Matching in the oil tanker industry: implications for energy efficiency

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I, Sophia Parker, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Abstract

This thesis seeks to explain the economic determinants of matches between shipowners and oil traders within a spatially explicit market for shipping crude oil. Previous approaches to modeling the tanker shipping market have employed an aggregate approach in which there is a single trade route and one market clearing price. This reduced form of trade ignores the inherently spatial nature of the tanker shipping market in which the matches, market prices, and speed ships travel reflect the demand for shipping crude oil on different trade routes, the supply of ships available in each location, and agents' opportunity costs and future expectations.

A matching model of the crude oil spot tanker market was developed in which the characteristics of ships and traders is reflected in the market price. The method employs a matching model to understand how supply equilibrates with demand to determine the set of shipping contracts exchanged and their prices as a function of the other agents in a competitive market.

Results described in this thesis show that the contracts that form in equilibrium depend on the demand for oil cargoes in each load area market and the supply of available ships within proximity to the market. Additionally, agents' opportunity costs and future expectations has also been found to influence the matching and contract prices. When ships are differentiated by physical characteristics (including energy efficiency) and location, results show that ships which are the most favored by physical characteristics cannot compete as strongly with less preferred ships located closer to the market. These findings can be used to inform industry stakeholders about strategic operating and investment decisions. They are also useful for environmental policy makers because they explain the key drivers of ship movements given ships' reliance on carbon-intensive fuel for propulsion.

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Chapter 1

Introduction

1.1 Background and context of study

The oil tanker shipping industry is an integral part of a complex energy infrastructure where getting the right sort of oil to the right place with the right ship at the right time is crucial. These product, space, and time features are particularly important because of the combination of inelastic demand for crude oil shipments and the geographical dispersion of tanker shipping market activities across regions where oil is produced and where it is refined and consumed. As such, large tanker ships almost always have to sail empty to another oil source once they unload their cargo, thus incurring a cost that is proportional to the distance travelled. The spatial nature of the market means that ships may not compete as strongly with ships located farther away from a source due to the presence of transportation costs and time preferences of oil traders. In addition to this spatial differentiation, ships can also distinguish themselves by their size, age, reputation, and energy efficiency, adding complexity to understanding how these resources are allocated in the spot market [1] for tanker shipping services.

Tankers are often compared to taxis, normally carrying only one customer's cargo from an oil source to a sink and taking on new assignments with new customers whenever they are available. Although some ships ferry between the same load and discharge area, most shipowners are free to send the ship wherever they choose after they discharge the cargo. Figure 1.1 below depicts a trajectory of a ship from its starting location l to a load port a to a discharge port b and a future destination $l\prime$.

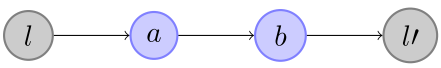


Figure 1.1: A ship's sailing trajectory

[1] A shipping contract on the spot market is negotiated shortly (within a few days to two weeks normally) and specifies the carriage of a particular cargo aboard a named ship between two points (for example, from the Arabian Gulf to the US Gulf), the loading and discharge dates, and the payment due to the carrier. The market in this case refers to a sub-market or class of tankers (ranked by size) and not the total tanker shipping market.

If l is a discharge port, the ship could match with an oil trader (the shipper) or it could remain unemployed or unmatched. If it matches with a trader, it sails to a to pick up the cargo. After the ship has dropped off the cargo at b, it can reposition to another location $l\prime$, which depends again on whether it has matched to an oil trader or not. On the other hand, if the shipowner decides not to match, it has to reposition to a waiting area near a load area where oil traders demand cargoes to be lifted. Shipowners must anticipate future demands from the discharge location because of the cost of repositioning to another load area. For example, if a shipowner has a choice between a voyage from the Arabian Gulf to Japan or the Arabian Gulf to the US Gulf, they have to assume that the first voyage will likely require the ship to ballast directly back to the Arabian Gulf, while the voyage to US Gulf will offer the possibility of loading out of West Africa next, considered to be a backhaul. The shipowner must therefore know the state of all markets and make decisions as to which voyage will provide the best returns, keeping in mind what the next voyage might look like (Reardon, 2011).

Despite the inherently spatial nature of the tanker market, since Tinbergen and Koopmans' seminal works on the tanker freight market (Tinbergen, 1931, 1934; Koopmans, 1939) many studies (Norman and Wergeland, 1981; Wergeland, 1981; Hawdon, 1978; Beenstock and Vergottis, 1993; Evans and Marlow, 1990; Evans, 1994; Strandenes, 1986; Engelen et al., 2006; Adland and Strandenes, 2007, among others) have modelled the market for bulk shipping (which includes the tanker market) using a classical supply/demand equilibrium framework in which there is a single trade route and one market clearing price. In this framework, the market is assumed to be perfectly competitive, given the large number of shipowners, ease of market entry and exit, and the dissemination of shipping market prices by ship brokers (Evans, 1994). The equilibrium price in the tanker freight market is determined by the marginal cost of the last unit of transportation required to satisfy transport demand, where demand is typically assumed to be inelastic.

Figure 1.2 (Engelen et al., 2006) depicts the aggregate short-run transport supply and demand curves and the equilibrium prices at two intersection points, E_0 and E_1. At low freight rates, the supply of transportation services is very elastic because rates are low enough to induce shipowners to withdraw a considerable number of ships from the market. All vessels withdraw from the market at the point where the trading losses are greater than the costs of lay-up. As fuel costs represent a significant portion of total operating costs, only ships which are the most fuel efficient can operate in this depressed state of the market. In the figure, it assumed that energy efficiency decreases with age. Below E_0, a large increase in demand only pushes freight rates up slightly because ships immediately come out of lay-up at a relatively low marginal cost.

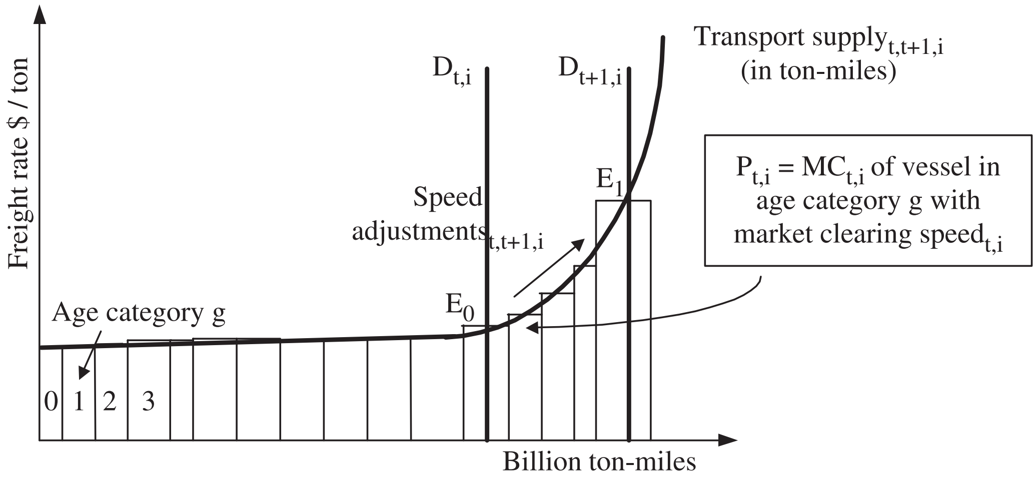


Figure 1.2: Market equilibrium in bulk shipping (Engelen et al., 2006)

At a higher demand level, the supply of ships gets scarce and is rationed to shippers. In this scenario, an equivalent increase in demand increases the freight rate by a larger amount as the freight rate is set by the least efficient ship. Between E_0 and E_1, the curvature of the supply curve becomes much steeper as the fleet is fully employed and variations in supply can only be brought about by changes in speed, time spent in port and under repair, and by the route travelled. Finally, when no further transport is available in the current period, the freight rate can reach very high levels as the supply curve is perfectly inelastic. This is considered an unstable situation, as shippers will look for cheaper supply sources (Stopford, 2009).

To derive the aggregate supply, the supply curve for an individual ship or a group of ships with the same energy efficiency (and in this case age category g) is first determined. The optimal speed is used to calculate the marginal costs of the marginal ship where speed is a function of the current period's freight rate, price of fuel, distance and the ship's technical efficiency (Stopford, 2009). Fuel consumption and speed are related by a cubic function such that reducing the sailing speed by 20% will reduce the bunker consumption by about 50% (Ronen, 1982). The distance used to calculate the optimal speed per ship is based on a representative route. Annual supply per ship (measured in tonne-miles) is equal to (speed x 24 x average loaded operating days per year x operating tonnage) where the average loaded operating days are estimates from data. The aggregate supply curve is comprised of the horizontal summation of all the marginal cost curves of the ships in the fleet.

The aggregate supply/demand model of the freight rate however has some fundamental weaknesses and shortcomings. First, the assumption that ships' only opportunity cost of trading in the market is lay-up is outdated. Lay-up is "only of importance during times of severe structural imbalances in the shipping markets, such as in the tanker markets in the mid-1980s" (Adland and Strandenes, 2007). In recent years, there has been a tendency for idle large tankers to wait fully operational in the loading area (Kennedy, 2002) given the cost to maintain their certification approval for the oil majors. Any tanker inactive for a minimum of six months will be required to undergo an expensive survey before being considered for use and the costs of returning it to service are prohibitive (Lloyd's List, 2012a). Instead, if ships do not match, their opportunity costs depend on the prospects of matching in the next period. These opportunity costs depend on its location relative to the next best cargo shipping opportunity in a load area.

The assumption of one trade route in the aggregate model simplifies the ship's movements to shuttle between a to b (see Figure 1), whereas there are many load and discharge areas which form trade routes in the global tanker market. This simplification might have been justified in past decades due to the dominance of the Arabian Gulf-Northern Europe route (Devanney, 1971), but changing trade flows due to demand from Asia and new oil production areas has increased the spatial complexity of ship movements [2] creating opportunities for repositioning strategies that influence ship movements through locational and speed choice. Kaluza et al. (2010) studies global cargo movements using information on the geographical position of ships and finds that oil tankers follow short-term market trends and have trajectories across different ports appearing to be essentially random. This can lead to situations in which the flow inbound to an area is often not equal to the flow out of an area, creating imbalances over time in the allocation of capacity over space.

Understanding the process through which prices are formed in the global tanker market is particularly important because of the existence of multiple regional shipping markets. Stopford (2009) defines a shipping market according to the origin-destination pair (i.e., Arabian Gulf-Japan, Arabian Gulf-Northwest Europe, West Africa-U.S. Gulf, etc.). A broader market definition from competition policy (Davis and Garces, 2010) defines a market in terms of "the products that impose constraints on each other's pricing or other dimension of competition (quality, service, innovation)." In the context of the global shipping market, geographical location plays an important role in defining the set of ships that can serve each shipping market. Assuming that all ships can operate on each route, the importance of the availability of geographically dispersed ships depends on the shipper's time preference for the ship to pick up its cargo. The shorter the duration between when the shipper comes to market to find a ship and the required date of loading, the smaller is the subset of ships that can meet this demand.

[2] an act of changing physical location or position; a particular manner of moving.

Pirrong (1993) is one of the few authors to discuss the influence of time and space factors in the spot market for bulk shipping. He refers to these factors as creating "temporal specificities" that can sometimes encourage costly haggling between shippers and carriers over how to split the rents, particularly if they rely on spot contracts because each party may have large opportunity costs if they do not match together. He argues that several factors affect the severity of temporal specificities, including the availability of geographically dispersed supply sources for the shipper and the competition in the shipping market. He defines a shipping market as competitive when there are a large number of ships arriving to carry cargo and a sufficiently large number of shippers placing orders in the load area for a particular route.

Another simplifying assumption is that the freight market operates in a perfectly competitive environment. A condition of perfectly competitive markets is that the products are homogenous, a strong assumption given their aforementioned differences. Adland and Strandenes (2007) estimate the marginal cost of the last unit of transportation (Figure 1.3) on a benchmark route compared to the actual freight rate and find that fluctuations in marginal costs cannot explain the much larger fluctuations in freight rates. Birkeland (1998) noted that a spot freight rate which clears a market reflects the vessels available in a particular area at a particular time,"exhibiting short-term fluctuations which seem to bear little, if any, relationship to its marginal cost." Instead, many authors have focused on explaining the changes in the freight rate level caused by the shipbuilding cycle (Tinbergen, 1934; Koopmans, 1939; Zannetos, 1966; Beenstock and Vergottis, 1993; Stopford, 2009) and the volatility in ship prices caused by the lag between when a ship is ordered and delivered (time to build constraints) (Kalouptsidi, 2013).

Another drawback of these models is the long time horizon. Beenstock and Vergottis (1993) discuss the drawbacks of modeling the tanker industry as one world market over a time horizon of a year. They suggest that a more disaggregate model may be particularly important in the oil market, where "speculative purchases are an important component of demand, and where the timing of oil trades in the short-run is not independent of associated fluctuations in freight rates." Surprisingly, none of the studies employing an aggregate approach have a time period of less than one month.

With the exception of Zannetos (1966), there is also no consideration of intertemporal decision making for shippers and shipowners which is particularly important in an industry which has highly volatile market prices. Shippers can negotiate a contract a month or more in advance of the agreed on loading date and ships can decide to wait to match depending on the market conditions. Furthermore, expectations about future market conditions can also impact the speed ships travel (Evans, 1994).

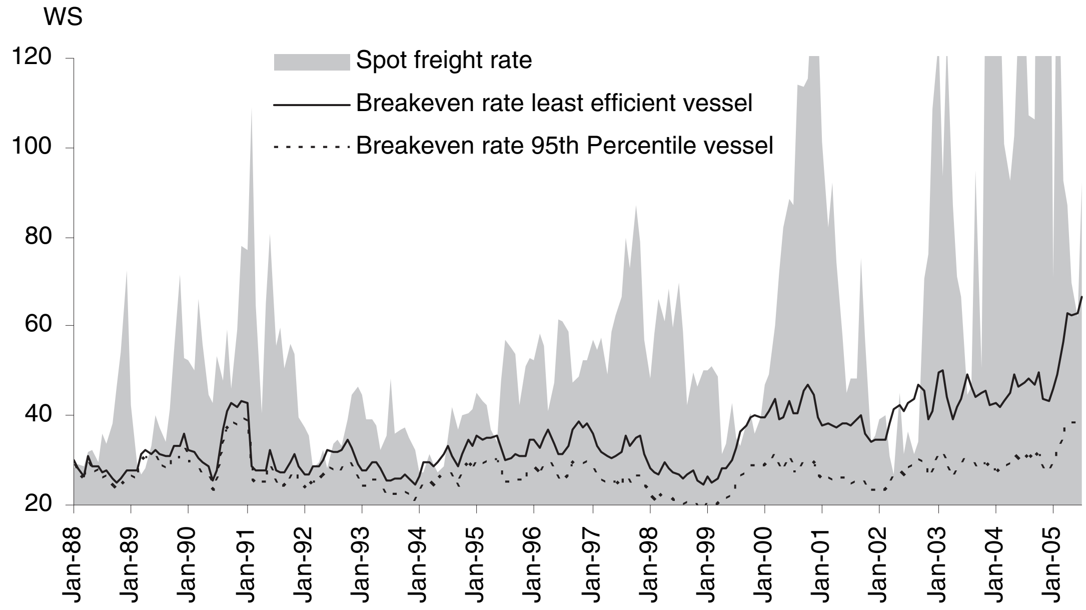


Figure 1.3: Spot freight rates compared to marginal cost (Adland and Strandenes, 2007)

Finally, there are several limitations of representing demand as a function of exogenous aggregate trade demand. First, there is no quantification of the willingness to pay of the shipper. This is important because of the implications for shipowners to earn quasi-rents when there is a demand shock. Evans (1994) argues that a large and sudden increase in demand may lead to the supply function becoming perfectly inelastic, leading to ships earning quasi-rents. The aggregate model cannot explain the conditions under which this situation would occur due to spatial and temporal factors. Second, to derive the optimal speed, existing studies assume that the freight rate is independent of speed (Ronen, 1982; Beenstock and Vergottis, 1993; Evans and Marlow, 1990; Evans, 1994; Strandenes, 1999; Corbett et al., 2009). This assumption is contrary to industry reports which state that speed can be negotiated between the shipper and shipowner (Lloyd's List, 2011). For example, a higher speed may result because a shipper has a higher willingness to pay for the service.

