, P. (1981). Profit Maximizing Perceptual Positions: an Integrated Theory for the Selection of Product Features and Prices. Management Science. 27 No. 1: p. 33-56.

Hauser, J. R., Tybout, A. M. and Koppelman (1981). Consumer-Oriented Transportation Service Planning, in Applications of Management Science. JAI Press Inc: Cambridge.

Hensher, D. A., Barnard , P. O. and Truong , T. P. (1988). The Role of Stated Preference Methods in Studies of Travel Choice. Journal of Transport Economics and Policy. XXII No. 1(January): p. 45-57.

Hirobata, Y. and Kawakami, S. (1990). Modelling Disagragate Behavioral Modal Switching Models Based on Intention Data. Transportation Research - B. 24 No.1: p. 15-25.

Huber, P. J. (1981). Robust Statistics. Wiley Series in Probability and Mathematical Statistics. New York: John Wiley & Sons, Inc.

Institute, S. (1990). Programming Tips and Users' Guide. SAS Institute.

Jain, A. K. and Acito, F. (1990). Evaluation of Conjoint Analysis: a Comparison of Methods. Journal of Marketing Research. XVII: p. 106-112.

Jonhson, R. A. and Wichern, D. W. (1988). Applied multivariate Statistical Analysis. Englewood Cliffs, N. J.: Prentice Hall.

Joreskog, K. and Sorbom, D. (1984). LISREL IV Analysis of Linear Structural Relations by maximum Likelihood, Instrumental Variables, and Least Squares Method. Users' Guide. Uppsala, Sweden: Department of Statistics, University of Uppsala.

Judge, G., et al. (1982). The Theory and Practice of Econometrics. Wiley & Sons.

Kanafani, A. (1983). Transport Demand Analysis. New York: McGraw-Hill Book Company.

Kaufman, L. and Rousseeuw, P. J. (1990). Finding Groups in Data: An Introduction to Cluster Analysis. Wiley Series in Probability an Mathematical Statistics. New York: John Wiley & Sons, Inc.

Koppleman, F. S. and Rose, G. (1983). Supply Factors and Transit Demand Impacts. Journal of Advanced Transportation. 17: p. 201-217.

Kroes, E. P. and Sheldon, R. J. (1988). Stated Preferences Method: an Introduction. Journal Transport Economics and Policy. XXII No. 1(January): p. 11-25.

Kulman, B. C. (1974). A Model of Rail-Truck Competition in the Intercity Freight Market. (Thesis). Cambridge: Ma

Lalwani, C., et al. (1990). Modelling Freight Traffic, in Department of Transport Seminar on Longer Term Issues in Transport Economics. TRRL.

Leigh, T. W., MacKay, D. B. and Summers, J. O. (1984). Reliability and Validity of Conjoint Analysis and Sef-Explicited Weights: a Comparison. Journal of Marketing Research. 21: p. 456-62.

Levin, R. C. (1982). Railroad Rates, Profitability, and Welfare Under Deregulation. The Bell Journal of Economics. : p. 1-26.

Lewin, R. C. (1978). Allocation In Surface freight Transportation: Does Rate Regulation Matter ? The Bell Journal of Economics. : p. 18-45.

Lewis, K. A. and Widup, D. P. (1982). Deregulation and Rail-Truck Competition. Journal of Transport Economics and Policy. (May): p. 139-149.

Little, P., Kwon, O. K. and Martland, C. D. (1991). An Assessment of Trip Times and Reliability in Boxcar Traffic. Massachusetts Institute of Technology / CTS.

Louviere, J. J. (1988). Conjoint Analysis Modeling of Stated Preferences. Journal of Transport Economics and Policy. XXII No.1(January): p. 93 to 119.

Maddala, G. S. (1983). Limited Dependent and Qualitative Variables in Econometrics. Econometric Society Monographs No. 3. Cambridge: Cambridge University Press.

Martland, C. D., et al. (1991). Bacground on Railroad Reliability. Massachusetts Institute of Technology / CTS.

McDonald, R. P. (1985). Factor Analysis and Related Methods. Hillsdale, N. J.: Lawrence Erlbaum Associates.

McFadden, D., Winston, C. and Boersch-Supan, A. (1985). Joint Estimation of Freight Transportation Decisions under Nonrandom Sampling, in Analytical Studies in Transport Economics. A. F. D. Iowa Editor. Cambridge University Press: New York. p. 137-157.

McFadden, D. (1986). The Choice Theory Approach to Market Research. Management Science. 5 No. 4(Fall): p. 275-297).

McGinnis, M. A. (1978). Segmenting Freight Markets. Transportation Journal. 18 No. 1(Fall): p. 59-71.

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

McKelvey, R. D. and Zavoina, W. (1975). A Statistical Model for Ordinal Level Dependent Variables. Journal of Mathematical Sociology.

Miklius, W., Casavant, K. L. and Garrod, P. V. (1976). Estimation of Demand for Transportation of Agricultural Commodities. American Journal of Agricultural Economics. (May): p. 217-223.

Morikawa, T. (1989). Incorporating Stated Preference Data in Travel Demand Analysis,. Massachusetts Institute of Technology.

Morikawa, T., Ben-Akiva, M. and McFadden, D. (1990). Incorporating Psychometric Data in Econometric Travel Demand Models.

Morlok, E. K. (1980). Types of Transportation Supply Functions and their Applications. Transportation Research - B. 14: p. 9-27.

Muthen, B. (1978). Contributions to Factor Analysis of Dichotomous Variables. Psychometrica. 43 No. 4: p. 551-560.

Muthen, B. (1983). Latent Variable Structural Equation Modeling with Categorical Data. Journal of Econometrics. 22: p. 43-65.

