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by

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Abstract

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Doctor of Philosophy in Civil and Environmental Engineering

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Professor Adib Kanafani, Chair

The objective of this research is to study the competition among ports. In particular we study the relation between port characteristics and port market share of maritime traffic.

Maritime carriers make two primary decisions that affect ports. In the long-term, they assign vessels to routes. In the short-term, they assign each shipment to a vessel and, with that vessel, a port. In this research, we assume that vessel schedules are fixed and model the assignment of shipments as a function of the attributes that describe each port. For a carrier, some assignments are simpler than other assignments. Each assignment should, however, take into account the same criteria.

We begin by examining the scheduling of vessels for its effect on the assignment of shipments. We measure the impact of being a vessel's first or last port of call on a port's market share, and we discuss factors that might influence these schedules. We then examine the assignment to ports for exports of various commodity types as a function of geographic location (oceanic and inland distances), port characteristics (vessel capacity and port charges), and characteristics of vessel schedules (frequency and the order of

visits). We use a multinomial choice model to analyze port choice. We find that the most significant factors are the geographic factors, which are beyond port control. The factors that ports can influence directly appear to be of far less significance. We also find that the choice processes vary with commodity type as well as carrier. The decisions are also found to differ between local and discretionary cargo.

Our findings could affect decisions made by port managers as well as carriers or shippers. With the recognition of geographic advantages, port managers could focus marketing more effectively. Recognizing the impact of each carrier’s schedules, they could suggest changes to carriers presently visiting the port or recruit new carriers to use present facilities more efficiently. Port managers could also evaluate more effectively investments designed to increase market share. Facilities or technologies could be incremented with a more accurate vision of future traffic levels at individual ports.

To my mother,

who has supported me most

from the beginning

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Chapter 1. Introduction

In this research we model the assignment of shipments to ports by a maritime carrier and explore the impact of this process on the economic performance of ports. We assess the importance of factors that affect port market share in an increasingly competitive environment, an environment that has arisen from the shifting of traditional patterns within the industry. In response to technological and organizational changes, maritime carriers have adopted new operating schemes. These schemes recognize factors that were not considered in earlier days, and port managers must evaluate markets from a new perspective.

We answer three specific questions about port market share:

- What factors influence a carrier's selection of a port for a shipment?
- In what manner and across what domain do ports compete?
- What strategies might a port follow to increase its market share?

We address these questions from a quantitative perspective by analyzing the port selection for shipments. In doing so, we measure the impact of various factors and examine trends within the scheduling of vessels. Qualitative analysis of these issues is abundant in the literature, and in many ways, the results of our quantitative analysis mirror the results of the qualitative analysis.

Before answering these questions, let us first describe the maritime industry and the changes that have influenced competition between ports. The first change is technological; competition between ports first intensified with the advent of containerization. When containers began replacing the breakbulk method of moving shipments, the transport process became more standardized at ports. Containerization simplified the inland transport of shipments, thus reducing the access cost of alternate ports. The process, though first introduced in 1956, did not become fully integrated at ports until the 1970s. Even today containerization continues to increase at ports worldwide.

The organizational changes during the early 1980s influenced port competition on a level that rivaled the advent of containerization. Prior to 1980, transportation was heavily regulated. Oceanic line-haul rates were equal within a range of ports (Foster, 1978a), and as a result, shippers considered inland distance the primary factor in port selection. Each vessel called at multiple ports to gather the available cargo. Under the Shipping Act of 1984, many restrictions were removed. Maritime carriers began setting point-to-point rates that were independent of the specific routing. Also for the first time, maritime carriers began establishing contracts with inland transportation providers.[1] With the establishment of point-to-point rates, port selection for each shipment shifted from the shipper to the carrier. Each shipper cared more about the overall service than a shipment's specific route and began allowing the carrier to select routes. This situation became apparent with the tariffs and service contracts available through the Federal Maritime Commission prior to the Ocean Shipping Reform Act of 1999. With each agreement a shipper's price resulted from the origin and destination and generally did not depend on the intermediate port.

As the selection of ports shifted from the shipper to the carrier, carriers began to concentrate operations around particular ports. More importantly, ports began to cater to the carriers in hope of attracting their traffic. Ports recognized that carriers' desires were shifting from the historic system that focused on direct measures of cost and time to an indirect system that focused on scale economies and just-in-time transportation. Ports have since attempted to accommodate carriers along many avenues, including:

- the dredging of terminal facilities to accommodate carriers' larger vessels,
- the enhancement of the transfer process to reduce the dwell time of shipments,
- the increase of terminal space to allow scale economies, and
- the negotiation of port-throughput contracts favorable to larger volumes.

Some observers have questioned the need for these investments (Luberoff et. al., 2000). Before continuing, let us give brief examples of each avenue.

With regard to dredging, vessel size has increased from approximately 2000 TEUs around 1980 to the 6600 TEUs that represent today's vessels;[2] vessel size increased particularly with the initiation of Post-Panamax vessels in the mid-1990s. Dredging costs were absorbed by ports wishing to attract the carriers (Jansson et al., 1987). Vessels began serving oceanic shuttle services and continued to be built even larger. In the United States, the vessel service through the Panama Canal began being replaced by the landbridge services offered through rail transportation. As vessel sizes and capital costs increased, carriers sought to reduce the time vessels spent in each port, and the average number of calls for each vessel dropped. Between 1993 and 1999, the average number of calls decreased along the United States West Coast more than along the East Coast (Lago et. al., 2001), suggesting that scale economies could be exploited more easily in some markets than others. Nevertheless, as ports faced increased competition, capital investments continued to grow.

One example of the importance of facility depth involves Maersk/SeaLand, whose vessels were the first to exceed 6000 TEUs. Maersk/SeaLand had called at the Port of New York/New Jersey (NY/NJ), but the depth of channels was insufficient to accommodate the modern vessels when filled to capacity. In 1998, the carrier solicited bids from five competing ports, ranging from Halifax to Hampton Roads, and asked how each port could accommodate their vessels (Lyons, 1996; Brennan, 1998). The perceived level of competition encouraged NY/NJ to absorb dredging costs for the benefit of the carrier. Oakland officials have consistently sought to raise the draft of channels to the level naturally present at Los Angeles and Long Beach. Many have suggested that carriers were exploiting the public nature of port authorities for their own benefits (Tolofari et. al., 1987a, 1987b).

With regard to the intermodal transfer process, each major United States West Coast port has had major plans for enhancement. The ports of Los Angeles and Long Beach have worked together to create the “Alameda Corridor,” a $2 billion project that will enhance access to both ports by separating rail facilities from other ground transportation. The Port of Oakland has a ten-year project to connect the Burlington Northern Santa Fe railroad to the port and to the Union Pacific railyard.

To offer larger terminals, ports develop land acquired through abandoned naval facilities, landfill, or the free market. In what many consider the first mega-terminal, the Port of Los Angeles constructed a 250-acre facility for American President Lines in 1998. To attract Maersk/SeaLand from the Port of Long Beach, Los Angeles initiated construction on a $1 billion, 484-acre terminal in 2000. Long Beach has begun converting an abandoned naval shipyard to a $600 million, 350-acre terminal for Hanjin Shipping Co., who just three years ago relocated to another terminal within the port. The Vision 2000 project at the Port of Oakland involves terminal expansion. The Stevedoring Services of America and the Port of Seattle recently established a $300 million terminal expansion project. These investments will reduce the costs for shipments already moving through the ports as well as attract traffic from other ports. In the following chapter, we discuss the evolution of a carrier's "load center". In many ways each port is fighting to become a load center.

Finally, ports can compete by offering different financial schemes to facility users. Not all ports receive public funding, as do the ports of Seattle and Tacoma in the form of property taxes. While the West Coast ports operate as lessors, leaving carriers to handle terminal operation, East Coast ports operate the terminals themselves and assess each carrier for the service provided. The East Coast ports, operated in a more public sense, do not face the same urgency as West Coast ports to become self-sufficient. The structure of a port's finances could affect the attractiveness of that port to a carrier. A brief examination of the preferential service agreements between West Coast ports and carriers shows that the rates charged differ between ports and that rates are progressively lowered as traffic volume is increased.

A maritime carrier makes two primary decisions that affect the assignment of shipments to ports. First is the assignment of a fleet of vessels to a particular set of ports in a network. In doing so, factors that are considered must include the level of traffic and competition within the shipping network, as well as political barriers that affect competition. After assigning each vessel, the carrier assigns each shipment to a vessel via a port at which this vessel calls. The vessel-assignment is a long-term decision and the routing of shipments is a short-term decision. In other words, a carrier assigns each vessel to a route and, given this assignment, assigns each shipment to a vessel. In this research, we examine this short-term decision and evaluate its impact on the competition between ports.

With an understanding of a carrier's decision process, port managers can assess their competitive position more clearly, and evaluate investment alternatives as well as marketing strategies. As a primary focus, in this research we examine the impact of different shipment-specific factors on the distribution of shipments among ports.

We could use two methods to analyze port selection. For one, we could use a multicommodity flow model, in which the generalized cost of transporting the shipments is minimized. After devising each carrier's objective function, we could assign each shipment to a port to satisfy this function. Alternatively, we could use the framework of a choice model to estimate the relative importance of each factor by examining actual port choices. Each alternative has its merits and its drawbacks. In this research, we follow the choice model approach.

With choice modeling, we measure the relative effect of each factor by modeling carrier's decisions instead of estimating that effect *a priori*, as would be required with a flow model. With choice modeling we can also model the decision for each shipment separately, thus allowing the extension of the model to a hypothetical shipment. We might actually find it easier to estimate a multicommodity flow model after estimating a choice model, since the relative importance of each factor could be measured before devising the objective function. We can observe the actual decisions that we explain with a choice model, while we can not measure the generalized costs faced by a carrier in a flow model.

In Chapter 2, we survey the relevant literature. To our knowledge, no previous work has analyzed the distribution of shipments on a disaggregate level. Information that contributes to our disaggregate model, however, comes from three primary areas. The first is the numerous stated preference surveys that have been conducted of industry participants. The second is the evaluation of carrier planning models that revolve around fleet assignment and the development of a hub-and-spoke system. The third area consists of the economic models that represent port operations and vessel operations.

In Chapter 3, we describe the data. We dissect the shipment-specific data to uncover patterns within the data. We discuss the factors that could influence a carrier's decision and manners in which these factors could be measured. We discuss the traditional choice model and introduce a formulation that suits particular characteristics of the data.

In Chapter 4, we examine the effect of a port's location along a vessel's string of calls. We focus particularly on the importance of being visited first, for imports, or last, for exports. We examine trends in carriers' present selection of ports to visit and the order in which ports are visited, and we then estimate the importance of factors that influence a carrier's selection of a last port of call.

In Chapter 5, we estimate the choice model to represent the selection of a port for each shipment. We examine categories (carrier, commodity-value) for which the decision process might vary and then generate a model for each category. We also examine the differences in the decisions typically made for cargo local to a port versus cargo that would be considered discretionary. We use the models estimated to examine the level of competition that exists under different scenarios.

In Chapter 6, we discuss one particular factor, port charges, more fully. We address port charges separately because of conditions that preclude the factor from being included directly in a choice model. We examine general trends in the financial agreements between carriers and ports. We evaluate the impact of port charges on the distribution of shipments and suggest analysis for port authorities in the establishment of rates.

We conclude with a summary of all findings and discuss manners in which the results of the research might be applied. We also discuss avenues of further research.

Chapter 2. Literature review

To our knowledge, no previous research has quantitatively addressed the disaggregate assignment of shipments. Literature that contributes to our background comes from three primary directions. First are empirical surveys of carriers and shippers. Second is the literature describing fleet assignment. Third is the economic modeling, in particular that applied to maritime transportation. This modeling includes primarily linear programming and cost modeling, but also choice modeling.

Qualitative analysis

Surveys of industry participants have addressed two major issues:

i) who selects the port for each shipment?, and

ii) what factors influence the selection of a port?

Neither question has generated consistent results. With regard to the first question, most authors have suggested that the carrier selects the port for each shipment. In analyzing the results of surveys, Slack (1985) wrote, "(carriers) … are the key actors in the port selection process." D'Este et al. (1992a; 1992b) found that in most cases the port is just another factor the shipper evaluates in the selection of a carrier. They suggested that as carriers increased their scale of operations and shippers began soliciting prices for door-to-door service rather than individual segments, the port selection shifted from the shipper to the carrier. With deregulation of the maritime industry, rates were no longer so closely related to distance. Carriers could offer less-direct routes that were cost-efficient for the shippers as well as themselves. As shippers adjusted to the deregulated environment, carriers began to select the route for shipments. In selecting the route, carriers would consider the shippers' interests to capture their business.

In the selection of a port, decisionmakers seem to value service characteristics more highly than price characteristics. In an early survey, Bardi (1973) found that transit time, reliability, capability, availability, and security were the most important characteristics. Two surveys conducted for *Distribution Worldwide* (Foster, 1978b; Foster, 1979) had conflicting results, however. According to the first survey, shippers valued service more than cost. With the second survey, the author found that transport costs and port charges were the most important criteria. Qualitative choice analysis can produce this inconsistency, since it focuses on statements rather than actions. Foster also remarked that only 30% of respondents "cared if the port they chose is the last port of call for the vessel carrying the goods," suggesting that more should. In analyzing these surveys, Slack (1985) found that the number of voyages and the inland freight rates were most important. Important port characteristics included the port's connection to inland transport services and the available container facilities. Slack concluded that "the choice of port depended more on the price and quality of service offered by land and ocean carriers than on the attributes of ports themselves."

From semi-structured interviews of industry participants, Hanelt et al. (1987) concluded that each participant valued characteristics differently. They argued that many important factors are beyond a port authority's control. Port managers cannot influence the two most important factors, the size of the local market and domestic transportation costs, but they can indirectly influence port labor productivity, rail transit times, port access, total transit time, and ocean carrier intermodal networks. They can also directly influence terminal gate capacity, channel and berth depth, indirect port charges, port charges on cargo or carrier, and cargo handling equipment.

Brooks (1984; 1985) noted one shortcoming of stated preference analysis, in finding similar results from her survey. She remarked that importance does not necessarily represent salience for a factor; the inconsistency of surveys noted earlier reflects this. A characteristic could be considered important yet not influence the decision process if the characteristic did not vary among alternatives. With quantitative research based on revealed preference, values can be assigned to each factor's importance to measure its true salience.

Maritime network development

Numerous researchers have discussed the development of the port system, with particular focus on load-centers. Ports designated load-centers are similar, for carriers, to hub airports for airlines. Carriers would focus larger vessels at the load-center to minimize the calls made by these vessels. Feeder vessels or inland modes would then distribute traffic between the load center and either feeder ports or inland locations. Ports could compete to be designated as a carrier's load-center.

In addressing the competition between ports, Kenyon (1970) focused on the Port of New York's advantage. He argued that demand from the population of New York resulted in more vessel calls. The increased traffic led to increased port development, which then led to more traffic, and so on. He suggested that the cycle would continue to increase a port's attractiveness until potential capacity was exceeded. Thus external characteristics are advantageous, particularly in seeking load-center status; local (at that time captive) population is one characteristic.

Al-Kazily (1979) compared a feeder system, in which only the hub port's facilities could accommodate larger vessels, to a traditional port system. In a study of the Arabian Gulf, she combined a vessel cost function with traffic projections to determine the efficiency of a feeder system, in which the feeder vessels represent spokes from the hub. This system may be different in the United States, where surface transportation represents the spokes, but the proposed hierarchical relationship between ports is important.

Hayut (1981) introduced a five-phase model to represent the development of load-centers. In the first phase, a precondition for change surfaces. A precondition might be the insufficiency of present conditions or a technological change. Phase two is the initial development of ports. (We can apply this concept most readily to ports' investment in containerization.) In phase three, ports begin to consolidate operations, and in phase four carriers center operations completely around a hub. By then, inland carriers and ocean carriers have already consolidated their operations, and smaller ports have accepted their role as feeders. In the final phase, peripheral ports challenge the load-center port as the load-center port faces diseconomies of scale.

Foggin et al. (1985) explained the development of load-centers as an effect of deregulation. With the development of load centers, ports' hinterlands disappeared. Shippers focused on the door-to-door package, and carriers concentrated services along particular routes to exploit economies-of-scale and density. Hayut (1981; 1991) and Foggin each describe qualitatively characteristics that allow one port to become a region's load-center. These characteristics mirror results from stated-preference surveys, with one obvious characteristic a large population.

Slack (1996) discussed carriers' role in the development of load-centers. He emphasized the vulnerability of smaller ports in the era of larger vessels. He suggested that smaller ports could be hindered more by the need for intense technological investment for containerization.

Helmick (1994) examined whether voyages had become more concentrated as the load-center concept projected. Using data from the US Census, he examined three hypotheses:

i) that traffic was becoming concentrated along routes,

ii) that traffic was becoming concentrated among ports, and

iii) that network connectivity was decreasing as carriers called at fewer ports

Not one hypothesis was consistently accepted. To explain this, Helmick suggested that three types of carriers existed. The first possessed modernized equipment and followed the hypothesized patterns. The second type was less modern but still followed the patterns of the first carrier. The third type of carrier, however, was represented by tramp lines and filled the lanes vacated by other carriers. He suggested that researchers address the differing behavior of carriers.

Lago et. al. (2001) examined changes in the schedules of vessels visiting United States ports along the East and West Coasts between 1993 and 1999[1] and found changes along the East Coast that were less significant than changes along the West Coast. Along the West Coast vessels did become larger and call at fewer ports. Behavior along each coast might differ as a result of the markets served by each coast's ports. The West Coast serves primarily the transpacific trade, for which carriers sail greater distances and transport larger volumes. East Coast ports cater to transatlantic and South American markets, both smaller in volume and closer in distance. As such, carriers cannot exploit scale economies as readily.

Economic Models

Three types of economic models have been developed: linear programming models that assign fleets in simplified environments, economic models that represent costs of carriers or ports, and economic models that represent carriers' decisions.

Benford (1981) first proposed a simple method to minimize vessel operating costs for a given load and a prespecified fleet. He assumed that carriers' revenues were fixed; thus the objective was cost minimization. If average costs increased with the volume transported by a vessel, then each group of vessels would operate at a speed that produced equal average costs between groups. Perakis (1985) corrected Benford's results with the Lagrangean method and showed that Benford's results were not always optimal. Lane et al. (1987) represented different aspects with cost components, e.g. late-loading costs, idle-time costs, and utilization costs.

Perakis et al. (1991) extended the optimization model further by including all operating costs. In each model, however, the flows were prespecified. More importantly, customer costs such as inventory costs were virtually ignored. Cho et al. (1996) attempted to incorporate demand forecasts with multiple ports, but demand was again prespecified and did not vary with service levels. In reality, shippers would often pay more to have shipments delivered sooner, more frequently, or more reliably. Our model does not address the issue of vessel scheduling but is designed to show how vessel scheduling influences a port's attractiveness.

Cost models influence each carrier's selection of port and ship size, and numerous authors have modeled costs for the maritime industry. Waters (1997) summarized researchers' options for estimating cost functions (engineering, econometrics, and statistical regression). Tolofari et al. (1987a; 1987b) estimated cost models for bulk shipping and tanker industries. Each model suggested scale economies in vessel size, but the authors emphasized that carriers could exploit these economies only at the expense of port operators or shippers. Port operators would incur additional dredging costs, and shippers might face higher inventory costs from lessened frequencies. Garrod et al. (1985) and Jansson et al. (1985) showed the importance of shippers' inventory costs when minimizing carriers' costs. Jansson et al. (1978), Talley (1990), and Lim (1998) found similar properties for general cargo and container ships.

In another direction, many authors have explored the optimization of port performance. The authors emphasize the measures gathered, and the objectives pursued, by port operators. Griffiths (1976a; 1976b) first modeled the optimal handling capacity at a berth. He assumed that vessels carrying a fixed load arrive either at a Poisson rate or at a uniform rate and that the time to service each vessel was distributed as a negative-exponential. He then predicted the delay for each vessel as a function of the port's handling rate. Griffiths used shippers' delay costs and port operators' service provision costs to estimate an optimal level of service. Wanhill (1976) and Chappell (1979) added minor elements to the model, such as the time required for vessels to access berthing facilities and the possible nonlinearity of port costs. Laing et al. (1989) showed that the congestion necessary to justify a new berth decreased with the number of available berths. With more berths, the reduction in delay from a new berth is smaller but can be spread over additional vessels.

By focusing on quay length and the number of cranes, De Neufville et al. (1981) confirmed that scale economies exist at container ports. He argued that the other two resources, land and manpower, could be represented by the first two as proxies. At six eastern U.S. ports, De Neufville found that productivity increased with port size. He argued that investing at major ports would be advantageous to investing elsewhere.

Bendall et al. (1987, 1988) measured port productivity as a function of labor, capital, and time for different ship-types. They found vessel age and vessel size to be important and that congestion was greater in certain years due to specific events. They also found that, to increase efficiency, ports could customize facilities for different ship-types. Talley (1988a; 1988b) argued that an incentive existed for smaller, neighboring ports to consolidate and for ports to invest efficiently as a group. He suggested that larger volumes could produce lower rail rates and that smaller ports might need to subsidize rail services to compete. He also suggested that ports compare actual throughput with maximum throughput only for a captive hinterland. In a competitive environment, unit-cost minimization or zero-deficit throughput maximization may be preferred.

Talley (1994a) later showed how a port could maximize efficiency with Lagrangean modeling, since the shadow cost represents the cost needed to handle an additional container. Minimizing the shadow price for a given volume would be equivalent to maximizing a port's operational efficiency. Tongzon (1995) argued that a port's throughput efficiency affects its overall throughput since it influences the port's attractiveness to shippers. With a Cobb-Douglas function, he showed that throughput efficiency is affected by container mix (20-ft. versus 40-ft.), work practices, crane efficiency, vessel size, and cargo exchange. He argued also that port charges are important, but less so than service factors.

Riendeau (1977) presented an early model of the shipper-port-carrier transportation system to describe the selection of ports. He discussed many of the elements that influence the route (and thus the port) chosen for each shipment. He merged the decision patterns of each party to establish a final route. He expected behavior to change at certain thresholds (i.e. the boundary of a port's hinterland), but his assumptions were simple. He gave little attention to carriers' scale economies. In addition, the present system is much less regulated. The routes available to carriers and the rates available to shippers are more flexible, making Riendeau's work less applicable to today's environment.

Numerous reports have also examined the economic impact of port charges. Authors (Gentle, 1989; Tongzon, 1989; Goss, 1990) have argued that these fees do not affect carriers' port selection. In a quantitative analysis, Tongzon examined the elasticity of the number of shipments with regard to wharfage in Australia. Due to relatively low elasticities, he predicted no significant increase in port traffic or port revenues would result from reduced wharfage. Thus, though port charges played a significant role in the generation of revenues by a port authority, they did not heavily influence port selection. In addition, the structure of port charges is not consistent across ports (Foster, 1978a).

Using microeconomic modeling, Allen (1977) and Daughety (1979; 1985) each defined a decision-maker with an objective of profit maximization. They represented profits as the difference between revenues and production costs, and they represented revenues as the difference between the product's final price and its transportation costs. With this equation they could determine the optimal level of inputs, including transportation services. Alternatively, they could generate a cost function to represent the desired output with the required amount of transportation. They proposed the inclusion of service characteristics, such as scheduling delay or shipment damage, if converted to lost revenues or added costs.

Discrete choice modeling, however, focuses on a measure that does not require the formulation of profits or costs (Winston, 1983). Researchers do not need to convert each factor to a monetary value. For an aggregate model, the basic unit of observation is a freight mode’s aggregate share. For a disaggregate model, the basic unit is the decision made for an individual shipment. Each type has been applied with freight transportation, most commonly for the study of mode selection or demand estimation for a new mode. Boyer (1977) and Oum (1979a; 1979b) have applied an aggregate model to freight transportation. Oum (1979c) discussed shortcomings of the linear logit model used for aggregate analysis, particularly with the elasticities of substitution between alternatives. Disaggregate models were applied by Winston (1981a; 1981b) and Nam (1997). Initial application of a disaggregate model toward the selection of a port was presented by Malchow et al. (2000). With a disaggregate model, we could represent more richly the situation faced by the decision-maker. A disaggregate model however required more precise data, data often considered proprietary by shippers.