1.2 Global economic, energy, and environmental context

International shipping has encountered several challenges in recent years. The cost of heavy fuel oil has more than tripled since 2000 and ships remain heavily reliant on oil for propulsion given the limitations of alternative energy sources and economically viable technological solutions. The Rotterdam 380 bunker fuel price averaged \$138.4 per ton in 2000, \$234 per ton in 2005, \$345.1 per ton in 2007 and \$639.6 per tonne in 2012 (Clarkson Research, 2012c). At same time, the international economy entered a global recession at the end of 2007, resulting in a decrease in shipping demand which has been slow to recover. With fuel costs accounting for a large share of operating costs (50-60%) (World Shipping Council, 2008), some tanker operators have adopted “slow steaming” (Ranheim, 2012), a practice used in container shipping to cut significant costs off their fuel bill due to loss-making freight rates by traveling at speeds below their as-designed speed. With little prospect of near-term radical technical efficiency improvement (IMO, 2010), some industry leaders are touting operational energy efficiency (which includes slow steaming) as the new norm (Jorgensen, 2010) while others are more skeptical, arguing that once the market picks up, operators will be back to steaming at “gas guzzling” speeds (UNCTAD, 2013).

The industry also faces the threat of regulation of international shipping carbon emissions through either a carbon tax or trading scheme. Ships engaged in international trade accounted for 2.7% of the world’s carbon emissions in 2007 (IMO, 2009). Emissions reductions are feasible through technical and operational measures, as well as market-based polices. But in the absence of global policies to control carbon emissions from international shipping, emissions are predicted to increase by between 200 and 300 percent by 2050 due to expected growth in international seaborne trade (IMO, 2009).

The future global energy map is also being redrawn amid the rise in oil and gas production in the United States, which will have a strong bearing on the tanker trade. The International Energy Administration expects the U.S. to become a net exporter of natural gas by 2020 and overtake Saudi Arabia as the largest global oil producer by the same year, before becoming completely self sufficient in energy by 2035 (IEA, 2012b). Understanding the economic drivers of ship movements across different trade routes will be even more important in a future with growing shipping volumes and changing trade routes. As aggregate emissions is the summation of emissions from both cargo-carrying and repositioning voyages, it is important to quantify the extent to which demand and supply side factors influence these movements especially if carbon pricing is applied in global emissions reductions schemes.

1.3 Aim and research questions

The aim of this study is to understand the economic determinants of matches between traders and ships within a spatially explicit market for shipping crude oil. To address this aim, it is useful to answer a number of more specific research questions:

- What determines the assignment of ships to traders (and therefore who is unmatched) given the spatial distribution of ships across locations in the oil tanker shipping industry?
- What determines the division of surplus in the matches between ships and traders and therefore equilibrium prices?
- What are the influencing factors of the contract (matched) speed and ballast (unmatched) speed?
- What are the impacts of supply side and demand side changes on the market in terms of matching outcome, earnings, prices and speed?

Given the energy and environmental context of this study, an increase in the fuel price, heterogeneity in the physical characteristics of ships, and a carbon tax will be simulated on the supply side. On the demand side, a transitory and permanent demand shock will be simulated. Finally, the impact of a simultaneous demand and fuel price shock will be addressed.

1.4 Contributions to existing knowledge

My contribution to the literature is by developing a micro level model of the tanker shipping market that incorporates different agents' choices and types of agents, including geographical location and energy efficiency of ships. Specifically, this research makes several contributions to the literature:

- It provides the first known theoretical and empirical matching model of the tanker market to:
  - explain the process through which prices are formed in the global tanker market as a function of individual agents trading in regional shipping markets
  - quantify intertemporal decision making for ships and traders
  - incorporate detailed demand side modeling at the micro level, including the trader's willingness to pay for transport service
  - investigate short-run decision making at a temporal resolution of one week
- It provides an understanding of the economic drivers of ship movements, in terms of both locational decisions and speed.

- It offers insight into the interaction between different shipping markets. For example, the conditions under which a demand shock to one market will ripple through to other markets.

1.5 Overview of the study

To achieve this study's aim, I review the literature relevant to the thesis in Chapter 2. I discuss the need to incorporate the spatial dimension of the market and the motivations of different agents in order to understand their matching patterns and contracts. In Chapter 3, I introduce the crude oil and tanker shipping market that is the basis for formulating the problem and introduces two key features of industry. First, demand for oil is inherently uncertain and volatile and will be modeled as exogenous. Second, supply adjusts slowly to new entrants because of the time it takes to build a ship (one to three years (Stopford, 2010)) and therefore market entry can be excluded from the short-run framework. While in the market ships have the option to go into lay-up, this typically represents a small percentage of the fleet, and therefore the model will focus on changes in supply through operating speed and locational choice.

In Chapter 4, I present the model structure which is divided into a static and dynamic matching model. A matching model is one theoretical framework for modeling the equilibrium formation of prices and can be used to explain the earnings of buyers and sellers when they form a contract together. In the model, firms are ships. Earnings are endogenously determined each period in a transferable utility matching game solved by maximizing the social welfare of the global tanker shipping industry which is equivalent to computing the competitive equilibrium. The game allows traders and shipowners to be unmatched and for different decision making approaches - quasi-myopic and forward looking. The method builds on previous work of single agent optimization (Rust (1987) and Devanney (1971)) and Chiappori et al. (2009) on matching models. The model is flexible to allow ships to adjust their speed in the matched and unmatched portions of their journeys. The modeling work is segmented into three parts. The baseline model focuses on understanding the spatial dimension of the global tanker shipping market by differentiating ships by their geographical location, holding physical characteristics constant in a static framework. It also aims to understand how the characterization of different agent beliefs affects the matching. This baseline model is used to simulate transitory changes to the market. The model is then extended to a multi-dimensional space in which ships are differentiated by their geographical location and physical characteristics. The third variation is exploring the dynamics of tanker shipping by modeling the baseline matching model in a dynamic setting which allows the simulation of permanent changes such as a demand shock and a carbon tax.

In Chapter 5 I describe the five datasets that were used to estimate the model and discusses the uncertainty of the data. The model focuses on a particular subset of the tanker shipping market - the Very Large Crude Carrier (VLCC) market - which is the largest size class of tanker ships. The model is estimated using a dataset which combines a sample of data on VLCC shipment transactions, data on the technical specifications of the tanker fleet, aggregate trade data, and prices on routes. In Chapter 6, I describe the estimation strategy and the inputs to the model as described in Chapter 5. In Chapter 7, I present the results of the static and dynamic matching models. Finally, I provide a discussion of the insights gained from the model results, their contribution to the literature and their limitations in Chapter 8.

Chapter 2

Literature review

Research in maritime economics has been devoted to understanding the equilibrium formation of freight rates and the interdependence between the freight rate and the ship market which includes the second hand, newbuild and scrapping markets. The first section presents a review of the approaches used in the maritime economics literature with a focus on the modeling of the freight market in the short-run.[1] The second section discusses methods used to solve resource allocation problems including matching models, transportation optimization models, and dynamic models. Finally, the last section concludes by summarizing the main gaps in the literature and need for micro level modeling of the matching of ships to traders.

2.1 Maritime economics literature

Previous models of the freight market can be divided into two types: aggregate structural models and reduced form models. Earlier models of the freight market followed a classical supply/demand aggregate model. Estimation of the freight rate using this approach employed a structural econometric model, typically assuming inelastic demand and instantaneous market clearing (Tinbergen, 1931, 1934; Koopmans, 1939; Norman and Wergeland, 1981; Wergeland, 1981; Hawdon, 1978; Beenstock and Vergottis, 1993). These models were incapable of replicating the short-run volatility in the freight rate. Later structural freight rate models tried to capture volatility in the freight rate (Tvedt, 1996; 2003; Engelen et al., 2006; Adland and Strandenes, 2007; Furset and Hordnes, 2013) by incorporating a stochastic element in demand and activity in the ship market using monthly rather than annual data. The advancement of econometric techniques changed the focus of researchers' attention to modeling the freight rate using reduced form models. These models were either autoregressive or multivariate (Lundgren, 1996; Clark et al., 2004; Hummels, 2007; Beverelli, 2010; Alizadeh and Talley, 2011, among others). Autogressive models were applied in order to understand the time series prop-

[1] In the short-run, capital is fixed, but ship owners can change their output by adjusting their speed, changing their route, or going into lay-up.

erties and stochastic nature of the freight rate, while more general multivariate reduced form models were used to understand the micro-level determinants of the freight rate, including the variation in prices observed across different trade routes.

2.1.1 Structural models

As discussed in the introduction, earlier studies employing an aggregate structural approach do not investigate the impact of the distribution of supply and demand for transport in different regions in order to understand how supply equilibrates with demand. Instead, there is one trade route and a single market clearing price which is equal to the marginal cost of the last unit of transportation required to meet aggregate transport demand. The assumption of one trade route inherently ignores the fact that competitors in the spot market are geographically distinguishable. Studies providing justification for this simplification either explained that trade was dominated by one route (Devanney, 1971) or assumed that the market is efficient (Evans, 1994; Strandenes, 1999).

The market efficiency hypothesis (EMH), developed by Eugene Fama (Fama, 1970) asserts that financial markets are "informationally efficient" and as a consequence, one cannot consistently achieve returns in excess of average market returns on a risk-adjusted basis. This is because prices on traded assets are assumed to already reflect all publicly available information and instantly change to reflect publicly available new information. If the notion of market efficiency prevails in the freight market, then no arbitrage profit can be made by trading in different shipping markets and therefore ship owners earn the same profits on each route. This statement contradicts the persistent differences in earnings across shipping markets observed in the data (Clarkson Research, 2012a; Adland, 2012). Adland and Strandenes (2006) provide the example of the impact of a public announcement from the cartel of Organization of Petroleum Exporting Countries (OPEC) on the intention to reduce the output of oil in three months time. While this is public information, the "current spot freight rate for large tankers need not reflect this information, as the spot freight rate is a result of the near-term (in the order of weeks) effective supply of ships and cargoes in a given loading area."

As a consequence of assuming one trade route, there is no modeling of ship owners' opportunity costs to relocate to another area. This provides a very limited picture of the drivers of ship movements, which can quickly adjust to short term market trends (Kaluza et al., 2010). Another drawback which was previously discussed is the long time horizon of the models, such that the short-run impact of changes in supply/demand (between weeks for example) on freight rates is overlooked.

In addition to the limitations on the supply side, demand is typically modeled as completely inelastic. This is based on the fact that on some routes there is no modal substitute and freight rates constitute only a small fraction of the final good price. This assumption is held to be sufficient as long as freight rates do not become very high relative to the value of the cargo. Koopmans (1939) points out that the pattern of oil trade is influenced by refineries' oil quality standards and trade agreements and these considerations would be relaxed at times when the freight rate represents a significant portion of the commodity value. Wergeland (1981) is one of the few studies to estimate the demand elasticity with respect to the freight rate. Using maximum likelihood estimation, he finds that aggregate transport demand is positively related to the level of world trade and negatively to freight rates, but the price elasticity of demand is very inelastic at -.007. However, there is no investigation of individual shippers' willingness to pay to understand the demand elasticity at high freight rate levels.

The theoretical aggregate model also ignores intertemporal decision making. Zannetos (1966) is one of the few authors to provide a theoretical framework for analyzing the impact of expectations on the inter-period substitution of shippers and shipowners. For example, if shippers believe that the change in prices in the future will be greater than the current increase in price, then they will rush to the market to secure tonnage which can lead to an increase in current period demand. Despite his insightful theory about inter-period substitution effects in the tanker market, he does not present a complete empirical model for spot rates which incorporates this theory.

By ignoring future periods, speed is modeled as a function of only the tradeoff between the ship's revenue and costs in the current period. Evans (1994) acknowledges that "shipowners should, if possible, take into account likely fixtures and estimated freight rates for consecutive voyages in determining optimum speed...actual steaming speed should be adjusted upwards or downwards in harmony with movements in the freight market whether or not a further fixture has been contracted." However, he then caveats his disregard of future periods in his optimum speed equation by stating that "it is doubtful, however, whether in practice such adjustments are generally made although the rational shipowner observing freight rates soaring would undoubtedly order his fleet to steam at maximum speed." Strandenes (1999) justifies using the same optimum speed irrespective of the trade route by stating that, "in equilibrium, the optimal speed for a vessel must be the same, irrespective of the actual trade. If not, the owner may profit from moving a vessel into a trade where optimum speed is higher, since higher speed increases the cargo lifted by the vessel in a specific period." Although studies have their own positive hypothesis about speed in the maritime economics literature, there has been no empirical investigation of tanker speeds to substantiate these claims.

The earlier aggregate structural models are estimated using an econometric structural approach. The short-run supply is specified to be a function of the annual operating fleet tonnage, variable operating costs, and the freight rate using data averaged over a long time horizon (quarterly or annual time interval). By assuming that the market clears and therefore supply and demand are equal, the freight rate can be solved in reduced form. The studies find world oil trade, the fleet tonnage and bunker prices to be determinants of the aggregate freight rate. Tinbergen's seminal contribution (Tinbergen, 1931) was to estimate the non-linear shape of the supply curve. Supply was determined by the fleet size, costs (using bunker prices as a proxy), and the freight rate. Beenstock and Vergottis (1993) show that the implied elasticities derived from Tinbergen's supply equation are .94 for fleet size, -.23 for bunker prices, and 0.59 for freight rates implying almost unit elasticity with respect to the fleet and a negative relationship between bunker prices and supply.

A few academic works have attempted to capture both supply-side information and the stochastic nature of the freight rate using a stochastic structural model (Tvedt, 1996; 2003; Engelen et al., 2006; Adland and Strandenes, 2007; Furset and Hordnes, 2013). Instead of applying an econometric approach to estimate supply, the supply curve is estimated using data on the fleet's technical specifications to determine the implied tonnage supplied to the market at different freight rates. This approach has the same theoretical framework as the classical supply/demand model, assuming there is one benchmark trade route so that the potential for geographical arbitrage in freight rates is ignored and allows such models to measure the supply curve in deadweight tonnage units. In these models, volatility is included in the freight rate through a stochastic element in the demand function and the ship market (aggregate newbuilding/scrapping). While these aggregate forecasts of the freight rate could be insightful for long-run investment purposes, they are not useful for predicting the short-run and often abrupt changes in the freight rate and for understanding differences in freight rates across different trade routes.

2.1.2 Reduced form models

Inspired by the developments of financial economics, a number of studies beginning in the 1990s applied reduced form autoregressive models to model the freight rate (Dixit and Pindyck, 1994; Bjerksund and Ekern, 1995; Tvedt, 1997; Veenstra, 1997; Adland and Cullinane, 2005). One of the objectives of these models is to understand the statistical properties of the data, including testing for stationarity and cointegration between the spot freight rate and other variables (see Glen and Martin, 2005 for a survey). This required examining the data at more frequent time intervals (quarterly and monthly). However, the reliance on autoregessive models disregards important supply-side information about the geographical distribution of ships, size of the order book, and stock characteristics (capacity of the fleet, age, and average speed) which lessens the predictive capability of these models.

A more recent reduced form approach (Lundgren, 1996; Clark et al., 2004; Hummels, 2007; Mirza and Zitouna, 2009; Beverelli, 2010; Alizadeh and Talley, 2011) has been to model the freight rate as a function of a number of exogenous explanatory variables. Variables used to explain the freight rate include (a) demand for shipping services (volume of trade and macroeconomic variables such as industrial production); (b) supply side variables (global fleet size for the relevant vessel type, distance, oil price); (c) product characteristics (the value of the good, the ad-valorem tariff, the elasticity of import demand); (d) market structure variables (number of firms operating on a route); (e) institutional variables (legislation, regulation and bilateral trade agreements); and (f) route specific effects. Only a few of these studies applied to bulk shipping have investigated the microeconomic determinants of freight rates using specific vessel and voyage details. Beverelli (2010) and Alizadeh and Talley (2011) both include tanker route specific dummy variables to understand the variation in prices across different routes controlling for other factors.