Muthen, B. (1984). A General Structural Equation Model with Dichotomous, Ordered Categorical, and Continuous Latent Variable Indicators. Psychometrika. 49 No. 1: p. 115-132.

Olsson, U. (1979). Maximum Likelihood Estimation of the Polychoric Correlation Coefficient. Psychometrika. 44 No. 4: p. 443-460.

Olsson, U., Drasgow, F. and Dorans, N. (1982). The Polyserial Correlation Coefficient. Psychometrika. 47 No. 3: p. 337-347.

Ortuzar, J. D. and Palma, A. (1983). Stated Preference in Refrigerated and Frozen Cargo Exports. PTRC Proceedings. : p. 267-278.

Oum, T. H. (1979). Derived Demand for Freight Transport and Inter-Modal Competition in Canada. Journal of Transport Economics and Policy. (May): p. 149-168.

Oum, T. H. (1981). A Cross Sectional Study of Freight Transport Demand and Rail-Truck Competition in Canada. The Bell Journal of Economics. : p. 463-482.

Oum, T. E. and Gillen, D. G. (1983). The Structure of Intercity Travel Demands in Canada: Theory Tests and Empirical Results. Transportation Research - B. 17(3): p. 175-191.

Parasuraman, A., Zethamil, V. A. and Berry, L. L. (1988). SERVQUAL: A Multiple-Item Scale for Measuring Consumers Perceptions of Service Quality. Journal of Retailing. 64 No.1: p. 12-37.

Parks, R. W. (1980). On the Estimation of Multinomial Logit Models from Relative Frequency Data. Journal of Economics. 13: p. 293-303.

Proussaloglou, K. E. and Koppelman, F. S. (1978). Use of Travellers' Attitudes in Rail Service Design. Transportation Resarch Record.

Ratchford, B. T. (1979). Operationalizing Economic Models of Demand for Product Characteristics. Journal of Consumer Research. 6: p. 76-87.

Rust, J. (1988). Statistical Models of Discrete Choice Processes. Transportation Research - B. 22(2): p. 125-158.

Saris, W. E., Pijper, M. d. and Mulder, J. (1978). Optimal Procedures for Estimation of Factor Scores. Sociological Methods & Research. 7 No. 1: p. 85-266.

Seidenfus, H. S. (1985). Changes in Transport User's Modal Split. Paris: ECMT Round Table 69.

Srinivasan, V. and Shocker, A. D. (1979). Multiattribute Approaches for Product Concept Evaluation and Generation: a Critical Review. Journal of Marketing Research. XVI: p. 159-180.

Stock, J. R. and La Londe, B. J. (1977). The Transportation Mode Decision Revisited. Transportation Journal.

Urban, G. and Hauser, J. (1980). Design and Marketing of New Products. England Cliff, N. J.: Prentice Hall.

Waderman, M. (1988). A comparison of Revealed Preference and Stated Prefrence Models of Travel Behaviour. Journal of transport Economics and Policy. XXII No. 1(January): p. 71-91.

Wilson, W. W., W., W. W. and Koo, W. W. (1988). Modal Competition in Grain Transport. Journal of Transport Economics and Policy. (September): p. 319-337.

Winston, C. (1979). A Disaggregated Qualitative Mode Choice Model for Intercity Freight Transportation . University of California, Berkley.

Winston, C. (1981). A Disaggregate Model of the Demand for Intercity Freight Transportation. Econometrica. 49(4): p. 981-1006.

Winston, C. (1983). The Demand for Freight Transportation: Models and Applications. Transportation Research - A. 17A(6): p. 419-427.

Wolfe, E. (1985). The Carload Waybill Statistics: a Content analysis. Transportation Research Forum.

Zlatopper, T. J. and Austrian, Z. (1989). Freight Transportation Demand: a Survey of Recent Econometric Studies. Transportation Journal. 16: p. 27-46.

Appendix A: Shippers' Perceptions of Reliability Costs

On outbound traffic, reliability costs include the cost of early arrivals, like providing extra storage space at the destination for holding shipments that arrive early, and the cost of late arrivals, like the buyer's stock-out and safety-stock carrying cost. In order to incorporate these costs in the shippers' mode choice decisions, it is necessary to formulate their effect on the overall logistic cost.

- **Formulation**

In terms of late arrivals, buyers seek to balance the marginal cost of an additional day of inventory carrying cost and the marginal decrease in the probability of a stock-out times the cost of an emergency supply. The size of the safety-stock then, reflects the buyer acceptable exposure to stock-out risk, i.e.

$$(\Pr[L] - \Pr[L+1]) \,.\, so \,.\, \frac{Q}{q} \leq i \,.\, \frac{p \,.\, Q}{365} \tag{A.1}$$

where Pr[L] = probability of stock-out with L-days of safety-stock

so = unit stock-out cost ($/stock-out)

Q = annual tonnage used at the destination (ton)

q = average shipment size

p = average price of the input ($/ton)

i = discount rate (per year).

Thus, if the stock-out unit costs (sc) are high, buyers will be more risk averse and increase their safety-stock. On the other hand, for low stock-out unit costs (so), there is no need to carry lots of additional inventory to prevent it.

From equation (A.1), an upper bound on the stock-out unit costs can be derived as to reflect buyers risk, i.e.

$$so \leq \frac{i}{\Delta\tau} \cdot \left(\frac{p \cdot q}{365}\right) \tag{A.2}$$

where $\Delta\tau$ = marginal decrease in the probability of stock-out due to an extra day of safety stock (= Pr[L] - Pr[L+1])

This unit stock-out cost includes not only the cost of disruptions in the production line or in the sales at the destination, but also the cost of an emergency supply using an alternative supplier and/or carrier.