Summary

From this literature, we pull three major points. First, because carriers do have an incentive to exploit scale economies, vessels are becoming larger. The trend, however, is not as apparent in all trade routes, for reasons such as traffic volume or route length. With this trend, ports are competing to attract carriers. We gave numerous examples in the first chapter of the ways in which ports are competing.

Second, though many authors suggest that service-related factors are more important than price, there is no consensus as to which factors are most significant. In addition, port authorities may be unable to control the factors that are most important.

Finally, we could use one of many methods to evaluate the significance of different factors. We could conduct another stated preference survey or use a cost model to represent the behavior that is optimized. We instead use the choice model that allows representation of each decision on a disaggregate level. In the next chapter we introduce the choice model in more detail.

Chapter 3. Model formulation

In this chapter we present the discrete choice model used for the analysis of port selection. We then discuss the data that describe individual shipments and introduce an alternative formulation of the model that accounts for particular characteristics of the data.

We use discrete choice analysis to model the probability of a port being used for a given shipment as a function of the factors describing the port and the shipment. For reasons discussed in Chapter 2, we assume that this decision belongs to the carrier. We use a multinomial logit (MNL) model, according to which the probability that port j is selected for shipment n, P_{nj}, is:

$$P_{nj} = \frac{e^{V_{nj}}}{\sum_k e^{V_{nk}}},$$

in which V_{nj} is a choice function that represents the systematic utility of port j for shipment n.[1] Under this formulation, each port competes equally for market share, as in Figure 1.

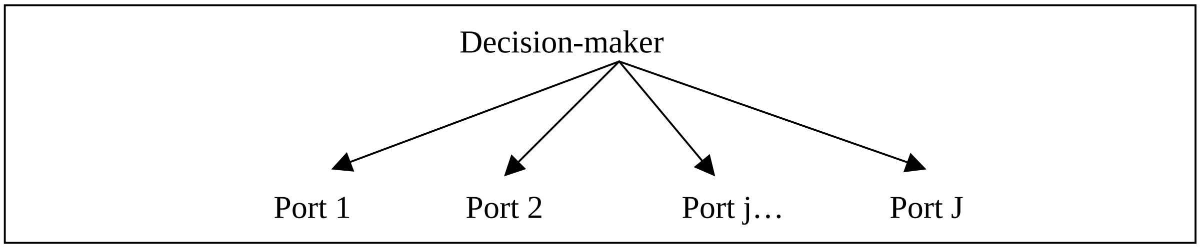

Figure 1. A MNL modeling of the alternatives faced by each carrier.

Data

The data used in this analysis describe shipments exported from the United States in December 1999. Shipments are classified into four commodity types using the first two digits of the harmonized commodity code (HS).[2] The four commodities are bulk materials (HS 25,26), foods (HS 07,08,10), fabrics (HS 52,54), and manufactured goods (HS 85). The data represent exports to eight foreign countries: Australia, Brazil, Egypt, Germany, Japan, Saudi Arabia, South Africa, and the United Kingdom. The commodity classifications provide variations in the values (and related characteristics) of the shipments, and the destination countries provide geographic distribution. We restrict shipments to those for which the carrier of record had a schedule listed with the Journal of Commerce, since we use a carrier's schedule to measure particular variables. Table 1 shows the distribution of shipments by country and commodity type.[3] For each carrier, the choice set consists of the eight ports shown in Figure 2. They are: Charleston, SC; Long Beach, CA (LB); Los Angeles, CA (LA); New York, NY (NY); Oakland, CA; Savannah, GA; Seattle, WA; and Tacoma, WA.

HS code	Australia	Brazil	Egypt	Germany	Japan	Saudi Arabia	South Africa	United Kingdom	Total
07	127	2	1	13	722	6	2	57	930
08	160	8	33	169	836	64	6	141	1417
10	7	1	0	7	70	2	0	12	99
25	63	18	7	85	352	6	23	56	610
26	1	4	0	2	13	0	2	7	29
52	33	25	0	26	190	18	21	52	365
54	25	17	2	35	12	7	18	28	144
85	164	61	15	79	254	69	36	162	840
All	580	136	58	416	2449	172	108	515	4434

Table 1. The distribution of shipments in the data set, by origin and commodity-type.

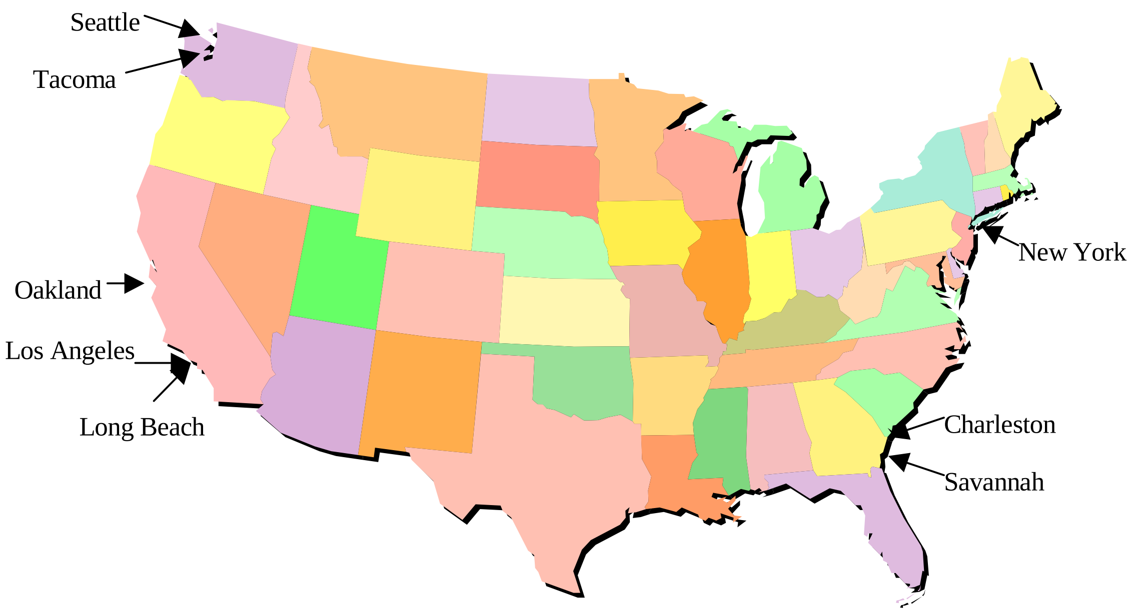

Figure 2. A geographic representation of the ports within the choice set.

Table 2 shows the ranking of United States ports by total traffic in 1999, and Table 3 shows the ports ranked by container traffic in 1999.[4] In each table, we highlight the ports that are included in the choice set.

Rank	Port	Dollars ($1000s)
1	**Long Beach, CA**	**88,956,058**
2	**Los Angeles, CA**	**83,073,994**
3	**New York/New Jersey**	**71,714,129**
4	Houston, TX	34,113,393
5	**Seattle, WA**	**32,226,702**
6	**Charleston, SC**	**29,134,630**
7	Hampton Roads, VA	27,666,351
8	**Oakland, CA**	**25,757,684**
9	Baltimore, MD	19,287,481
10	**Tacoma, WA**	**16,985,066**
11	New Orleans, LA	16,441,711
12	Miami, FL	15,435,987
13	**Savannah, GA**	**13,530,592**
14	Port Everglades, FL	10,431,949
15	Jacksonville, FL	9,845,875
16	Portland, OR	9,515,293
17	South Louisiana	8,752,745
18	Corpus Christi, TX	6,964,935
19	Philadelphia, PA	6,911,923
20	Boston, MA	5,748,034

Table 2. The ranking of ports by foreign trade value, 1999.

Rank	Port	TEUs
1	**Long Beach, CA**	4,408,480
2	**Los Angeles, CA**	3,828,851
3	**New York/New Jersey**	2,828,878
4	**Oakland, CA**	1,663,756
5	**Seattle, WA**	1,490,048
6	**Charleston, SC**	1,482,995
7	Hampton Roads, VA	1,306,537
8	**Tacoma, WA**	1,271,011
9	Vancouver (BC)	1,070,171
10	Houston, TX	1,001,170
11	Montreal (QU)	993,486
12	**Savannah, GA**	793,165
13	Miami, FL	777,821
14	Jacksonville, FL	771,882
15	Port Everglades, FL	715,585
16	Baltimore, MD	498,108
17	Halifax (NS)	462,766
18	Honolulu, HI	411,156
19	Anchorage, AK	367,810
20	Portland, OR	293,262

Table 3. The ranking of ports by TEUs shipped, 1999.

We select the eight ports in our choice set for two primary characteristics: i) the volume of trade moved through the port, and ii) the proximity of the port to other significant ports. If two ports were geographically close, factors other than location would influence a selection between them. We want to capture the impact of such factors. Table 4 shows the distribution, among ports, of shipments within our sample set.

Rank	Port	Shipments
1	**Oakland, CA**	1314
2	**Los Angeles, CA**	1010
3	**Charleston, SC**	675
4	**Long Beach, CA**	650
5	**New York/New Jersey**	618
6	**Seattle, WA**	515
7	**Savannah, GA**	462
8	Houston, TX	346
9	Norfolk, VA	290
10	**Tacoma, WA**	254
11	Miami, FL	184
12	Portland, OR	172
13	Port Canaveral, FL	111
14	New Orleans, LA	108
15	Gramercy, TX	76
16	Baltimore, MD	57
17	Philadelphia, PA	34
18	Port Hueneme, CA	27
19	Jacksonville, FL	24
20	Newport News, VA	23

Table 4. The distribution of shipments within the data set among ports.

The largest ports, according to Tables 2 and 3, are also among the largest within our sample data set. The ranking however is not identical, and we must consider whether the data set is representative. If it were not representative, then the estimates for alternative-specific constants would be biased. The estimates for attribute-specific coefficients would be unaffected. We can not compare the different rankings directly since the units of comparison differ. Perhaps ports rank differently in the context of exports or, more likely, the commodities on which we focus. Nonetheless, since we collect them randomly with regard to the choice set, we assume that the data are representative.

Figure 3 shows the distribution across ports, by value, of the shipments in the data set as well as all shipments.[5] Shipments within the sampled data set are more concentrated among the available ports. Most likely, this relationship results from the specialization of certain ports for commodities/markets not included in the data set. The eight ports within our choice set represent approximately 75% of all shipments within the data set.

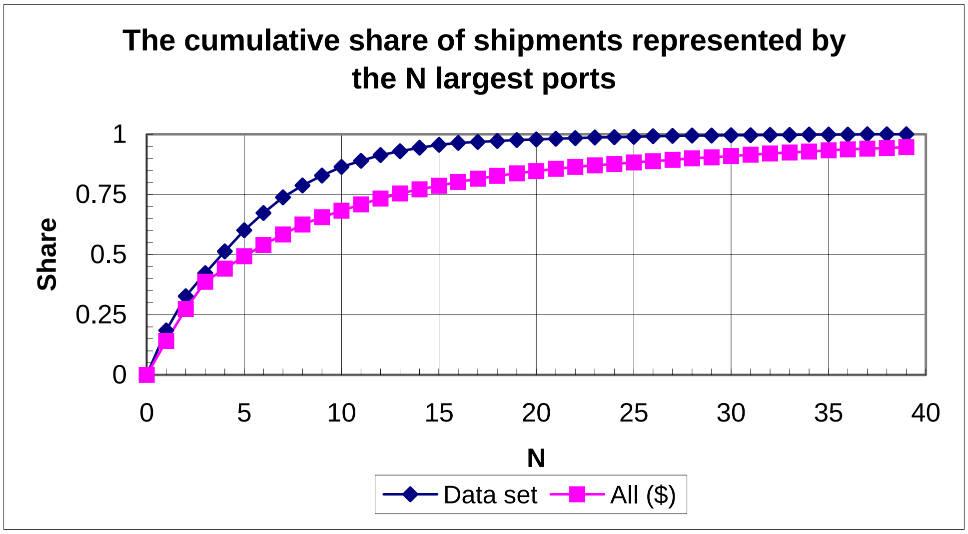

Figure 3. The distribution of shipments across ports.

Table 5 shows the total value of shipments, for each commodity class, exported from the United States to each country in December 1999. As shown, the four commodities represent 22% of all shipments, and the eight countries represent 23% of all shipments. Thus the data set represents just above 4% of all shipments exported from the United States in December 1999.[6] For each country the eight commodities represent between 11% and 35% of all shipments, and for each commodity the eight countries represent between 7% and 34% of all shipments.

Value of Exports, December 1999 ($millions)	Australia	Brazil	Egypt	Germany	Japan	Saudi Arabia	South Africa	United Kingdom	All countries	Share within dataset
07 (Vegetables)	1.84	0.21	0.00	0.98	19.17	0.42	0.15	5.29	168.70	16.6%
08 (Fruits)	3.30	0.52	0.60	13.87	48.46	2.12	0.12	10.15	313.10	25.3%
10 (Grains, Cereals)	0.12	0.20	90.91	1.96	162.49	10.50	13.06	7.83	855.20	33.6%
25 (Bulk)	4.16	1.82	0.27	2.79	29.21	0.18	0.40	2.81	134.60	30.9%
26 (Bulk)	0.12	0.07	0.00	0.62	4.78	0.00	0.02	2.16	111.30	7.0%
52 (Fabrics; cotton)	0.94	4.52	0.01	1.74	12.13	0.21	0.12	2.19	281.30	7.8%
54 (Fabrics; yarn)	1.56	2.94	0.00	1.80	1.42	0.30	1.17	3.47	156.60	8.1%
85 (Electronics)	98.68	209.00	14.25	341.40	807.65	34.21	15.06	534.09	11795.20	17.4%
All commodities	996.00	1038.50	306.40	2388.30	5146.10	1545.40	214.50	3063.90	63704.80	23.1%
Share within dataset	11.1%	21.1%	34.6%	15.3%	21.1%	3.1%	14.0%	18.5%	21.7%	

Table 5. The value of exports to the countries in the data set, December 1999.

From Table 1 we can see that Japan is the most represented destination, with 53% of the shipments, and foodstuffs is the most represented commodity (53%). The data were collected, however, independent of the ports; therefore, the collection did not represent choice-based sampling.[7] Thus the distribution of the data should not affect the estimated model, except that estimates of the coefficients will be less precise. The lack of variance in the shipment data would produce a greater variance in the estimates of the coefficients.

Table 6 shows the distribution of shipments across the inland regions of the 48 contiguous United States. Shipments originating in California dominate the data set, with 48% of the shipments, though again this should not bias the results of the model.

	Charleston	LB	LA	NY	Oakland	Savannah	Seattle	Tacoma	All ports
Washington	12	25	75	21	25	5	102	100	365
Oregon	0	1	3	6	14	0	30	23	77
California	75	375	445	50	983	28	115	63	2134
Wyoming, Idaho, Montana, North Dakota, and South Dakota	0	0	0	0	6	0	18	2	26
Nevada, Utah, Colorado	0	3	3	2	29	0	1	0	38
Minnesota, Wisconsin, Michigan	6	10	31	10	17	3	7	2	86
Iowa, Illinois, Missouri, Kansas, Nebraska	11	18	46	64	27	18	12	11	207
Arizona, New Mexico	1	38	44	0	0	0	0	0	83
Texas, Oklahoma, Arkansas	6	4	38	4	2	17	2	0	73
Kentucky, Tennessee, Ohio, Indiana	9	14	41	21	24	23	9	5	146
Georgia, South Carolina	141	3	16	5	0	93	0	2	260
Alabama, Mississippi, Louisiana	12	7	10	2	2	25	1	0	59
Florida	28	2	3	3	9	21	0	4	70
North Carolina, Virginia, West Virginia, Maryland	53	23	11	2	10	48	3	2	152
Pennsylvania, Delaware, New Jersey, New York	159	17	53	266	18	51	3	4	571
New England	6	3	22	26	5	23	0	2	87
All regions	519	543	841	482	1171	355	303	220	4434

Table 6. The distribution of the inland origins of the shipments included in the data set.

Table 7 shows the distribution of shipments among carriers. The set consists of shipments moved by thirty-six carriers, but the ten largest carriers moved 72% of the shipments, and the sixteen largest carriers moved 90%.

Carrier	All	Charleston	LB	LA	NY	Oakland	Savannah	Seattle	Tacoma
Evergreen Lines	527	163	0	241	15	46	0	0	62
Maersk/Sealand	450	96	84	0	48	164	0	0	58
Hanjin Shipping Co.	367	0	136	0	5	157	19	50	0
P& O Containers/Nedlloyd	359	18	16	84	44	80	49	68	0
Yang Ming Lines	297	17	87	59	14	97	19	1	3
Hapag Lloyd	278	17	0	11	55	127	50	18	0
American President Lines	270	33	0	79	26	72	0	16	44
Australia New Zealand Direct Line	237	0	0	161	1	59	2	14	0
Orient Overseas Container Line	209	7	10	34	50	26	32	50	0
N K Lines	205	0	1	35	8	37	71	53	0
K Lines	157	5	40	4	3	93	0	4	8
Maersk	147	25	48	0	16	25	0	0	33
Cho Yang Shipping Co.	145	0	32	0	17	84	9	3	0
Hyundai Merchant Marine	118	6	8	52	2	35	0	3	12
Fesco Straits Pacific Lines	99	0	67	0	0	15	0	17	0
Columbus Lines	92	5	0	74	1	0	12	0	0
Mediterranean Shipping Co.	86	43	0	4	39	0	0	0	0
Senator Lines	61	0	2	0	9	35	9	6	0
Lykes	54	30	0	0	24	0	0	0	0
Sealand	48	18	10	0	4	15	1	0	0
Atlantic Container Line	38	11	0	0	26	0	1	0	0
Zim Container Lines	36	0	1	0	11	0	24	0	0
Safbank	30	7	0	0	23	0	0	0	0
Wallenius-Wilhelmsen Lines	24	0	1	0	0	0	23	0	0
CMA-CMG	22	5	0	2	5	4	6	0	0
United Arab Shipping Co.	15	0	0	0	12	0	3	0	0
National Shipping Co. of Saudi Arabia	14	0	0	0	4	0	10	0	0
Mexican Lines (TMM)	12	10	0	0	2	0	0	0	0
Marfret	10	0	0	0	1	0	9	0	0
Crowley American Transport, Inc.	10	2	0	0	8	0	0	0	0
Pan American Independent Line	6	0	0	0	4	0	2	0	0
Contship Container Lines, Inc.	5	0	0	1	2	0	2	0	0
Chilean Lines	2	0	0	0	1	0	1	0	0
Euroatlantic Container Lines	2	0	0	0	2	0	0	0	0
Libra Navegacao Sa	1	0	0	0	0	0	1	0	0
Nordana	1	1	0	0	0	0	0	0	0
All carriers	**4434**	**519**	**543**	**841**	**482**	**1171**	**355**	**303**	**220**

Table 7. The distribution of the shipments in the data set among carriers.

From Table 7 we see that most carriers do not use every port. For example, the most-used carrier, Evergreen Lines, has a choice set that consists of five ports, with no shipments moved through Long Beach, Savannah, or Seattle. This is probably because an individual carrier has no reason to operate different terminals at nearby ports.[8] This would prevent a carrier from achieving scale economies without increasing his accessibility to other markets. If a carrier moves shipments through neighboring ports, then he is likely using an alliance member's facilities. Evergreen is unique in that they have not formed an alliance with another carrier, instead operating their round-the-world service alone. Many carriers, however, do operate within an alliance. As a result, many carriers will have shipments moved through neighboring ports, but most carriers will not use all ports.

Variables in the model

Many factors affect the choice process being modeled. Before discussing these factors, we define the scenario in which a carrier selects a port for a shipment. First, the carrier selects the port and vessel for each shipment simultaneously. Remember that when modeling the short-term decision, we assume that the long-term fleet assignment has already been established. Thus, we can represent each port by the vessel distribution rather than the characteristics of a particular vessel. We also assume that sufficient space exists for each shipment on vessels scheduled along each route. Because we analyze exports rather than imports, this assumption should be valid. During the 1990s, the ratio of imports to exports fluctuated around 1.5, implying that significant space existed on outbound vessels. Carriers transported empty containers on outbound vessels, and they have tried repeatedly to assign higher rates to US-bound shipments to cover return costs. Empty space suggests that each shipment is exported through the preferred port.

We model the systematic utility, V_{nj}, of each port as a linear function of five variables:[9]

$$\mathbf{V_{nj} = \alpha_j + \beta_1 * O_{nj} + \beta_2 * I_{nj} + \beta_3 * H_{inj} + \beta_4 * C_{inj} + \beta_5 * P_{inj}}$$

where: O_{nj} is the oceanic distance from port j to shipment n’s destination (km, 1000s),
I_{nj} is the inland distance from the origin of shipment n to port j (km, 1000s),
H_{inj} is the average headway between voyages by carrier i from port j to the destination of shipment n (days),

C_{inj} is the average size of vessels sailed by carrier i from port j to the destination of shipment n (TEUs, 1000s), and
P_{inj} is the probability that port j would be the last port visited by a vessel sailed by carrier i to the destination of shipment n
α, β are coefficients estimated in the model

The variables O_{nj} and I_{nj} are of course independent of the carrier, but the remaining variables are measures of the carrier as well as the port.[10] For the variable O_{nj}, we use the shortest sailing distance from port j to the destination of shipment n. For I_{nj}, we use the shortest inland road distance, which should approximate the inland rail distance as well.

We measure the variables H_{inj}, C_{inj}, and P_{inj} for each carrier through an Internet database maintained by the Journal of Commerce.[11] For each destination, we use the schedule of all voyages from one of twelve United States ports to any port near the destination.[12] From this database we measure the variables H_{inj} and P_{inj} for each carrier directly. We measure the capacity of each vessel scheduled along a corridor, in TEUs.[13] We calculate the variable C_{inj} to represent the average capacity of vessels sailing along the corridor for carrier i.

The variables in this choice function are selected to represent the common objective of the shipper and the carrier: to get each shipment from its origin to its destination as efficiently as possible. This efficiency is ultimately dependent on transit time and cost. For each shipment, four factors influence the transit time associated with each port:

i) the distance from the origin to the port,
ii) the time needed to transfer the shipment from the ground to the vessel,
iii) the time incurred as the vessel calls at other ports in transit, and
iv) the oceanic distance from the port to the shipment's destination.

Likewise, four factors influence the operating cost associated with each port:

i) the inland distance from the origin to the port,
ii) the charges assessed by the port,
iii) the oceanic distance from the port to the destination of the shipment, and
iv) the average vessel size, representing economies-of-scale and density

With regard to oceanic distance, intuition suggests that closer ports would have a competitive advantage. For example, the West Coast ports represent 83% of shipments to Japan but only 40% of shipments to the United Kingdom, as shown in Table 8.

	Australia	Brazil	Egypt	Germany	Japan	Saudi Arabia	South Africa	United Kingdom	Total
Charleston	7	38	6	108	198	20	37	105	**519**
Long Beach	78	1	0	14	417	2	11	20	**543**
Los Angeles	288	3	1	15	507	2	0	25	**841**
New York	15	50	15	103	6	49	54	190	**482**
Oakland	99	1	3	155	740	12	6	155	**1171**
Savannah	56	43	6	18	190	28	0	14	**355**
Seattle	36	0	14	3	231	13	0	6	**303**
Tacoma	1	0	13	0	160	46	0	0	**220**
Total	**580**	**136**	**58**	**416**	**2449**	**172**	**108**	**515**	**4434**

Table 8. Geographic distribution of shipments, December 1999.

As shown in Table 6, inland distance is also important. For example, 84% of shipments exported from California moved through California ports, and the majority of shipments originating in Washington moved through Washington ports. In areas such as the Midwest, where no port has a great advantage, competition is greater. California ports attracted only 53% of shipments coming from the Midwest, while the share of Northwest ports fell to 9%.

The frequency of voyages from port j to the destination of shipment n affects the total transport time for a shipment. Decreased frequency produces higher inventory costs that are directly related to the headway between voyages. We measure the frequency for each carrier. Multiple carriers can sometimes be listed with alliances or vessel-sharing agreements. We include all vessels for which a carrier is listed.

We learned earlier about carriers' desires to develop load-centers to exploit economies of scale in terminal and vessel operations. One advantage of scale economies in the transport of freight is the increased vessel size, a variable include in the model. In the model, vessel capacity represents the average capacity of all vessels, for which a carrier is listed, that sail along a route.