Alizadeh and Talley (2011) is the only study that incorporates both vessel and voyage details for estimating tanker freight rates. They estimate the Worldscale multiplier (see the glossary in Appendix A for the definition) on major tanker routes and find it can be explained by the Baltic Dirty Tanker Index (also known as BDTI, a price index of freight rates), the hull type of the ship, the utilization of the ship, the age, the volatility of the BDTI, and a route specific dummy variable to identify the route. However, they specify a separate regression to explain the days between the fixture date and the first day a ship can load the cargo, which is incorrectly defined as the laycan period. The system of simultaneous equations is solved using Three Stage Least Squares. For VLCCs, they find that there is a negative estimated coefficient for westward routes and the West Africa-China route compared to other routes which can be explained by the back haul opportunities. The multiplier discounts the benchmark rate (which is representative of the roundtrip cost) more than other routes. The paper has several limitations. First, they incorrectly explain the contractual process which renders their justification of a simultaneous relationship to be weak. Second, they do not discuss the problems arising from using censored fixture data collected by shipbrokers which has a potential to bias their results (Cridland, 2010). Third, there is no inclusion of the fuel price and time effects.

Several studies (Hawdon, 1978; Beenstock and Vergottis, 1993; Lundgren, 1996; Hummels, 2007; Poulakidas and Joutz, 2009; Mirza and Zitouna, 2010; Beverelli, 2010) have particularly focused on the link between oil prices or bunker prices and freight rates. Poulakidas and Joutz (2009) model the West Africa-United States Gulf spot tanker rates as a function of the West Texas intermediate crude oil spot prices, 3-months futures contract rates and the United States weekly petroleum inventories using a Vector Autoregression model. They find that the increase in demand for oil increases tanker demand which increases tanker rates. Second, when the spread between the 3-month futures contract is trading above the spot price there is upward pressure on tanker rates. Third, when the day's supply of crude oil inventories increases, the spot tanker rate declines.

Glen and Martin (2005) discuss the difficulty in predicting a priori the correlation between tanker freight rates and oil prices in a reduced form model. This is because a rise in oil price could be caused by an increase in demand or a reduction in the supply of oil due to a shock to the overall world supply. The former would increase demand for transportation, resulting in a positive association, whereas the latter could lead to a fall in the demand for oil transport and an expected fall in the freight rate. There is also complexity in understanding this relationship given the correlation between oil prices and bunker prices as bunker fuel is a derivative of the crude oil refining process (UNCTAD, 2013). However, movements in the bunker price are also determined by other factors, such as growing demand for bunkers from the world fleet and refinery distillate processing (Clarkson Research, 2012c). Finally, the reduced form model can only test the relationship between freight rates and oil/bunker prices within the variation of historical data. Given the nonlinearities in the supply curve, the freight rate elasticity with respect to the bunker price would not necessarily hold outside the region of historical variation and therefore cannot be used to simulate a radical change in the bunker price. Given the magnitude of the change in bunker prices in recent years and shipowners' dependence on bunker fuel to propel their ships, this is an important area of research.

2.2 Resource allocation models

Resource allocation models are concerned with understanding the efficient allocation of goods to people and in some cases, the process through which equilibrium prices are formed for these goods. These models have a rich history in economics and operations research because they provide a way to analyze the way in which people may have different preferences for goods, how prices can decentralize the allocation of goods to people, and the way in which these prices can lead to a socially optimal outcome. There are three classes of models I will discuss: transportation optimization models, dynamic economic models and matching models.

2.2.1 Transportation optimization models

Transportation optimization models are used in the operations research literature to match resources (trucks, cars, planes) to tasks (transportation of cargo) where these entities have a number of attributes. In this formulation, each driver and load is represented individually, making it possible to capture attributes of each driver (number of miles to travel to pick up the load, ability to pick up on time, etc.) and load (location, etc.) at a high level of detail.

There has been little application of the resource allocation problem in shipping that focuses on the spot market for bulk shipping (also referred to as tramp shipping). Instead, the majority of research in this domain has applied optimization models to industrial shipping applications in which the shipper is also the shipowner and therefore the objective is to schedule vessels in the most cost efficient way (see Christiansen et al. (2004) for a survey of these models). The possible reasons for the lack of research on tramp shipping optimization models include the shipping industry having had a long tradition for manual routing based more on a "gut" feel for the market, the industry is highly secretive about their strategies, and there are a large number of small operators who do not have the resources for research (Christiansen et al., 2004). Studies that have applied optimization methods to tramp shipping (Appelgren, 1969, 1971; Bausch et al., 1998; Fagerholt, 2004) have focused on the problem of scheduling long-term contracted cargoes and optional cargoes that become available on the spot market. While the formulation includes realistic geographical routing characteristic of the bulk shipping market, it is not designed to model the equilibrium price in the spot market for bulk shipping nor the interactions between different agents because it focuses on the operations of one shipping company. Furthermore, the models are static assignment problems which contain no value of future periods. This is problematic considering the need to anticipate future demands when repositioning resources.

Transportation assignment problems can also have a time dimension. In a dynamic setting, information about resources and tasks changes over time, and decisions have to balance profits now and in the future (Psaraftis, 1988; Spivey and Powell, 2004). In these problems, a value function known as Bellman's equation (Bellman, 1957; Dixit and Pindyk, 1994) is used to represent both the current period's profits and the value of expected future profits. The problem is solved recursively using dynamic programming, a method which breaks the problem up into a number of sequential decisions. This problem can suffer from the "curse of dimensionality" if the state space is too large. Devanney (1971) uses dynamic programming to solve for the optimal operating decision for a ship owner where the decisions include time chartering a ship, transacting in the spot market, going into lay-up or scrapping the ship in each time period. He avoids the curse of dimensionality by reducing the spatial dimension to one trade route and assumes inelastic demand.

Approximate Dynamic Programming has emerged as a powerful technique for solving dynamic programs that would otherwise be computationally intractable given their large state space (Powell, 2011). Simao et al. (2008) apply this technique to a large-scale trucking fleet management problem. The model differentiates trucks by a number of attributes, including location. The objective is to build a model that closely matches the actual operational statistics of a company's truck driver movements of loads over time. The model maximizes the expected sum of all the profits generated by matching trucks to cargo loads, where the profit includes an approximation of the Bellman equation and is solved using linear programming. Although these models provide insight into the actual movements of resources over time and include expectations about earnings in future periods, they are not designed to model a market and have a limited representation of demand. Demand is represented by "loads" which arrive continuously and randomly and therefore there is no representation of the decisions of the buyer.

Several studies in the operations research literature have focused on determining the optimal speed of ships given its significance in determining profits over the voyages of ships. Ronen (1982) determines a daily optimal speed which is dependent on whether the ship is in an income generating leg (transiting from a load area to a discharge area) or a repositioning (ballast) leg. Similar to the optimal speed function in the aggregate model, he solves for the optimal speed in the income generating leg by assuming that income (and hence the freight rate) is independent of speed, thereby ignoring the possibility that income is endogenously determined by the speed. In addition, there is no consideration of the influence of future periods on speed. In the ballast leg, the problem is formulated to minimize costs, which includes the daily alternative value of the ship in order to factor in the opportunity cost of slow steaming. Devanney (2010) follows a similar approach for optimizing speed on a single trade route. In both approaches, the opportunity cost is a constant value, such that there is no consideration of the state of shipping markets in different regions.

2.2.2 Dynamic economic models

Dynamic programming has also had a long tradition in economics for solving problems of optimization over time. There is a large body of research focusing on the estimation of dynamic economic models, such as Conrad and Clarke (1987), Rust (1987), Hotz and Miller (1993), Adda and Cooper (2003) on single agent dynamics and Bajari, Benkard and Levin (2008), Pakes (2007), Aguirregabiria and Mira (2007), Jofre-Bonet and Pesendorfer (2003) and others on dynamic games. The main focus of these papers is on the drivers of the decision to enter and exit a market in strategic settings of imperfect competition where there are multiple equilibria. Estimated per period payoffs are used to recover value functions, which in turn give values for entry, exit, prices and quantities. Kalouptsidi (2013) is the only application of a dynamic game to the bulk shipping market, but her focus is on the impact of demand uncertainty and time to build on investment and ship prices rather than freight market dynamics.

2.2.3 Matching models

Matching models with transferable utility are used to understand who matches with whom when the population of buyers and sellers is heterogenous. Associated with each match is a gain or economic surplus which is match-specific. This gain is not only a function of the characteristics of the buyer and seller forming a match but also the distribution of supply and demand in the market. Therefore the bargaining power between the pair is endogenized (Chiappori et al., 2009). There is a large body of literature studying matching models with transferable utility in marriage markets, labor markets and the matching of students to schools (Gale and Shapley, 1962; Roth and Sotomayor, 1990; Kelso and Crawford, 1982; Mortensen and Pissarides, 1994; Diaz and Jerez, 2013).

The seminal paper in matching models was Koopman and Beckman's 1957 paper on Assignment Problems and the Location of Economic Activities (Koopmans and Beckman, 1957). This paper develops methods for solving and analyzing problems in the efficient allocation of indivisible resources using linear programming. They show that there are prices associated with the solution to this linear assignment problem which have the property of preserving the optimal assignment under decentralized profit-maximizing decision making. For this property to hold, it must be the case that the market is competitive. Another assumption in matching markets with transferable utility is there are personalized prices because they allow bilateral-specific utility. The most popular metric is maximizing the sum of all individuals' valuations or the social welfare of the group in the matching. Although this mechanism maximizes the total utility, this does not mean that this will give everyone their preferred object; it therefore must allow agents to make transfers amongst themselves.

The equilibrium concept in matching models is stability. This concept was formalized when two mathematical economists, David Gale and Lloyd Shapley (Gale and Shapley, 1962), asked the question about whether it would be possible to design a college admission process that was self-enforcing. What they meant by self-enforcing was there was a matching (in this case, colleges to students) that lead to stable assignments, such that no one would want to deviate from their existing pairings.

General methods for solving static matching problems can be broken into two problem types. In the first method, only one buyer can be assigned to one seller. Linear integer programming can be used to solve this type of linear assignment problem to ensure these constraints are met (Matousek and Gartner, 2007). The second method relaxes this restriction using linear programming (LP), which dates back to mathematicians Gaspard Monge (1781) and Kantorovich (1958) who won the nobel prize in 1975 for using LP to solve resource allocation problems related to transportation. The technique was introduced to reduce the computational time of the solution. The Monge-Kantorovich transportation problem changes the interpretation of a one-to-one matching or assignment problem to allow fractional assignments. Thus LP problems are suitable when a buyer may be matched to multiple sellers and vice versa; shipping is a natural application because ships can load multiple cargoes in different locations up to their capacity. Chiappori et al. (2009) show there is equivalency between a matching model with transferable utility and an optimal transportation linear programming problem.

Although it has been recognized that models examining how buyers and sellers trade with each other would be useful to explain the pricing in the spot market for bulk shipping (Adland and Strandenes, 2007), actual modeling is sparse. A recent paper by Tvedt (2011) uses a matching model to derive a short-run equilibrium freight rate in the VLCC market, including some aspects of the bargaining process. However, the model is simplistic in that it only considers one representative trade - all vessels sailing to AG at a constant speed - whereas the shipping sector is global and speeds can potentially vary a lot. In addition, demand is assumed to be completely inelastic such that there is no consideration of intertemporal decision making.

2.3 Summary of the literature

Previous approaches in maritime economics contain a number of simplifying assumptions that limit their usefulness to describe supply, demand and hence the equilibrium freight rate. Specifically, aggregate structural models (including stochastic partial equilibrium models) do not model the distribution of supply and demand in different shipping markets, intertemporal decision making of agents, willingness to pay for the shipping service, nor the expectations of agents in the freight market in one framework. Time series models disregard important supply-side information which lessens the predictive capability of these models. Finally, reduced form models only model the marginal effects of variables on the freight rate and cannot explain how radical changes in these variables (such as the fuel price) might affect both the freight rate and ship movements.

In addition to the limitations on modeling the equilibrium freight rate, the aforementioned models of the freight market cannot explain the characteristics that lead certain agents to match with each other. Understanding these matches (and therefore who is unmatched), can also provide useful information on ship movements (and therefore loaded and ballast days), the implied supply of ships in each area, and the earnings of each agent as a function of their bargaining power. There has been renewed interest in applying matching models to markets with contracts. A class of these models uses linear programming which makes it possible to model transportation problems at the micro level, taking into account the impact of future information on the current decision. This level of detail, common in transportation optimization models, is important for understanding whether agents are forward-looking in the tanker market and to model the impact of radical changes on the shipping system and for fundamental purposes has not been satisfied by existing approaches.

Chapter 3

Description of the Industry

This chapter describes the tanker industry in the context of the crude oil and Very Large Crude Carrier (VLCC) shipping markets and provides the basis for formulating the structure of the model. The discussion is divided into two parts. The first part uses quantitative data to describe the demand side for crude oil and crude oil transportation and the supply side of the tanker market, examining the tanker fleet and tanker market structure, the types of tanker shipping contracts and the factors influencing the short-run and long-run supply of tanker shipping. The demand side of the market for crude oil is important because it influences an oil traders' willingness to pay for oil transportation. The second part uses qualitative data from industry interviews that were conducted with two companies in the shipping industry as part of this study to corroborate and enhance the quantitative analysis of the industry.

3.1 Demand for crude oil

3.1.1 Crude oil trade

The demand for shipping oil is derived from world demand for oil which cannot be met by domestic production or pipeline supply. At the buyer end of the crude oil market are refineries who refine crude oil and at the seller side of the spectrum are oil producers. The flow of crude oil from producer to end user can be described using a number of layers of analysis starting with actual oil production (the first layer). The second layer is the mapping from oil producers to exporters, and the third layer is determining how much oil is shipped by pipeline and ship.

3.1.1.1 Sources

Figure 3.1 shows the oil producers [1] by region in 2011. The Middle East is the largest producer, producing a third of total oil production, followed by Europe and Eurasia (which includes Russia) at 21.0%, North America (16.8%), Africa (10.4%), Asia Pacific (9.7%), and South and

[1] Includes crude oil, shale oil, oil sands and NGLs (the liquid content of natural gas where this is recovered separately).

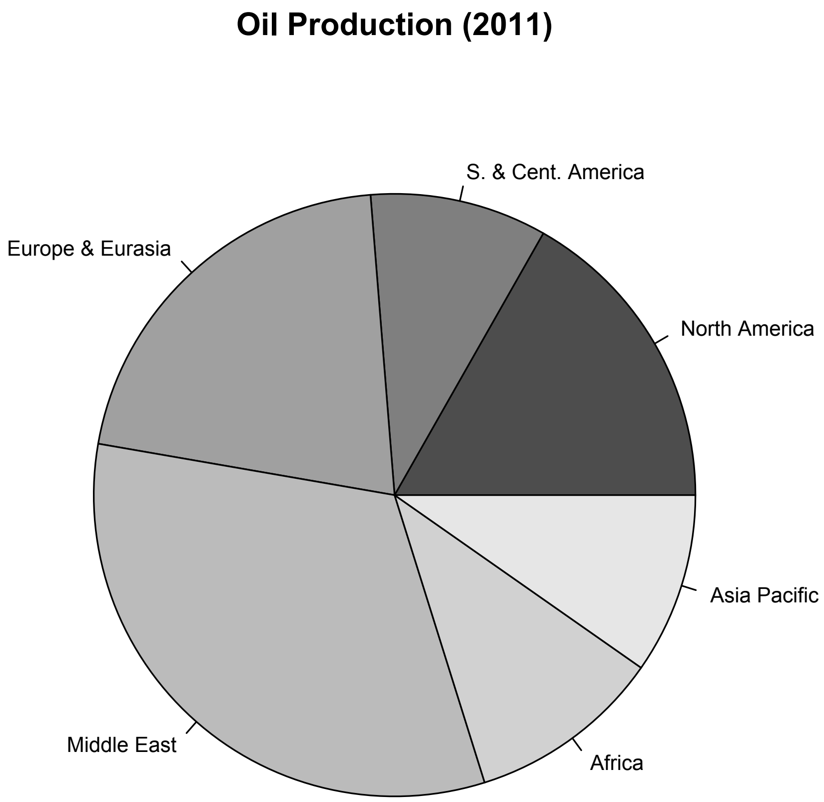


Figure 3.1: Share of Oil Production by Region. Source: BP, 2012.