Assuming that buyers were able to balance their costs of late arrivals with L-days of safety-stock, the additional inventory carrying cost (ssc) and the expected stock-out costs (soc) can be formulated as[1]:

$$ssc = i \cdot L \cdot \left(\frac{p \cdot Q}{365}\right) \qquad \text{and}$$

assuming that $so = \frac{i}{\Delta\tau} \cdot \frac{p \cdot q}{365}$

$$soc = (1 - \tau) \cdot so \cdot \frac{Q}{q} = i \cdot \left(\frac{1-\tau}{\Delta\tau}\right) \cdot \left(\frac{p \cdot Q}{365}\right) \tag{A.3}$$

where $\tau = 1 - Pr[L]$ (i.e. probability of not stocking-out)

Finally, the cost of late arrivals is given by the sum of safety-stock carrying cost and the expected stock-out costs, i.e.

$$cla = i \cdot \left(\frac{p \cdot Q}{365}\right) \cdot \left(L + \frac{1-\tau}{\Delta\tau}\right) \tag{A.4}$$

The above specification can be interpreted as adjusting the perceived safety-stock carried at the destination, by the risk of arriving later than the period covered. Since a balance between safety-stock and stock-out costs was assumed, the later was expressed in terms of additional days of inventory.

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[1]this derivation was obtained from discussions with Carl Martland, at MIT

On the other hand, a shipment that arrives early may be unloaded early if the buyer accepts, or have to wait until the buyer is able to process it. The cost associated to early arrivals have been usually neglected in the logistic and transportation literature. In part, this is because in U.S. demurrage costs due to vehicle retention are negligible compared to the overall logistic cost of the shipment. In addition, it also includes a grace period of up to two days for rail carriers. Thus, the cost of early arrivals was not included in the final formulation of the reliability costs.

- **Empirical Estimation**

Given the above components of reliability costs, the issue is how shippers perceive and incorporate them in their mode choice decisions. Even though delivery delays may cause stock-out situations only at the destination, they may affect the shippers' future sales if buyers needs are not satisfied. On the other hand, it is difficult for shippers to differentiate stock-out costs related to each shipment, since not only they do not have control over the inventory policies at the destination, but also buyers may be supplied by different shippers and modes. Only when shippers are involved in an emergency shipment situation, can they assess the importance of stock-out cost.

Besides the typical transit time and reliability associated to each mode, shippers perceptions of the latest (L^*) acceptable delivery time were also elicited in the survey. These perceptions related to no shipment or carrier in particular, but rather to a general statement about how important reliability of transit time is perceived to be for the buyers or receivers of the shipments. A high value for the maximum acceptable delay (L^*) is translated into buyers keeping high levels of safety stock, and as a consequence, having low expected stock-out costs.

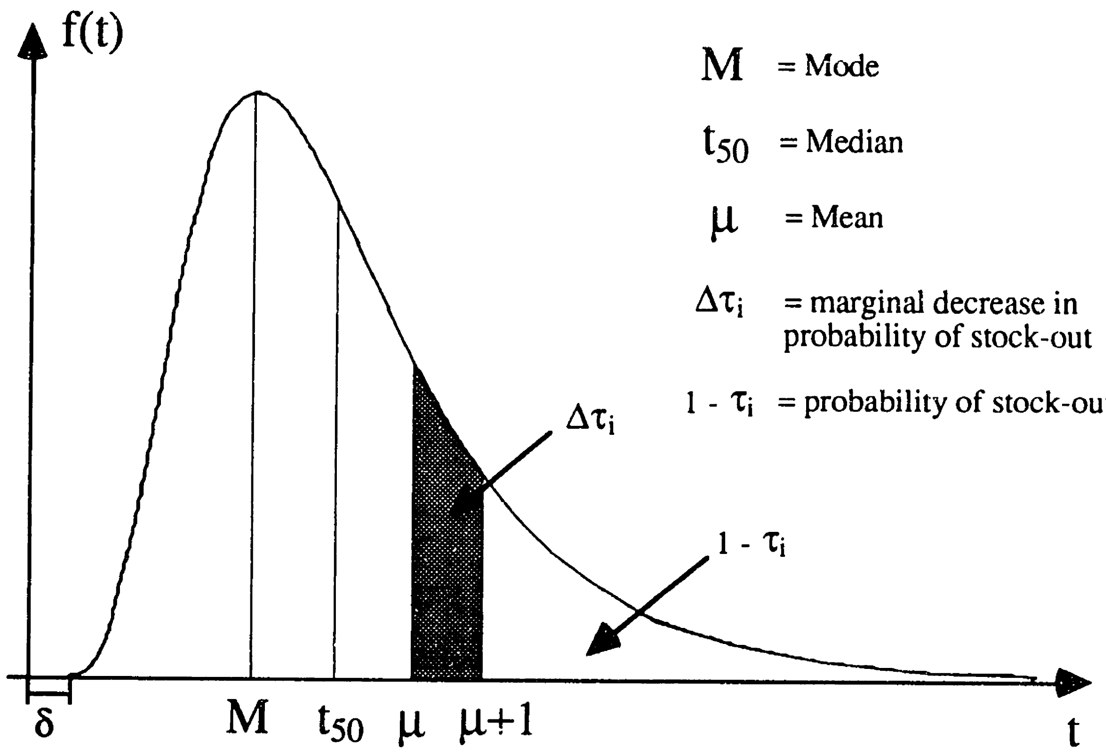
In order to use the reliability costs as formulated in (A.4), it is necessary to assume that shippers perceptions (L^*) do reflect the safety-stock carried at the destination. However, to adjust for the stock-out risks, the ratio $(1 - \tau) / \Delta\tau$ needs to be evaluated for different modes available. In fact, since the perceived reliability τ^* was measured as the percentage of times shipments arrive when wanted, its complement $(1 - \tau^*)$ was considered to be the probability of a stock-out situation at the destination due to delays above the maximum acceptable L^*. For the calculation of $\Delta\tau^*$ associated to each mode, a theoretical distribution of transit time was characterized from L* and the typical transit time for each mode (see Chapter 4).