The number of ports at which a vessel calls between a shipment’s loading and discharge affects the distance that the shipment is transported. This distance translates to transit time. Thus, if a vessel calls at multiple ports, exports are often loaded at a vessel's last port of call. In the next chapter, we show that a port’s location along a string of calls significantly affects its share. We include in the choice model a variable that represents the likelihood of a port being visited last.

Before concluding, we must mention those variables that are not included in the model but may be significant on a disaggregate level. These include port charges, the cost of the transportation services, and the intermodal transfer process at each port.

Increased port charges could make a port less attractive to a decision-maker. The most prevalent port charge is wharfage. (Nearly 70% of the operating revenues received by the Port of Los Angeles in 1999 came from wharfage.) We discussed in chapter 2 the insignificance of port charges found in an earlier study. A listing of port charges is publicly available through the tariffs issued by ports. However, because of complexities with the tariffs and the service contracts more prevalent with terminal operators, port charges are difficult to measure accurately on a disaggregate level. We discuss these matters and examine port charges in a chapter separate from that examining the impact of other variables.

Ocean freight rates are no longer publicly disclosed, as of the Ocean Shipping Reform Act (OSRA) of May 1999 (Lewis, 2000). Two reasons can be given, however, for why rates might not be significant in port selection. First, earlier inspection of the tariffs and service contracts available through the Federal Maritime Commission showed that the freight rates prior to OSRA varied little among West Coast ports. Rates also varied little among East Coast ports, with a slight difference between the rates for ports on different coasts. Second, a shipper cares little about the intermediary points through which a shipment is moved, so long as the shipment arrives at the destination at the expected time. Thus, the port should not affect the rate that a shipper is willing to pay for transportation services. There is also some empirical evidence from Nam (1997), who analyzed the selection of mode for shipments. He found that the rate charged was in most cases insignificant, perhaps because service characteristics were more important or because rates did not vary by alternative.

Finally, data are not available for intermodal transfer time. We contacted terminal operators (American President Lines, Maersk/SeaLand, and the Stevedoring Services of

America) but none was willing to provide the necessary data.[14] In any case, two factors would complicate this variable's inclusion into the model. First, if we did not simplify the scenario, we would have to collect data for each terminal operated by each carrier at each port within the choice set, or approximately 10^3 terminals. Second, and perhaps more importantly, a carrier could know a shipment's intermodal transfer time prior to a decision only as an expected value, which does not lend itself to disaggregate choice analysis.

An alternate formulation of the choice model

Under the traditional model, the utility of a port for a shipment is a linear function of the variables describing that port. The carrier is observed as selecting one port from among the alternatives, and we assume the carrier has selected the port that provided the greatest utility in the context of that shipment. By observing the decisions for multiple shipments, we can estimate the importance of the factors that describe each port. We estimate the contribution of each factor to each port's utility, and we estimate a variable (referred to as the port-specific constant) that represents the average utility of all unobserved factors. These estimates influence the likelihood of each decision by the carrier, and we estimate each factor's contribution to maximize the likelihood of the observations.

The stratification of the data among commodity groups, foreign destinations, and inland origins shows that the data set is to some extent unbalanced, though these conditions should not bias the estimation of the model. The data do, however, represent panel data, with the shipments moved by each carrier representing a separate group. Correlation likely exists among the decisions of each carrier. For example, the intermodal transfer process could influence each carrier's selection of a port for each shipment, and the transfer process at each port varies at each carrier's terminal. This factor could not be included directly in the model. It thus affects the constant term associated with each port; as a result, the port-specific constants should vary by carrier.[15]

We could capture the auto-correlations with a fixed-effects model, i.e. by estimating a set of port-specific constants for each carrier. For the nth shipment to be moved by carrier i, the utility of port j would be represented as:

$$V_{inj} = \alpha_{ij} + \boldsymbol{\beta}\mathbf{x}_{inj},$$

in which: α_{ij} is a carrier-specific constant for port j, for carrier i,
$\mathbf{x}_{inj}$ represents the vector of attributes that influence the choice by carrier i of port j for shipment n (i.e. O_{nj}, I_{nj}, H_{inj}, C_{inj}, and P_{inj}), and
$\boldsymbol{\beta}$ is a parameter vector common to all groups

This, however, would require the estimation of 288 constants (36 carriers, 8 ports). For some carriers the number of shipments would be too small for estimation. In addition, we have greater interest in the coefficients that relate to the observed variables. Chamberlain (1980) introduced an alternative approach that uses a conditional likelihood function to account for the characteristics of the panel data. Rather than modeling the selection of a port for each shipment, with his approach we model a carrier's distribution of shipments from the set of feasible distributions. Two properties determine the feasibility of a distribution; these properties are the statistics for sufficiency with the conditional distribution. First, each shipment must be transferred through exactly one port. Second, the number of shipments predicted by the distribution to move through each port must equal the number actually observed as moving through that port.[16]

To see how this model is formulated, assume first that we have two observations (N=2; y_{i1}, y_{i2}) of a binomial (0,1) decision by carrier i. If $y_{i1} + y_{i2} = 0$ or 2, then the situation is deterministic and does not interest us. If $y_{i1} + y_{i2} = 1$, the two possible distributions are $(y_{i1}, y_{i2}) = (0,1)$, referred to as $w_i = 1$, and $(y_{i1}, y_{i2}) = (1,0)$, referred to as $w_i = 0$. The independent variables $\mathbf{x}_{i1}$ and $\mathbf{x}_{i2}$ describe each distribution. The conditional density is:

$$\text{prob}(w_i=1 \mid y_{i1} + y_{i2} = 1) = \frac{\text{prob}(w_i = 1)}{[\text{prob}(w_i = 0) + \text{prob}(w_i = 1)]} =$$

$$\frac{e^{\beta' x_{i2}}}{e^{\beta' x_{i1}} + e^{\beta' x_{i2}}} = \frac{e^{\beta'(x_{i2}-x_{i1})}}{1+e^{\beta'(x_{i2}-x_{i1})}} = F[\beta'(x_{i2} - x_{i1})]$$

where we use the difference between the independent variables in place of the independent variables themselves. Note that the probability does not depend upon α. The conditional log-likelihood function becomes:

$$L = \Sigma_i \{ w_i \ln F[\beta'(\mathbf{x}_{i2} - \mathbf{x}_{i1})] + (1 - w_i) \ln F[-\beta'(\mathbf{x}_{i2} - \mathbf{x}_{i1})] \},$$

For general N, conditioning on $\Sigma_n y_{in}$ gives the following conditional log-likelihood function:

$$L = \Sigma_i \ln[\exp(\beta' \Sigma_n \mathbf{x}_{in} \mathbf{y}_{in}) / \Sigma_{d \in B_i} \exp(\beta' \Sigma_n \mathbf{x}_{in} d_{in})]$$

where:

$$B_i = \{ \mathbf{d} = (d_1, \ldots d_N) \mid d_n = 0 \text{ or } 1 \text{ and } \Sigma_n d_n = \Sigma_n y_{in} \}.$$

B_i represents all distributions that meet the constraints, regardless of whether they were chosen. For our multinomial decision, let:

- w_{inj} equal 1 if carrier i actually sends shipment n through port j, and 0 otherwise,
- s_{ij} equal the number of shipments moved by carrier i through port j ($\Sigma_n w_{inj}$), and
- d_{inj} equal 1 for each feasible distribution, and 0 for all others.

The two constraints specify that:

- $\forall_{in}$, $\Sigma_j w_{inj} = 1$, and

- $\forall_{ij}$, $\Sigma_n\, d_{inj} = s_{ij}$

The log-likelihood for all observations is then:

$$L = \sum_i \ln[\exp(\beta' \sum_{n,j} x_{inj} w_{inj}) / \sum_{d \in D} \exp(\beta' \sum_{n,j} x_{inj} d_{inj})],$$

in which D represents all feasible distributions of the shipments. In relating this model to the original logit model, we note that the term V_{nj} has been replaced by $\beta' \sum_{n.j} x_{inj} w_{inj}$ and V_{nk} by $\beta' \sum_{n.j} x_{inj} d_{inj}$, summed over all feasible distributions D. The new terms represent the utility of the chosen distribution and the sum of the utilities of all feasible distributions, respectively.

In a simplified example, imagine one carrier that distributes three shipments across a simplified choice set as shown in Table 9.

Shipment #	Los Angeles	Oakland	Seattle	Total
1	1	0	0	**1**
2	0	0	1	**1**
3	1	0	0	**1**
Total	**2**	**0**	**1**	**3**

Table 9. The distribution of shipments observed from a hypothetical carrier.

Under the two constraints, only two other distributions are feasible, given in Table 10. With each distribution, the carrier would consume an aggregate amount of each factor (O_{nj}, I_{nj}, H_{inj}, C_{inj}, and P_{inj}). We can model the choice on the basis of the aggregate consumption of the factors that describe each distribution.

	Shipment #	Los Angeles	Oakland	Seattle	Total
Scenario #2	**1**	0	0	1	**1**
	2	1	0	0	**1**
	3	1	0	0	**1**
	Total	**2**	**0**	**1**	**3**
	Shipment #	**Los Angeles**	**Oakland**	**Seattle**	**Total**
Scenario #3	**1**	1	0	0	**1**
	2	1	0	0	**1**
	3	0	0	1	**1**
	Total	**2**	**0**	**1**	**3**

Table 10. Feasible distributions that were not selected by a hypothetical carrier.

With this model, the potential distributions of shipments would require extensive computation. A carrier moving N shipments through J alternatives faces J^N alternative schemes that satisfy the first constraint. Evaluating each of these for the second constraint for a carrier such as American President Lines (N = 270) would require a computational time on the magnitude of 8^{270} seconds, making complete enumeration infeasible. In addition, the number of observed distributions would be equivalent to the number of carriers, a number too small to allow estimation of the model. Therefore, we select random samples of five shipments for each carrier. For each sample, we determine the other distributions that meet the conditional requirements (up to 5!, or 120 distributions). We generate 100 samples for each of the 19 largest carriers to ensure that a sufficient number of samples exist for estimation of the model.[17]

Chapter 4. The effect of port location in a network

In Chapter 2 we mentioned one author (Foster, 1978b) who suggested, long ago, that shippers concern themselves with moving their exports through a vessel's last port. In this chapter we examine carriers' behavior and discuss the likelihood of a port being visited last. To show the significance of a port's being visited last, we examine its effect on a port's market share. Using vessel schedules, we examine the distribution of ports visited last. We develop a choice model to represent the probability of a port being the last port visited.

Description of data

To analyze the importance of a port's location along a string of calls, we use two data sets. The first set represents exports from December 1999, and the second represents imports from Japan from September 1996. The first data set was described extensively in Chapter 3. The second data set contains records for approximately 27,000 shipments, of which 21,000 were destined for locations within the 48 contiguous United States.[18]

Data analysis

For each shipment, we know its vessel and the port at which the shipment was loaded or discharged. Using this information, we first construct a record of voyages for each vessel in each data set. This record consists of all ports where the vessel called and the records for shipments discharged or loaded at each port.

We analyze twelve ports from among the nation's largest, in terms of containerized trade: the eight ports in our choice set plus Houston, Miami, Norfolk, and Portland. For each vessel calling at more than one port, we aggregate shipments that were loaded or discharged at each port. Table 11 shows an example of the record for a vessel. According to this record, the Cape Henry called at Savannah, Norfolk, and New York. It called at Savannah on December 1, 1999 and loaded 51 shipments, representing 39.8 percent of all shipments. These shipments averaged 26.5 metric tons. We create records for 490 multi-port vessels that sailed in December 1999 and 231 vessels that sailed in September 1996.

Vessel: Cape Henry	# Shipments	Total weight (mt)	Average weight (mt)	% shipments	Date
Savannah	51	1353	26.5	39.8	12/1/99
Norfolk	27	292	10.8	21.1	12/3/99
New York	50	742	14.8	39.1	12/4/99

Table 11. A typical vessel record.

Table 12 shows the distribution of vessels for December 1999. Each cell represents the number of vessels that called at the port represented by the row and the port represented by the column. To simplify the analysis, we combine the neighboring ports of Charleston and Savannah, Los Angeles and Long Beach, and Seattle and Tacoma. No vessel stopped at both ports within any pair, and combining ports produces fewer categories. In this table we highlight the records that correspond to pairs that we examine further.

	Cha/Sav	Houston	LA/LB	Miami	New York	Norfolk	Oakland	Portland	Sea/Tac	Other ports
Cha/Sav	142									
Houston	**24**	50								
LA/LB	11	0	122							
Miami	**17**	5	4	26						
New York	**69**	4	7	**10**	98					
Norfolk	**56**	4	4	5	**63**	78				
Oakland	9	0	61	3	7	6	**90**			
Portland	0	0	5	0	0	0	2	27		
Sea/Tac	2	0	**22**	0	2	2	**15**	10	74	
Other ports	29	26	6	6	33	24	1	1	0	169

Table 12. The distribution of vessels loading exports in December 1999.

The numbers along the diagonal represent the total number of vessels that called at each port. Table 13 represents the records for vessels loading imports in September 1996.

	Cha/Sav	Houston	LA/LB	Miami	New York	Norfolk	Oakland	Portland	Sea/Tac	Other ports
Cha/Sav	12									
Houston	0	9								
LA/LB	**11**	0	109							
Miami	**6**	0	4	6						
New York	**24**	0	**9**	5	39					
Norfolk	**12**	0	5	3	**10**	13				
Oakland	5	0	**36**	2	4	3	41			
Portland	0	0	**9**	0	0	0	2	19		
Sea/Tac	2	0	**14**	0	1	2	4	6	53	
Other ports	16	7	21	5	18	3	5	6	29	100

Table 13. The distribution of vessels discharging imports in September 1996.

For each pair highlighted in Tables 2 and 3, we analyze the shipments that were transported on vessels visiting both ports. We expect the last port to be favored for exports and the first port to be favored for imports, because of shippers' desire to minimize transit time. We compare the share that each port represents when visited last or first to the share that it represents when not visited last or first. From these shares we can measure the importance of being visited last or first, since all other characteristics that describe the port would be unaffected.

Table 14 shows an example of the distribution among port pairs for vessels that loaded exports at a Northwest port (Seattle/Tacoma) and a southern California port (LA/LB) in December 1999.

Vessel	Sea/Tac # shipments	Sea/Tac weight (mt)	LA/LB # shipments	LA/LB weight (mt)	Port visited last	Share of NW ports (shipments)	Share of NW ports (weight)
CHUAN HE	26	1427	1	17	Sea/Tac	96.3	98.8
HYUNDAI DISCOVERY	7	497	5	273	Sea/Tac	58.3	64.5
HYUNDAI FORTUNE	12	792	1	19	Sea/Tac	92.3	97.7
HYUNDAI INDEPENDE	9	242	5	37	Sea/Tac	64.3	86.7
KNUD MAERSK	41	1519	3	1295	Sea/Tac	93.2	54.0
LU HE	42	2275	5	73	Sea/Tac	89.4	96.9
SANTA BARBARA	42	1944	2	32	Sea/Tac	95.5	98.4
SANTA CRUZ	10	488	2	31	Sea/Tac	83.3	94.0
SUSAN MAERSK	8	230	5	83	Sea/Tac	61.5	73.5
SVENDBORG MAERSK	11	355	3	609	Sea/Tac	78.6	36.8
WANHE	3	232	1	63	Sea/Tac	75.0	78.6
YUN HE	37	2420	4	102	Sea/Tac	90.2	96.0
APL JAPAN	4	389	23	668	LA/LB	14.8	36.8
APL KOREA	1	107	9	391	LA/LB	10.0	21.5
APL PHILIPPINES	2	108	15	431	LA/LB	11.8	20.0
APL THAILAND	5	212	1	3	LA/LB	83.3	98.6
DIRECT EAGLE	5	44	36	774	LA/LB	12.2	5.4
DIRECT JABIRU	7	65	46	631	LA/LB	13.2	9.3
FANAL TRADER	2	99	10	178	LA/LB	16.7	35.7
HYUNDAI FREEDOM	11	577	3	56	LA/LB	78.6	91.2
KAPITAN BYANKIN	1	61	30	487	LA/LB	3.2	11.1
MEKHANIK KALYUZHN	6	148	18	399	LA/LB	25.0	27.1

Table 14. An example of the vessel-specific record created for each pair of ports.

For the majority of vessels, Northwest ports represent a greater share among those visiting a Northwest port last.[19]

Table 15 shows the average share of each port within an examined pair for the vessels sailing in December 1999, and Table 16 represents the same for the vessels sailing in September1996.

Port A	Port B	Number of vessels (shipments)	Share of vessels visiting Port A last	Share of shipments loaded at Port A when visited last	Share of shipments loaded at Port A when visited first	Ratio between shares
Sea/Tac	LA/LB	22 (520)	55	87.0	18.7	4.7
Sea/Tac	Oakland	15 (340)	27	89.8	24.4	3.7
LA/LB	Oakland	61 (2059)	21	57.8	53.3	1.1
Cha/Sav	NY	69 (932)	64	63.4	39.2	1.6
Cha/Sav	Norfolk	56 (691)	75	76.4	49.0	1.6
Cha/Sav	Houston	24 (377)	83	46.5	39.7	1.2
Cha/Sav	Miami	17 (272)	35	69.8	37.6	1.9
NY	Miami	10 (230)	40	78.5	46.9	1.7
NY	Norfolk	63 (618)	46	70.5	44.4	1.6

Table 15. Shares of ports visited by the same vessel, exports, December 1999.

Port A	Port B	Number of vessels (shipments)	Share of vessels visiting Port A first	Share of shipments loaded at Port A when visited first	Share of shipments loaded at Port A when visited last	Ratio between shares
NY	Norfolk	10 (632)	50	74.0	69.9	1.1
NY	Cha/Sav	23 (1921)	0	-	51.6	
NY	LA/LB	9 (1213)	0	-	25.1	
Oakland	LA/LB	36 (10614)	28	43.3	8.8	4.9
Portland	LA/LB	9 (194)	0	28.4	-	
Sea/Tac	LA/LB	14 (976)	57	79.0	17.0	4.6
Sav/Cha	LA/LB	11 (1354)	0	-	28.4	
Sav/Cha	Miami	6 (735)	0	-	24.6	
Sav/Cha	Norfolk	12 (737)	0	65.0	-	

Table 16. Shares of ports visited by the same vessel, imports, September 1996.

In each pair, a port's share is greater for exports when that port is visited last and greater for imports when that port is visited first. To test for statistical significance of the difference between the shares, we assume that the distribution of shipments among port pairs is binomial. Under the binomial distribution, the estimated probability is:

$$\hat{p}_i = n_i / N$$

with variance:

$$\frac{\hat{p}_i(1-\hat{p}_i)}{n_i},$$

in which: $\hat{p}_i$ represents the estimated probability

n_i represents the number of shipments loaded (discharged) at port i, and N represents the total number of observations.

With exports in 1999, the difference between shares was statistically significant, beyond the 95% level, for seven of the nine cases. With imports in 1996, the difference was statistically significant beyond the 95% level for two of the three cases. In other cases, the difference is as expected but not significant, perhaps due to fewer data. Of all shipments exported aboard vessels making multiple stops in December 1999 (6039), 62% were exported from the last port. Of all shipments (18376) imported from Japan in 1996, 77% were discharged at the first port. Each share is statistically different from that that would occur randomly.

For a number of pairs in 1996, these shares could not be calculated. Why might this be? The 1996 data set represent only shipments being imported from Japan; thus the data describe only vessels sailing from Japan to the United States. Vessels sailing from Japan to the East Coast follow a logical pattern, sailing north along the East Coast after crossing the Panama Canal. Vessels also visit a West Coast port before visiting an East Coast port. No vessels sailed in the opposite direction; thus we can not compare certain pairs. This clearly shows that distance impacts the routing of vessels. We examine the significance of this factor later.

We analyze vessels calling at three ports, and similar results follow. Table 17 and Table 18 show the vessels calling at three ports in December 1999 and September 1996, respectively.

Case 1: Port A - Seattle/Tacoma; Port B - Oakland; Port C - Los Angeles/Long Beach							
Case 2: Port A - New York; Port B - Norfolk; Port C; Charleston/Savannah							
Case 3: Port A - New York; Port B - Charleston/Savannah; Port C - Los Angeles/Long Beach							
Case	**Number of Vessels (shipments)**	**Share at A when visited last (shipments)**	**Share at A when not visited last (shipments)**	**Share at B when visited last (shipments)**	**Share at B when not visited last (shipments)**	**Share at C when visited last (shipments)**	**Share at C when not visited last (shipments)**
1	**7 (276)**	**81.2**	**9.9**	**-**	**21.0**	**66.0**	**6.2**
2	**46 (782)**	**54.5**	**18.9**	**-**	**21.1**	**60.2**	**24.1**
3	**6 (272)**	**36.1**	**3.0**	**-**	**47.1**	**39.0**	**33.3**

Table 17. Shares of ports among vessels calling at three ports, exports, December 1999.

Case 1: Port A - Seattle/Tacoma; Port B - Oakland; Port C - Los Angeles/Long Beach							
Case 2: Port A - New York; Port B - Oakland; Port C - Los Angeles/Long Beach							
Case 3: Port A - New York; Port B - Los Angeles/Long Beach; Port C - Charleston/Savannah							
Case 4: Port A - New York; Port B - Norfolk; Port C; Charleston/Savannah							
Case	**Number of Vessels (shipments)**	**Share at A when visited last (shipments)**	**Share at A when not visited last (shipments)**	**Share at B when visited last (shipments)**	**Share at B when not visited last (shipments)**	**Share at C when visited last (shipments)**	**Share at C when not visited last (shipments)**
1	**3 (612)**	**69.8**	**-**	**-**	**15.2**	**-**	**15.0**
2	**4 (823)**	**-**	**20.8**	**35.4**	**-**	**-**	**43.9**
3	**9 (1546)**	**-**	**19.9**	**59.2**	**-**	**-**	**20.9**
4	**9 (930)**	**-**	**42.5**	**-**	**48.3**	**39.2**	**-**

Table 18. Shares of ports among vessels calling at three ports, imports, September 1996.

We observe two trends, particularly from the 1999 data. First, the centrally located port, in each case, is never visited last. (Hence, we could not measure its share when visited last.) Second, a port's location along a vessel's string of calls does affect its share. For 1999, with each of the three triplets, we can measure the effect upon a port's share of being visited last. The share of a port designated as A or C, in each case, is much greater when that port is visited last. The ratio between the shares appears even greater for triplets than it did for pairs. For three of the six cases the ratio is on the order of 10:1. In five of the six cases, the difference between the shares is statistically significant; in the sixth it is different as expected, but not significant. With regard to the 1330 shipments exported on a vessel visiting three or more ports in December 1999, 56% were exported through the last port, again statistically different from the share that would occur randomly.

With 1996 data, of the 3911 shipments imported aboard vessels making three calls, 51% were discharged at the first port. This amount exceeds with significance the 1/3 that would occur randomly. We could not compare differences at ports since the order in which carriers visited ports did not vary. Each vessel traveling from Japan to any of the four triplets visited the same port first. Thus some geographical pattern exists for vessels sailing from the Far East:

1. A vessel visits each port along the West Coast before visiting the East Coast.
2. A vessel visiting both coasts would traverse the West Coast in a north-south direction, heading toward the Panama Canal.
3. Vessels sailing along the East Coast again followed a south-north direction.

We acknowledge that these records could represent the multiple vessels operated by one carrier or alliance. These vessels would follow the same route as other vessels operated by the same carrier(s). For some triplets, however, the number of vessels visiting each port exceeds the number of vessels operated by one carrier or alliance.

Modeling the selection of a last port

Having shown the effect that being visited last has on a port’s share, we now examine the vessel distribution for a pattern in the selection of the port visited last. We focus on the ports visited last because the 1999 data contain greater variation. We first identify the distribution of ports visited last by vessels sailing to a particular country and then examine variables that might influence a carrier's selection of a last port-of-call. We incorporate these variables into a choice model to describe the distribution of ports visited last.

To determine the proportion of vessels visiting each port last, given the destination of the vessel, we used the records from the Journal of Commerce for March 2000.[20] Table 19 represents the observed shares. In the table we highlight the number that represents the largest share for any port for each country.