Central America (9.5%). The main use of crude oil is as an input to be processed into refined products such as gasoline for the transportation sector and ethylene for the petrochemical sector. The intensity of the refining process depends on the type of crude oil. Crude oil comes in different grades, classified by its gravity and sulphur content, where oil that is lighter (high gravity) and contains less sulphur is more valuable. Low sulphur oils are referred to as sweet crude oils, whereas oil with a relatively high sulphur content are referred to as sour crude oils.

Table 3.1 shows crude oil imports and exports by region and selected countries in 2011. The top three importers of crude oil are Europe (24.5%), the US (23.5%), and China (13.4%), while the top three exporters of crude oil are the Middle East (46.4%), Russia (16.9%) and West Africa (11.8%).

The third layer maps exports of oil into sea and pipeline. Russia exports most of its oil via pipeline to Europe and Canada to the U.S. Therefore the largest exporters of total seaborne crude oil are the Middle East, West Africa, and South & Central America.

Table 3.1: Crude Oil Imports and Exports in 2011

	Crude Imports	Share	Crude Exports	Share
Country/Region	Million Tonnes	%	Million Tonnes	%
US	445.0	23.49	1.0	0.05
Canada	26.6	1.40	111.7	5.89
Mexico	-	-	67.5	3.56
S. & Cent. America	18.7	0.98	139.0	7.33
Europe	464.2	24.50	12.9	0.68
Former Soviet Union	-	-	319.3	16.85
Middle East	10.7	0.56	879.4	46.41
North Africa	21.0	1.11	72.3	3.81
West Africa	-	-	224.1	11.83
East & Southern Africa	2.4	0.13	16.6	0.88
Australasia	26.8	1.41	14.2	0.75
China	252.9	13.35	1.5	0.08
India	169.7	8.96	0.1	0.00
Japan	177.3	9.36	-	
Singapore	55.1	2.91	0.7	0.04
Other Asia Pacific	224.4	11.84	34.3	1.81
Total World	**1894.7**		**1894.7**	

Source: BP, 2012.
Tonnes=metric tonnes

3.1.1.2 Sinks

Oil demand growth is largely now centered in the transportation sector, which accounted for 61.5% of total consumption in 2010 (IEA, 2012a), given the rise in global motorization and freight transport and the fuel limited substitution possibilities. Geographically, global oil demand has shifted to non-OECD countries as shown in Figure 3.3 as disposable income in Asia and South America has risen. The Asia Pacific region surpassed North America as the largest consumer of oil in 2004. China's consumption dominates the region, with an extensive refinery building program underway and is expected to match US oil consumption within the current decade (Braemar Market Insight, 2012). At the same time, the US has increased its domestic production and sourced oil from Canadian tar sands production.

The shift in demand to the Far East has implications for tanker tonne-miles; a journey from Ras Tanura, Saudi Arabia to LOOP, US is 13,424 nautical miles (via the Cape of Hope) or about 41 days, whereas a journey from Ras Tanura to Ningbo, China is 5717 nautical miles or about 18 days. In 2001, the Middle East's share of oil exports to the US and Europe was 14.6% and 18.6%; by 2010 these shares decreased to 9.2% and 12.5%, respectively (BP, 2012). Meanwhile, China's share increased from a meager 3.6% to 12.7% in 2010.

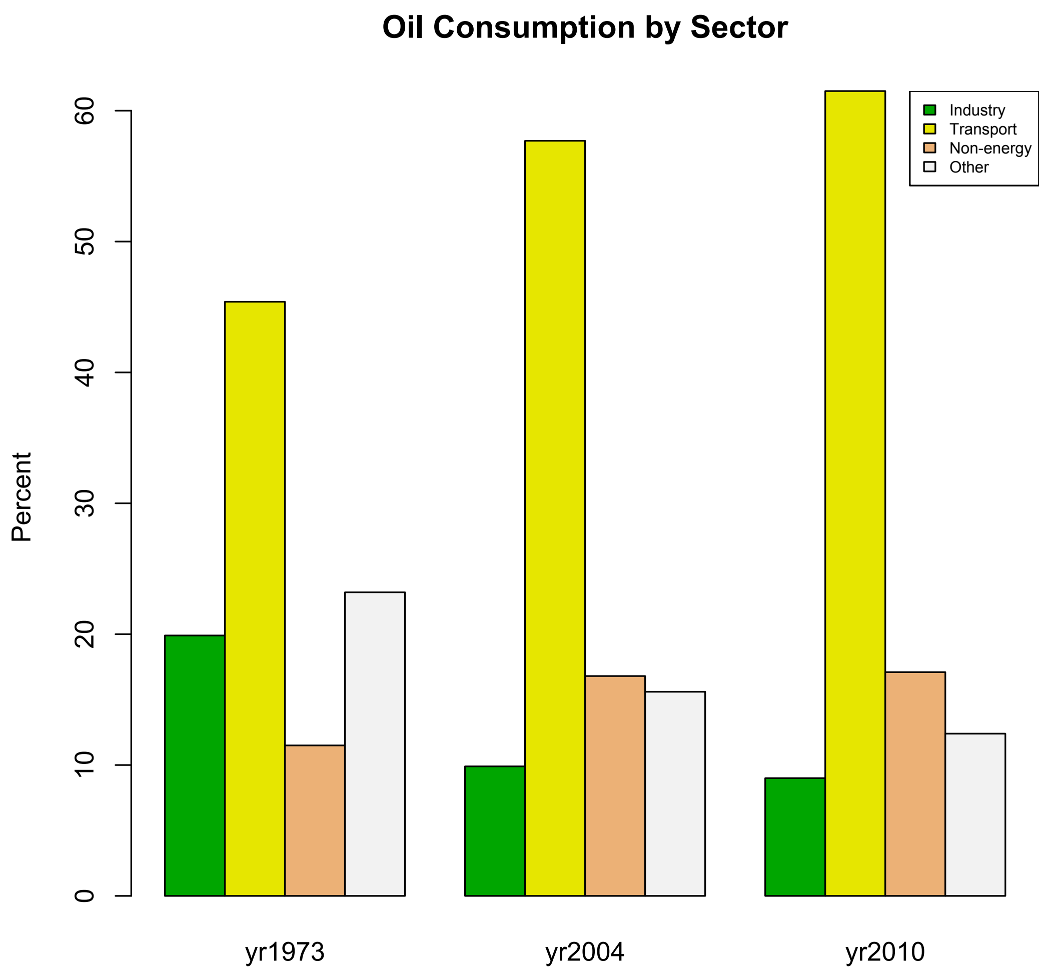


Figure 3.2: Source: IEA, 2012.

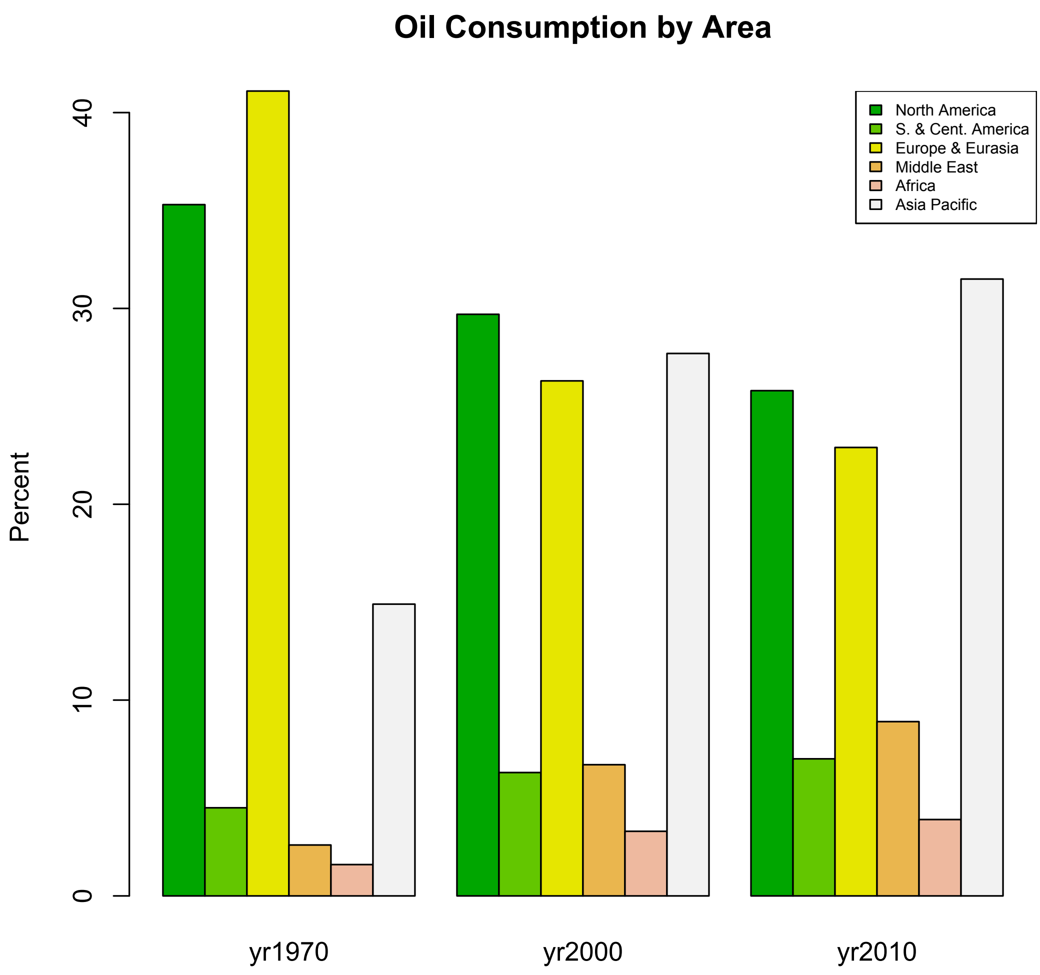


Figure 3.3: Source: BP, 2012.

3.2 Crude oil pricing and trading

The pricing of oil in the 1960's and 70's was based on a fixed pricing system by OPEC. The oil price shock in 1973 led refiners to diversify their portfolio of oil sources which was enabled by the oversupplied oil market in the 1980's. This initiated oil spot trading, also called physical markets, which eliminated price controls by the producer and gave more control to the consumers (Fattouh, 2011). The emergence of spot markets attracted a large number of oil traders from oil trading houses and more recently hedge funds - who act as intermediaries, buying oil from oil producers and selling it to refineries.

The price of a particular crude oil sold by a producer is set at a premium or discount compared to a benchmark crude. The differential between the reference price and the agreed price is often agreed at the time when the deal is concluded and could be set by an oil exporting country or assessed by a price reporting agency (Fattouh, 2011). There are three benchmarks used to set prices: Brent crude oil, West Texas Intermediate (WTI), and Dubai Mercantile Exchange (DME) Oman. Each has its own associated futures exchange used for pricing in different markets. These benchmark prices are identified or assessed prices carried out by oil pricing reporting agencies (namely Platts and Argus) which is required because not all bilateral transactions are observed.

All crude oil is not created equally; oil is differentiated by its gravity and sulphur content. Crude oils that are light (higher degrees of gravity) and sweet (low sulphur content) are usually priced at a premium to heavy, sour (high sulphur content) crude oil grades because they require less refining to turn them into products. A general trend is the standardization of the grade of fuel, though there is still much variation due to different country regulations and refiners' technology. When a buyer of crude oil trades with a seller, the parties have to decide the grade of the oil, the volume, which party is responsible for shipping it, what the payment terms are, the basis of pricing and payment and the person responsible for quality assurance of the oil grade (Chapplow, 2013).

Although the spot market has increased the liquidity of the market, it has also introduced more volatility in the oil price (Benigni, 2007; Ellefsen, 2010) which can sometimes be extreme in the oil markets (Figure 3.4).

This is particularly problematic due to the long delivery time (sometimes more than a month) involved between when an oil cargo transaction is completed, loaded onto a ship and delivered to a discharge port. The risk of the price changing between when a cargo is purchased and sold has lead to the emergence of hedging techniques known as derivatives (Downey, 2009). Derivatives help to protect physical barrels from price volatility by locking in a price in the

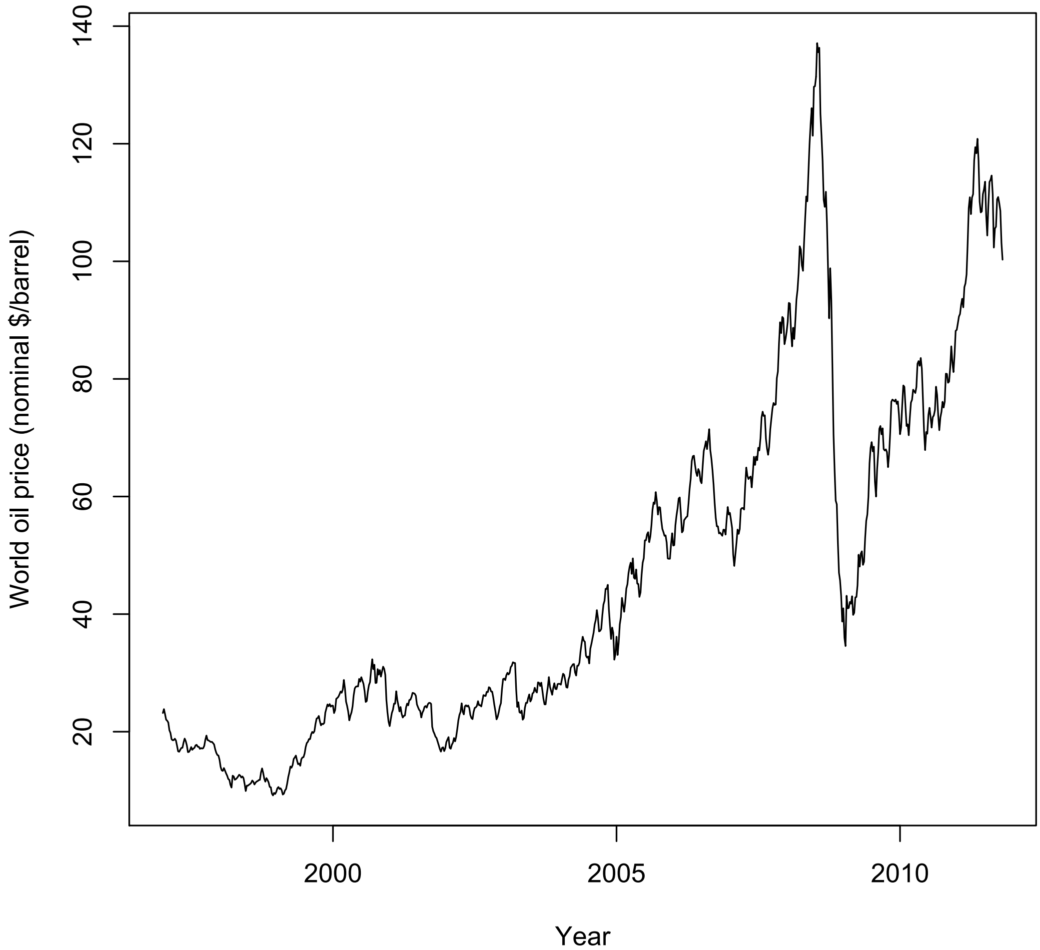


Figure 3.4: World Oil Price (Source: Energy Information Administration, 2011.)

future. Typical derivatives in the oil market are forward contracts, swaps, and future contracts and their value depends on the underlying market structure of the oil market. The most common derivative in the physical market are forward contracts, which are privately negotiated over-the-counter (OTC) transactions in which a buyer and a seller of an oil cargo agree on a price and a delivery date and there is a commitment to deliver the cargo at a specified forward price (which can be agreed upon in advance or at the time of delivery). Delivery is usually between 1 and 45 business days after the trade date (Reuters, 2000). The contract is settled in cash using a physical price index, such as Platt's Crude Oil price.