The issue then, is the derivation of the marginal decrease in the probability of a stock-out due to an additional day of safety stock ($\Delta\tau_i$). Alternative assumptions for the transit time distribution provide different values for $\Delta\tau_i$ (see Figure 7.3). However, only the typical transit time (t_i^*) and the probability of arriving later than (t_i^* + L*) when using mode i were elicited in the survey. The approach then, was to use this information to fully characterize a theoretical distribution for transit time. Note that an additional degree of freedom exists in terms of interpreting the typical transit time (t_i^*) as being the mode or the mean or any other location measure of the distribution.

From a qualitative assessment of the empirical distributions of transit time in the shippers' survey as well as in the car cycle database, the log-normal distribution was chosen to characterize the perceived transit times (see Figure A.1). As discussed in Little et al [1991], rail transit times are generally skewed to the right as a result of minimum trip time and frequent long trip times due to possible long delays. Besides the scale (μ) and the shape (σ) parameters, the log-normal distribution was defined only over a portion of the positive real line, i.e. for values of $t_i^* \geq \delta$, where δ is the minimum trip time.

Since the perceived reliability varied from 0.4 to 0.95, it is reasonable to assume that shippers reported the mean transit time ($\mu_i = t_i^*$). Nevertheless, for reliability values less than 0.5, the data would not conform to the positive skewness of the log-normal distribution. Only for those cases, t_i^* was considered to be the mode of the distribution in order to determine $\Delta\tau_i^*$. In addition, the location (δ) parameter was interpreted as the minimum possible transit time. It was estimated using the maximum number of miles per day for each mode perceived by all shippers in the survey and the length of haul between each origin-destination region.

Figure A.1
The Log-Normal Distribution



$$f_{LN}(t; \mu, \sigma, \delta) = \frac{1}{(t-\delta)\sqrt{2\pi}} \exp\{-\frac{1}{2}(\frac{\ln(t-\delta)-\mu}{\sigma})^2\}$$

for $\delta < t$; $0 < \sigma$; $-\infty < \delta, \mu < \infty$

where $E\{t\} = \delta + \exp\{\mu + \frac{\sigma^2}{2}\}$

$t50 = \delta + \exp\{\mu\}$

$M = \delta + \exp\{\mu - \sigma^2\}$

Table A.1 summarizes the results obtained assuming a log-normal distribution of transit times. Truck was usually perceived as the fastest an most reliable mode. Buyers should then, carry small amounts of safety-stock when using it, and as observed, have the highest benefits from adding an additional day of safety-stock. On the other hand, rail being perceived as more unreliable, needs more safety-stock to adjust for the risks of stock-out, which was translated into having the highest ratio $(1 - \tau_i) / \Delta\tau_i$ among all modes. Intermodal was, on average, in-between the truck and rail mode, but closer to truck users' safety-stock.

Even though the results were consistent, the level of risk-adjusted safety stock were, in general, higher than those observed in practice. It is unusual to keep safety-stocks higher than the equivalent usage during the transportation lead time, specially when the current operations management trend is to minimize inventory levels. Two facts may have influenced the results. First, the minimum transit time (δ) may be underestimated, since the maximum number of miles per day on short trips may be different from those of long trips. Second, the distribution of transit time should also be bounded from above, which would then, increase $\Delta\tau_i^*$ and reduce the safety-stocks.

Instead of trying different theoretical distributions, a negative exponential curve was used to approximate the right most branch of the empirical distribution of transit time. Given t_i^*, τ_i^* and L^*, the rate λ of the exponential curve can be found from solving the following equation for each shipper and mode:

$$\int_{t_i^*+L^*}^{\infty} e^{-\lambda x}dx = 1 - \tau_i^* \quad \therefore \; - \lambda\,(t_i^* + L^*) = \log(\lambda) + \log(1 - \tau_i^*) \qquad \text{(A.5)}$$

With the value of , the marginal decrease in the probability of stock-out can be found by:

$$\Delta\tau_i^* = \frac{e^{-\lambda(t_i^*+L^*)} - e^{-\lambda(t_i^*+L^*+1)}}{\lambda} \qquad \text{(A.6)}$$

Since the exponential curve decays at a slower rate than the log-normal does, the net effect is to increase $\Delta\tau_i^*$ and decrease the risk-adjusted safety-stock. Note that both curves are very close for high enough values of transit time or for reliability above 90%.

Also in Table A.1, the results for the exponential approximation are summarized. While the truck users kept on average, 1.6 days of safety-stock, the level for rail users went up to a maximum of one-week of inventory. These values are more reasonable, while keeping the relative differences among the modes the same as in the log-normal distribution.