	Australia	Brazil	Egypt	Germany	Japan	Saudi Arabia	South Africa	United Kindgom
Charleston	6.8	5.1	**48.2**	22.2	4.4	**24.5**	**37.5**	21.2
Houston	11.4	28.8	8.9	5.6	9.4	11.3	16.7	6.1
Long Beach	6.8	3.4	0.0	1.6	5.5	0.0	0.0	1.0
Los Angeles	13.6	6.8	7.1	4.0	10.5	0.0	8.3	4.0
Miami	1.1	**44.1**	3.6	2.4	1.7	5.7	8.3	3.0
New York/ New Jersey	10.2	5.1	25.0	**34.9**	8.3	22.6	8.3	**31.3**
Norfolk	1.1	1.7	1.8	14.3	1.1	3.8	0.0	14.1
Oakland	**35.2**	3.4	3.6	4.0	**32.0**	**24.5**	0.0	4.0
Portland	0.0	0.0	0.0	0.8	7.2	0.0	0.0	1.0
Savannah	9.1	0.0	1.8	2.4	2.8	7.5	20.8	3.0
Seattle	0.0	1.7	0.0	7.9	11.0	0.0	0.0	11.1
Tacoma	4.5	0.0	0.0	0.0	6.1	0.0	0.0	0.0

Table 19. The proportion of vessels sailing to each country that called at each port last.

The port with the largest proportion, in each case, does follow a logical geographic pattern. For example, the most common "last-port" for a vessel sailing to Brazil is Miami, the port geographically closest to Brazil. This trend resembles the pattern of vessels sailing to the United States from Japan in 1996 or the vessels visiting three ports in 1999. These vessels often called last at the port geographically closest to the foreign country it would visit. The distance between a port and a foreign country is one variable that affects our model of the selection of a last port.

To minimize inland transport distance, a carrier might call last near an area that exports a large volume. Many have argued that the inherent advantage of a large city such as Los Angeles or New York is its population. A large population could represent a large trade volume, and carriers could capture this trade by calling at a nearby port last. As an attempt to capture this factor, we include the value of exports from the region surrounding each port. Therefore, for a vessel sailing to a foreign country, we include in the choice model for the selection of a last port:

- E_{nj}, the economic value of the exports from the state containing port j to the destination of vessel n; and
- O_{nj}, the oceanic distance (km) from port j to the destination of vessel n.

We examine data for the variable E_{nj} from multiple sources. The data collected from the Office of Trade and Economic Analysis, through the Exporter Location Series within the U.S. Census Bureau and available in the annual form of state merchandise exports, produced the most explanatory power.[21] The data representing the export values are shown in Table 20.

	Australia	Brazil	Egypt	Germany	Japan	Saudi Arabia	South Africa	United Kingdom
Charleston	85.54	119.02	10.04	654.41	236.04	26.85	11.91	295.58
Long Beach	1012.38	566.20	72.70	2031.66	7033.51	389.36	120.81	2493.84
Los Angeles	1012.38	566.20	72.70	2031.66	7033.51	389.36	120.81	2493.84
NY/NJ	912.72	1506.90	185.73	2726.42	6104.39	1026.66	328.52	4491.11
Oakland	1096.74	613.39	78.76	2200.97	7619.64	421.81	130.88	2701.66
Savannah	484.52	281.86	25.93	403.77	708.22	83.67	44.43	916.76
Seattle	574.44	188.52	11.89	2249.19	6056.15	1255.17	35.89	4431.86
Tacoma	574.44	188.52	11.89	2249.19	6056.15	1255.17	35.89	4431.86

Table 20. The economic value of goods exported from each port's state in 1999 ($ million)

We measure the oceanic distance, O_{nj}, in kilometers (1000s). Table 21 shows the estimates of a multinomial logit model for the probability of each port being visited last by a vessel sailing to a particular destination.

Variable	Coefficient estimate	Standard Error	Z-statistic	P-statistic
Economic output (E)	1.71E-04	5.51E-05	3.102	0.002
Oceanic distance (O)	-0.124	0.015	-8.401	0.000
A_Charleston	2.149	0.299	7.176	0.000
A_Long Beach	0.178	0.339	0.525	0.600
A_Los Angeles	1.041	0.295	3.531	0.000
A_New York	1.884	0.280	6.726	0.000
A_Oakland	1.838	0.277	6.633	0.000
A_Savannah	0.752	0.337	2.230	0.026
A_Seattle	1.001	0.302	3.316	0.001
A_Tacoma	0.000	-	-	-
Log-Likelihood				-865.69
Log-Likelihood from constants				-1072.99
No coefficients				-948.81

Table 21. Estimated values for coefficients in a traditional choice model for last-port visited.

Each coefficient is significant, through both the z-statistic and the log-likelihood test. In addition, each coefficient has the expected sign.

We also estimate the model that uses Chamberlain's formulation to account for the effect of panel data, with the data from each carrier representing one group. To estimate the Chamberlain model, we first separate the data by carrier. As discussed in Chapter 3 with shipments, we select a random set of ports visited last for each carrier. From this set we determine the set of feasible distributions and measure the variables describing each distribution. To allow for variation within the random samples, we need a number of vessels for each carrier. The number of vessels affiliated with each carrier is represented in Table 22.[22]

Carrier	Number of Vessels	Carrier	Number of Vessels
ATLANTIC CONTAINER LINE	1	MAERSK	65
AUSTRALIA NEW ZEALAND DIRECT LINE	5	MEDITERRANEAN SHIPPING COMPANY	35
AMERICAN PRESIDENT LINES	17	MEXICAN LINE (TMM)	3
CHO YANG SHPG CO. LTD	10	Not specified	60
CMA-CMG	17	NORDANA	2
COLUMBUS LINES	3	NATIONAL SHIPPING CO OF SAUDI ARABIA	2
CONTSHIP CONTAINERLINES LTD	5		
EVERGREEN LINE	41	N Y K LINE	10
FESCO STRAITS PACIFIC LINES	5	OOCL	40
HANJIN SHIPPING CO LTD	26	P & O CONTAINERS / NED LLOYD	7
HAPAG LLOYD	28	SAFBANK	3
HYUNDAI MERCHANT MARINE	24	UNITED ARAB SHPG	3
K LINE	8	WALLENIUS-WILHELMSEN LINES	23
LIBRA NAVEGACAO SA (LIBRA)	2	YANG MING LINE	47
LYKES	15	ZIM CONTAINER	9

Table 22. The distribution of vessels among carriers.

To estimate the model, we select random sets of four vessels for each carrier that sailed more than 20 vessels. The results for the Chamberlain model are shown in Table 23. Recall that alternative-specific constants are not estimated with the Chamberlain model, as described in Chapter 3.

Variable	Coefficient estimate	Standard Error	Z-statistic	P-statistic
Economic output (E)	1.25E-04	5.32E-05	2.343	0.019
Oceanic distance (O)	-0.111	0.013	-8.222	0.000
Log-Likelihood				-367.45
Log-Likelihood from constants				-510.18
No coefficients				-635.61

Table 23. Coefficients estimated in a Chamberlain choice model for last port visited.

Each coefficient is significant at a level exceeding 95%, with regard to both the z-statistic and the log-likelihood test.[23]

We compare the estimated models to determine whether the Chamberlain model does have more explanatory power. According to Hausman's test,[24] we measure a statistic that represents the precision of the estimated coefficients:

$$W = \chi^2[K] = [\mathbf{b} - \hat{\boldsymbol{\beta}}]' \hat{\boldsymbol{\Sigma}}^{-1} [\mathbf{b} - \hat{\boldsymbol{\beta}}],$$

$$\text{in which } \boldsymbol{\Sigma} = \text{Var}(\mathbf{b} - \hat{\boldsymbol{\beta}}) = \text{Var}(\mathbf{b}) - \text{Var}(\hat{\boldsymbol{\beta}}),$$

and K represents the number of coefficients estimated, for our model two. We evaluate the test-statistic as 40.23, which exceeds the critical statistic for 95% significance, 5.99.

To determine the sensitivity of port share to these variables, we estimate the carrier-specific probabilities themselves. We do this for the three most represented carriers, Maersk/SeaLand (65 shipments), Yang Ming Lines (47), and Evergreen (41). We estimate the traditional choice models for each carrier for both the entire choice set and the constrained-choice set (in which the ports that represent zero probability were removed). We hold the coefficients for the variables E_{nj} and O_{nj} at the values shown in Table 23. In each case, the elasticity of the probability with regard to either variable is small. For the oceanic distance, the elasticity is on the magnitude of 10^{-3}, for the export value even less. This might result from insufficient data (forty decisions used to estimate as many as seven variables). Carriers also might not have strong preferences as to which port to visit last, once they have selected the ports to visit at all.

Neither variable has an elastic effect toward the carriers' selection of a last port, even though the coefficients estimated are statistically significant. Perhaps other variables not included, such as storage space, influence the decision more significantly. The selection of the last port might be random. Perhaps carriers have different vessels visit different ports as the last port; vessel sharing among carriers or alliances that behave differently might affect this hypothesis.

We initially wanted to include an instrumental variable to represent $P_{nj,}$ the probability that a vessel sailing to the destination of shipment n would visit port j last. With this, we could determine the variables that (indirectly) influence the probability of each shipment being loaded at each port. However, because P_{nj} is difficult to explain with other variables, we will include P_{nj} in the final choice model as the observed value rather than the predicted value. Remember that the model is intended to represent the short-term selection of a port for each shipment, and we assume that carriers' schedules remain fixed. This variable will be measured for each carrier according to the records published by the Journal of Commerce.

These observations could be used for the planning of maritime facilities and port marketing strategies. Analysis might encourage port managers to have carriers visit their port last (or first). For centrally located ports, the small likelihood that vessels making multiple calls would call there first or last might encourage them to focus marketing or investments toward one-call vessels. In addition, as carriers lessen the number of calls made by each vessel, port managers can recognize that ports with a significant local population hold an advantage. The significance of this variable, particularly with discretionary cargo, becomes even more apparent in the following chapter.

Chapter 5. Model estimation

To model the selection of a port for each shipment, we use data representing exports of four commodity-types to eight countries in December 1999. As discussed in Chapter 3, we use a multinomial logit model, in which the random utility of port j for carrier i and shipment n is modeled as:

$$U_{inj} = V_{inj} + \varepsilon_{inj}, \text{ or}$$

$$U_{inj} = \alpha_{ij} + \beta_1 * O_{nj} + \beta_2 * I_{nj} + \beta_3 * H_{inj} + \beta_4 * C_{inj} + \beta_5 * P_{inj} + \varepsilon_{inj},$$

where: U_{inj} is the utility of port j for carrier i and shipment n,
V_{inj} is the systematic component of U_{inj},
ε_{inj} is the random component of U_{inj},
O_{nj} is the oceanic distance to the destination of shipment n from port j (km, 1000s);
I_{nj} is the inland distance from the origin of shipment n to port j (km, 1000s);
H_{inj} is the average headway between carrier i's voyages to the destination of shipment n from port j (days);
C_{inj} is the average capacity of carrier i's vessels sailing to the destination of shipment n from port j (TEUs, 1000s); and
P_{inj} is the probability that vessels sailed by carrier i to the destination of shipment n call at port j last.

We estimate the constants, α_{ij}, to represent the effect of all unobserved attributes for carrier i at port j. We estimate the coefficients, β, to represent the impact of each variable on carriers' port-selection.

Multinomial choice model estimation

Using the data set described in Chapter 3, we first estimate a standard multinomial choice model, in which the probability of choosing port j is given by:

$$P_{inj} = \frac{e^{V_{inj}}}{\sum_k e^{V_{ink}}},$$

with α_{ij} constant across carriers. Table 24 shows the results of the estimation.

Variable	Estimate	Standard error	z-statistic	p-statistic
Oceanic distance (O)	-0.092	0.007	-12.602	0.000
Inland distance (I)	-0.671	0.019	-35.767	0.000
Sailing headway (H)	-0.041	0.002	-25.271	0.000
Vessel capacity (C)	-0.109	0.036	-3.067	0.002
Prob. of last (P)	0.012	0.001	13.877	0.000
A_Charleston	0.047	0.101	0.464	0.643
A_Long Beach	0.066	0.086	0.764	0.445
A_Los Angeles	0.466	0.081	5.772	0.000
A_New York	-0.243	0.101	-2.398	0.016
A_Oakland	0.381	0.080	4.759	0.000
A_Savannah	-0.158	0.104	-1.522	0.128
A_Seattle	-0.226	0.095	-2.364	0.018
A_Tacoma	0	-	-	-
Log-Likelihood				-6242.2
Log-Likelihood, constants only				-8650.6
Log-Likelihood, No coefficients				-9220.2

Table 24. Results of the standard multinomial logit model estimation (not as panel data).

The estimate for each of the five coefficients is statistically significant at a level beyond 99%. However, only four of the five estimates have the expected sign. The negative coefficient of vessel capacity does not match expectations. Why might this be? Perhaps there is no immediate advantage in placing a shipment aboard a larger vessel if space is available. In the case of exports, space should always be available. Therefore, our expectation about the impact of vessel capacity is not definite. We learn later that the impact of vessel capacity, when modeled alone, is actually positive.

The Chamberlain model

To examine these results further, we apply the Chamberlain model described in Chapter 3. We select five-shipment samples for each of the nineteen carriers that had more than 50 shipments, with 100 samples collected for each of these carriers. Table 25 shows the coefficients estimated with the 1840 observations that were retained.[1]

Variable	Coefficient estimate	Standard Error	Z-statistic	P-statistic
Oceanic distance (O)	-0.122	0.0078	-15.641	0.000
Inland distance (I)	-0.774	0.0223	-34.709	0.000
Sailing headway (H)	-0.033	0.0021	-16.195	0.000
Vessel capacity (C)	-0.021	0.0532	-0.389	0.697
Prob. of last (P)	0.003	0.0010	2.524	0.011
Log-Likelihood				-2980.421
Log-Likelihood from constants				-6525.781
Log-Likelihood, no coefficients				-7533.594

Table 25. The coefficient estimated with the Chamberlain model (panel data).

Each coefficient is significant with the exception of vessel capacity. To understand why, we examine the significance of each variable individually with the Chamberlain model. Table 26 represents the results from each of the five models.

Variable that defines model	Coefficient estimate	Standard Error	Z-statistic	P-statistic	Log-likelihood
Oceanic distance (O)	-0.128	0.0041	-31.222	0.000	-4844.949
Inland distance (I)	-0.701	0.0181	-38.729	0.000	-3476.259
Sailing headway (H)	-0.039	0.0013	-29.248	0.000	-4876.411
Vessel capacity (C)	0.698	0.0387	18.023	0.000	-5281.053
Prob. of last (P)	0.017	0.0008	22.008	0.000	-5227.644

Table 26. Results of univariate model estimations.

When estimated as the only variable, each is highly significant. Inland distance provides the greatest explanatory power. The sign of each variable's coefficient is consistent with the sign estimated in the multinomial model for four of the five variables, with the lone exception being that for vessel capacity. The insignificance of vessel capacity in the multivariate model could result from its correlation with another variable. Table 27 represents the correlation between each of the variables.

Correlation Coefficents	O	I	H	C	P
Oceanic distance (O)	1.00	0.33	0.34	0.04	-0.34
Inland distance (I)	0.33	1.00	0.24	0.17	-0.29
Sailing headway (H)	0.34	0.24	1.00	-0.14	-0.39
Vessel capacity (C)	0.04	0.17	-0.14	1.00	-0.40
Prob. of last (P)	-0.34	-0.29	-0.39	-0.40	1.00

Table 27. The correlation between the variables used in the multivariate model.

The variable that is most correlated with vessel capacity is the probability of being visited last. However, vessel capacity remains insignificant when this variable is removed. The correlation between vessel capacity and inland distance could not be logically explained. The correlation between vessel capacity and the headway between voyages is negative, though we could expect a relation between these variables in either direction. If the total number of shipments remains constant, an increase in headway should accompany an increase in vessel capacity. An increase in trade volume along a route, however, should produce a decrease in headway and an increase in vessel capacity. The latter scenario, one that is more realistic, would produce the negative correlation. When we construct separate models and compare their log-likelihoods, the largest reduction in the impact of vessel capacity comes from the inclusion of the headway between voyages. For these reasons, we remove the variable representing vessel capacity from further models. Ignoring vessel capacity, we estimate another model as shown in Table 28.

Variable	Coefficient estimate	Standard Error	Z-statistic	P-statistic
Oceanic distance (O)	-0.123	0.0077	-15.856	0.000
Inland distance (I)	-0.775	0.0222	-34.899	0.000
Sailing headway (H)	-0.033	0.0020	-17.119	0.000
Prob. of last (P)	0.003	0.0010	2.516	0.012
Log-Likelihood				-2980.497
Log-Likelihood from constants				-6525.781
No coefficients				-7533.594

Table 28. The coefficients estimated in the final model (panel data).

To test the impact of removing vessel capacity from the model we use the likelihood ratio test. The test statistic is:

$$\Delta = -2(\mathrm{LL}(\hat{\beta}_R) - \mathrm{LL}(\hat{\beta}_U)),$$

in which $\mathrm{LL}(\hat{â}_R)$ and $\mathrm{LL}(\hat{â}_U)$ represent the log-likelihoods of the restricted and unrestricted models. In the restricted model, we restrict the coefficient of a particular variable (in this case, vessel capacity) to a particular value (in this case, zero). In the unrestricted model, the coefficients can assume any value. This statistic, Δ, is a χ^2 statistic, distributed with (K_U - K_R) degrees of freedom, where K_U and K_R represent the number of coefficients estimated in the unrestricted and restricted models, respectively. In this case, the test would have one degree of freedom. We estimate this statistic as 0.15, compared to the critical value of 3.84 that corresponds to the 95% level, clearly suggesting that we discard the variable that represents the average capacity of vessels.

Before continuing, we examine the results of each model to see if modeling as panel data is appropriate. According to Hausman's test[2], the statistic is:

$$W = \boldsymbol{\chi}^2[K] = [\mathbf{b} - \hat{\boldsymbol{\beta}}]' \hat{\boldsymbol{\Sigma}}^{-1} [\mathbf{b} - \hat{\boldsymbol{\beta}}],$$

$$\text{in which } \boldsymbol{\Sigma} = \mathrm{Var}(\mathbf{b} - \hat{\boldsymbol{\beta}}) = \mathrm{Var}(\mathbf{b}) - \mathrm{Var}(\hat{\boldsymbol{\beta}}),$$

and K represents the number of coefficients in the model (five). The null hypothesis is that the data do not represent panel data and that the data for all carriers can be combined as that from one carrier. The null hypothesis implies that the effect of the unobserved variables across alternatives is independent of the carrier. We found the statistic to have a value of 503.1, allowing the rejection of the null hypothesis at a level above 99%. Consequently, we use the Chamberlain model for the remainder of the analysis.

Discretionary cargo

Here we postulate that the decision made for discretionary cargo, cargo originating in a region that does not contain a port, differs from that made for cargo originating in a port's hinterland. Table 29 shows that the share of each port is greater for shipments of nearby origin than for all shipments. This subset is not small, either; shipments originating within California represented 48% of the entire data set.

Region	Ports within region	Share for shipments exported from within own state	Share for shipments exported from within other states
CA	Oakland, LA, LB	0.845	0.576
WA	Seattle, Tacoma	0.553	0.118
South	Savannah, Charleston	0.693	0.197
NY	New York	0.466	0.109

Table 29. The differing competition between ports for in-state shipments.

Clearly this distribution is affected by inland distance. To see how the decision process might differ for discretionary cargo, we estimate a model using only shipments that originated in the Midwest. For these shipments, inland distance would not vary as much among ports, allowing the impact of other variables to increase.

At first glance, the results of this model appear similar to those from the model for all shipments. However, closer examination of the variables reveals that the variables do play different roles for the discretionary cargo. Table 30 shows the results.

Variable	Coefficient estimate	Standard Error	Z-statistic	P-statistic
Oceanic distance (O)	-0.287	0.0253	-11.344	0.000
Inland distance (I)	-1.746	0.1047	-16.670	0.000
Sailing headway (H)	-0.053	0.0059	-8.902	0.000
Prob. of last (P)	0.019	0.0038	5.039	0.000
Log-Likelihood				-3820.021
Log-Likelihood from constants				-2275.865
No coefficients				-681.22

Table 30. The coefficients estimated for shipments from the Midwest.

For shipments from the Midwest, the probability of being the last port visited is significantly more important. We compare the impact of this to the impact of other variables in Table 31. The relative importance of other variables decreases significantly. One common belief within the industry is that discretionary cargo in particular is sent through the port visited last by a vessel to minimize transit time. This evidence of shifting values supports this idea.

Ratio	Meaning	Value, all shipments	Value, Midwest shipments
β_O/β_P	The increase in the probability of being the last port that would be equivalent to a reduction of 1000 km in oceanic transit	41.0	15.1
β_I/β_P	The increase in the probability of being the last port that would be equivalent to a reduction of 1000 km in inland transit	258.3	91.9
β_H/β_P	The increase in the probability of being the last port that would be equivalent to a reduction of one day, expected headway	11.0	2.8
β_O/β_I	The decrease in inland distance (km) that would be equivalent to a reduction of one km, oceanic transit	0.16	0.16
β_O/β_H	The decrease in headway (days) that would be equivalent to a reduction of 1000 km in oceanic transit	3.7	5.4
β_I/β_H	The decrease in headway (days) that would be equivalent to a reduction of 1000 km in inland transit	23.5	32.9

Table 31. The importance of being the last port visited for discretionary cargo.

Though we wish to emphasize the magnitude of this variable's changing importance, we must recognize that uncertainty exists in our estimated values. Each estimated coefficient has a standard error. A ratio between two estimates has an even larger standard error, and the ratio between two ratios has a still-larger error. To ensure that the ratios are statistically significant, we construct a density function for each ratio. The results are given in Appendix B. From each comparison we see that the significance of being visited last is greater for discretionary cargo than for the generic shipment.

From the results in Table 31 we can also see that a port's share of shipments from the Midwest is less affected by the headway between voyages, relative to the distances. The additional day or so of headway becomes less significant when consuming an additional 48 hours of inland transit.

Commodity-specific models

We now consider the proposition that the importance of attributes varies with commodity-type. The commodity groups used and their characteristics are shown in Table 32.

Commodity	# Records	Shipment Size (metric tons)	Average Value ($/metric ton)
Bulk	610	53.9	285
Fruits & Vegetables	2347	30.6	1198
Fabrics	509	27.7	4287
Manufactured	840	9.8	11087
All	4434	30.5	1885

Table 32. Characteristics of the shipments from different commodity groups.

The shipment size for each shipment corresponds to that filed with the shipment's customs form. Because the declared value of each shipment is confidential, the Journal of Commerce estimated the value of each shipment according to the trade route and commodity code associated with each shipment. We find that the average shipment size for a commodity decreases as its average value increases, perhaps to minimize shippers' inventory cost. We expect the importance of different attributes of each port to vary with the characteristics that describe each shipment.

The negative impacts of distance are the transit time and the operating costs associated with it, and we expect the transit time to be less important relative to the operating costs for lower-valued commodities. Inland distance is covered by modes (rail, truck) that are faster and more expensive than water-based transportation; thus, shippers of lower-valued goods would place a lower priority on oceanic distance than on inland distance. Carriers would more likely send lower-valued commodities through nearby ports. For example, a low-valued commodity being sent from California to the United Kingdom would be loaded at a California port and sent on an extended ocean voyage, whereas a higher-valued commodity might be transshipped via landbridge to a waiting vessel on the East Coast. Table 33 shows the results of the estimation for each commodity.