Another common type of derivative to hedge against the oil price is a futures contract. The futures market trades oil much like stocks. They are traded on an exchange and change owners very quickly and physical delivery is rare (Reuters, 2000). Although oil futures rarely take physical delivery, they are useful market indicators, conveying information about the current state of the market and of market expectations. A buyer of a futures contract is betting that the future spot price will increase, while a seller bets that it will decrease. The term structure of prices for future delivery - between for example the price of the front month and twelfth month futures contracts - is one key indicator of market participants' expectations. There are two trading strategies according to the difference between the spot and futures price. If the spot price is trading at a premium to the futures (or forward) price, the market is described as "backwardation" and there is tightness in the current market. The tightness is caused by some risk or fear in the market, and this causes oil to be bought today rather than a few years in the future, driving up the current price. If the spot price is trading at a discount to the futures (or forward) price, then the market is described as "contango." The latter effect causes oil traders to hoard oil until the spot price increases above the futures price, either by storing it in tanks at the destination port or delaying the ship's arrival into port by hiring the vessel for additional days (called offshore floating storage) (Krauss, 2009). In this case, if the ship's delivery date has expired, the trader is responsible for paying demurrage. Demurrage rates depend on the strength of the tanker market. A decrease in the spot oil price in the future provides an incentive for the oil trader to wait. Therefore volatility has an impact on the trader's option value of waiting, trader revenues, the number of traders demanding oil in each period and the importance of demurrage.

Although the majority of crude oil trading is through forward contracts (Chapplow, 2013), another contractual arrangement is a long-term contract (Fattouh, 2011). These contracts are negotiated between buyers and sellers for the delivery of a series of oil shipments over a period of time, usually one or two years. They specify the parcel size to be delivered, the delivery schedule, the actions to be taken in case of a default, and the pricing method for the oil shipment. Oil companies supplying crude oil to their refineries will use these types of contracts.

3.3 Market structure, tanker shipping contracts, and supply side factors

3.3.1 Tanker fleet and market structure

The majority of tanker shipments are for crude oil, reflecting the location of refineries which are typically near consumption areas. The total volume of global crude-oil shipments reached 55.3 million bpd in 2012. Crude oil carried on board tankers accounted for two thirds of this total with a total volume of 1.78 billion tonnes in 2012 (UNCTAD, 2013).

There are five ship size categories, ranging from about 50,000 to around 450,000 deadweight tonnes (DWT): Handymax (50,000 or less), Panamax (50,001-80,000), Aframax (80,001-120,000), Suezmax (120,0001-200,000), and VLCC (200,000 +). Table 3.2 shows that of the 492 million tonnes of capacity in 2012[2], VLCCs accounted for 37.9% and 52.3% of tanker capacity transporting crude oil.[3]

Table 3.2: Tanker fleet composition (m.Dwt)

	2008	2009	2010	2011	2012 (Dec 1)	No. in 2012
VLCC (200,000+)	151.7	159.6	163.2	176.1	186.3	609
Suezmax (120-200,000)	54.6	59.1	63	68.5	72.5	469
Aframax (80-120,000)	81	87.8	93.1	96.6	97.4	911
Panamax (60-80,000)	26	27.4	28.2	29.4	30.1	417
Small (10-60,000)	90.1	97.6	101.1	104.1	105.8	3351
Total (m.Dwt)	403.4	431.5	448.6	474.7	492.1	5757
VLCC total share (%)	37.6	37.0	36.4	37.1	37.9	10.6
VLCC crude tanker share (%)	52.8	52.1	51.1	51.6	52.3	30.6

Source: Clarkson Research, 2012b.

The shipping industry treats each size class as a different shipping markets. Vessels in different size categories vary in the type of product they carry, the routes they take, and the trade flows they serve. Economies of scale make larger vessels more fuel efficient per tonne-mile, but the length of the route, port and canal constraints, and shippers' cargo size preferences

[2]As of December 1, 2012.

[3]Suezmax and Aframax tankers also transport crude oil.

means there are different optimum sizes for trade routes according to these parameters. Larger ships dominate long haul routes where fuel costs account for a larger proportion of operating costs. However the size restrictions of many ports limits VLCCs geographical coverage. Data from Clarkson Research (2012b) shows that the tanker industry has around 1,750 firms, with the largest firm, Mitsui O.S.K. Lines accounting for only 2.6% of total output. A large proportion of firms own only a few ships; seventy-five percent own 5 or fewer ships, with 42% owning only one ship. As such, some tanker companies pool their ships together to form tanker "pools" to operate as a fleet, sharing the profits of this joint operation. A subset of 129 firms own VLCCs; the largest firm is Mitsui which owns 4.9% of the fleet, followed by National Iranian Tanker at 3.8%. The industry is competitive in terms of the distribution of output shares. Lun et al. (2012) perform a detailed analysis of the tanker market and finds that there is competition in the spot market. Compared to other industries, the scope for ships to differentiate themselves is much narrower. Ships differ by age, the shipyard where it was built, the reputation of the shipowner, their energy efficiency, and their geographical location. Because of the spatial dispersion of ships across different locations and the time preference of shippers, there are situations when ships can take advantage of other ships' being farther away in order to strategically price their service above marginal cost.

3.3.2 Tanker shipping contracts

3.3.2.1 Types of contracts

Shipping market contracts, also referred to as "charters", are negotiated between the shipper which requires transportation of oil between two ports, and the "carrier", typically the shipowner. A charterer arranges the transportation required by the shipper. In practice, there are a number of different types of contracts in shipping, including spot contracts, forward contracts, and medium to long-term contracts which involve different arrangements between the charterer and shipowner. Spot contracts are negotiated within a short period of time (typically two days to two weeks) before the loading of the cargo. The loading date can be up to 6 weeks in the future from the fixture date so they operate like a forward market (Adland and Strandenes, 2007). Forward-contracts are similar to spot contracts but are negotiated farther in advance, usually a month or more before the agreed loading date. Medium contracts are typically arranged as time charters and long-term contracts are known as contracts of affreightment (see Stopford (2009) for an overview). In a time charter, the charterer hires a ship for a specified period of time (from a month to several years) and pays a fixed hire rate which includes the cost of crew. Similar to leasing a car, the charterer pays the fuel costs of journeys undertaken.

For this analysis, I will focus on the spot market, which is accounts for 70% of the fleet

(Stopford, 2009). Charterers can work for either an oil major - a vertically integrated company involved in exploration, production, refining, marketing - or a trading house and work closely with oil traders. Oil majors also own their own fleet of ships to transport a portion of the oil shipments they make. Brokers serve as intermediaries, working for either a charterer or a shipowner to communicate information about the market when fixing a ship and earn a commission from the deal. Charterers in tanker shipping are dominated by oil majors. These companies have a division for trading and shipping business operations. The core of their upstream business is to market crude oil and sell it for the highest negotiable price, purchase most of the crude oil used as a feedstock for their refineries, import and export petroleum products to align supply to local demand, and select and charter safety-vetted tankers to transport cargo to its destination without mishap.

In the spot market, a ship is "fixed" to transport cargo from A to B for a price per tonne (called a fixture) or a total freight rate in lumpsum dollars (Platts, 2012). The terms of the contract include a speed. In the current market, this is typically 13.5 knots with an option to speed up (though this option is getting less popular due to high bunker prices) (Shipbroker, 2011; Ship Operator, 2012). It is common practice to designate just the load area and discharge area at the time that the fixture is settled between the charterer and the shipowner (Downey, 2009). This allows the charterer the flexibility to decide on the exact port within the region later on. Ports are classified into regions according to their proximity to a common sea area, as opposed to regional definitions from the UN that are land-based, and region will be synonymous with area in this study. Tables 3.3 and 3.4 list the regions which are associated with VLCC tanker fixtures.

Table 3.3: Load Areas (VLCC class)

LoadArea	Name
AG	Arabian Gulf
ARG	Argentina
BALT	Baltic Sea
BRZ	Brazil
CAR	Caribbean
CMED	Central Mediterranean
ECC	East Coast Canada
ECMX	East Coast Mexico
EMED	Eastern Mediterranean
JAP	Japan
KOR	Korea
REDS	Red Sea
SPOR	South Pacific Oceania Region
UKC	United Kingdom Continent
USG	US Gulf
WAF	West Africa
WCSA	West Coast South Africa
WMED	Western Mediterranean

Source: Clarkson Research, 2011.

Table 3.4: Discharge Regions (VLCC class)

DischargeArea	Name
AG	Arabian Gulf
BRZ	Brazil
CALI	California
CAR	Caribbean
CMED	Central Mediteranean
ECC	East Coast Canada
ECI	East Coast India
EMED	Eastern Mediteranean
JAP	Japan
KOR	Korea
NCH	North China
PHIL	Philippines
REDS	Red Sea
SAF	South Africa
SCH	South China
SPATL	South Pacific Atlantic
SPOR	South Pacific Oceania Region
THAI	Thailand
TWN	Taiwan
UKC	United Kingdom Continent
USAC	US Atlantic
USG	US Gulf
WCI	West Coast India
WCSA	West Coast South Africa
WMED	Western Mediteranean

Source: Clarkson Research, 2011.

Due to port restrictions, VLCCs operate 18 load regions (17 regions less than other crude tankers) and 25 discharge regions (12 less than other crude tankers). Not all loading areas are near oil fields; some are connected to crude oil storage sites (i.e., Korea and Bahamas in the Caribbean).

3.3.2.2 Contract pricing

In the tanker spot market, the price for transporting cargo by tanker ship is called the freight rate and is normally expressed as a function of two components. The first is an annual benchmark called the Worldscale (WS) flat rate (nominal $ per tonne) to allow for an apples-to-apples comparison of different sized ships on roundtrip voyages. The rate represents the voyage costs for a standard vessel and is calculated on a roundtrip basis based on the assumption that the vessel will have to ballast to some other destination empty, although there is no obligation to sail back to the port of origin. The rate is determined by the distance, a standard vessel's fuel consumption, an average service speed, a benchmark bunker price, and the port costs for each combination of ports.

The second component of the freight rate is a Worldscale (WS) multiplier. The multiplier adjusts the flat rate. A WS multiplier of 100 equals the WS flat rate; a WS multiplier of 50 means the spot rate is one half of the flat rate. In contrast, a time charter rate is specified in $/day terms and reflects capital, operating costs and the prevailing market conditions. The spot and time charter markets are part of the same shipping market and shipowners often tradeoff between operating in the spot market and chartering out their vessels. Given the volatility in the spot freight rate, the spot market can be more risky but can be highly lucrative given good market conditions. A time charter contract is more stable as it locks in a fixed rate over a longer time period (6 months to 3 years normally) (Clarkson Research, 2012a).

It is common in shipping to report a Time-Charter Equivalent (TCE) Rate $/day as a way to compare the two markets. It is calculated by subtracting all voyages costs from all voyage revenue, and then dividing by the number of days in the voyage. TCE allows for a comparison of returns for different voyages for the same ship, or the same voyage completed by different ships. As the numbers being compared relate to the given voyage and not to items like how the ship was financed and make assumptions about the ballast voyage and speed, it does not give the actual earnings for a shipping company (Clarkson Research, 2012d).

Spot and charter contracts are arranged over the counter by brokers who serve as the interface between charterers and shipowners. The brokers' objective is to forge an agreement between the oil company and the shipowner at a mutually acceptable price. Often there are two brokers involved, one for each agent. Tvedt (2011) provides a description of the bargaining process. When a charterer needs a vessel for transportation of oil from a loading location to a refinery, it calls up a broker or a number of brokers, typically 15-20 days before it wants the cargo shipped as it might take that long to get a vessel to the loading area. The charterer's broker announces to its network of shipowner's brokers. The shipowner's brokers are in constant contact with the shipowners who advertise when their ships will be available. The shipowner's broker drafts a list of ships available in the market and gets an asking price (valid for a certain amount of time) from the shipowner, which it passes onto the charterer's broker. The game is now in the charterer's hands to come up with a counteroffer. Normally, a charterer will not accept the first offer, making counteroffers. Now it is the shipowner's turn to either accept the offer, continue bargaining, or work with another cargo. Part of a broker's job is to know the market conditions in order to offer advice. The ship's location, the ask prices from the other ships, time preference of shipowners and charterers as well as other cargoes, are all important factors in the bargaining process.

3.3.3 Supply side factors

3.3.3.1 Short-run supply

Supply in the short-run is determined by the number of voyages that shipowners carry out and is restricted by the current fleet stock. The number of voyages is influenced by voyage distance, route choice (where there are multiple routes between origin and destination), speed, and days in port. The major route choice for VLCCs is on westward journeys (i.e., from the Middle East to US Gulf), where ships can take either the Suez Canal or go around the Cape of Good Hope (tip of South Africa). Because of draught restrictions, the first option requires the ship to partially unload the cargo at the start of the Sumed pipeline in the Red Sea, transit the Suez, and pick up an equivalent shipment on the Mediterranean Coast. The second option is to sail a longer distance around the Cape of Good Hope.

Costs can be divided into fixed and variable costs. In a competitive market, agents supply to the market where marginal (variable) cost equals price. Based on Stopford (2009), operating costs are considered as fixed costs and will be treated as such in this analysis under the assumption that they are incurred regardless of whether a ship is employed. Voluntary insurance to cover piracy zones is assumed to be separate from general insurance because it depends on the voyage and will therefore be included in variable costs. Capital costs depend on the way the ship has been financed. Ships are a large upfront investment; the price of a new VLCC costs around \$100 million (Clarkson Research, 2012a). There are a variety of ways ships can be financed, including maritime funds, but on the whole, financing is through traditional owners' equity and senior-secured bank debt finance (O'Callahan, 2011). Shipowners often refer to their "break-even rate." This is a daily fixed cost rate which includes interest expense. For VLCCs, this rate was around \$30,100 per day in 2011 (Frontline, 2011). Finally, in a competitive market, firms add on the opportunity cost of trading per unit of output to the marginal production cost (Sijm, Neuhoff, and Chen, 2006) which in shipping equals the rental rate or the time charter rate (\$/day). In theory, the time-charter rate should at least cover daily operating and capital costs for firms to break even.

Variable costs include fuel, port charges, and canal dues. There are two key non-linear relationships in shipping that affect fuel costs. The first key relationship is between the size of a ship and fuel cost. Economies of scale in shipping exist because of the physical property that the water resistance on a ship's hull does not increase at the same rate as the volume of the hull (Smith et al., 2013). The second key non-linear relationship is between fuel consumption and speed, which is typically approximated by a cubic law. Fuel costs currently comprise the greatest voyage cost, which is approximately two-thirds[4] (Stopford, 2009). Other variable costs include canal costs which consist of canal tolls, extra insurance risk premium for transiting the piracy zone of Somalia and the use of services such as tugs, pilotage and mooring.

As ships age, their fuel efficiency deteriorates. In general, older vessels have lower employment prospects over newer ones because they are viewed as more risky and have higher fuel costs per tonne-mile. For example, "The anaemic tanker market has left 1970s-built, turbine-powered VLCCs and ULCCs queuing up in the Middle East Gulf (MEG) with bleak employment prospects" (Kennedy, 2002). The importance of fuel efficiency has increased due to the significant rise in the fuel price in recent years. Figure 3.5 shows the price of heavy fuel oil (HFO) since 1990 in Singapore and Fujairah which are major bunkering areas. Since 1990, the price of HFO has risen more than 5 fold, beginning its ascent in 2005, averaging $645 per tonne in 2011.

Another consequence of aging vessels is their risk profile changes due to hull deterioration, leaving it more vulnerable to oil spill accidents. Following the Exxon Valdez oil spill, the U.S. required ships to have a double hull, leading to quality differentiation (Strandenes,1999).