Table A.1
Average Risk-Adjusted Safety Stock by Mode

Distribution of Transit Time		Truck	Rail	Intermodal
log-normal distribution	$\Delta\tau_i^*$	0.036 (0.059)	0.033 (0.063)	0.027 (0.047)
	$L + \frac{(1-\tau_i)}{\Delta\tau_i}$	3.11 (1.84)	8.64 (4.03)	4.63 (1.89)
exponential fitting	$\Delta\tau_i^*$	0.052 (0.035)	0.050 (0.013)	0.043 (0.024)
	$L + \frac{(1-\tau_i)}{\Delta\tau_i}$	1.64 (0.50)	3.07 (0.84)	1.92 (0.43)

Obs.: standard deviations in parenthesis

Appendix B

The Attribute Levels in the Conjoint Experiment

PRICE

50% lower than average rates I pay now
25% lower than average rates I pay now
10% lower than average rates I pay now
Same average rates I pay now
10% higher than average rates I pay now
25% higher than average rates I pay now
50% higher than average rates I pay now

TRANSIT TIME

50% faster than average dock to dock transit time at present
25% faster than average dock to dock transit time at present
10% faster than average dock to dock transit time at present
Same as average dock to dock transit time at present
10% slower than average dock to dock transit time at present
25% slower than average dock to dock transit time at present
50% slower than average dock to dock transit time at present

CONSISTENCY OF TRANSIT TIME

95% of shipments arrive when I want them to
90% of shipments arrive when I want them to
85% of shipments arrive when I want them to
80% of shipments arrive when I want them to
75% of shipments arrive when I want them to
70% of shipments arrive when I want them to
60% of shipments arrive when I want them to
50% of shipments arrive when I want them to
40% of shipments arrive when I want them to

LOSS OR DAMAGE

Less than 0.1% of shipment value lost or damaged

0.1% to 1% of shipment value lost or damaged

1% to 2% of shipment value lost or damaged

2% to 3% of shipment value lost or damaged

More than 3% of shipment value lost or damaged

INITIAL USEABILITY OF EQUIPMENT

99% of time a sufficient quantity of acceptable equipment is provided

95% of time a sufficient quantity of acceptable equipment is provided

90% of time a sufficient quantity of acceptable equipment is provided

75% of time a sufficient quantity of acceptable equipment is provided

50% of time a sufficient quantity of acceptable equipment is provided

EDI

Offers EDI

Does not offer EDI

PAYMENT TERMS AND BILLING

Payment terms and billings are always satisfactory (100% of the time)

Payment terms and billings are usually satisfactory (75% of the time)

Payment terms and billings are sometimes satisfactory (50% of the time)

Payment terms and billings are seldom satisfactory (25% of the time)

RESPONSIVENESS

Always provides a satisfactory response to my inquiries (100% of time)

Usually provides a satisfactory response to my inquiries (75% of time)

Sometimes provides a satisfactory response to my inquiries (50% of time)

Seldom provides a satisfactory response to my inquiries (25% of time)

LEVEL OF EFFORT

Carrier is relatively easy to work with

Carrier is neither difficult nor easy to work with

Carrier is relatively difficult to work with

Appendix C: Optimal Shipment Size

In Chapter 3, the annual logistic cost for outbound shipments using mode j was defined as:

$$W_j^0 = o \,.\, (\frac{Q}{q_j}) + r_j \,.\, Q + i \,.\, d_j \,.\, m \,.\, p. \, Q + i \,.\, t_j \,.\, x + i \,.\, p \,.\, (\frac{q_j}{2}) + + i \,.\, (1 - u_j) \,.\, n \,.\, x + i \,.\, (L + \frac{1 - \tau_j}{\Delta \tau_j}) \,.\, x \quad \text{(C.1)}$$

where $x = p \,.\, Q / 365$,

and other terms have been previously defined.

The cost of early arrivals was neglected, since its formulation did not include the mode-specific variables.

The optimal shipment size q_j^* can be derived from maximizing (C.1) with respect to q. The following first order conditions are then, obtained:

$$\frac{\partial W_j^o}{\partial q_j} = 0 \;\therefore\; - o \,.\, \frac{Q}{q_j^2} + \frac{\partial r_j}{\partial q_j} \,.\, Q + i \,.\, \frac{p}{2} = 0$$
$$q_j^* = \sqrt{\frac{o \,.\, Q}{\frac{\partial r_j}{\partial q_j} \,.\, Q + i \,.\, \frac{p}{2}}} \quad \text{(C.2)}$$

Transportation rates were assumed to be a function of the shipment size, in which larger shipments usually receive larger rate discounts (i.e. $\frac{\partial r_j}{\partial q_j} \leq 0$). Note that if rates per ton are constant, (A.2) reduces to the traditional economic order quantity (EOQ) model. Thus, by allowing rates to depend on shipment size, a bigger q_j^* is obtained.

Substituting the optimal shipment size q_j^* back into the annual logistic cost specification:

$$W_j^0 = (o \, . \, Q)^{0.5} \; . \; (\frac{\partial r_j}{\partial q_j} \, . \, Q + i \, \frac{p}{2})^{0.5} \; + \; (o \, . \, Q)^{0.5} \; . \; (\frac{i \, \frac{p}{2}}{\frac{\partial r_j}{\partial q_j} \, . \, Q + i \, \frac{p}{2}})^{0.5} \; +$$

$$r_j \, . \, Q + i \, . \, d_j \, . \, m \, . \, p. \, Q \; + i \, . \, (\, 1 \, - \, u_j) \, . \, n \, . \, x \; + \; i \, . \, (\, t_j + L + \frac{1 - \tau_j}{\Delta \tau_j}) \, . \, x \qquad \text{(C.3)}$$

In order to continue the development of (A.3), it is necessary to assume a functional form for the rate function that is at least one time differentiable. The following flexible specification was used:

$$r_j = b_{oj} + b_{1j}.q_j + (b_{2j} + b_{3j}.q_j) \, . h_j \qquad \text{(C.4)}$$

where r_j = rate by mode j (\$ / ton)

hj = length of haul (miles)

Note that the coefficients (b_{oj}, b_{1j} , b_{2j} , b_{3j}) are also mode-specific to capture intrinsic economies of scale of each mode in the pricing mechanism. Even though different restrictions on these coefficients may apply depending on the mode used, the above general specification was used to combine the development of the logistic cost function.