Commodity	Variable	Coefficient estimate	Standard Error	Z-statistic	P-statistic
Fruits & Vegetables	Oceanic distance (O)	-0.383	0.0383	-10.000	0.000
(HS 07, 08)	Inland distance (I)	-1.046	0.0471	-22.208	0.000
(1500 simulated shipments)	Sailing headway (H)	-0.018	0.0024	-7.441	0.000
	Prob. of last (P)	-0.007	0.0021	-3.349	0.001
Bulk	Oceanic distance (O)	-0.115	0.0137	-8.404	0.000
(HS 25)	Inland distance (I)	-0.795	0.0385	-20.652	0.000
(1100 simulated shipments)	Sailing headway (H)	-0.047	0.0041	-11.412	0.000
	Vessel capacity (C)	0.575	0.1558	3.693	0.000
	Prob. of last (P)	-0.025	0.0038	-6.667	0.000
Fabrics	Oceanic distance (O)	-0.120	0.0131	-9.144	0.000
(HS 52, 54)	Inland distance (I)	-0.511	0.0379	-13.468	0.000
(800 simulated shipments)	Sailing headway (H)	-0.039	0.0063	-6.259	0.000
	Prob. of last (P)	0.011	0.0020	5.680	0.000
Manufactured	Oceanic distance (O)	-0.261	0.0112	-23.288	0.000
(HS 85)	Inland distance (I)	-0.467	0.0267	-17.484	0.000
(1300 simulated shipments)	Sailing headway (H)	-0.012	0.0030	-4.025	0.000
	Vessel capacity (C)	0.425	0.1215	3.502	0.000
	Prob. of last (P)	-0.005	0.0017	-2.744	0.006

Table 33. The model estimation results for the different commodity-types.

Table 34 shows the marginal rate of substitution between oceanic distance and inland distance for each of the different commodities.

Commodity	Average Value ($/metric ton)	The marginal rate of substitution between inland transit and oceanic transit
Bulk	285	0.145
Fruits & Vegetables	1198	0.366
Fabrics	4287	0.234
Manufactured	11087	0.560
All	1885	0.158

Table 34. The importance of inland and oceanic transit for each commodity-type.

As expected, the marginal rate of substitution between inland and oceanic transit increases with the commodity value. The only deviation arises with fruits and vegetables, for which oceanic distance has a greater negative impact. One possible reason is the perishability of fruits and vegetables. This condition becomes important when examining the shares for certain commodities from carrier-specific models. With carrier-specific models, we can examine how a port's share is affected by distance and how this impact varies with the value of the commodity.

To see if the coefficients estimated for the general model are affected by commodity-type, we examine the results of the commodity-specific models. We first compare the sign for each estimate, and we see that the sign is consistent for each variable except that representing the probability of being visited last. This suggests that the variable representing this characteristic is either not significant, has not been captured correctly for the model, or is not represented accurately due to correlation with other variables.

In another test, we compare the log-likelihoods for the commodity-specific models with the log-likelihoods that result from the general model. Table 35 represents the log-likelihoods.

Commodity Group	Log-likelihood with coefficients from general model	Log-likelihood with coefficients from commodity-specific model	Number of variables estimated
Bulk	-2009.46	-1940.188	4
Fruits & Vegetables	-763.42	-723.63	5
Fabrics	-885.01	-858.33	4
Manufactured	-1693.73	-1275.49	5

Table 35. A comparison of the all-inclusive model with the commodity-specific models.

For each commodity, the general model is rejected for the commodity-specific model. The difference between the log-likelihoods exceeds the χ^2 statistic that corresponds to the 95% level. Thus, carriers behave differently with each shipment, depending upon the type of commodity being shipped. This implies also that a general model should be applied only if data are heterogeneous with respect to commodity-type.

Carrier-specific models

We use the elasticity of choice to measure the effect of each variable:

$$E_{jx_{nj}} = \frac{(\text{ä}\, P_{nj} / \text{ä}\, x_{nj})}{P_{nj}/x_{nj}}$$

$$= (\delta\, V_{nj}/\delta\, x_{nj}) * x_{nj} * (1 - P_{nj})$$

where: E_{jx} is the elasticity of the probability of alternative j with respect to variable x_{inj}
P_{inj} is the probability that shipment n is moved through port j
x_{inj} is a variable describing the shipment n-alternative j pair
V_{inj} is the deterministic utility for shipment n of alternative j

To measure these elasticities, we first estimate a model with port-specific constants for a carrier. We calculate the average elasticity by weighting the elasticity for each shipment by the probability that the port was chosen for that shipment. With the Chamberlain model, the utility functions held port-specific constants that varied across carriers. We estimate the choice model for six of the largest individual carriers, subject to the constraint that the variable-specific coefficients equal those estimated for the combined data set. We estimate the model for:

- American President Lines (AMPL),
- Evergreen (EVER),
- Hanjin (HJSC),
- Maersk/SeaLand (MLSL),
- P&O Nedlloyd (PONL), and
- Yang Ming Lines (YMAL).

Appendix C contains the alternative-specific constants estimate for each carrier, and the estimated elasticities are given in Table 36. The italicized ports for each carrier are those through which the carrier transported no shipment. The logit model allows infinitesimally small probabilities to exist, but the predicted share of these alternatives would be zero.

Carrier	Port	Oceanic distance (O)	Inland distance (I)	Sailing headway (H)	Prob. of last (P)	Carrier	Port	Oceanic distance (O)	Inland distance (I)	Sailing headway (H)	Prob. of last (P)
AMPL	**Cha**	-1.617	-1.965	-0.154	0.011	**MLSL**	**Cha**	-1.176	-1.902	-0.102	0.051
	LB	-1.425	-1.294	-0.411	0.000		**LB**	-1.243	-1.126	-0.182	0.000
	LA	-1.021	-1.025	-0.234	0.000		*LA*	-1.528	-1.217	-0.218	0.000
	NY	-1.731	-2.165	-0.164	0.018		**NY**	-1.353	-2.099	-0.171	0.033
	Oak	-1.058	-1.081	-0.258	0.118		**Oak**	-1.007	-1.046	-0.165	0.036
	Sav	-1.841	-2.101	-0.482	0.000		*Sav*	-1.480	-2.141	-1.019	0.001
	Sea	-1.379	-1.399	-0.326	0.000		*Sea*	-1.667	-1.477	-1.110	0.037
	Tac	-1.223	-1.285	-0.430	0.000		**Tac**	-1.517	-1.362	-1.184	0.017
EVER	**Cha**	-1.429	-1.879	-0.192	0.010	**PONL**	**Cha**	-1.775	-1.891	-1.183	0.019
	LB	-1.212	-0.947	-1.980	0.000		**LB**	-1.323	-1.330	-0.937	0.000
	LA	-0.698	-0.804	-0.116	0.042		**LA**	-1.068	-1.173	-0.480	0.012
	NY	-1.983	-2.434	-0.240	0.025		**NY**	-1.765	-2.006	-0.142	0.016
	Oak	-1.108	-0.964	-0.583	0.036		**Oak**	-1.117	-1.231	-0.585	0.000
	Sav	-1.957	-2.254	-0.320	0.000		**Sav**	-1.623	-1.843	-0.403	0.004
	Sea	-1.198	-1.389	-1.980	0.000		**Sea**	-1.230	-1.383	-0.625	0.000
	Tac	-1.084	-1.311	-0.491	0.043		*Tac*	-1.461	-1.543	-1.980	0.000
HJSC	*Cha*	-1.956	-2.394	-1.934	0.000	**YMAL**	**Cha**	-1.960	-2.010	-1.763	0.008
	LB	-0.760	-0.486	-0.118	0.029		**LB**	-0.829	-0.905	-0.231	0.034
	LA	-1.190	-0.677	-1.975	0.000		**LA**	-0.920	-0.944	-1.433	0.000
	NY	-2.053	-2.610	-0.098	0.059		**NY**	-2.062	-2.144	-0.057	0.047
	Oak	-0.690	-0.501	-0.125	0.049		**Oak**	-0.780	-0.953	-0.060	0.058
	Sav	-1.933	-2.373	-0.194	0.001		**Sav**	-1.952	-2.011	-0.059	0.015
	Sea	-1.014	-1.063	-0.174	0.040		**Sea**	-1.088	-1.567	-0.320	0.000
	Tac	-1.166	-1.216	-1.980	0.000		**Tac**	-1.086	-1.558	-0.426	0.000

Table 36. The choice elasticities for the individual ports and carriers.

From these estimates, we see that distance influences port selection most. The probability of being the last port appears to have a very inelastic effect, and the effect of the headway between voyages is largest for ports not visited at all.[3] The elasticities among shipments bound to the Midwest would also be of interest. Unfortunately, we do not have enough data to estimate consistent carrier-specific models for the Midwest.

Finally, to examine the generality of the model for all shipments, we compare the results of the carrier-specific models to the general model. Recall that when we estimated a model for each carrier, the coefficients of the four variables were constrained to the estimates from the general model. By relaxing these constraints, we estimate a new model for each carrier, with the results shown in Appendix D. Table 37 represents the log-likelihoods of the estimated models.

Carrier	Number of shipments	Log-Likelihood, no coefficients	Log-Likelihood, constants only	Log-Likelihood, constrained	Log-Likelihood, unconstrained
AMPL	270	-561.4	-447.5	-383.9	-370.1
EVER	527	-1095.9	-678.1	-703.8	-603.0
HJSC	367	-763.2	-445.7	-387.4	-368.9
MLSL	450	-935.7	-681.1	-492.8	-465.2
PONL	359	-746.5	-648.8	-423.9	-383.0
YMAL	297	-617.6	-473.8	-366.2	-325.7

Table 37. The log-likelihoods of the carrier-specific models.

To examine the applicability of the model, we compare the log-likelihood of the unconstrained models to the log-likelihood of the constrained models. For each carrier, we generate a statistic that is χ^2-distributed with four degrees of freedom, since the constraints are relaxed on four variables. For each of the carriers, we reject the general model in favor of the carrier-specific model. For Evergreen in fact, the model that incorporates only port-specific constants describes the data better than the general model. The behavior of individual carriers does not appear to be replicated among other carriers.

Discussion

One interview with a carrier suggested that the selection of a port is not entirely predictable, suggesting that the group deciding often does so without much evaluation. Some might suggest that if this is true, we can not model the process. However, a fundamental belief underlying economics is the rational behavior principle. Carriers will in most cases make rational decisions and it might be that some decisions do not require the same level of analysis. We should be able to model this process to some extent.

The carrier-specific models allow analysis of the share of traffic for each port. Port managers could use such models in port marketing. Estimates of the effect of certain factors could be used to assess port investment. Ports can also consider marketing to improve their position in an established market or enter a new market.

To show how this model could be used, we create a simple environment with three of four ports:[4]

1) Los Angeles or Long Beach,
2) Oakland, and
3) Seattle or Tacoma
4) Charleston.

We examine the competition of these ports for a shipment under various scenarios. We use American President Lines and Maersk/SeaLand to discuss the models. The destination of the first hypothetical shipment is Japan, with the oceanic distance and the headway between voyages for each alternative as observed.[5] The independent variable represents the shipment's origin and moves inland from the Port of Oakland. We estimate the distance to each port geometrically. Figure 4 shows the market share for each port in this scenario.

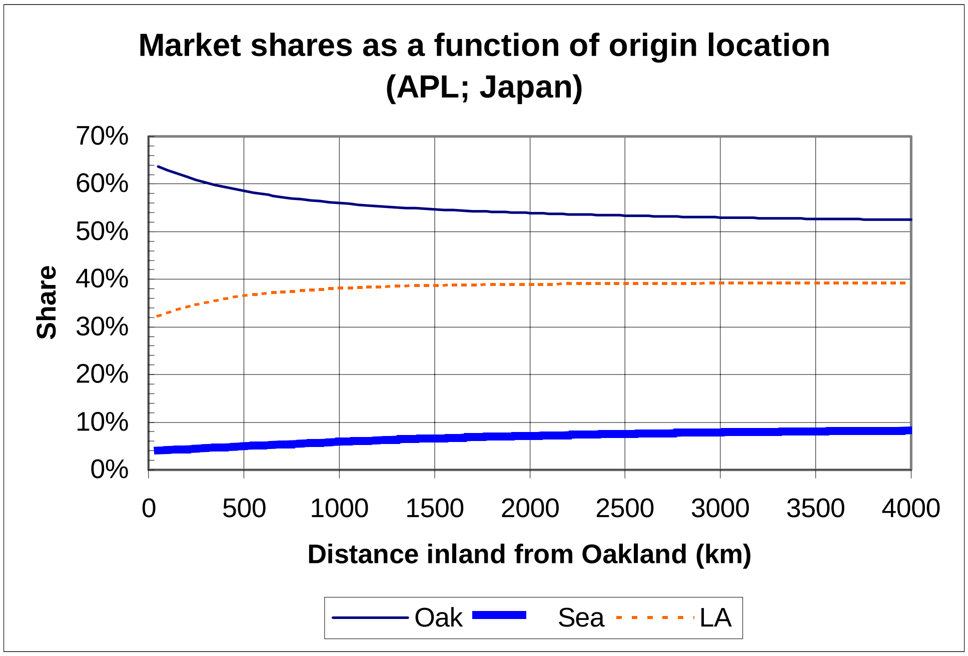

Figure 4. The impact of inland origin location on a port's market share.

The predicted market share of the Port of Oakland decreases from 64% within its hinterland to 53% as the origin of the shipment moves inland. The market share of competing ports increases as expected to account for this lost share. Thus, each port does hold an advantage for shipments within its hinterland, but the predicted advantage is not enough to ignore competition. Thus we must question the common belief that a port would have a "stranglehold" on traffic from its hinterland. The impact of inland distance becomes more apparent when comparing market shares of ports along different coasts. In another theoretical case, the export of a shipment by Maersk to Japan, the market share that would be exhibited by each of three ports is shown in Figure 5. In this figure, the Port of Oakland has been replaced by the Port of Charleston, which is located along the opposite coast.

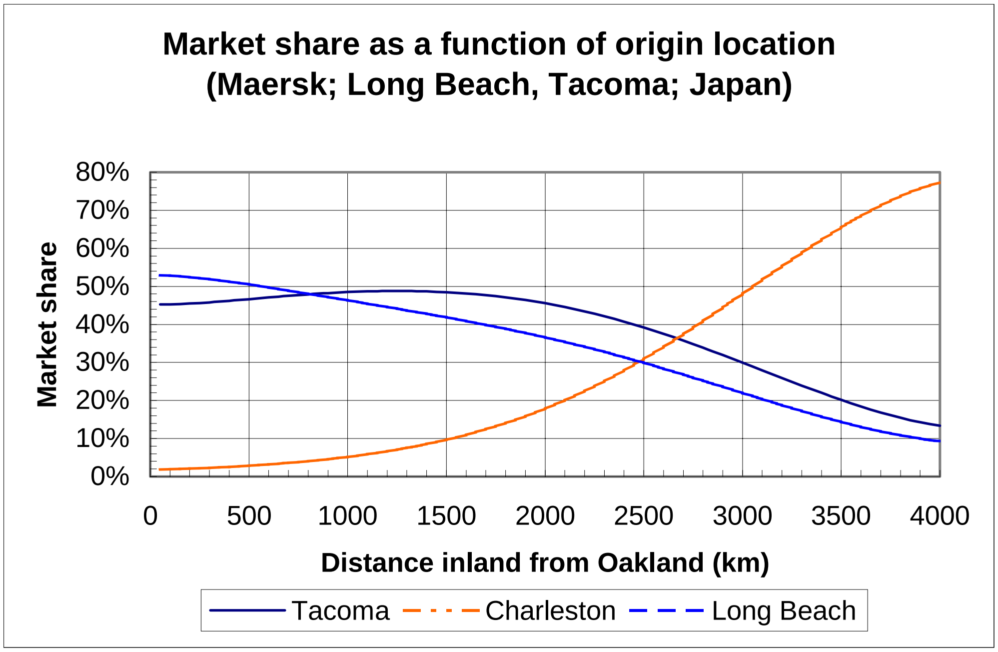

Figure 5. The impact of inland origin location on a port's market share.

Market share for the Port of Charleston initially remains insignificant, while the Port of Tacoma attracts a small market share from the Port of Long Beach.[6] The Port of Charleston does not begin to steal significant market share from the West Coast ports until the origin of the shipment has shifted halfway across the country, and Charleston does not steal significant market share until the origin has shifted even further.

In earlier analysis, we found that the value of transit time in relation to transit costs made a local port more attractive to shipments of lower value. A carrier would transport higher-valued shipments to a distant port to minimize oceanic distance relative to inland distance. Figure 6 shows the share predicted for the Port of Charleston, but for manufactured goods as well as the generic shipment. For this example, we had to estimate a model that was carrier-specific as well as commodity-specific. We estimate a model for P&O Nedlloyd.

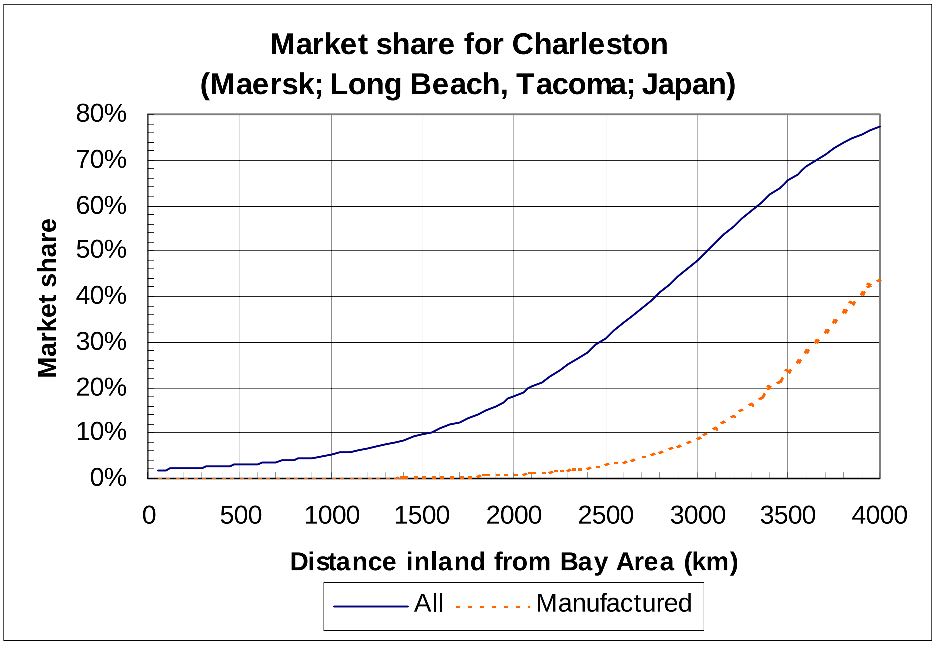

Figure 6. The market share represented by an Atlantic port for different commodity-types.

Clearly, the market share predicted for an East Coast port is smaller for higher-valued commodities bound to Pacific regions than for lower-valued commodities.[7] This confirms that lower-valued goods are more likely be loaded at a neighboring port and transited a longer distance via ocean, and higher-valued, time-sensitive goods are more likely to be shipped via landbridge to a port with greater access to the shipment's destination.

We now focus on the impact of oceanic distance. To analyze this, we model a theoretical shipment from Kansas. We calculate the oceanic distance not as a linear variable but instead to represent a range of destinations along the Pacific Rim.[8] The destination was represented on a scale of 0-40, with the following designations:

- 0 - Tokyo, Japan
- 12 - Hong Kong
- 24 - Singapore
- 40 - Sydney, Australia

We construct a line from Tokyo to Singapore and designate intermediate locations along the line. We construct an additional line between Singapore and Sydney, with intermediate locations again designated accordingly. We ignore the frequency of voyages from each port by setting the frequency at one voyage per week for each port.[9] Figure 7 shows the predicted market shares.

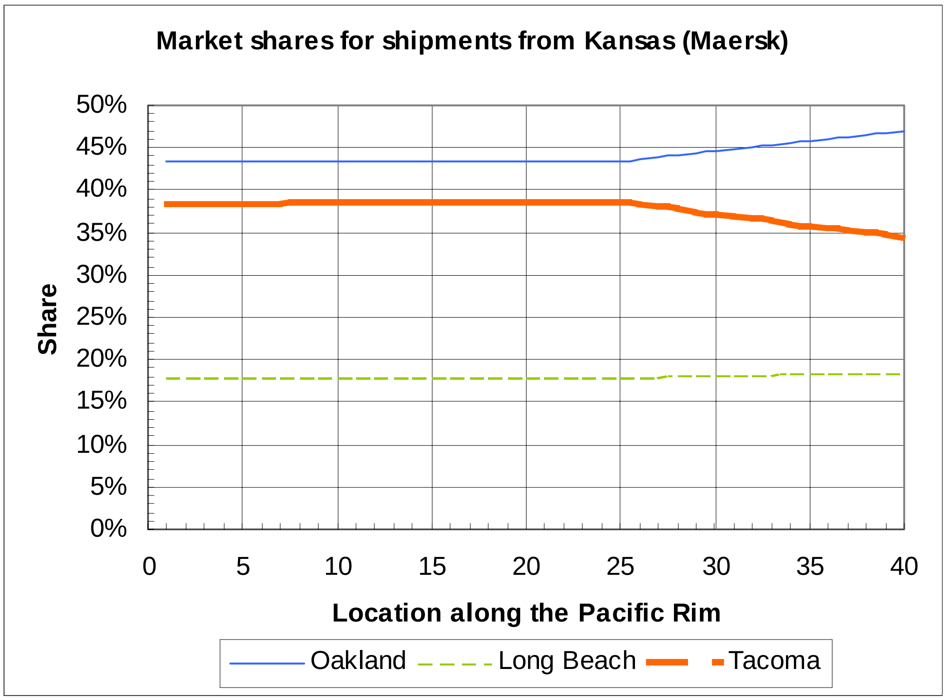

Figure 7. The competition between ports for transpacific shipments.

Oceanic distance does not appear to affect competition significantly in the Northern regions of Asia. Each port's predicted share remains virtually constant along the entire corridor between Japan and Singapore and shifts only with destinations in the South Pacific. Even here the shift is not significant, on the order of 10% for each port. The impact of oceanic distance seems significant only when evaluating competition from ports on opposite coasts.

Figure 8 represents the significance of the headway between voyages for a theoretical shipment moved by American President Lines from Oregon to Japan.

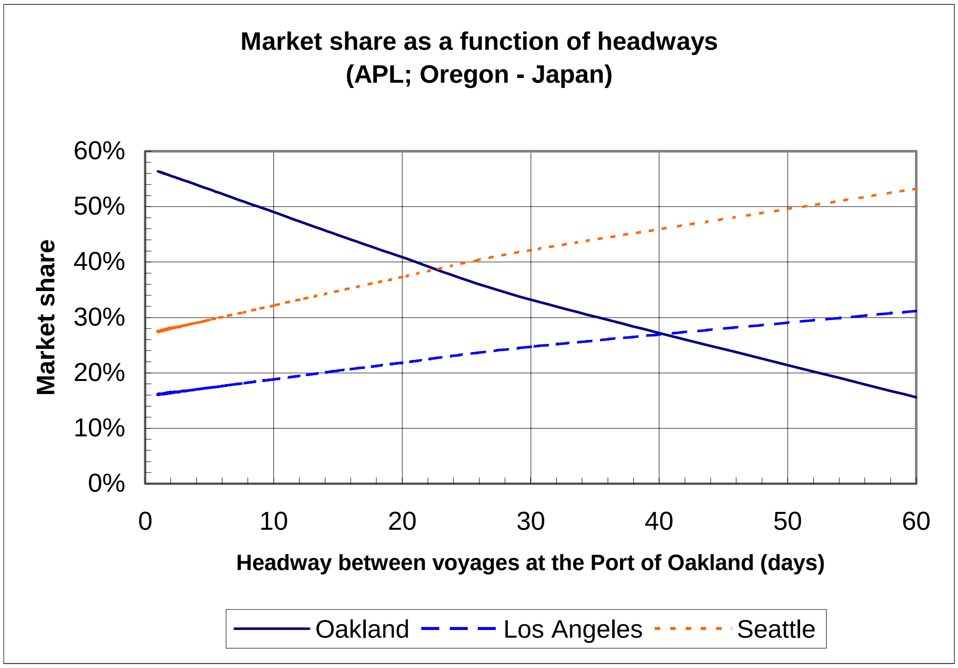

Figure 8. The impact of the headway between voyages in the market shares of ports.

Though the market share decreases steadily as headway increases, the actual impact is not as dramatic. To decrease the headway from sixty days to thirty days, a carrier needs to add only one voyage per month. A second voyage reduces the average headway again from thirty to fifteen days. Once a carrier has scheduled a sufficient number of voyages, an incremental voyage adds insignificantly to a port's market share. The potential impact becomes more apparent when observing the predicted market share as a function of frequency, as shown in Figure 9.