As Chapter 2 described, the short-run describes the market in which the stock of ships is fixed but ships can change their status. According to Clarkson Research (2012b), they can have the following status:

1. In port
2. At sea
3. Loitering
4. In floating storage
5. Laid-up
6. In long term storage (greater than 60 days)

Data on fleet statistics contains information on ships' status, but it is not completely accurate, comprehensive, nor up to date. The data (Clarkson Research, 2012b) shows that of the 602 ships in the fleet in 2012, 4 were laid-up and 2 were in long term storage. This represents less than 1% of the market, having a negligible impact on the market. Floating storage is a strategic option for traders and producers. Traders use it when the oil price is not high enough to sell

[4] Subject to the price of fuel

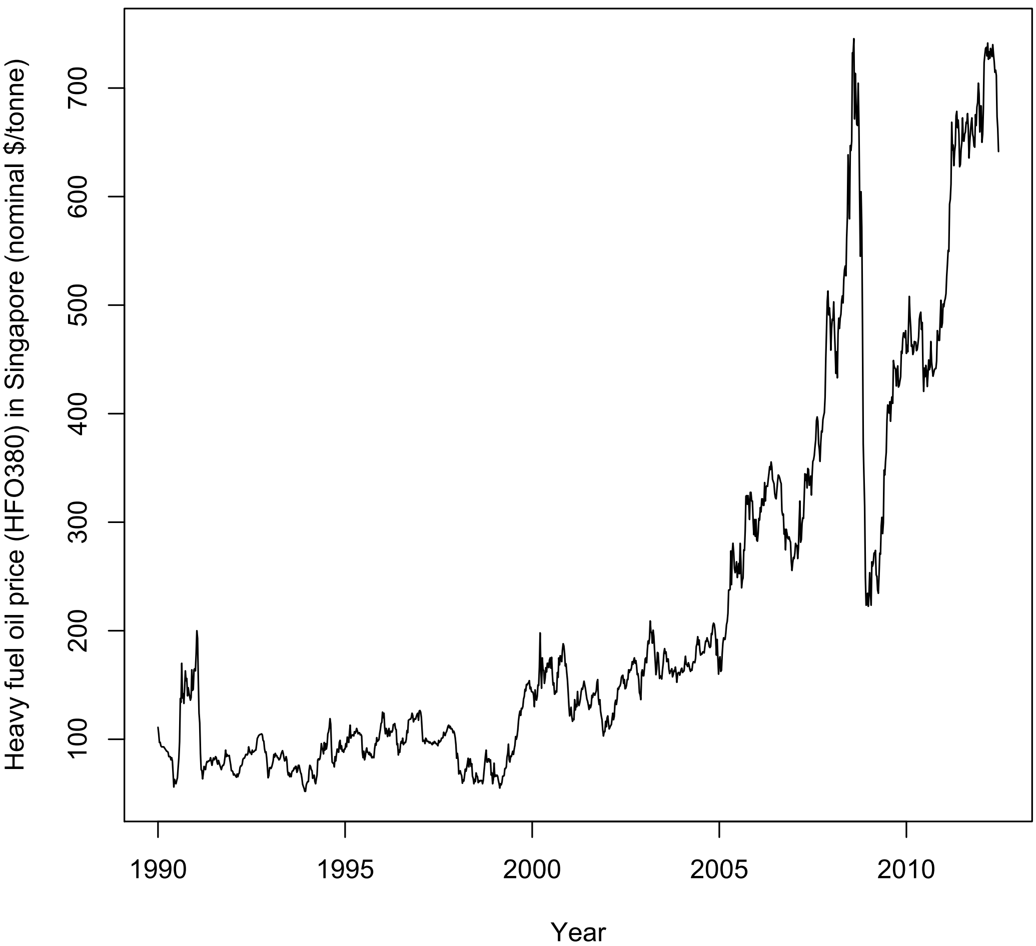


Figure 3.5: Source: Clarkson Research, 2012a.

the cargo, and producers use it when their tank farms are full (Davis, 2007). According to Gibson (Gibson, 2013), a ship brokerage firm, floating storage has been negligible (0%) between 2010-2012, accounting for 7% of supply in 2010.

3.3.3.2 Long-run supply

In the long-run, supply changes due to new entrants and exits. Shipowners buy vessels, adding to the stock of the fleet, and sell ships in the scrap market when they reach maximum age or when prices for scrap metal outweigh the present value of the ship. The shipping market is characterized by cycles of booms and depressions. A sustained momentum of high freight rates creates shipowner purchasing wealth and expectations that rates will continue to surge, which leads to new orders (see Stopford, 2009 for an overview of the shipbuilding cycle). New entrance into the market is lagged by the time to build a ship, which can take between 1-3 years on average, depending on the productivity of the shipyard and the number of orders. Any downward pressure on future demand can therefore create an oversupply of ships, exemplified by the 2008 financial crisis. Given the high rates of return during a boom however, shipowners are willing to suffer zero or even negative profits for multiple time periods, waiting for periods where the demand jumps high and the supply response is limited (Kalouptsidi, 2013). According to Stopford (2009), "Each company faces the challenge of navigating its way through the succession of booms and depressions that characterize the shipping market." Giving a specific example, "For several years the company had accepted this drain on its cashflow, in the hope that the market would improve." The market would improve in a depression if some shipowners scrapped their vessels. However, the competitive nature of the market and the debt tied to banks ensures that there is no cooperation in reducing output. Of course, shipowners can only absorb so much loss before they go bankrupt, exemplified by companies filing for bankruptcy in 2012.[5]

3.4 Industry Interviews

This section describes the key findings of two interviews conducted with a major tanker shipping company (Tanker Operator, 2012) and a shipbroking and shipping research company (Shipbroker, 2011).[6]

3.4.1 Spot fixing: agents and process

- The broker typically arranges the deal for either the shipowner and trader or both. More recently, there is one intermediary representing both parties such as Exxon Mobil - Clark-

[5] Since the 2008, the financial crisis has helped to drive shipping companies into bankruptcy, including Overseas Shipping Group, General Maritime Corp., Korea Line Corp., Britannia Bulk Plc, Armada (Singapore) Pte Ltd. and Transfield ER Cape. (Church et al., 2012)

[6] The names of companies were kept anonymous for confidentiality reasons.

sons - Greece, though sometimes there are two brokers representing both sides or the shipowner directly approaches the charterer.

- Oil majors and independent oil trading houses demand oil shipping services. Oil majors have more predictable contracts with oil production companies (for example, Shell works with Statoil in Norway) and they need oil shipped to Shell's refineries and use the left-over oil (after supplying the oil refineries) to sell oil on the spot market which is more speculative. Major oil trading houses are Vittal and Glencore.

- Shipowners advertise their ships on a daily basis through email with brokers. They are responsible for knowing when they will arrive in port.

- The bargaining process between the shipowner, broker and trader can take between 5 minutes and two weeks. The broker draws up a list of candidates, eliminating ships which are too small or too unreliable because of port inefficiencies.

- The shipowner normally provides an ask price to the trader using the previous day's Worldscale rate as a starting point and factors in the daily bunker price as a proxy for costs. The shipowner runs a voyage calculation of what they would make, taking into account where they would ballast next, but some shipowners make poor economic decisions partly because they need cash to pay the bank. Port costs can be high in some areas so sometimes it makes sense to wait than make a bad decision. Brokers also use the demand/supply ratio to advise clients, and shipowners take advantage of a bottleneck to exploit the price and put up the price.

- The speed is negotiated by the charterer and the shipowner which is based on the type of ship and the cost. The shipowner does a number of different prices and tries to pick what is attractive for other commercial drivers, including where the next voyage is going to be picked up and which way prices are going. The speed is typically between 13-14.5 knots for the laden voyage. There can be an option to speed up, though this option is becoming less popular due to high bunker prices.

- Ships which are over 15 years are viewed as more risky by charterers. The trader doesn't provide information about the cargo size they choose, but it is related to port restrictions.

- The route choice is not always based on the shortest distance. It is influenced by piracy and port dues (high in the Suez canal), and time. VLCCs that go through the Suez have to unload their cargo in the Sumed pipeline and pick it up in Ain Sukhna. These are sometimes picked up by Aframaxes which can enter ports in the Mediterranean rather than just Rotterdam.

3.4.2 Voyage optimization

- The oil market has changed to the advantage of the shipowner in recent years due to new areas of oil production opening up, new demands from China and India, and historical trade relationships changing. Hugo Chavez (the past president of Venezuela) fell out with the US so now Venezuela is shipping oil to China. Traditionally trade was dominant on the AG-US route and back, but now there is more demand from the Far East. The shipowner has to make more decisions about which direction to go based on the market, and can profit since the Worldscale benchmark is based on a round-trip cost. Often times, ships go around the Cape of Good Hope more slowly to avoid the Suez. It will also sail to the area with the most options and want to fix their ship at the port of discharge to ensure they get another job.

- Ships try to fix (sell the ship for hire) their ship at discharge areas, and will typically never go to a load area unless they have a cargo to pick up. If a ship still hasn't fixed, then it goes to a waiting area in Fujairah located in the Arabian Gulf or West Africa, another waiting hub to look for the next fix. Shipowners use AIS data to track each other to see where the ships are to decide where to wait for loading. The waiting time can be a couple of days or a couple of weeks, depending on the market.

- Shipowners almost never know the exact destination until they are within close proximity to the destination area. This depends on the type of trader; oil majors generally know where they are going whereas there is more uncertainty with traders because it is a speculative game based on the volatility in the market. If oil traders are not ready to unload their cargo, they will pay the shipowner a demurrage rate to compensate for the extra days not included in the contract or a storage rate.

- The speed in the ballast voyage is a trade-off between fuel costs and time costs. If the next voyage is known, then the voyage is optimized for the laycan period. The speed is also adjusted for other factors such regulations around berthing in daylight (in Japan) and demurrage rates. If the demurrage rates are high then it is more profitable to sit around instead of slow steaming. The ballast leg is where there are more differences between owners; some companies run their ships at 9 knots because they have newer ships but many ships are forced to go faster, at 13 knots or so due to design speed and safety restrictions.

- Shipping companies use financial instruments to purchase bunker fuel in advance or bunker in Fujairah and Singapore 95% of the time for re-fueling their ships.

3.5 Summary

This chapter has described the demand for crude oil transportation as being derived from world demand for crude oil. The crude oil market is a complex business involving many agents, which was described using quantitative and qualitative data. The major seaborne exporters described are the Middle East, West Africa and the South and Central America, while the major importers are countries in the Far East, India, and the US. A general shift of global oil demand to non-OECD countries has shifted seaborne trade to the Asia Pacific region, which surpassed North America as the largest consumer of oil in 2004. The largest volume of oil traded physically is on the forward market. Trading behavior is governed by expectations of the market in relation to current prices and the relationship was classified as being either a backwardation or contango market, but long-term contracts between oil producers and oil majors also exist.

The tanker market was described as a competitive market, with the largest firm representing only 3% of the total output. Two types of contracts, spot and time charter, and their pricing were examined. The market was characterized in terms of short-run and long-run determinants and the cyclicality of the industry was explained. The interviews provided confirmation of some of the quantitative data findings and additional information about voyage optimization strategies. The key findings from this analysis were that shipping companies reposition to the Arabian Gulf or West Africa when they do not have a fixture lined up whereas the option to lay-up is rare. Operators adjust their speed for fuel and time costs, which include future expectations about the market. Another finding was that there is heterogeneity in speeds, particularly in ballast, with some ships going significantly slower compared to others due to perceived design speed and safety restrictions. Changes in trade patterns have increased the spatial complexity of these repositioning voyages which provides opportunities for shipowners to earn better profits.

Chapter 4

Model Structure

The previous two chapters described the market structure of the tanker industry as competitive. This assumption lays the foundation for modeling the key agents in the tanker shipping industry as behaving competitively in a matching (assignment) game. In this chapter, a two-sided [1] matching model is constructed for allocating charterers (oil traders) to ships (shipowners) which can be used to simulate the VLCC market. This is a resource allocation problem in which ships are the resources and traders have tasks (the shipment of oil) that need to be completed by the resources. I will compute a competitive equilibrium allocation which includes the assignment (which buyers match with which sellers) and the set of prices that result from each assignment.

In a competitive equilibrium, each agent chooses the task that maximizes his profits given the current prices such that the quantity supplied is equal to quantity demanded. In a matching economy, an alternative way to compute an equilibrium is to find the allocation that maximizes the total valuation of the assignment (the social surplus) subject to the constraints on resources and tasks. The multipliers on these constraints are used to construct prices, and the allocation and prices that result from solving this problem is a competitive equilibrium.

This study reports prices generated from the model both as a total rate for chartering a ship, expressed as a lumpsum in dollars and as a percentage of Worldscale flat rates or the WS multiplier (multiplier units). The total freight rate (hereto referred to as the freight rate) is useful as it simplifies the price derivation using the model's inputs and outputs which will be derived in this chapter. It is equivalent to the revenue for shipping the cargo. Nevertheless, as the industry negotiates the majority of rates using the multiplier, Chapter 7 will also present results of the implied WS multiplier price using a simple accounting relationship between the total rate from the model, an estimated benchmark price in Chapter 6, and an average cargo size.

The simplest way to compute the competitive equilibrium is to solve a linear programming

[1] The shipping market is two-sided because there are two key user groups, traders and shipowners, that provide each other with economic benefits.

program, which is a simple but large combinatorial optimization problem where the combinations to be optimized are the surpluses from the pairings of agents. The condition that agents must match (i.e., buyers to sellers and vice versa) or not places a constraint on the utility that each agent can achieve. Associated with the constraint is a shadow price or marginal value of using the resource, formally known as the Lagrangian multiplier on the constraint. The multiplier captures the sensitivity of the optimal solution to a small change in the availability of that resource, holding everything else constant. The problem is solved as if the traders and shipowners are a joint venture, and the payoff (surplus) of assigning a ship to a trader's cargo demand is the revenue from assigning the resource to the cargo demand minus the cost of the shipment plus the ship's option value to be in the discharge location. The problem is then decentralized through the Lagrange multiplier on the constraints.

Outcomes that maximize social surplus are efficient when there is no other outcome in which all payoffs are at least as large and one is larger which would result in a higher sum of payoffs. Certain informational conditions must be met to guarantee this outcome in a matching economy. Each trader needs to know only the freight rates that are relevant to the shipping route he is considering and the profitabilities of his cargo given these matching possibilities.

Matching problems can also have a time dimension. The problem of matching buyers (traders) to sellers (shipowners) at a single point in time is called a static matching problem, while the problem of dynamically assigning ships to traders is a dynamic matching problem. In a dynamic setting, information about resources changes over time and the previous matching can impact the current and the expected future matching can influence the present one. The static problem is like solving the dynamic version for one period. In both problems, ships and traders are each characterized by a set of attributes, where the surplus generated will depend on the attributes of each resource and task. Ships do not have to be used and cargoes demanded by traders do not have to be met, although there is a cost for holding either one which takes into account each agent's inter-temporal choices.

In order to understand the fundamentals of the matching game, the model is first described for the static case and then extended to a dynamic model. The following approach is applied:

1. Define the environment: description of environment and attributes of agents.

2. Specify the general model assumptions used to build the model.

3. Describe the agent behavior and payoffs of matching or remaining unmatched. Two strategies for shipowners (Policy 1 = quasi-myopic; Policy 2 = forward looking policy) define their expectations about the future. In the quasi-myopic policy, shipowners only

consider the cost of returning to the original loading area after they finish their current journey, whereas the forward looking policy considers future employment prospects in terms of profits earned.

4. Describe the solution algorithm for the one period matching game: the matching model can be analyzed as a linear programming problem.

5. Describe the timing, sequence of events and the solution algorithm for the two period model for the dynamic matching game.

4.1 Environment

This section uses the formulation of assignment games with transferable utilities to describe a competitive spot market for shipping crude oil. The model consists of N^z potential shipping contracts, N^y potential buyers and N^x sellers, where buyers are oil traders and sellers are firms who own ships. A ship is a shipowner and the terms will be used interchangeably. Time is discrete and the unit is one week. Traders and ships interact in the market place every week and decide whether to match or remain unmatched.

Agents are characterized by a vector of attributes that define the type space of each. The model abstracts from reality by excluding charterers and brokers who typically work as intermediaries with traders and ships to find a ship that is suitable. A trader i at time t has a type vector y_i belonging to a set of trader types $\mathcal{Y}$ embodying its characteristics. Likewise, a ship j has a type vector x_{jt} belonging to a set of ship types $\mathcal{X}_t$. To allow for the possibility that some agents choose not to participate and remain unmatched, each set includes a "dummy" agent type from the other side of the market. A dummy ship type $\emptyset_x$ is a partner for any unmatched trader types, and $\emptyset_y$ is a dummy trader type for any unmatched ship types. The set of ship and trader types are defined as:

$$\begin{aligned} \mathcal{X}_t &= \{x_{jt}\}_{j=0}^{J} \\ \mathcal{Y} &= \{y_i\}_{i=0}^{I} \end{aligned} \tag{4.1}$$

where:

x_{0t}	dummy ship type, $\emptyset_x$
y_0	dummy trade type, $\emptyset_y$
J	number of ship types
I	number of trader types

Each trader who participates in the market obtains profits from the shipping service z which is derived from a vector of ship attributes. The model is a partial equilibrium model of the tanker market which considers only the market for shipping large cargoes using Very Large Crude Carriers (VLCCs), the largest class of tankers, and therefore assumes that the demand for VLCCs is a function of the relative prices of VLCCs in the market. In practice, tankers in smaller size categories (Suezmax and Aframax) also transport crude oil but are less competitive with VLCCs on long trade routes where VLCCs dominate trade given economies of scale in shipping.