Thus,

$$\frac{\partial r_j}{\partial q_j} = b_{1j} + b_{3j}.h_j \quad \text{and}$$

$$\begin{aligned} W_j^0 = Q^{0.5} \; . \; [\; & (o. \, b_{1j}.Q + o. \, b_{3j}.h_j.Q + \\ & o \, . \, \frac{i \, . \, p}{2})^{0.5} + (\frac{i \, . \, p}{2}) \, . \, (o. \, b_{1j} \, . \, Q + o \, . \, b_{3j} \, . \, h_j \; + o \, . \, \frac{i \, . \, p}{2})^{-0.5} \;] \\ & r_j \, . \, Q + i \, . \, d_j \, . \, m \, . \, p. \, Q \; + i \, . \, (\, 1 \, - \, u_j) \, . \, n \, . \, x \; + \; i \, . \, (\, t_j + L + \frac{1 - \tau_j}{\Delta \tau_j}) \, . \, x \qquad \text{(C.5)} \end{aligned}$$

To understand the non-linearities in (C.5), it is important to introduce the parametric version of the logistic cost function. The parameters then, incorporate the information not available to each shippers. In addition, it was assumed that the information on rates per ton elicited in the survey reflects the optimal shipment size by different modes.

$$W_j^0 = \beta_1 \,.\, r_j \,.\, Q + \beta_2\,(t_j + L + \frac{1 - \tau_j}{\Delta\tau_j})\,.\, x + \beta_3 \,.\, d_j \,.\, p.\, Q + \beta_4 \,.\, (\,1 - u_j)\,.\, x +$$

$$Q^{0.5} \,.\, [\,(\delta_j.Q + \xi_j.h_j.Q + \gamma \,.\, \frac{p}{2}\,)^{0.5} + \; + (\gamma \,.\, \frac{p}{2})\,(\delta_j.Q + \xi_j.h_j.Q + \gamma \,.\, \frac{p}{2})^{-0.5}\,] \tag{C.6}$$

where, besides the parameters already defined in Chapter 3, there are additional ones entering the above specification in a non-linear form, i.e.

$$\delta_j = o \,.\, b_{1j}\,;\; \xi_j = o \,.\, b_{1j};\ \text{and}\ \gamma = o \,.\, i \tag{C.7}$$

Taylor series expansion was then, used to linearize (C.6) with respect to the parameters (δ_j, ξ_j, γ). Since Q is known, the non-linearities can be separated in two terms and the following series expansion derived.

$$(\delta_j.Q + \xi_j.h_j.Q + \gamma \,.\, \frac{p}{2}\,)^{0.5} \cong k_j^{0.5} + \frac{1}{2\,k_j^{0.5}}\,[Q.\,(\delta_j - \delta_{0j}) + h_j.Q \,.\, (\xi_j - \xi_{0j}) + \frac{p}{2} \,.\, (\gamma - \gamma_0)\,]$$

$$(\gamma.\frac{p}{2})\,.(\delta_j.Q + \xi_j.h_j.Q + \gamma \,.\, \frac{p}{2}\,)^{-0.5} \cong k_j^{-0.5} \,.\, \frac{p}{2} \,.\, (\gamma - \gamma_0) +$$

$$\frac{1}{2\,k_j^{1.5}} \,.\, (\gamma_0.\frac{p}{2}) \,.\, [Q.\,(\delta_j - \delta_{0j}) + h_j.Q \,.\, (\xi_j - \xi_{0j}) + \frac{p}{2} \,.\, (\gamma - \gamma_0)\,]$$

where $k_j = (\delta_{0j}.Q + \xi_{0j}.h_j.Q + \gamma_0 \,.\, \frac{p}{2}\,)$

And adding these two terms,

$$k_j^{0.5} + \gamma \,.\, \frac{p}{2} \,.\, k_j^{-0.5} + \frac{1}{2\,k_j^{0.5}}\,(1 - \frac{\gamma_0 \cdot p}{2 \,.\, k_j}) \,.\, [Q.\,(\delta_j - \delta_{0j}) + h_j.Q \,.\, (\xi_j - \xi_{0j}) + \frac{p}{2} \,.\, (\gamma - \gamma_0)\,] \tag{C.8}$$

Since the expansion is only up to the first order terms, the choice of the point of approximation (δ_{0j}, ξ_{0j} , γ_0) close to the solution is very important. From the definition of the parameters, the relevant data are the estimated coefficients of the rate function

(b_{1j}, b_{3j}), the unit order cost (o), and the storage costs (c'). Unfortunately actual data from the shippers in the survey was not available and auxiliary data sources were used to get a good approximation. In particular the unit order cost was assumed to be $ 10 / per order and the storage costs 20% per year (see Ballou[1985]).

For the coefficients of the rate function, different hypothesis were made depending on the mode involved. Using the waybill sample data (see Chapter 4), the rail rate function was estimated as:

$$r_r = \underset{(0.402)}{44.945} + \underset{(0.0002)}{0.0316}\ h_r - \underset{(0.0055)}{0.5336}\, q_r \qquad (R^2 = 0.569) \tag{C.9}$$

The improvement in the goodness of fit was not enough to justify the inclusion of the interaction term between the shipment size and the length of haul (i.e. $b_{3r} = 0$). The point of approximation is then given by (δ_{0j}, ξ_{0j} , γ_0) = (-0.3, 0, 2) for the rail mode.