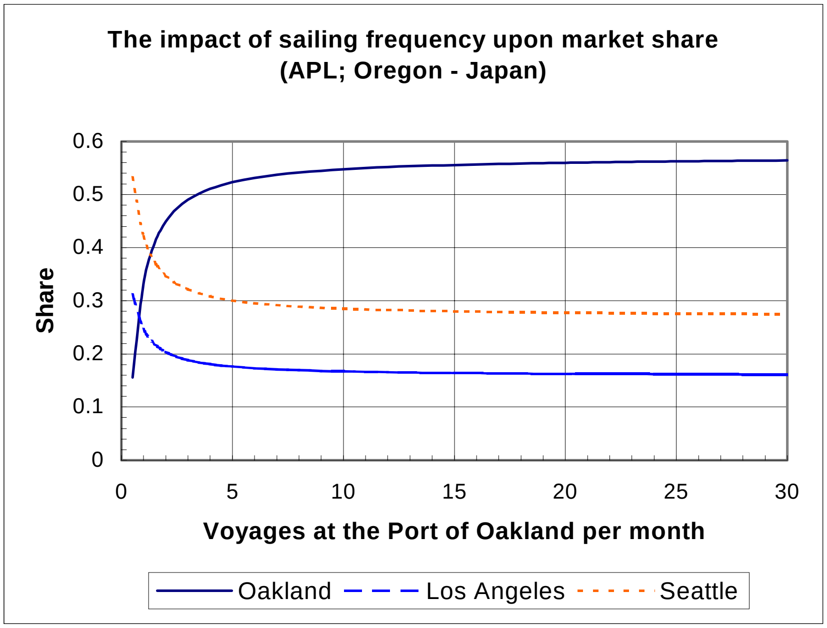

Figure 9. The significance of the number of voyages.

The impact of sailing frequency decreases quickly once a minimum number of voyages (on the magnitude of one per week, or 4+ per month) has been scheduled. An additional voyage would reduce the expected headway by an insignificant amount. A second voyage (if the voyages were spaced evenly) would reduce the headway by fifteen days, and a third voyage by five days, but a fifth sailing would reduce the headway by only one day. Therefore, so long as a port has voyages scheduled at the frequency of one per week or greater, additional voyages do little but increase the capacity available for shipments.

The significance of being visited last is greatest with discretionary cargo. Figure 10 represents the Port of Oakland's predicted share for a theoretical shipment transported by APL from Kansas to Japan.

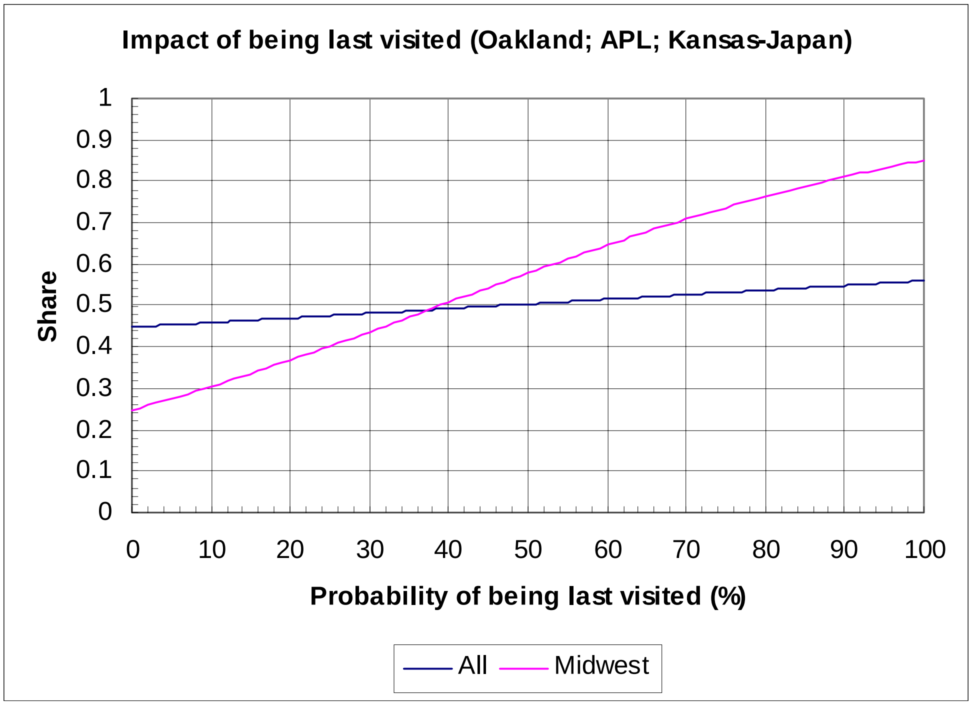

Figure 10. The impact of being visited last upon the market share of a port.

As mentioned earlier, the significance of being visited last is much greater for a port with discretionary cargo. Simply by convincing APL to make all of its last calls there, the Port of Oakland could increase its predicted market share for discretionary cargo from 24% to 85%.

Finally, an important finding of the analysis is that choice behavior varies significantly across carriers as well as commodities as well as the origin of the shipments. Because a sufficient set of data must be used for each model, and data are not free, one might focus the analysis even further, e.g. by carrier or by origin. Of course that is what we have done within this chapter, but with a larger data set the results might become more significant.

In addition to these findings, we must remember that the distribution of shipments across ports is but one part of the larger picture. An equally significant (if not more significant) task faced by the carriers is the assignment of vessels to particular routes. The assignment of vessels would influence the variables that affected the estimation of this model. We will discuss the scheduling of vessels along with other factors in our conclusion.

Chapter 6. The significance of port charges

As mentioned earlier, the inconsistent structure of port charges precludes us from including them in a discrete choice model. The rates often do not vary between shipments. In addition, the number of agreements that exist between carriers, terminal operators, and ports is extensive. In this chapter we analyze the significance of port charges in a different way. To begin, we discuss further the relationship between ports and terminal operators. We then present examples of agreements and analyze aggregate measures that represent the ports.

Background

Carriers operate private terminals at some ports, while at others they must use public terminals. In each case, a carrier compensates the port for use of the terminal facilities. The most prevalent charges for the use of a port's facilities are wharfage and dockage, but others include pilotage, crane rental, and storage and handling.

We discussed earlier other port characteristics that influence port selection. These include the geographic location of the port, the scheduling of vessels, and the size of available berth facilities. The structure of port charges differs from that of other variables in a way that precludes its inclusion in the choice model.

To clarify the structure of these charges, we first examine the tariffs that exist at each port. Each tariff lists prices for port services, the most significant being wharfage and dockage. Wharfage is assessed on each shipment and varies with commodity type.

Dockage is assessed on each vessel and varies with the vessel's length. Table 38 and Table 39 show examples of these rates.

Full Dockage Rates on Vessels Engaged in All Trades					
Length of Vessel-Overall in meters		Rate for first 24-hout period or part thereof	Length of Vessel-Overall in meters		Rate for first 24-hout period or part thereof
over	not over		over	not over	
0	30	$76	210	225	3257
30	45	110	225	240	3766
45	60	153	240	255	4312
60	75	215	255	270	4895
75	90	318	270	285	5512
90	105	501	285	300	6167
105	120	717	300	315	6859
120	135	970	315	330	7587
135	150	1260	330	345	8351
150	165	1586	345	360	9152
165	180	1949	360	375	9988
180	195	2350	375	390	10864
195	210	2785	390	-	10864 +30*(L-390)

Table 38. The dockage rates in the Port of Oakland's tariff.

Section VII: Wharfage, Non-containerized cargo			
Except as otherwise specified, below are the applicable non-containerized cargo rates which will be assessed in cents per 1,000 kilogramsor cubic meter as specified in the applicable items below; or according to vessel's manifest, on whichever basis water freight charges are assessed.			
Commodity Description	Rate Basis	Rate	Item No.
Scrap, N.O.S.	WT	165	07722
Steel coils, viz: Minimum 1,000 tons, one consignor, one vessel	WT	450	07724
Wire rod, steel; in bundles or coils, minimum 500 tons, one vessel, one consignor, one consignee	WT	475	07728
Empty drums, used, returning in the Hawaiian trade only. Does not apply on Coastwise, Inland Waterway nor Intercoastal Trade. (Rate also applies when in containers.)	WT	1175	07730
Aluminum foil			
Local	WT	500	07760
OCP	WT	425	07761
Vehicles, engines, or motor, self-propelling viz: Automobiles, pleasure, passenger, including pickup truck or chassis; not to exceed ten passengers per vehicle, not boxed, not crated, SU, on wheels	Per vehicle	$23.00	(I) 07870

Table 39. Wharfage rates in the Port of Oakland's tariff.

If such prices were common for all carriers, we could include this variable in the choice model, though the data would be cumbersome. We could measure the impact of port charges on carriers' port selection for individual shipments with the choice model.

However, most users of the port's facilities enter into separate agreements with each port. Tariff rates only apply to each port's infrequent users, and carrier agreements can specify rates quite different from those in the tariff. Rates might be lowered due to the traffic volume guaranteed by the carrier or terminal operator. Examples of the agreements are given in Table 40.

Carrier	Port	Year of agreement	Minimum throughput guarantee	Charges
APL	Oakland		1,149,500 TEUs	$53/TEU for first 120,000 TEUs; $25.00/TEU thereafter
APL	Los Angeles	1980	2,695,000 revenue tons	50% of tariff charges for first 1,786,000 revenue tons; 25% thereafter
Evergreen	Los Angeles	1998	$14,127,655	(not directly specified)
Hanjin	Long Beach	1989	$5,970,061 minimum annual compensation	50% of wharfage to 1,350,000 tons, 25% thereafter; 50% of all dockage; 100% of all other tariff charges
Maersk	Long Beach	1992	$12,277,400 minimum annual compensation	50% of wharfage to 1,350,000 tons, 25% thereafter; 50% of all dockage; 100% of all other tariff charges

Table 40. Examples of the rates in agreements between carriers and port authorities.

As shown by these examples, port charges are not simple or consistent. To examine the impact of port charges on port selection, we use an alternative method. We analyze aggregate data to see if the amount of traffic at each port is correlated with the cost of using the port. The cost that carriers incur in using a port should be proportional to the port's operating revenues. To analyze the significance of charges, we collect the annual operating revenues of fifteen United States ports for 1998 and 1999. Table 41 shows the revenues and throughput for each port, divided into domestic cargo and three types of foreign cargo: liner, tanker, and tramp. We collect the traffic data from the United States Army Corps of Engineers (USACE) and the United States Maritime Administration

(MARAD). The USACE releases each port's throughput as domestic cargo and foreign cargo, dividing the foreign cargo into imports and exports. MARAD releases measures for foreign cargo, with imports and exports subdivided as liner traffic, tanker traffic, and tramp traffic. We assume that the liner traffic is largely containerized, that tanker traffic is liquefied, and that tramp traffic is primarily bulk. Minor differences exist between the foreign traffic from each organization (on the order of 5%), but each set provides similar results.

			Throughput (kilograms)			
Port	Year	Revenues ($)	Domestic	Foreign Liner	Foreign Tanker	Foreign Tramp
Boston	1998	22,354,000	8,877,577,792	503,967,526	8,422,990,846	1,235,347,997
South Carolina Ports	1998	80,965,000	4,956,911,911	7,508,831,684	464,421,087	5,325,423,963
Houston	1998	97,156,000	54,903,893,677	7,731,131,888	70,214,777,329	20,305,669,423
Jacksonville	1998	27,475,000	9,928,113,036	1,326,057,511	2,770,956,732	5,109,500,763
Long Beach	1998	188,587,000	16,529,623,514	14,333,885,002	7,978,090,150	11,677,752,696
Los Angeles	1998	185,425,000	8,602,508,392	13,412,277,051	4,909,210,208	11,453,583,181
Miami	1998	41,045,000	1,538,767,123	2,990,491,150	410,845,637	1,244,190,086
Virginia ports	1998	128,259,779	14,988,933,140	6,442,002,252	4,298,834,853	36,618,005,420
NY/NJ	1998	111,745,000	68,944,187,608	12,633,921,455	35,679,450,842	8,020,207,234
Oakland	1998	72,988,000	2,184,848,045	5,738,645,563	191,261,232	1,805,824,734
Portland	1998	56,193,493	11,092,477,547	2,168,266,193	831,509,548	11,378,615,868
San Diego	1998	8,489,282	498,204,663	169,743,436	148,075,504	897,974,834
Georgia ports	1998	89,180,000	3,096,330,400	5,460,271,323	2,115,258,142	7,568,936,494
Seattle	1998	87,485,000	6,464,894,312	7,072,306,090	120,019,963	6,284,706,642
Tacoma	1998	55,557,031	6,774,530,527	2,875,092,920	472,192,464	5,265,479,449
Boston	1999	30,098,000	8,464,429,829	777,954,451	8,741,686,180	3,782,603,355
South Carolina Ports	1999	84,801,000	4,653,095,346	9,343,409,694	599,336,903	4,128,989,657
Houston	1999	95,428,000	51,470,339,291	7,738,365,569	68,716,863,151	18,644,841,848
Jacksonville	1999	27,934,000	9,132,557,380	1,321,671,961	3,095,735,245	3,737,966,125
Long Beach	1999	198,483,000	16,941,522,272	18,324,978,253	9,033,232,192	8,351,566,678
Los Angeles	1999	209,292,000	5,088,475,914	17,013,837,180	6,724,225,836	9,067,739,826
Miami	1999	38,848,000	1,472,484,804	3,990,491,179	389,036,674	556,533,021
Virginia ports	1999	127,662,892	14,244,224,803	7,968,671,345	4,189,493,126	24,455,180,617
NY/NJ	1999	112,400,000	63,713,221,446	16,053,513,322	36,235,639,020	5,310,441,278
Oakland	1999	74,687,000	2,341,207,475	6,896,642,652	701,343,977	928,358,670
Portland	1999	49,799,819	11,703,137,984	2,543,018,376	1,677,621,940	8,624,795,938
San Diego	1999	11,213,880	461,906,015	183,689,824	126,747,500	1,588,250,810
Georgia ports	1999	88,270,000	2,735,759,775	6,509,043,610	2,557,647,850	6,634,835,836
Seattle	1999	98,583,000	8,214,033,385	7,613,946,598	167,146,669	6,556,104,813
Tacoma	1999	57,238,074	7,058,699,084	3,845,143,662	271,976,918	7,500,280,105

Table 41. Port throughput and revenue statistics.

We estimate an equation that describes each port's revenues as a function of its traffic. We compare the revenue generated by ports of a particular size (small, medium, large) to the revenue that would be predicted for those ports. If the revenues at large ports exceed the revenues predicted more frequently than revenues at small ports, we conclude that port charges are insignificant and that larger ports assess higher rates to account for other advantages of the port. If the revenues at larger ports are less than predicted, we conclude that lower port charges contribute to a port's attractiveness.

To estimate each port's revenue from its traffic, we use a Cobb-Douglas model. This function would best represent the scale economies of terminal operations.

$$R = \alpha * DT^{\beta_1} * L^{\beta_2} * T^{\beta_3} * B^{\beta_4} * e^{\beta_5 Y}$$

where R = Annual Revenues, maritime operations ($)
DT = Domestic throughput (kg)
L = foreign traffic moved by liner (kg)
T = foreign traffic moved by tanker (kg)
B = foreign traffic moved by tramp, e.g. bulk (kg)
Y = year (0 if 1998; 1 if 1999)

The first five variables are self-explanatory. We include the year to account for a time-series in the data. We showed earlier how, under many agreements, revenue is linear with traffic. However, terminal operators negotiate lower rates for higher traffic volumes[1], and the Cobb-Douglas model allows us to include this effect.

Estimation of the model

Starting with the model that includes all variables, we estimate each model with 30 observations, or fifteen for each year.

R =	14.4	* $DT^{-0.122}$	* $L^{0.566}$	* $T^{0.0467}$	* $B^{0.208}$	* $e^{-0.0437Y}$
	(σ = 0.701)	(σ = 0.00496)	(σ = 0.0298)	(σ = 0.0263)	(σ = 0.0420)	(σ = 0.0593)
	(t = 3.80)	(t = -2.47)	(t = 19.0)	(t = 1.780)	(t = 4.95)	(t = -0.737)
R^2 = 0.966						

The coefficient that describes the impact of traffic on each port's revenues is significant for three of the four traffic types and of the expected sign for two. The effect of domestic traffic does not have the expected sign (positive). To examine the data further, we regress the revenues against each traffic category separately, with the results shown below:

R =	17980	* $DT^{0.361}$	* $e^{0.070Y}$	R^2 = 0.324
	(σ = 2.290)	(σ = 0.100)	(σ = 0.247)	
	(t = 4.28)	(t = 3.59)	(t = 0.281)	
R =	78.41	* $L^{0.618}$	* $e^{-0.0649Y}$	R^2 = 0.927
	(σ = 0.740)	(σ = 0.0335)	(σ = 0.0816)	
	(t = 5.89)	(t = 18.5)	(t = -0.794)	
R =	1451000	* $T^{0.178}$	* $e^{0.0214Y}$	R^2 = 0.183
	(σ = 1.56)	(σ = 0.0728)	(σ = 0.271)	
	(t = 9.08)	(t = 2.45)	(t = 0.0789)	
R =	684.5	* $B^{0.511}$	* $e^{0.114Y}$	R^2 = 0.441
	(σ = 2.49)	(σ = 0.111)	(σ = 0.225)	
	(t = 2.62)	(t = 4.61)	(t = 0.508)	

Revenues are in fact positively correlated with each type of traffic. In addition, the level of significance that is associated with each variable exceeds the 95% level. The greatest explanatory power comes from the liner traffic, as expected, and the least from the foreign tanker traffic.

We can understand these models by examining the relationships that carriers establish with port authorities. Note first that domestic traffic is likely to be liquid, since bulk or containerized traffic would be moved by rail or truck (USDOT, 1999). In 1998 the United States deep-sea domestic waterborne traffic measured 244 million metric tons and the inland waterway traffic was 655 million metric tons.[2] For deep-sea trade, the top three commodities were petroleum products (41%), crude petroleum (31%), and crude materials (7%). Each of these commodities is liquefied. For shipments moved by inland waterway, the top three commodities were petroleum (27%), coal and coke (27%), and crude materials (20%). The correlation between domestic traffic and foreign tanker traffic suggests that the domestic traffic is moved by tanker, as shown in Table 42.

	Revenue	Domestic	Liner	Tanker	Bulk	Year
Revenue	1.00	0.26	0.92	0.19	0.46	0.03
Domestic	0.26	1.00	0.43	0.87	0.35	-0.02
Liner	0.92	0.43	1.00	0.29	0.25	0.13
Tanker	0.19	0.87	0.29	1.00	0.37	0.01
Bulk	0.46	0.35	0.25	0.37	1.00	-0.10
Year	0.03	-0.02	0.13	0.01	-0.10	1.00

Table 42. The correlation coefficients that describe the relationship between cargo types.

The correlation between all traffic types is positive. Revenues are most strongly correlated with liner traffic, as expected with the higher value of liner traffic; most port authorities, when asked, considered containers their primary source of revenue. Bulk commodities are lower value and generate less revenue. We could say the same for liquid commodities; in addition, the transfer mechanism for liquid commodities might prevent a port from assessing a marginal fee on the traffic. Finally, the correlation between domestic traffic and tanker traffic (0.87) is high. This suggests that domestic traffic is the same type as tanker traffic. This makes sense, since the facilities that handle tanker traffic are specialized. The correlation between the traffic types suggests that we discard either domestic traffic or foreign tanker traffic from the model, allowing the other to serve as a proxy. We discard domestic traffic to produce the following equation:

$R =$	10.3 *	$L^{0.546}$	* $T^{0.001}$	* $B^{0.161}$	* $e^{-0.0318Y}$
	($\sigma = 0.751$)	($\sigma = 0.031$)	($\sigma = 0.020$)	($\sigma = 0.041$)	($\sigma = 0.065$)
	($t = 3.10$)	($t = 17.4$)	($t = 0.02$)	($t = 3.91$)	($t = -0.49$)
$R^2 = 0.958$					

Because of the insignificance of tanker traffic, we remove the tanker and domestic traffic completely and model the revenue as a function only of the liner traffic and tramp traffic. Regression produces the following best-fit model:

$R =$	10.6 *	$L^{0.546}$	* $B^{0.161}$	* $e^{-0.0316Y}$	$R^2 = 0.958$
	($\sigma = 0.741$)	($\sigma = 0.0305$)	($\sigma = 0.0366$)	($\sigma = 0.0634$)	
	($t = 3.18$)	($t = 17.9$)	($t = 4.40$)	($t = -0.499$)	

Studentized residuals primarily determine whether the inclusion of a particular observation biases the estimated model. To confirm that outliers do not influence the estimation, we calculate the studentized residuals for each observation and present these in Appendix E. We find the outliers to be Boston for 1998 and Los Angeles for 1999. Removing these two observations, however, does not change our estimation. Finally, the coefficient for the year, Y, is insignificant with each model. We thus combine data for the two years and estimate the following model:

$R =$	10.0	* $L^{0.544}$	* $B^{0.163}$	$R^2 = 0.958$
	($\sigma = 0.724$)	($\sigma = 0.0299$)	($\sigma = 0.0359$)	
	($t = 3.19$)	($t = 18.2$)	($t = 4.55$)	

We will use this equation for further analysis of port charges' impact on carriers' port selection. Note that the exponents for the two explanatory variables are positive and less than one, as expected under scale economies.[3] We compare each port's revenues to the predicted revenues in Figure 11.

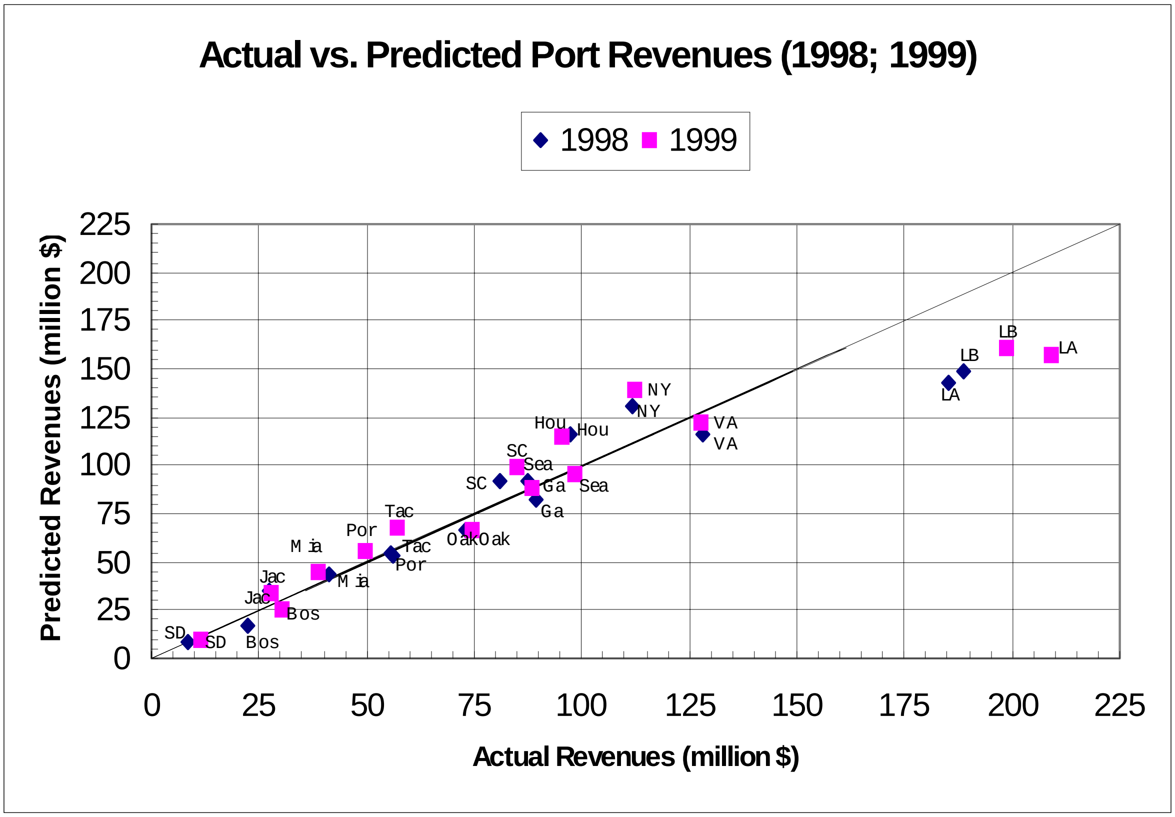

Figure 11. The relationship between observed and predicted revenues.