Each oil trader owns a quantity of oil ($> 200,000$ tonnes) that needs to be shipped. Profits depend on the expected oil price arbitrage between locations, the freight rate, and the estimated time of the ship's arrival to the load and destination area. A trader also has the option to remain unmatched in the current period, in which case it has to store the oil at a cost at the load area and ship it next period.

A trader's type has 4 dimensions that affect profits and costs:

$$y_i = \begin{pmatrix} a \\ b \\ q^b \\ \beta^y \end{pmatrix} = \begin{pmatrix} a \text{ is a location in the load location set } \mathcal{A} \\ b \text{ is a location in the discharge location set } \mathcal{B} \\ \text{Cargo size (barrels)} \\ \text{Discount factor} \end{pmatrix}$$

Ships are located in different locations at the start of the period; locations are sea areas and include load areas, discharge areas, and waiting areas. Waiting areas are sea areas located near a load area where ships can sit idle until they match with trader. A shipping firm has to choose a trader to match with and its associated cargo to load and move if one is available. Alternatively, it has the option of moving empty to another location (even if a load is available) and remain unmatched in the current period. There is a value to remaining unmatched for both agent groups, which differs from most of the matching literature (see Shapley and Shubik (1972) and Chiappori, McCann and Nesheim (2009)) that assigns a value of 0 to null matches. When a shipping firm has a fixture prospect, it has to consider factors such as the cost associated with the number of nautical miles the ship must move empty to pick up the cargo, the ability of the operator to deliver the cargo on time, and the possibility of fixing the ship after unloading the cargo at the destination port.

Ships are characterised by 7 dimensions that affect profits and costs at time t:

$$x_{jt} = \begin{pmatrix} l \\ \omega \\ \alpha \\ v^d \\ k \\ c^r \\ \beta^x \end{pmatrix} = \begin{pmatrix} \text{Current location of ship } l \in \mathcal{A} \cup \mathcal{B} \cup \mathcal{W} \\ \text{Deadweight tonnage of ship} \\ \text{Age} \\ \text{Design speed} \\ \text{Daily fuel consumption (tonnes)} \\ \text{Daily opportunity costs} \\ \text{Discount factor} \end{pmatrix}$$

Ship j of type x_{jt} changes over time because of changes in its location, whereas its physical attributes are constant during the model period. The current location of a ship is a vector of all location sets $l \in \mathcal{A} \cup \mathcal{B} \cup \mathcal{W}$, where $\mathcal{W}$ is a vector of waiting locations. The discount factor is used to discount the expected payoff in future periods at the time of matching.

A contract z has one attribute:

$$z_t = v^{op} = \text{average matched speed}$$

Contracts can be specified with either a constant or "optimal" speed. A constant speed is reasonable given the stickiness of changes in speeds dictated in the clause of the contract; currently industry practitioners use 13.5 knots in their calculation of earnings per day for modern VLCCs and this is the constant speed used in the model. According to a statement from the chief of Frontline in 2011 (Lloyd's List, 2011), a leading shipping company, "We are trying to discuss with the charterers if there is a possibility of a lower speed, but so far they seem to prefer to maintain 13 or 13.5 knots, but that is a discussion we are always having." However, there is no rule of thumb, and the optimal speed model variant relaxes this assumption to represent the case when speed is bargained over in the contract. Once a ship has matched to a trader, it is assumed that the ship must sail at this speed from its current location to the discharge location.

4.2 General Model Assumptions

The following general model assumptions apply across all models of different policy types, justified by Chapter 2 (Literature Review) and Chapter 3 (Description of Industry):

1. Traders demand cargoes above 200,000 tonnes to be shipped from a load area.

2. The aggregate number of ships and cargo quantity demanded are exogenously determined.

3. Oil traders live until they make a shipment and then "die," replaced by a new trader drawn from a truncated normal distribution of trade demand. They are impatient; there are opportunity costs for waiting to ship oil because each week they buy oil and have to pay a storage cost for the days until the ship arrives at port.

4. Ships can only match at discharge and waiting areas, and once they are matched, they cannot match to another trader until they discharge the cargo at the discharge area.

5. There are no search costs for matching.

6. The market is competitive. Ships consider market conditions, but do not focus on analyzing how rival ships will respond if they take particular decisions.

7. Where there are multiple routes, ships travel on the route most travelled for the area-area pair based on a distribution.

8. Agents are rational and maximize profits.

4.3 The theoretical static matching model

I first develop the theoretical static matching model for the tanker market. The static model is defined as one period model and is the same as solving for the terminal period T in a finite horizon dynamic model.

4.3.1 Supply side of the market

The supply side of the market is defined as follows:

- A ship j has characteristics defined by its type x_{jt} described in section 4.1.

- The vector $\mathbf{n}(x_{jt}, t) = [n(x_{1t}, t), ..., n(x_{Jt}, t)]$ holds the quantities of each ship type x_{jt} at time t.

- If a ship j matches with a trader i, it receives a payoff $W^x(x_{jt}, t)$ equal to:

$$\max_{y_i} \left[P(x_{jt}, y_i, t) - C(x_{jt}, y_i, t) + \beta^x W^x(x_{j,t+1}, t+1)\right] \tag{4.2}$$

where:

1. $P(x_{jt}, y_i, t)$ is the freight rate in lumpsum units ($).
2. $C(x_{jt}, y_i, t)$ is the shipment cost which includes the fuel and opportunity costs associated with traveling from the ship's current location to the discharge location.
3. $W^x(x_{j,t+1}, t+1)$ is the expected future payoff from the discharge location, known as the option value for ship i of type $x_{j,t+1}$ defined by the function $g(x_{jt}, y_i, t)$ which determines the ship's discharge location.

The option value depends on the policy employed. Policy 1 approximates the option value using a "quasi-myopic" approximation. In shipping, it is almost always the case that ships must ballast empty to another load area after they have dropped off the cargo at the discharge location and discounting the future completely would ignore this cost. The option value in Policy 1 is therefore the discounted cost of returning to the original load area. I include this policy in the model for two reasons; the first is simply for comparison purposes, and the second is because we do not know whether shipowners are forward-looking. In contrast, Policy 2 includes the value of employment in future periods, but because the freight rate is volatile, there is uncertainty about future payoffs. Therefore the shipowner only looks ahead one period.

The forward-looking policy differs from the quasi-myopic policy in two ways. First, the repositioning cost from the current period's match in Policy 1 is the repositioning cost from the discharge location back to the same load area where the ship matched, whereas in Policy 2 the ship considers other load area locations such that it is an expected repositioning cost. The second difference is the option value in Policy 2 also includes the expected future payoffs if it matches to a trader or if it doesn't match to a trader and has to relocate to a waiting area. It is important to include these future payoffs when considering different matching options because there could be instances in which the repositioning costs are similar between two matches, but the future matching payoffs are different because they are specific to the load and/or waiting area. The option value is discounted by β^x which equals $1/(1+r^x)^{d(x_{jt}, y_i)}$, where r^x is the discount rate and the discounting is over the duration $d(x_{jt}, y_i)$ of the current voyage.

- If a ship j doesn't match with a trader i, it has to relocate to a waiting area $w \in \mathcal{W}$. In the model, this is equivalent to matching to a dummy trader $\emptyset_y$ and the payoff (the ship's surplus) of this match is equal to:

$$s(x_{jt}, \emptyset_y, t) = \tilde{s}(x_{jt}, \emptyset_y, t) + \beta^{x_{jt}, d(x_{jt}, \emptyset_y)} W^x(g(x_{jt}, \emptyset_y), t+1) \tag{4.3}$$

where $g(x_{jt}, \emptyset_y)$ denotes the function determining the ship's type which includes its new location when it remains unmatched. In the model, there are two waiting areas: one in Fujairah in the Arabian Gulf and the other in West Africa and the surplus from these matches are:

$$s(x_{jt}, \emptyset_{y_1}, t) = \tilde{s}(x_{jt}, \emptyset_{y_1}, t) + \beta^{x_{jt}, d(x_{jt}, \emptyset_{y_1})} W^x(g(x_{jt}, \emptyset_{y_1}), t+1)$$
$$s(x_{jt}, \emptyset_{y_2}, t) = \tilde{s}(x_{jt}, \emptyset_{y_2}, t) + \beta^{x_{jt}, d(x_{jt}, \emptyset_{y_2})} W^x(g(x_{jt}, \emptyset_{y_2}), t+1)$$

where $\emptyset_{y_1}$ represents the dummy trader in Fujairah and $\emptyset_{y_2}$ is the dummy trader in West Africa. The maximum value of these options will be the preferred unmatched option:

$$s(x_{jt}, \emptyset_y, t) = \max \left[s(x_{jt}, \emptyset_{y_1}, t), s(x_{jt}, \emptyset_{y_2}, t) \right] \tag{4.4}$$

4.3.2 Demand side of the market

The demand side of the market is defined as follows:

1. A trader i has characteristics defined by its type y_i described in section 4.1.

2. The vector $\mathbf{n}(y_i, t) = [n(y_1, t), ..., n(y_I, t)]$ is a vector holding the quantities of each trader type.

3. If a trader i matches with a ship j, it receives a payoff $W^y(y_i, t)$ equal to:

$$\max_{x_{jt}} \left[\pi(x_{jt}, y_i, t) - P(x_{jt}, y_i, t) \right] \tag{4.5}$$

   where $\pi(x_{jt}, y_i, t)$ is the profits from the sale of the oil, and $P(x_{jt}, y_i, t)$ is the freight rate in lumpsum units (\$) if a trader of type y_i matches to a ship of type x_{jt}.

4. If a trader i doesn't match with a ship j then it has to pay a storage cost to store the oil in the load area until it can match with a ship. In the model, traders which are unmatched match to a dummy ship $\emptyset_x$ with a payoff (surplus) equal to:

$$s(\emptyset_x, y_i, t) = \tilde{s}(\emptyset_x, y_i, t) + \beta^{y, d(\emptyset_x, y_i)} W^y(y_i, t+1) \tag{4.6}$$

   where $\tilde{s}(\emptyset_x, y_i, t)$ is the storage cost and $W^y(y_i, t+1)$ is the expected future payoff in the next period.

4.3.3 Pairwise surplus function

The combined payoff of a match between a ship and trader is known as the pairwise surplus function. It provides the total valuation of a ship of type x_{jt} matched to a trader of type y_i and equals the sum of the payoffs $W^x(x_{jt}, t)$ and $W^y(y_i, t)$ from equations 4.2 and 4.5 respectively:

$$\begin{aligned} s(x_{jt}, y_i, t) &= \max_{z_t} \left[\big(\pi(x_{jt}, y_i, t) - P(x_{jt}, y_i, t)\big) + \right. \\ &\quad \left. + \big(P(x_{jt}, y_i, t) - C(x_{jt}, y_i, t) + \beta^x W^x(x_{j,t+1}, t+1)\big) \right] \\ &= \pi(x_{jt}, y_i, t) - C(x_{jt}, y_i, t) + \beta^x W^x(x_{j,t+1}, t+1) \\ &= \tilde{s}(x_{jt}, y_i, t) + \beta^x W^x(x_{j,t+1}, t+1) \\ &= W^x(x_{jt}, t) + W^y(y_i, t) \end{aligned} \tag{4.7}$$

Because the pairwise surplus function includes a transfer of $P(x_{jt}, y_i, t)$ from the trader to the ship, the freight rate cancels out. The surplus function can be split into the current period's surplus $\tilde{s}(x_{jt}, y_i, t)$ and the surplus in the future period $\beta^x W^x(x_{j,t+1}, t+1)$.

4.4 Matching economy, assignment problem and competitive equilibrium

This section defines the matching economy, assignment problem, and competitive equilibrium associated with a linear programming problem. The matching economy is first described which will be used to formulate the assignment problem. The assignment problem is solved as a linear programming problem. A competitive equilibrium is derived from the solution to the linear programming problem.

4.4.1 Matching economy

A matching economy at time t consists of:

1. A vector $\mathbf{n}(x_{jt}, t) = [n(x_{1t}, t), ..., n(x_{Jt}, t)]$ consisting of the quantities of each ship type x_{jt}.

2. A vector $\mathbf{n}(y_i, t) = [n(y_1, t), ..., n(y_I, t)]$ consisting of the quantities of each trader type y_i.

3. A set $\Theta_t = \mathcal{X}_t \times \mathcal{Y}$ of possible assignment pairs θ_t such that each trader type $y_i \in \mathcal{Y}$ and each ship type $x_{jt} \in \mathcal{X}_t$ is at most one pair in Θ_t.

4. A surplus function s: $\Theta_t \longmapsto \mathbb{R}_t$ giving the value $s(x_{jt}, y_i, t)$ of each pair of ship and trader type; $s(\emptyset_x, y_i, t)$ for an assignment of a trader to a dummy ship; $s(x_{jt}, \emptyset_y, t)$ for an assignment of a ship to a dummy trader.

4.4.2 Assignment definition and associated conditions

Definition 1. *An assignment (or a matching) is defined as a non-negative function m mapping Θ_t into $\mathbb{R}_t$. For a particular pair (x_{jt}, y_i, t) where $j > 0$ and $i > 0$, the value $m(x_{jt}, y_i, t) > 0$ represents the number of traders of type y_i that are matched to a ship of type x_{jt} and to the shipping contracts. For $j = 0$, the value $m(x_{jt}, y_i, t)$ or $m(\emptyset_x, y_i, t)$ represents the number of traders who are not matched. Similarly, for $i = 0$, $m(x_{jt}, y_i, t)$ or $m(x_{jt}, \emptyset_y, t)$ represents the number of unmatched ships.*

A feasible assignment is one in which all traders are assigned to ships and satisfies the following constraints:

$$\sum_{y_i \in \mathcal{Y}} m(x_{jt}, y_i, t) = n(x_{jt}, t) \; \forall \; x_{jt} \text{ and } t \tag{4.8}$$

$$\sum_{x_{jt} \in \mathcal{X}_t} m(x_{jt}, y_i, t) = n(y_i, t) \; \forall \; y_i \text{ and } t \tag{4.9}$$

$$m(x_{jt}, y_i, t) \geq 0 \tag{4.10}$$

Equation 4.8 captures the constraint on ships; the assignment of traders and dummy traders to a particular type of ship cannot exceed the total amount of ships of that type. Equation 4.9 captures the constraint on traders; the assignment of ships and dummy ships to a particular type of trader cannot exceed the total amount of traders of that type. Equation 4.10 restricts the assignment to be positive because a negative assignment is not allowed.

Traders and ships can be matched to more than one ship and trader type respectively. Following Chiappori, McCann and Nesheim (2009), the interpretation of a positive $m(x_{jt}, y_i, t)$ for a trader of type y_i assigned to multiple ship types x_{jt} is a conditional distribution implied by $m(x_{jt}, y_i, t)$ as a mixed strategy for trader y_i.

Definition 2. *An outcome of the matching game is defined as a triple $(m(x_{jt}, y_i, t), W^x(x_{jt}, t), W^y(y_i, t))$ where $(W^x(x_{jt}, t), W^y(y_i, t))$ is a payoff corresponding to $m(x_{jt}, y_i, t)$. Following the literature (Roth and Sotomayor, 1990), an outcome is stable if* *for any assignment pair θ_t:*

$$W^x(x_{jt}, t) + W^y(y_i, t) \geq s(x_{jt}, y_i, t) \tag{4.11}$$

In other words, a match is stable if two conditions are met:

1. No matched agent would be better unmatched.

2. No two agents of type x_{jt} and y_i, who are not matched together, would prefer being matched together compared to their current pairing. If $s(x_{jt}, y_i, t) > W^x(x_{jt}, t) + W^y(y_i, t)$, then a ship and trader could improve their payoff by leaving their current situation and rematching so matching could not be stable.