Substituting these values back into (C.8),

$$k_r^{0.5} + \gamma \cdot \frac{p}{2} \cdot k_r^{-0.5} + \frac{1}{2\, k_r^{0.5}} (1 - \frac{p}{k_r}) \cdot [\delta_r \cdot Q + \xi_r \cdot h_r.Q + \gamma \cdot \frac{p}{2} - k_r] \tag{C.10}$$

where $k_r = p - 0.3\ .Q$

Any term without a mode-specific coefficient to be estimated, i.e. without involving (δ_r, ξ_r), can be incorporated in the mode-specific constants of the demand model. Thus, the relevant terms in (C.10) are:

$$\frac{1}{2\, k_r^{0.5}} (1 - \frac{p}{k_r}) \cdot [\delta_r \cdot Q + \xi_r \cdot h_r .Q] \tag{C.11}$$

Note that (C.11) is a linear expression in the parameters (δ_r, ξ_r), as wanted.

In order to gain some additional insights, it was useful to go through the same calculations using (-1, 0, 0) as the point of approximation. (C.11) would then, reduce to:

$$Q^{0.5} + \gamma \cdot \frac{p}{2} \cdot Q^{-0.5} + \frac{Q^{-0.5}}{2} [Q \cdot (\delta_j + 1) + Q \cdot h_j \cdot \xi_j + \gamma \cdot \frac{p}{2}] =$$

$$\delta_j' \cdot Q^{0.5} + \xi_j \cdot Q^{0.5} \cdot h_j + \gamma \cdot \frac{p}{Q^{0.5}} \qquad (C.12)$$

where $\delta_j' = \delta_j + 1.5$

And, back into the logistic cost specification,

$$\delta_j' \cdot Q + \xi_j \cdot Q \cdot h_j + \gamma \cdot p \qquad (C.13)$$

In this case, only the first two terms are dependent of the mode chosen, through the mode-specific coefficients (δ_j', ξ_r) and the length of haul h_j. Thus, if one assumes that order costs are negligible for the railroad in the point of approximation, making $\gamma_0 = 0$, the parametric logistic cost function should include the ton-miles for the annual shipments as an independent variable specific to the rail mode.

For the truck and intermodal modes, it was hypothesized that the economies of scale from shipping multiple carloads or containers are not significant in pricing decisions. While this is a reasonable assumption for the truckload segment of the motor carriers market. where rates are predominantly a function of the length of haul[1], in the less-than-truckload market railroads and intermodal companies usually do not constitute a competitive alternative to shippers. The average transportation distance should then, be considered as an independent variable in the logistic cost function for truck, by which short trip favor the use of these modes. For the intermodal mode, rates per ton were assumed to be constant and no additional terms were included in their logistic cost function.

[1]From discussions with Prof. Sheffi at MIT.

Appendix D:

Using the Delta Method to Derive Standard Errors for Functions of Parameters

Let $\hat{\beta} \sim N(\beta, \hat{\sigma}_{\beta})$ and $\mu \sim N(\hat{\mu}, \hat{\sigma}_{\mu})$ be coefficients estimated in the demand model. Define γ to be a function of as follows:

$$\gamma = f(\beta, \mu) \qquad \text{where } f(.) \text{ will be specific to the analysis} \tag{D.1}$$

The parameter γ can be approximated by the following Taylor series expansion around the estimated values $(\hat{\beta}, \hat{\mu})$, i.e.

$$\gamma \cong \hat{\gamma} + \left(\frac{\partial f}{\partial \beta}\right)_{(\hat{\beta},\hat{\mu})} (\beta - \hat{\beta}) + \left(\frac{\partial f}{\partial \mu}\right)_{(\hat{\beta},\hat{\mu})} (\mu - \hat{\mu}) \tag{D.2}$$

From (D.2), the variance of γ is given by:

$$\mathrm{var}(\gamma) \cong \left(\frac{\partial f}{\partial \beta}\right)^2_{(\hat{\beta},\hat{\mu})} \mathrm{var}(\beta) + \left(\frac{\partial f}{\partial \mu}\right)^2_{(\hat{\beta},\hat{\mu})} \mathrm{var}(\mu) + 2\left(\frac{\partial f}{\partial \beta}\right)_{(\hat{\beta},\hat{\mu})} \left(\frac{\partial f}{\partial \mu}\right)_{(\hat{\beta},\hat{\mu})} \mathrm{cov}(\beta, \mu) \tag{D.3}$$

Finally, (D.3) can be applied with estimates of the variance-covariance matrix of the original parameters (β, μ) to get the standard error of γ.

The following two specifications for f(.) were used as examples:

- scaling the coefficient β by μ, i.e. $\gamma = \mu \beta$

$$\mathrm{var}(\gamma) = \hat{\mu}^2 \mathrm{var}(\beta) + \hat{\beta}^2 \mathrm{var}(\mu) + 2 \hat{\mu} \hat{\beta} \mathrm{cov}(\beta,\mu)$$

- normalizing the coefficient β with μ, i.e. $\gamma = \frac{\beta}{\mu}$

$$\mathrm{var}(\gamma) = \frac{1}{\hat{\mu}^2} \mathrm{var}(\beta) - \left(\frac{\hat{\beta}}{\hat{\mu}^2}\right)^2 \mathrm{var}(\mu) - 2 \left(\frac{\hat{\beta}}{\hat{\mu}^3}\right) \mathrm{cov}(\beta,\mu)$$

Appendix E:

The Classification Model in the Latent Structure Approach to Market Segmentation

In the clustering process, the objective is to assign shipper i to cluster c_i so that the sum of squared distances to cluster means (sc_i) for all shippers is minimized, i.e.