First, economies-of-scale do exist. We estimate the exponent for liner (container) traffic as 0.54 (σ=0.03), significantly less than 1. Second, qualitatively, cost does not appear to affect carriers' port selection. The revenues for each of the three largest ports, for each year, exceed expectations. Similarly, most small ports have revenues that are less than expected. These observations are shown in a contingency table in Table 43.

	Revenues (million $)		
	0-50	50-100	100+
Revenues less than predicted	6	7	2
Revenues greater than predicted	3	6	6

Table 43. The distribution of model results.

In these observations, small ports appear to generate less revenue than expected, and large ports appear to generate more revenue than expected. We test this relationship with the Pearson's chi-squared statistic (Rice, 1995), though we do have a limited number of observations due to the small number of competitive ports. Under the null hypothesis, the number of observations in each cell would be a function of the number of observations in the corresponding row and column. That is,

$$H_0: \pi_{ij} = \pi_i \bullet \pi_j = \frac{n_i}{n} \times \frac{n_j}{n}$$

Under the alternative hypothesis, H_1: $\pi_{ij} = \frac{n_{ij}}{n}$. That is, observations within a column are independent of each other. The Pearson's chi-squared statistic is of the form

$$\chi^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \frac{(O_{ij} - E_{ij})^2}{E_{ij}}$$

where: O_{ij} represents the number of actual observations in cell (i,j), and
E_{ij} represents the number of observations expected for cell (i,j) under H_0:

$$E_{ij} = n\pi_{ij} = \frac{n_i n_j}{n}$$

The Pearson's statistic is calculated as 3.08, with 2 degrees of freedom. This corresponds to a p-statistic of approximately 0.23 and is not large enough to be significant. This statistic does, however, suggest that port charges are not important. This also implies that larger ports are extracting larger rents due to other attributes of their facilities. A further categorization (into revenue divisions of $25 million rather than $50 million) would allow rejection of the null hypothesis with 99% certainty; however, the data become so sparse that the pattern in Table 43 disappears.

We can also examine the data with a signed rank test (Rice, 1995), in which we rank all observations by annual revenue (r_i). Under linear regression, each observation has an error term, which is the difference between the actual revenues and the predicted revenues. This error term has an expected value of zero. The probability that the error term is negative (that the predicted revenues exceed the actual revenues) is ½, and the probability that it is positive is ½. In Table 44 we present the error terms and the rank associated with each observation, according to revenue.

	Year	Actual Revenue (million $)	Predicted Revenue (million $)	Revenues less than expected?	Rank
San Diego	1998	8.49	8.77	Yes	1
Jacksonville	1998	27.48	35.66	Yes	4
Jacksonville	1999	27.93	33.82	Yes	5
Miami	1999	38.85	45.22	Yes	7
Miami	1998	41.05	44.07	Yes	8
Portland	1999	49.80	55.36	Yes	9
Tacoma	1999	57.24	67.77	Yes	12
South Carolina Ports	1998	80.97	92.24	Yes	15
South Carolina Ports	1999	84.80	99.67	Yes	16
Seattle	1998	87.49	91.73	Yes	17
Georgia ports	1999	88.27	88.46	Yes	18
Houston	1999	95.43	115.06	Yes	20
Houston	1998	97.16	116.61	Yes	21
NY/NJ	1998	111.75	130.91	Yes	23
NY/NJ	1999	112.40	139.43	Yes	24
San Diego	1999	11.21	10.05	No	2
Boston	1998	22.35	16.70	No	3
Boston	1999	30.10	25.40	No	6
Tacoma	1998	55.56	54.60	No	10
Portland	1998	56.19	53.11	No	11
Oakland	1998	72.99	66.79	No	13
Oakland	1999	74.69	66.21	No	14
Georgia ports	1998	89.18	82.14	No	19
Seattle	1999	98.58	96.15	No	22
Virginia ports	1999	127.66	122.21	No	25
Virginia ports	1998	128.26	116.26	No	26
Los Angeles	1998	185.43	143.34	No	27
Long Beach	1998	188.59	149.09	No	28
Long Beach	1999	198.48	161.34	No	29
Los Angeles	1999	209.29	157.05	No	30

Table 44. Results of the model estimation.

Exactly 1/2 (15) of the observations had positive error terms. Under the signed rank test, the sum of this group's ranks (W_+) should be distributed as:

$$E(W_+) = \frac{n(n+1)}{4} = 232.5$$

$$V(W_+) = \frac{n(n+1)(2n+1)}{24} = 2364\,; \qquad \sigma = 48.6$$

For our data, $W_+ = 265$ (W_-=200). This measure is 2/3 of one standard deviation from the expected value, much less than required to accept the hypothesis that larger ports extract additional rents with any level of significance. However, the data with this model have a p-statistic of 0.25. Thus, though the results can not be considered significant, the variation is in the direction expected.

Discussion

With each comparison between the observed and fitted data, the results suggest that port charges are not important and that larger ports generate excess revenue. In each case, however, the results are not statistically significant.

Before evaluating these findings, we must first recognize the limitations of the data. The ports included in the data set could reasonably be limited to those in the United States, since ports in other countries undoubtedly operate under a different structure. Even the ports in different regions of the United States operate under different structures.[4] Ports operating along the East Coast do not have private terminals, as do the large carriers operating along the West Coast. In the Pacific Northwest, ports have agreements with carriers that vary less with traffic than the agreements at California ports. Northwest ports also receive funding from external sources; California ports do not. These conditions affect the relationship between revenues and traffic observed at each port. Including data from ports outside the United States would only exacerbate the variation among ports' structures.

Including data for additional years, however, could improve the model. With Figure 11, we see that the revenues generated by individual ports across years are consistent. In fact, the predicted revenues remain consistent as well, likely because the traffic patterns for an individual port are steady. With speculation, increasing the data set to include 1996 and 1997 would, if the revenues follow the same patterns as 1998 and 1999, make the Pearson's chi-squared statistic significant at the 95% level. We could then claim with significance that larger ports generate increased revenues due to other attributes.

The differences between ports, however, also suggest a role for other variables not included in the model. This importance might be exacerbated by the unique location of each port. One primary factor that contributes to a port's costs, and thus must be passed to carriers, is the cost of land. The Port of Long Beach includes this value directly when determining the minimum throughput. The value of land for California ports exceeds the value of the land for other ports. The actual revenue for each major California port exceeds the predicted revenue, implying that land values contribute to the revenues that ports must generate to break even.

Another factor influencing our model is the level of efficiency at a port. Technological investment by a port could have a compound effect on the model. Equipment that increases cost-efficiency reduces the revenues needed for each shipment, if the port is to break even. This equipment could make the port more attractive to carriers, if cargo-handling costs and the reduction in berthing time are more important than the port charges, as suggested earlier by the literature. The attraction of carriers to more efficient ports would imply that lower costs are in fact significant, but the attraction would come from other factors.

Conclusion

The model estimated to show the significance of port charges is clearly a simplification. Port charges are intended to cover port costs more than to maximize profits, so regional factors might affect revenues. To measure the importance of port charges, data-oriented methods would involve measuring the impact of charges on a lower level, through specific carrier agreements or the choice model itself.

If port charges do not significantly affect port selection, why do port authorities not raise them? Perhaps the public nature of ports discourages this.[5] In California, a port can only reinvest its profits to improve the port's fisheries or facilities; thus it cannot generate excess profit.[6] In addition, transportation is only a derived demand. Freight transportation is not consumed for the service itself but to promote other activities. Increasing ports' revenues would only detract from the surplus generated by consumers or producers from these activities. Some benefits would disappear altogether if users abandoned marginal activities. For a public agency, the objective might be to collect the revenue needed to cover operating costs, without exceeding this amount, to maximize the benefits of port users without public funds.

The impact of port charges is by itself not as important, of course, as their impact relative to other factors in port selection. Relative to other factors, in particular those beyond the control of port authorities, port charges do not appear to be significant.

Chapter 7. Conclusion

In this research we have quantitatively modeled the assignment by maritime carriers of individual shipments to ports. We have used a choice model that accounts for the correlation that could be expected among the decisions made by each carrier. We have examined the characteristics of vessel scheduling and ways in which this schedule, presumed to be fixed for the short-term, could affect the assignment of shipments to ports. With the choice model we have measured the impact toward the decision process of different attributes: oceanic distance, inland distance, vessel schedule (headway between voyages and a port's likelihood of being visited last), and the capacity of vessels visiting the port. We have also measured, in an alternative manner, the significance of port charges toward a port's attractiveness toward shipments.

We have found the most influential factors in the assignment of shipments to be the geographic factors. The inland distance between a shipment's origin and the port and the oceanic distance between the port and a shipment's destination are both highly significant. These factors represent the cost and time of transportation. They are of course beyond the control of a port authority, but a measure of their effects is important to a port's assessment of its competitive position within a market. The importance of these factors suggests that port managers should recognize the limits of their market potential. For example, the ports in the Pacific Northwest might be wise to not focus marketing on shipments bound for Europe or South America. Port managers could evaluate markets with this model before pursuing great investment.

We also found that port authorities can indirectly influence two significant factors. First, the frequency of voyages does increase a port's attractiveness, but the marginal impact is decreasing. A carrier today is often scheduled so frequently, due to vessel-sharing agreements with other carriers, that the marginal impact of another voyage would be small. This suggests, however, that ports should favor certain methods of expansion once a minimum level of service has been attained. Rather than encouraging present facility users to call at their port more frequently, authorities should encourage additional carriers to call at their port or solicit carriers that serve additional destinations. Ports could focus on unserved areas if the present level of service is sufficient for others.

A second significant factor is a port's location along a vessel's string of calls. In Chapter 4 we showed that a port's market share of exports increases when it is visited last, and its market share for imports increases when visited first. Ports could influence this factor by encouraging carriers with multicall vessels to visit their port first or last. The effect is even greater with cargo destined to or leaving from an area not immediately near a port. Thus, ports might focus their marketing on areas that produce this discretionary cargo. Ports without a sufficient hinterland should place significant interest in this discretionary cargo. We have also found that the likelihood of a port being visited first or last can be significantly affected by its geographic location. Port managers should recognize this factor in choosing where to focus their marketing.

We find also that factors within the greatest influence of port operators impact selection least. According to our model, vessel capacity is altogether insignificant.[1] Port charges also appeared insignificant, though we evaluated this without using the choice model. These results are similar to the responses generated in surveys and should be examined further. The likely insignificance of port charges might suggest that charges be raised at individual ports to ensure their self-sufficiency and forces us to question whether public funding should be used for port activities.

Having recognized the relative importance of the attributes, we found also that port selection varies between the different commodities. Variations do, however, match our expectations. For example, we showed how an East Coast port could expect a lower share among higher-valued Asia-bound exports from its vicinity than among lower-valued Asia-bound exports. Higher-valued shipments incur a greater disutility with slower modes of transit; oceanic transit is slower than inland transit. Thus the port share predicted for a transcontinental shipment would be inversely related to the value of the shipment. Port managers should recognize this, for the revenue that is generated from each shipment is likely also inversely related to the shipment’s value. If market forecasts were to be accurate, separate forecasts should be conducted for each commodity.

Port selection also varies among carriers. A model that allows the impact of unobserved factors to vary between carriers describes decisions better. This is logical. However, the model representing the behavior of each carrier differs from the general-carrier model with regard to the observed factors as well as the unobserved factors. This suggests that accurate forecasting requires separate modeling of different carriers. Complexities perhaps exist within each carrier's network, and the structure of this network can not be included in the choice model by the present factors.

This choice model could be applied in many ways. Applications might include an analysis of the interaction between competing ports. As an example, we modeled earlier the competition between ports along the West Coast as well as the competition between ports along different coasts. We showed how this competition would be affected by changes in different factors. A planner could evaluate many hypothetical situations with this model. He could project the future demand for a port as populations and production patterns change. Numerous planning methodologies used today include some aggregate forecast of traffic in a future year. With the model presented in this research, a planner could predict the manner in which this traffic would be divided among ports. In applying the model, he would have to determine the level of accuracy desired. Modeling for each commodity or carrier separately would produce more accurate results, but the application of separate models would require additional work. Particular commodities (e.g. lumber) might be routed differently.

If evaluating the market from a social perspective, we could use this model to evaluate the distribution of investment among ports. Authors referenced earlier have suggested that ports might be investing too heavily. If influential characteristics are beyond each port's control, a federal agency could evaluate the long-term potential of the different ports before allocating federal investments. Federal agencies have always been involved with the dredging of port facilities. Local agencies could also regulate port investment, if there is reason to believe that benefits would be greater in other areas. Local agencies could consider raising port fees, if they are insignificant, such as to generate more revenue for the community.

Limitations of the model

In conducting this research, we have encountered limitations from two primary directions. The first involves difficulties with the data used to estimate the model; certain factors could simply not be included, either because we could not measure them or because they did not vary on a disaggregate level. The second limitation involves shortcomings of the chosen model itself as a representation of the real-world decisions.

We addressed difficulties with the data in Chapter 3, with particular focus on the intermodal transfer process. We indirectly include these factors with the port-specific constant term in a choice model, but we could not represent the variation among shipments. We envision ports as directly competing in four areas: depth, port charges, intermodal transfer facilities, and terminal area. We addressed the first two within our analysis, and we believe that the fourth should be insignificant for individual shipments. For exports, since empty containers are stacked at chassis-based terminals as well as stacking terminals, space should be sufficient for the storage of shipments at each terminal. The impact of storage space could be greater on imports, and greater still on the scheduling of vessels. With imports, large shippers could negotiate contracts that allow the use of terminals as storage space; with exports, shippers wish to have the shipment moved as quickly as possible. Of course, with the scheduling of vessels and the assignment of terminal space, this desire for imports could indirectly influence the decisions for exports. The intermodal transfer process could be significant, however, since goods of higher value might be attracted to more efficient processes.

We must recognize that, with exports, we have only modeled the distribution of half of all shipments. The decisions made for imports may very well differ from those we have modeled for exports. Many researchers have suggested the importance of a port's local market. This factor should be more significant for imports, since imports must be transported to a point of consumption or redistribution. Similar to storage space, a local population would result in a distribution that could encourage carriers to schedule vessels differently. Large shippers (e.g. WalMart) that employ distribution centers at which imported containers are unloaded and sorted would locate around centers of population, thus encouraging carriers to call near these distribution centers. Areas that produce a large volume of exports would be attractive to carriers selecting their last port of call, but distribution centers for individual firms would not be as prevalent among exports. Our data would recognize these distribution centers as the origin of exports, but an unmeasured factor, known as the gateway concept, could prove advantageous to a port in the larger picture.

Also more important with regard to imports is a carrier's need to relocate containers. The traffic imported to the United States presently exceeds the traffic exported; consequently, containers are often returned empty. Carriers can minimize the effect of this imbalance by filling containers along domestic links with domestic cargo. More populated areas, e.g. Los Angeles/Long Beach, are more likely to serve as the destination of a domestic shipment. In the context of exports this issue is not as important, since exports would fill a container themselves. Domestic traffic thus could affect the scheduling of vessels. It could also produce increased rail frequency, making a port in a populated area more attractive for shipments to be exported. Unfortunately, we could not examine this with rail schedules that represented service along corridors. Discussion with rail service providers did suggest that service could be scheduled as frequently as desired, however.

Finally, we hoped to determine how port investment could increase market share. Our results suggest that ports cannot always influence the characteristics affecting carriers' decisions. We can examine the changes at ports, such as the Alameda Corridor or the recent implementation of the "world's largest cranes" at the Port of Oakland. Technologies deployed at terminals are, however, highly transferable and easily replicable. Many technologies must be transferable due to the sharing of customers between ports. Many technologies are the property of the ports' clients and not the ports themselves, thus making them transferable. In examining competition, Porter (1980) emphasized the need for firms to have a distinct advantage if they are to remain competitive. Any advantage for a port might come from a factor beyond its control. A port's advantage might result from external factors, including those that lead to technological initiatives, such as rail schedules, and those that do not, such as population.

Future research

A number of questions require further research. The importance of intermodal transfer time remains uncertain. We could examine the different transfer processes themselves or the cost structure required for these processes. Many planners have debated the merits of on-dock rail transfer and off-dock rail transfer, but no measure has been given of the attractiveness each adds to a port. During this research, we learned that the last terminal operator with access to on-dock rail transfer at Long Beach had recently abandoned the facility to use the space for storage. Was this done because space was too limited or because off-dock transfer simply offered greater flexibility?

With regard to port charges, we mentioned briefly the differences between different regions (e.g. California, Washington, the East Coast). When financing his port, a port operator must decide whether the port should act as a lessor (as they do on the West Coast) or as an operator (as they do on the East Coast). If port charges are insignificant, as suggested by our analysis, port charges might be structured in different ways to meet different objectives. The objectives of ports might differ such as to suggest alternative financial structures. Some ports could seek profit-maximization while others seek throughput maximization. The optimal pricing mechanism might differ along with the level of prices.

As mentioned in the beginning, we could also examine the assignment of shipments to ports on an aggregate level. We discussed earlier the merits of a multicommodity flow model relative to the choice model. We could apply a flow model to the assignment of shipments for each carrier, using the values for factors that were estimated in this model. Values for other factors could be estimated, perhaps, and included in a different manner. This model could account for the redistribution of containers and the assurance that no routes would require traffic that exceeded capacity. With this model we could address many of the limitations discussed earlier that involve the balance between imports and exports and the relocation of equipment. The approach could identify constraints to be addressed for future traffic levels.

Finally, we emphasize that our research focuses on only one of the two decisions faced by carriers. The assignment of shipments to ports and vessels requires the assumption that the assignment of vessels to ports is fixed. Our model showed that frequency of sailing is more significant than vessel capacity in the short-term decision. Why do carriers not sail the smallest vessels as frequently as possible? Scale economies would prevent such carriers from competing with other carriers. Oceanic rates are justifiably assumed to not affect the selection of a port for a shipment, since the rates do not vary among ports. Rates would vary, however, among carriers if each sailed a vessel of different size. Particularly in a market with overcapacity, carriers' rates are set to recover costs, and these costs do not reflect the frequency of service directly. These costs do reflect scale economies, and carriers must therefore exploit scale economies in order to remain competitive. Ports must be able to accommodate the larger vessels if they wish to compete.

A realistic assignment of vessels needs to be studied. This long-term decision can also be studied with a model that emphasized logistics. With the flow model, we could subject the assignment of vessels to particular constraints and determine how the constraints impact the assignment of vessels. Cost components could be derived from earlier literature. Again, many constraints (e.g. depth, storage space) would be within the control of port authorities, such that ports could invest to attract carriers' vessels. At the same time, however, many factors are beyond the control of ports, such as the origin-destination distribution of traffic. Given this assignment of vessels, we could use the choice model estimated here for the short-term decision to assign the shipments to ports. We could then reassign the vessels, following the iterative manner until certain conditions have been satisfied.

Our model of short-term shipment assignment does explain the economic viability of ports in a fixed situation. We could combine this model with an analysis of vessel-assignment to represent the competition faced by ports, both today and in the future.

Endnotes

Chapter 1

[1] Inland transport service providers, however, were not allowed to establish contracts with maritime carriers, perhaps because of the greater competition within the maritime environment.

[2] One TEU is one twenty-foot equivalent unit, the length of a standard container that was used to measure the capacity of vessels.

Chapter 2

[1] The authors acknowledged limitations in the data, since the data available through the Maritime Administration did not cover years prior to 1993.

Chapter 3

[1] For discussion of the multinomial logit model, see McFadden (1973; 1978; 1981); Ben-Akiva et. al. (1985), Train (1986), or Oppenheim (1995).

[2] The Harmonized System is an international six-digit commodity classification developed under the auspices of the Customs Cooperation Council. Individual countries have extended it to ten digits for customs purposes, and to 8 digits for export purposes. The system classifies goods by what they are, not according to their stage of fabrication, use, or origin. The first pair of digits represent a chapter, the next pair a heading, the third pair a subheading.

[3] The data set was reduced to include only shipments that were moved from one of the 48 contiguous United States through one of the eight ports by one of the carriers whose schedules are available from the Journal of Commerce.

[4] This data was found through the American Association of Port Authorities web-page, at http://www.aapa-ports.org/industryinfo/statistics.htm#Statistics.

[5] We use as the value of each shipment an estimate from the Journal of Commerce, according to the corresponding commodity and the trade lane.

[6] The data on aggregate values were collected through the database available on the web-site of the International Trade Commission. The values there represented all types of transport, so the share represented of maritime shipments likely exceeded 4%.

[7] If the data set had represented choice-based sampling, then the choice model to be estimated would have required weighting to make the results representative.

[8] Evergreen moves shipments through the neighboring ports of, respectively, Los Angeles, Charleston, and Tacoma.

[9] We modeled the decisions with other variables as well. For example, we used the average number of sailing days in place of oceanic distance or the frequency of voyages in place of the headway between voyages. In each case, the explanatory power of the model decreased.

[10] In fact, the headway between (or frequency of) voyages was found to be insignificant when included as the average across all carriers, a result quite different from the model resulting from carrier-specific values. We would intuitively expect the carrier-specific values to have more explanatory power as well.

[11] The site was at: http://www.joc.com/scheds/index.shtml. Because data for a vessel is maintained only until the vessel's voyage has been completed, data for December 1999 were no longer available. Instead, data for March 2000 were used to represent the variables. Comparison was made with the schedule for June 2000 (likewise, separated by three months) and a correlation coefficient of 0.95 existed between the schedules, implying that carriers' schedules did not change much over three months.

[12] These records were downloaded from the web and analyzed with a spreadsheet. The twelve U.S. ports consisted of the eight within the choice set, along with Houston, Miami, Norfolk, and Portland. The foreign ports were not constrained to the country that was the destination of the shipment. For example, shipments destined for Germany could also be moved through the nearby ports of Rotterdam and Antwerp. A complete list of foreign ports is given in Appendix A.

[13] The capacity of individual vessels was measured through the web-site MaritimeData.com.

[14] One of the three did say in refusing to give the information that the transfer times were not significant, though of course this is not as explanatory as the data itself.

[15] If the alternative-specific constants remain constant across carriers, then the unobserved error term would be correlated for each carrier's shipments and not distributed with a mean of zero, as required for the model estimation.

[16] These conditions for sufficiency do not add any additional constraints to the traditional logit model. As shown in Train (1986), the inclusion of a port-specific constant mandates that the share predicted for each port is equivalent to the share observed for each port. If the constants vary by carrier, then the property will hold for each carrier. If we use universal port-specific constants, the property will hold for all shipments.

[17] Each of the samples was extracted with MATLAB, which was also used to evaluate the feasibility of the distributions. Approximately 3% of the samples had a number of feasible distribution sets that were too large for the statistical estimation software, LIMDEP, to handle. These samples were discarded, resulting in 1840 samples.

Chapter 4

[1] The data from 1996 regarded shipments from one destination and could not be used as effectively with the choice model that we are developing. However, the significance of being visited first, in the context of imports, can still be demonstrated.

[2] The Hyundai Freedom visited Seattle/Tacoma on December 1 and Los Angeles/Long Beach on December 30. These visits represented two different voyages, with Seattle/Tacoma being visited at the end of the first and LA/LB being visited at the beginning of the next. To the program, however, the vessel appeared to visit LA/LB after visiting Seattle/Tacoma.

[3] These records correspond to those discussed in Chapter 3 for the measurement of the carriers' schedules.

[4] To divide the exports from California into two regions, we use a measure of metropolitan area exports released by the International Trade Administration. The regions represent Northern California (where the Port of Oakland is located) and Southern California (where the Ports of LA/LB are located). At the time of the work, metropolitan-level exports were not available yet for 1999, and so the share represented by each region in 1997 and 1998 were used with the statewide data to estimate each region's share for 1999.

[5] A number of vessels were cross-listed, or listed under multiple carriers. So that the vessels could be classified without repetition across groups, each vessel was assigned to the first carrier for which it was listed. In most cases, carriers that shared vessels according to agreements would be represented by identical schedules, and so the model representing each carrier would be identical with this assignment.