$$\min \varphi = \sum_{i=1}^{N} (\hat{\eta}_i - s_{c_i}) (\hat{\eta}_i - s_{c_i})' = \sum_{i=1}^{N} \sum_{j=1}^{M} (\hat{\eta}_{ij} - s_{c_ij})^2 \tag{E.1}$$

Given the MIMC model used in the market segmentation, the fitted values of $\hat{\eta}_i$ can be obtained from the coefficient estimated in the structural equations, i.e.

$$\hat{\eta}_i = \hat{\Gamma} (\mathbf{x}_i - \mu_x) \tag{E.2}$$

where $\mathbf{x}_i$ is the vector of observed characteristics for individual i, and
μ_x is the mean vector of observed characteristics across all individuals

Thus, the objective function in the clustering algorithm can be re-written as,

$$\varphi = \sum_{i=1}^{N} (\hat{\Gamma} (\mathbf{x}_i - \mu_x) - s_{c_i}) (\hat{\Gamma} (\mathbf{x}_i - \mu_x) - s_{c_i})' \tag{E.3}$$

In addition, for each shipper, the following inequality should hold

$$\sum_{j=1}^{M} (\hat{\eta}_{ij} - s_{c_ij})^2 \leq \sum_{j=1}^{M} (\hat{\eta}_{ij} - s_{c\,j})^2 \quad \text{for all } c \neq c_i \tag{E.4}$$

Otherwise shipper i would not have been assigned to cluster c_i.

Now, expanding (E.4) by substituting on the right hand side the fitted values of the clustering variables $\widehat{\eta}_i$ from the structural equations,

$$\sum_{j=1}^{M} (\widehat{\eta}_{ij} - s_{cj})^2 = \sum_{j=1}^{M} \sum_{k=1}^{K} (\widehat{\gamma}_{jk}(x_{ik} - \mu_{ik}) - s_{cj})^2 =$$

$$= \sum_{j=1}^{M} (\sum_{k=1}^{K} (\widehat{\gamma}_{jk}(x_{ik} - \mu_{ik}))^2 - 2\, s_{cj} \sum_{k=1}^{K} \widehat{\gamma}_{jk}(x_{ik} - \mu_{ik}) + s_{cj}^2 \qquad \text{(E.5)}$$

Finally define,

$$\alpha_c = \sum_{j=1}^{M} s_{cj}^2 + 2 \sum_{j=1}^{M} s_{cj} \sum_{k=1}^{K} \widehat{\gamma}_{jk}\, \mu_{ik} \quad \text{and} \qquad \text{(E.6)}$$

$$\beta_{ck} = -\,2 \sum_{j=1}^{M} s_{cj}\, \widehat{\gamma}_{jk} \qquad \text{(E.7)}$$

which can be used in the logit classification model as the cluster-specific constants and the coefficient associated to each observed characteristic. Note that the first term in (E.5) does not depend on cluster c, and as such, cancels out in the logit model where all coefficients are cluster specific.

Given that (E.6) and (E.7) can be calculated directly from the estimated coefficient in the MIMC model, there is no need to estimate the logit model. Therefore, each individual i should be assigned to the cluster for which $\alpha_c + \beta_c\, \mathbf{x}_i$ is maximized.

Appendix F
Variable Thresholds in Ordered Response Models

Similar to Bolduc and Poole [1989], the individualized bounds were assumed to be linear functions of variables that explain the cognitive or other processes influencing the position of shippers' discrete responses, i.e.

$$\alpha_{n,j} = \theta_j' \mathbf{z_n} + \varepsilon_{n,j} \tag{F.1}$$

The response $y_n = j$ occurs when $\alpha_{n,j-1} \leq \beta' \mathbf{x_n} \leq \alpha_{n,j}$, for $\beta' \mathbf{x_n}$ being the difference in the logistic cost implied by the service offerings in a given scenario. Note that to identify the full model, it was assumed standardized errors for the bounds. Besides relevant socioeconomic variables, the vector $\mathbf{z_n}$ includes a constant term to allow testing the restriction of constant bounds.

The probability that the indicator $y_n = j$ manifest itself is then given by:

$$\begin{aligned} \Pr(y_n = j) &= \Pr(\theta_{j-1}' \mathbf{z_n} + \varepsilon_{n,j-1} \leq \beta' \mathbf{x_n} + u_n \leq \theta_j' \mathbf{z_n} + \varepsilon_{n,j}) = \\ &\Pr(u_n - \varepsilon_{n,j} \leq \theta_j' \mathbf{z_n} - \beta' \mathbf{x_n}) - \Pr(u_n - \varepsilon_{n,j-1} \leq \theta_{j-1}' \mathbf{z_n} - \beta' \mathbf{x_n}) \end{aligned} \tag{F.2}$$

Given that u_n, $\varepsilon_{n,j}$ are independent and identically distributed and postulating that $\mathrm{cov}(u_n, \varepsilon_{n,j}) = 0$, the log-likelihood of the ordered logit model with variable bounds is given by:

$$L = \sum_{n=1}^{N} \sum_{j=1}^{J} d_{n,j} \ln [\Lambda(\theta_j' \mathbf{z_n} - \beta' \mathbf{x_n}) - \Lambda(\theta_{j-1}' \mathbf{z_n} - \beta' \mathbf{x_n})]) \tag{F.3}$$

where $j = 1, 2, \ldots J$ categories in the response scale;
$n = 1, 2, \ldots.$ N observations;
$\Lambda(.)$ is the cdf for the logistic distribution; and
$d_{n,j} =$ 1, if y_n falls in jth category; 0, otherwise.