[6] Recall that with the Chamberlain model, no values are estimated for the alternative-specific constants. See Chapter 3 or Chamberlain (1980) for more details.

[7] For more information, see Greene (1997).

Chapter 5

[1] We discarded sixty observations because the number of feasible distribution was too large for LIMDEP to handle. LIMDEP is the statistical package used to estimate the choice model.

[2] For more information regarding the derivation of the Hausman test, see Greene (1997).

[3] Recall that to allow the variable to be assigned a finite value, ports for which the observed frequency of sailing during March 2000 was zero were assigned an arbitrarily high headway of sixty days.

[4] The model applies regardless of the available choice set. In addition, because carriers do not operate multiple terminals within a region, each port competes with ports in other regions for the assignment of a shipment.

[5] To simplify the analysis, the variable representing the probability of being the last port selected is ignored.

[6] The Port of Long Beach is closer to Oakland than Tacoma, so with the shifting of the origin, Long Beach's advantage is lessened.

[7] The generic commodity would be of lower value than the highest-value manufactured goods.

[8] If increased in a manner similar to the inland distance, any advantage would be lost before a significant market was reached.

[9] Without knowing the destination, we could not know the exact frequency.

Chapter 6

[1] The effect of volume on rates could be affected by the scale economies of terminal operation or the desire of ports to attract the marginal elements of traffic, for which the port's attractiveness might otherwise not be so great.

[2] Note that the domestic traffic here would most likely represent deep-sea, due to the ports under consideration.

[3] The operating revenues generated by a port would be proportional to the operating costs for terminals, since ports are public agencies. Therefore a scale-economy relationship between port revenues and traffic would imply a similar relationship between terminal operating costs and traffic levels.

[4] Dowd (1984) surveys the different types of financing schemes available.

[5] An extensive amount of literature exists describing the objectives of ports. Heggie (1974) was among the first to emphasize the need for cost-based fees to ensure efficient usage of funds. Strandenes et. al. (2000) gives a good summary of the different methods that have been suggested and evaluated for port pricing. Talley (1994b) introduces a cost-axiomatic approach that would allow ports to cover fixed costs while pricing efficiently.

[6] This condition has existed for many years and was confirmed with a conversation with an official from the Port of Los Angeles.

Chapter 7

The average capacity of vessels sailing from a particular port would be affected by the depth of the port's waterways. The larger vessels deployed today, e.g. the 6600-TEU line deployed by Maersk, are precluded from calling at ports of insufficient depth, such as the Port of Oakland.

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Appendix A. Foreign ports

The Journal of Commerce lists the vessels scheduled between port-pairs. With the specification of a United States port and a foreign port, a database returns a listing of all vessels scheduled to sail between those ports. For each shipment, we measured the characteristics that describe the vessels sailing from a U.S. port to the destination of the shipment. These characteristics include the frequency of voyages, the capacity of vessels sailing the route, and the share of vessels visiting each port last. Measures of these characteristics depend upon the foreign ports considered. For each shipment, we use a set of potential foreign ports that were near the shipment's destination country. For each U.S. port, the frequency of voyages represents the total number of vessels sailing from that port to any of the potential foreign ports. Vessel capacity represents the average capacity of all vessels sailing from the U.S. port to any of the potential foreign ports. The probability of being visited last represents the share of all vessels that called at the U.S. port last before sailing to a potential foreign port.

For foreign ports, we consider all ports visited by any vessel from one of twelve United States ports during March 2000. The twelve United States ports are:

- Charleston
- Houston
- Long Beach
- Los Angeles
- Miami
- New York
- Norfolk
- Oakland
- Portland (Oregon)
- Savannah
- Seattle
- Tacoma

Because of natural boundaries, our selection was less discretionary for some countries (e.g. Australia or Japan) than others. The potential foreign ports for each country were as follows:

<u>Australia</u>
Brisbane
Fremantle
Melbourne
Sydney

<u>Brazil</u>
Belem
Fortaleza
Manaus
Paranagua
Rio de Janeiro
Salvador
Santos
Sao Francisco do Sul
Suape
Vitoria

<u>Egypt</u>
Alexandria
Damietta
Port Said

<u>Germany</u>
Amsterdam
Antwerp
Bremerhaven
Bremen
Hamburg
Rotterdam
Zeebrugge

<u>Japan</u>
Hachinohe
Hakata
Kobe
Nagoya
Osaka
Sendai
Shimizu
Tokyo
Toyohashi
Yokkaichi
Yokohama

<u>Saudi Arabia</u>
Abu Dhabi
Bahrain
Damman
Doha
Dubai
Khor Fakkan/Fujairah
Kuwait
Mesaieed
Mina Qaboos

<u>South Africa</u>
Cape Town
Durban
East London
Port Elizabeth

<u>United Kingdom</u>
Bristol
Felixstowe
Liverpool
Sheerness
Thamesport

Appendix B. Significance of the different models

A density function for the ratio between two variables that themselves have density functions is given by:

$$f_{w_1/w_2}(y) = \int_{-\infty}^{\infty} w f_{w_1}(yw) f_{w_2}(w) dw$$

We construct density functions for each ratio to test for statistical significance. In the first case, we represent the factors of oceanic distance and the probability of being visited last. We compare the density functions representing the ratio between these two factors, in each scenario, to determine the likelihood of equality between the ratios. The densities for the ratio representing the tradeoff between oceanic distance and the probability of being last are shown in Figure 12.

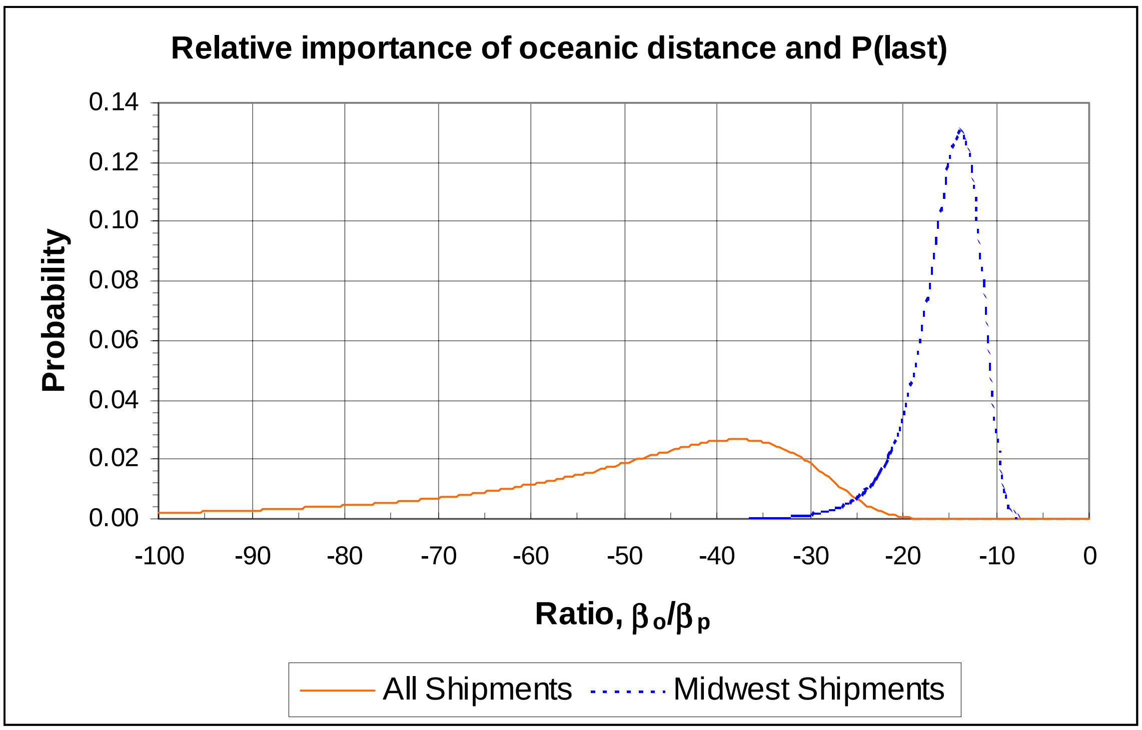

Figure 12. The relative importance of oceanic distance and being visited last.

Similarly we represent the densities for the ratio representing the tradeoff between inland distance and the probability of being visited last in Figure 13.

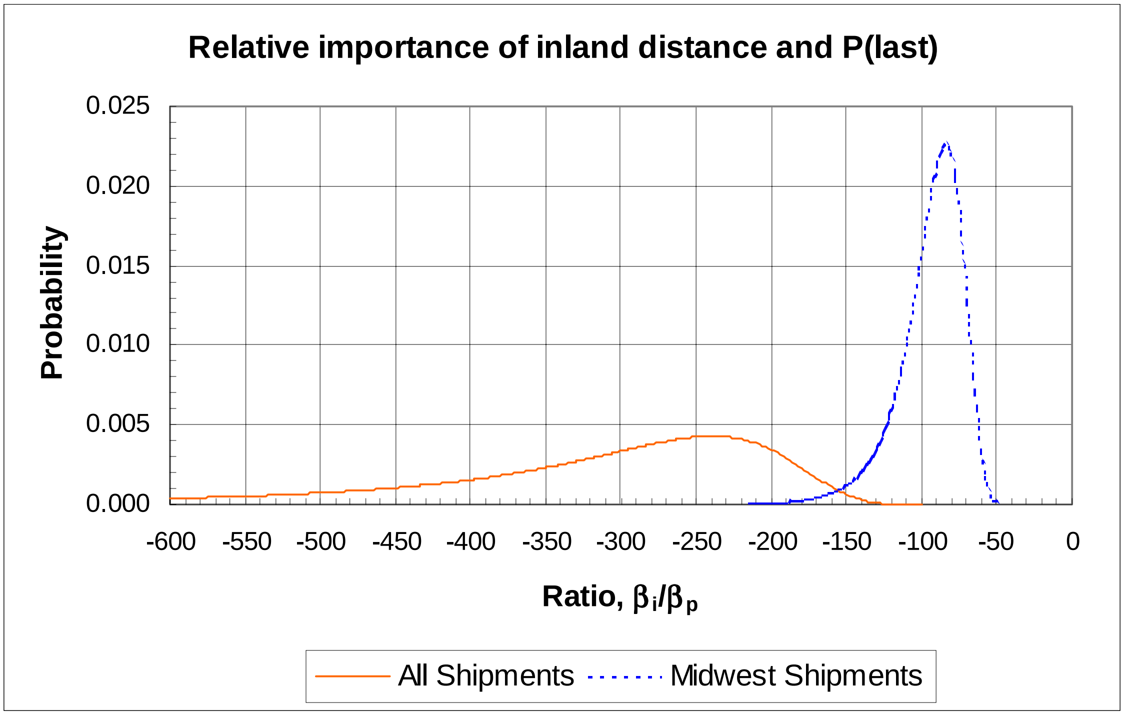

Figure 13. The relative importance of inland distance and being visited last.

We represent the densities for the ratio representing the tradeoff between the expected headway and the probability of being visited last in Figure 14.

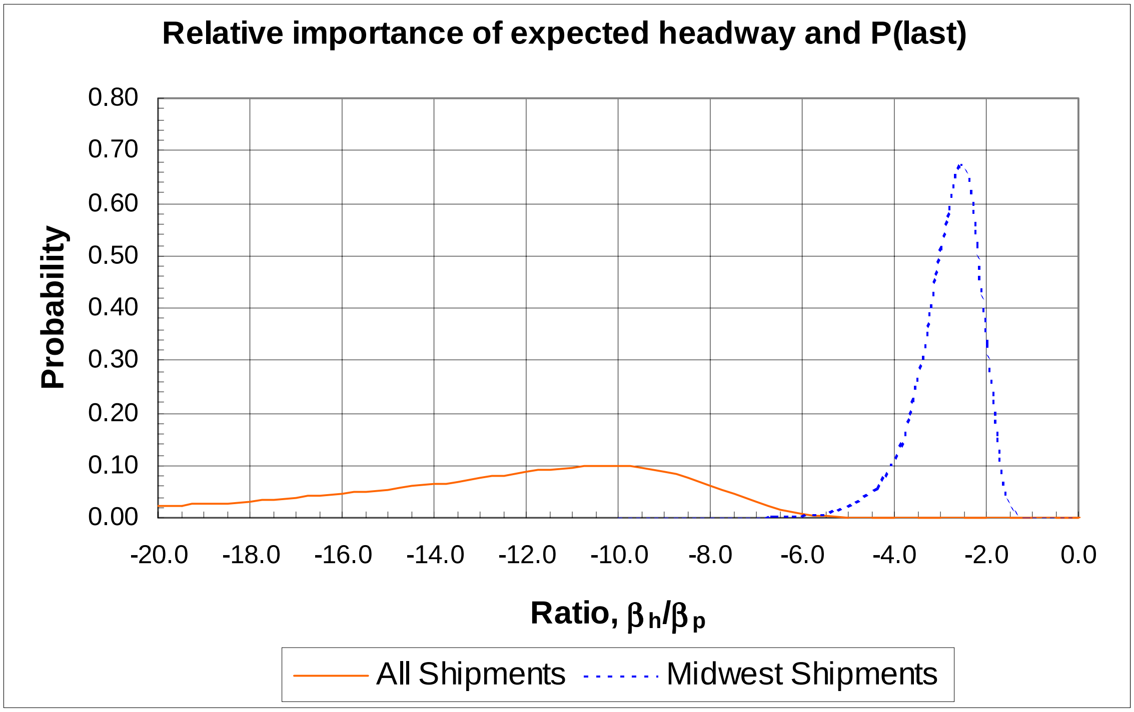

Figure 14. The relative importance of voyage headway and being visited last.

From each comparison we see that the significance of being visited last is greater for discretionary cargo than for the generic shipment

Appendix C. Constrained carrier-specific models

In this appendix we present some results from the carrier-specific models. For these models, we constrained the variable coefficient to the values estimated with the Chamberlain model to represent decisions for all shipments. We use these models to estimate the carrier-specific elasticities given in Table 36 in Chapter 5. As shown in Table 45, the data for some carriers produced models more precise than the models for other carriers.

American President Lines - 270 shipments

Port	Port-specific constant	Standard error	z-statistic	p-statistic
Charleston	-0.536	0.267	-2.008	0.045
Long Beach	-14.628	200.080	-0.073	0.942
Los Angeles	0.289	0.194	1.487	0.137
New York	-0.549	0.283	-1.941	0.052
Oakland	0.051	0.195	0.262	0.793
Savannah	-14.898	279.780	-0.053	0.958
Seattle	-1.152	0.294	-3.921	0.000
Tacoma	0.000	-	-	-

Maersk/SeaLand - 450 shipments

Port	Port-specific constant	Standard error	z-statistic	p-statistic
Charleston	-0.299	0.214	-1.400	0.162
Long Beach	-0.611	0.184	-3.316	0.001
Los Angeles	-16.057	246.890	-0.065	0.948
New York	-1.158	0.245	-4.733	0.000
Oakland	0.041	0.165	0.250	0.803
Savannah	-16.210	382.700	-0.042	0.966
Seattle	-16.189	425.320	-0.038	0.970
Tacoma	0.000	-	-	-

Evergreen - 527 shipments

Port	Port-specific constant	Standard error	z-statistic	p-statistic
Charleston	2.693	0.196	13.740	0.000
Long Beach	-14.097	302.340	-0.047	0.963
Los Angeles	0.911	0.149	6.122	0.000
New York	0.349	0.321	1.087	0.277
Oakland	-0.502	0.198	-2.533	0.011
Savannah	-13.593	280.830	-0.048	0.961
Seattle	-14.157	366.430	-0.039	0.969
Tacoma	0.000	-	-	-

P&O Nedlloyd - 359 shipments

Port	Port-specific constant	Standard error	z-statistic	p-statistic
Charleston	10.199	132.210	0.077	0.939
Long Beach	11.108	132.210	0.084	0.933
Los Angeles	12.474	132.210	0.094	0.925
New York	11.231	132.210	0.085	0.932
Oakland	12.516	132.210	0.095	0.925
Savannah	12.046	132.210	0.091	0.927
Seattle	12.531	132.210	0.095	0.924
Tacoma	0.000	-	-	-

Hanjin Shipping Co. - 367 shipments

Port	Port-specific constant	Standard error	z-statistic	p-statistic
Charleston	-1.938	580.720	-0.003	0.997
Long Beach	14.395	371.620	0.039	0.969
Los Angeles	0.029	468.490	0.000	1.000
New York	10.956	371.620	0.029	0.976
Oakland	14.542	371.620	0.039	0.969
Savannah	12.340	371.620	0.033	0.974
Seattle	13.888	371.620	0.037	0.970
Tacoma	0.000	-	-	-

Yang Ming Lines - 297 shipments

Port	Port-specific constant	Standard error	z-statistic	p-statistic
Charleston	1.917	0.664	2.886	0.004
Long Beach	2.770	0.588	4.708	0.000
Los Angeles	4.297	0.593	7.243	0.000
New York	0.851	0.653	1.303	0.193
Oakland	2.854	0.587	4.860	0.000
Savannah	1.371	0.635	2.157	0.031
Seattle	-1.041	1.155	-0.902	0.367
Tacoma	0.000	-	-	-

Table 45. The constrained models estimated for specific carriers.

Appendix D. Unconstrained carrier-specific models

To measure the applicability of the model estimated with all data, we estimate a model to represent the decisions of each carrier. For some carriers, the variability within the data prevented estimates from becoming too precise. The distribution of the carriers' shipments, across ports, is given in Chapter 3, Table 7. In Table 46, we present the results of the model estimated for each carrier.

American President Lines - 270 shipments				
Variable	**Estimate**	**Standard error**	**z-statistic**	**p-statistic**
Oceanic distance (O)	-0.361	0.066	-5.460	0.000
Inland distance (I)	-1.137	0.161	-7.072	0.000
Sailing headway (H)	-0.003	0.010	-0.259	0.796
Prob. of last (P)	-0.001	0.004	-0.275	0.783
A_Charleston	0.206	0.294	0.701	0.483
A_Long Beach	-15.053	241.170	-0.062	0.950
A_Los Angeles	0.277	0.202	1.369	0.171
A_New York	0.175	0.307	0.570	0.569
A_Oakland	0.299	0.322	0.927	0.354
A_Savannah	-13.834	204.690	-0.068	0.946
A_Seattle	-1.037	0.295	-3.511	0.000
A_Tacoma	0.000	-	-	-
Evergreen - 527 shipments				
Variable	**Estimate**	**Standard error**	**z-statistic**	**p-statistic**
Oceanic distance (O)	0.101	0.059	1.714	0.086
Inland distance (I)	-0.373	0.040	-9.373	0.000
Sailing headway (H)	-0.054	0.013	-4.136	0.000
Prob. of last (P)	0.026	0.025	1.037	0.300
A_Charleston	0.883	0.216	4.095	0.000
A_Long Beach	-12.737	248.780	-0.051	0.959
A_Los Angeles	0.516	0.369	1.399	0.162
A_New York	-1.673	0.394	-4.246	0.000
A_Oakland	-0.233	0.222	-1.051	0.293
A_Savannah	-14.915	232.360	-0.064	0.949
A_Seattle	-12.674	241.430	-0.052	0.958
A_Tacoma	0.000	-	-	-

Table 46. The unconstrained models estimated for specific carriers.

Hanjin Shipping Co. - 367 shipments				
Variable	**Estimate**	**Standard error**	**z-statistic**	**p-statistic**
Oceanic distance (O)	-0.237	0.064	-3.728	0.000
Inland distance (I)	-0.550	0.129	-4.269	0.000
Sailing headway (H)	-0.783	0.176	-4.455	0.000
Prob. of last (P)	0.005	0.009	0.591	0.555
A_Charleston	-8.685	851300	0.000	1.000
A_Long Beach	3.099	851300	0.000	1.000
A_Los Angeles	-5.380	851300	0.000	1.000
A_New York	0.848	851300	0.000	1.000
A_Oakland	3.970	851300	0.000	1.000
A_Savannah	2.374	851300	0.000	1.000
A_Seattle	3.284	851300	0.000	1.000
A_Tacoma	0.000	-	-	-

Maersk/SeaLand - 450 shipments				
Variable	**Estimate**	**Standard error**	**z-statistic**	**p-statistic**
Oceanic distance (O)	-0.219	0.033	-6.586	0.000
Inland distance (I)	-0.879	0.076	-11.611	0.000
Sailing headway (H)	-0.010	0.007	-1.299	0.194
Prob. of last (P)	-0.039	0.006	-6.216	0.000
A_Charleston	0.790	0.297	2.661	0.008
A_Long Beach	-0.564	0.227	-2.490	0.013
A_Los Angeles	-16.769	359.450	-0.047	0.963
A_New York	-0.738	0.299	-2.467	0.014
A_Oakland	0.872	0.237	3.687	0.000
A_Savannah	-15.880	289.120	-0.055	0.956
A_Seattle	-15.842	343.490	-0.046	0.963
A_Tacoma	0.000	-	-	-

P&O Nedlloyd - 359 shipments				
Variable	**Estimate**	**Standard error**	**z-statistic**	**p-statistic**
Oceanic distance (O)	-0.218	0.042	-5.162	0.000
Inland distance (I)	-1.546	0.139	111.104	0.000
Sailing headway (H)	-0.034	0.008	-4.431	0.000
Prob. of last (P)	0.045	0.009	5.142	0.000
A_Charleston	7.764	196.670	0.039	0.969
A_Long Beach	11.883	196.670	0.060	0.952
A_Los Angeles	13.013	196.670	0.066	0.947
A_New York	10.815	196.670	0.055	0.956
A_Oakland	13.411	196.670	0.068	0.946
A_Savannah	11.835	196.670	0.060	0.952
A_Seattle	13.377	196.670	0.068	0.946
A_Tacoma	0.000	-	-	-

Table 46 (cont.). The unconstrained models estimated for specific carriers.

Yang Ming Lines - 297 shipments				
Variable	Estimate	Standard error	z-statistic	p-statistic
Oceanic distance (O)	-3.182	56.955	-0.056	0.955
Inland distance (I)	-2.379	0.454	-5.239	0.000
Sailing headway (H)	1.124	18.273	0.062	0.951
Prob. of last (P)	1.949	25.277	0.077	0.939
A_Charleston	-47.829	830.690	-0.058	0.954
A_Long Beach	-24.953	360.630	-0.069	0.945
A_Los Angeles	-54.288	938.870	-0.058	0.954
A_New York	-9.044	510.290	-0.018	0.986
A_Oakland	-55.863	758.620	-0.074	0.941
A_Savannah	22.603	554.520	0.041	0.967
A_Seattle	-9.883	120.680	-0.082	0.935
A_Tacoma	0.000	-	-	-

Table 46 (cont.). The unconstrained models estimated for specific carriers.

Appendix E. Residuals from analysis of ports' revenues

A studentized residual represents how much of an outlier one observation represents, based upon the model that would be estimated without that observation. Values are distributed as a [0,1] standard normal distribution. To analyze the effect of individual observations, we use the studentized residual associated with each observation. A theoretical discussion of studentized residuals is on the web page for the Econometrics Laboratory Software Archive at the University of California at Berkeley. The information is located within an online SST help guide at http://emlab.berkeley.edu/sst. We used SST, a statistical software package, to estimate the studentized residuals for each observation, shown in Table 47.

Port	Year	Studentized residual		Port	Year	Studentized residual
Boston	1998	1.952		Boston	1999	1.056
South Carolina ports	1998	-0.783		South Carolina ports	1999	-0.989
Houston	1998	-1.145		Houston	1999	-1.166
Jacksonville	1998	-1.649		Jacksonville	1999	-1.182
Long Beach	1998	1.462		Long Beach	1999	1.284
Los Angeles	1998	1.613		Los Angeles	1999	1.834
Miami	1998	-0.446		Miami	1999	-1.046
Virginia ports	1998	0.627		Virginia ports	1999	0.263
NY/NJ	1998	-0.968		NY/NJ	1999	-1.356
Oakland	1998	0.543		Oakland	1999	0.791
Portland	1998	0.337		Portland	1999	-0.641
San Diego	1998	-0.227		San Diego	1999	0.740
Georgia ports	1998	0.481		Georgia ports	1999	-0.016
Seattle	1998	-0.284		Seattle	1999	0.140
Tacoma	1998	0.099		Tacoma	1999	-1.021

Table 47. The studentized residual associated with each port observed.