Definition 3. *A feasible assignment is optimal at time t if it maximizes the sum of surpluses:*

$$\sum_{(x_{jt}, y_i) \in \Theta_t} m(x_{jt}, y_i, t) s(x_{jt}, y_i, t) \tag{4.12}$$

4.4.3 A competitive equilibrium associated with a linear programming problem

Definition 4. *A linear programming problem is the problem of maximizing or minimizing a linear function (the objective function) subject to linear constraints.*

The linear programming problem of an assignment problem is to choose $m(x_{jt}, y_i, t)$ to maximize:

$$\begin{aligned} \sum_{(x_{jt}, y_i) \in \Theta_t} m(x_{jt}, y_i, t) s(x_{jt}, y_i, t) \\ \text{subject to:} \\ \sum_{y_i \in \mathcal{Y}} m(x_{jt}, y_i, t) = n(x_{jt}, t) \; \forall \; x_{jt} \text{ and } t \\ \sum_{x_{jt} \in \mathcal{X}_t} m(x_{jt}, y_i, t) = n(y_i, t) \; \forall \; y_i \text{ and } t \end{aligned} \tag{4.13}$$

The solution to an assignment problem using linear programming can be used to compute a competitive equilibrium (Koopmans and Beckman, 1957). Prices are constructed through a simple accounting relationship between the multipliers on the resource and task constraints which equal the ship's payoff $W^x(x_{jt}, t)$ and the trader's payoff $W^y(y_i, t)$ respectively. From the trader's payoff function, the total freight rate is determined as:

$$P(x_{jt}, y_i, t) = \pi(x_{jt}, y_i, t) - W^y(y_i, t) \tag{4.14}$$

From the ship's payoff function, the equivalent price is determined as:

$$P(x_{jt}, y_i, t) = C(x_{jt}, y_i, t) + W^x(x_{jt}, t) - \beta^x W^x(x_{j,t+1}, t+1) \tag{4.15}$$

The following definition provides the conditions under which prices and the matching assignment are in a competitive equilibrium:

Definition 5. *A feasible assignment $m(x_{jt}, y_i, t)$ and a price vector p satisfy the competitive equilibrium condition when:*

- *For every pairing it is the case that all agents maximize their individual surplus:*

$$\begin{aligned} W^y(y_i, t) &= \max_{x_{jt}} \left[\pi(x_{jt}, y_i, t) - P(x_{jt}, y_i, t)\right] \\ W^x(x_{jt}, t) &= \max_{y_i} \left[P(x_{jt}, y_i, t) - C(x_{jt}, y_i, t) + \beta^x W^x(x_{j,t+1}, t+1)\right] \end{aligned} \tag{4.16}$$

- *Supply equals demand:*

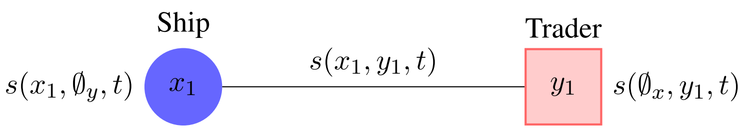
$$\begin{aligned} \sum_{x_{jt} \in \mathcal{X}} \left[m(x_{jt}, y_i, t) + m(\emptyset_x, y_i, t)\right] &= n(y_i, t) \ \forall \ y_i \ \textit{and} \ t \\ \sum_{y_i \in \mathcal{Y}} \left[m(x_{jt}, y_i, t) + m(x_{jt}, \emptyset_y, t)\right] &= n(x_{jt}, t) \ \forall \ x_{jt} \ \textit{and} \ t \end{aligned} \tag{4.17}$$

4.4.4 Model outputs and intra-allocation of the pairwise surplus

There are four outputs of the model:

1. $m(x_{jt}, y_i, t)$: the number of traders of type y_i that are matched to a ship of type x_{jt}
2. $W^x(x_{jt}, t)$: the payoff for the ship
3. $W^y(y_i, t)$: the payoff for the trader
4. $P(x_{jt}, y_i, t)$: the price or freight rate of each match
5. $\mathbf{n}(x_{jt}, t+1), \mathbf{n}(y_i, t+1)$: the implied supply of ships and traders in the next period

The matching between two agents is graphically depicted in the figure below for a simple market where there is one ship type x_1 and a trader type y_1.



Following the literature on the Nash Bargaining Solution (Easley and Kleinberg, 2010), the ship and the trader are bargaining about how to split the surplus, and suppose that the total surplus if they match is $s(x_1, y_1, t)$. But both x_1 and y_1 have outside options; x_1 has the outside option of $s(x_1, \emptyset_y, t)$ and y_1 has the outside option of $s(\emptyset_x, y_1, t)$ which are the values to remain unmatched. These outside options can be defined as their threat points because they can leave the negotiation if they do not receive this outside option. If $s(x_1, \emptyset_y, t) + s(\emptyset_x, y_1, t) > s(x_{jt}, y_i, t)$, then no agreement will be reached because they cannot divide the surplus so that the ship gets at least $s(x_1, \emptyset_y, t)$ and the trader gets at least $s(\emptyset_x, y_1, t)$. Therefore, in order for them to match, $s(x_1, \emptyset_y, t) + s(\emptyset_x, y_1, t) \leq s(x_1, y_1, t)$ (Model Definition 2).

In a match between a ship and a trader, once their outside earnings options are met which is the minimum requirement to match (in this case, the value to remain unmatched or the dummy surplus value), they have to decide how to split the rest of the surplus or " residual pie". In the simple example this is given by:

$$R_{pie} = s(x_1, y_1, t) - s(x_1, \emptyset_y, t) - s(\emptyset_x, y_1, t) \tag{4.18}$$

where R_{pie} stands for residual pie. With a finite number of agents, the equilibrium conditions impose constraints on individual shares, but there exists in general an infinite set of intra-match allocations and therefore prices. At the extreme ends of the distribution, an agent could obtain the entire R_{pie} or 0. Each agent's share boils down to their relative bargaining ability. In shipping, bargaining power depends on the market conditions and each agent's ability to bargain. In the model, the market conditions fully determine the agent's share of the surplus.

The global or aggregate VLCC market consists of about six local markets where traders demand cargo to be shipped from by VLCC (Clarkson Research, 2011). In theory, any VLCC is capable of serving these local markets, but some ships may be favored more over others based on their location and physical characteristics. The market conditions depend on the aggregate demand to supply ratio ($aggDSR$) or the demand for cargoes to be shipped as a proportion of the available supply of ships, and the local demand to supply ratio (the demand for ships in the load area to the supply of ships located in the load area).

Agents are referred to as being either on the short or long side of the market. For example, if a ship is on the short side of the market, its type is scarce relative to the amount of traders demanding its service, whereas if it is long there is an excess supply of ships of this type (Diaz and Jerez, 2013). If an agent is on the long side of the market, it obtains a payoff equal to the surplus of remaining unmatched, with the interpretation that they are indifferent between matching and remaining unmatched.

The $aggDSR$ determines the extent to which agents in each side of the market have the possibility of extracting any of the residual surplus. If $aggDSR < 1$, then there is at least one ship which is long, and the traders' earnings are determined by the relevant substitution possibilities for the ship which is most favored. On the other hand if $aggDSR > 1$, then ships are short and all traders receive their dummy surplus values. This has a Walrasian frictionless market flavor, in which traders on the short side of the market trade with probability one (subject to payoff of remaining unmatched being less favorable), while buyers on the long side are rationed (Diaz and Jerez, 2013). Demand rationing occurs in markets in which there are capacity constraints (which applies to the shipping market at least in the short-run).

Taking the case that $aggDSR < 1$ such that traders have the upper hand in the aggregate market, if a ship is long it means that the ship's payoff must be greater than or equal to the payoff to remain unmatched (Equation 4.19). Equation 4.20 follows from this by solving for the price a ship must receive in order to match with a trader, which equals the surplus of remaining unmatched plus the shipment cost minus the discounted option value from the destination:

$$P(x_{jt}, y_i, t) - C(x_{jt}, y_i, t) + \beta^x W^x(x_{j,t+1}, t+1) >= s(x_{jt}, \emptyset_y, t) \tag{4.19}$$

$$P(x_{jt}, y_i, t) >= s(x_{jt}, \emptyset_y, t) + C(x_{jt}, y_i, t) - \beta^x W^x(x_{j,t+1}, t+1) \tag{4.20}$$

If on the other hand, a ship is on the short side of the market, the price is given by:

$$P(x_{jt}, y_i, t) = P(x_{j't}, y_i, t) + \Delta WTP(x_{jt}, x_{j't}, y_i, t) \tag{4.21}$$

$$P(x_{jt}, y_i, t) = P(x_{j't}, y_i, t) + \Delta\pi(x_{jt}, x_{j't}, y_i, t) \tag{4.22}$$

where $x_{j't}$ is the substitute to x_{jt} and ΔWTP is the trader's marginal willingness to pay for the shipping service.

4.5 Specification of the matching surplus

This section provides the specification of the matching surplus (or payoff) function. As discussed in Section 4.3, the matching surplus function $s(x_{jt}, y_i, t)$ consists of the combined payoffs to the trader and ship if they match together which is comprised of the trader's revenue from the oil cargo, the shipment cost, and the ship's option value. The section is divided into three subsections, the trader's revenue, the ship's cost function, and the ship's option value which depends on the shipowner's policy.

4.5.1 The trader's revenue

As discussed in Chapter 3, a trader's profits can be complicated and depend on the type of contract. Oil can be bought on the spot market, in a forward contract or in the futures market. I focus on the case where oil is bought in the forwards market since this represents a large majority of the physical oil trading volume. The model assumes that the trader has only one destination in mind for selling the oil, specified in the exogenous demand vector at time t. This is a simplifying assumption because in some cases he will consider other markets.

Under this contract type, the expected present value of the net revenue from selling the cargo at date $t+d$ is:

$$\pi(x_{jt}, y_i, t) = \beta^y \mathbb{E}(p^b_{t'} | x_{jt}, y_i, t) - p^a_t) q^b) - c^{store} q^b d^{la}(x_{jt}, y_i) \tag{4.23}$$

where:

$\mathbb{E}(p^b_{t'} \| x_{jt}, y_i, t)$	expected average price of oil bought at location a and sold at location b at time t'
t'	$t + d(x_{jt}, y_i)$
p^a_t	the price of oil paid at location a at time t
β^y	the discount factor
q^b	cargo size (barrels)
c^{store}	daily storage cost per tonne
$d^{la}(x_{jt}, y_i)$	days from the ship's starting location to the loading area

The discount factor is equal to:

$$\beta^y = \frac{1}{(1 + r^y)^{d^{lb}(x_{jt}, y_i)}} \tag{4.24}$$

where r^y equals the interest rate to reflect the inventory cost and $d(x_{jt}, y_i)$ equals the total duration in days until the shipment gets to destination b:

$$d(x_{jt}, y_i) = \frac{\phi_{la}}{24 v^{op}} + \frac{\phi_{ab}}{24 v^{op}} + d^p \tag{4.25}$$

4.5.2 Shipment costs

Costs are comprised of fuel, port and fixed costs. Fuel cost is a function of distance, speed, and the price of heavy fuel oil. Fixed costs include operating costs (crew wages, repairs and maintenance, spares, and insurance) and the capital cost of the ship. The implicit rental rate (opportunity cost) should approximate these costs and is included in the marginal cost of production as a daily implicit rental rate.

Following the literature (Ronen, 1982; Evans, 1994; Stopford, 2009, among others) fuel cost[2] equals:

$$c^{f}_{ll',t} = p^{hfo} k \left(\frac{v^{op}}{v^{d}}\right)^{3} \frac{\phi_{ll'}}{24 v^{op}} \tag{4.26}$$

$\phi_{ll'}$	distance between two areas l and l' (nautical miles)
v^{op}	operating speed
v^{d}	design speed
$\phi_{ll'}/24v^{op}$	days at sea
p^{hfo}	heavy fuel price ($/tonne)
k	daily fuel consumption (tonnes)

The repositioning cost from one location l to another location l' is:

$$c^{rep}_{ll',t} = c^{r}\left(\frac{\phi_{ll'}}{24 v^{op}}\right) + c^{f}_{ll',t} \tag{4.27}$$

where c^r is the daily rental rate or opportunity cost of trading in the spot market. The voyage cost from a to b is:

$$c^{voy}_{ab,t} = c^{r}\left(\frac{\phi_{ab}}{24 v^{op}}\right) + c^{f}_{ab,t} + d^{p} c^{p} \tag{4.28}$$

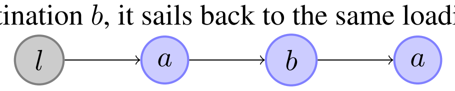
where d^p equals days in port and c^p are the daily port costs. Broker commissioning fees are not included since the model does not include the broker. Combining the repositioning and voyage costs, the total shipment cost from the ship's current location l to destination b is:

$$C(x_{jt}, y_i, t) = c^{rep}_{la,t} + c^{voy}_{ab,t} \tag{4.29}$$

Once the cargo is discharged, the owner selects the speed for the ballast leg back to the load area. Rushing back to a load or waiting area at full speed is not a wise decision if there is no employment, so the speed of the ballast leg depends on whether the ship is matched or not.

4.5.3 A quasi-myopic option value

With a quasi-myopic policy (Policy 1), it assumed that once the ship drops off the cargo at the destination b, it sails back to the same loading port a as depicted in the figure below.



[2]The fuel burned is for the main engine. The ship's auxiliary engine, and impact of draught (payload) and weather is not modeled.

The discounted option value equals the discounted repositioning cost to travel from the discharge location b to the load area a where the ship matched with the trader:

$$\beta^x W^x(x_{j,t+1}, t+1) = \beta^{x,d(x_{jt},y_i)} c^{rep}_{ba,t} \tag{4.30}$$

4.5.4 A forward-looking option value

In the forward-looking policy, the ship considers not only the repositioning cost to sail to a load area, but also the future payoff from the load area if it matches with a trader and the future payoff if it does not match with a trader and has to relocate to a waiting area. Therefore, if a ship is at a discharge port b, it has the following options:

1. Go to a load area $a \in A$
2. Go to a waiting area $w \in \mathcal{W}$

The option to go to a discharge port is not allowed. The value to be at a discharge area $b \in B$ is then the value to be at each of these locations, weighted by the probability of the option:

$$\begin{aligned} W^x(x^b_{j,t+1}, T+1) = \sum_{a \in A} \mathbb{P}(a|b)\Big(- c^{rep}_{ba,t+1} + \\ \beta^{x,d^{ba}(x_{j,t+1},y_i)} W^x(x^a_{j,t+1}, T+1)\Big) + \sum_{w \in W} \mathbb{P}(w|b)\Big(- c^{rep}_{bw,t+1} + \\ \beta^{x,d^{la}(x_{j,t+1},\emptyset_y)} W^x(x^w_{j,t+1}, T+1)\Big) \end{aligned} \tag{4.31}$$

It is apparent from this equation that the value to be at b depends on the values of locations $a \in A$ and $w \in W$. Note that the time period when the ship reaches its destination depends on its location such that it may be greater than $T + 1$. This notation was used since the average repositioning time is under one week and allows for simplicity of exposition. I assume that ships only go to a loading area if it has a cargo to pickup. This assumption is based on several interviews with the shipping industry. Therefore a ship that is at load area a will pick up cargo and immediately sail to a discharge area. The option to go to another load area is not allowed in the model.

The value to be at a load area $a \in A$ is the expected value to be at the load area, weighted by the probability distribution of trade flows from the load area:

$$\begin{aligned} W^x(x^a_{j,t+1}, T+1) = \sum_{b \in B} \mathbb{P}(b|a)\Big(P(x_{j,t+1}, y_i, T+1) \\ - c^{voy}_{ab,t+1} + \beta^{x,d^{ba}(x_{j,t+1},y_i)} W^x(x^b_{j,t+1}, T+1)\Big) \end{aligned} \tag{4.32}$$

The final type of location is a waiting area. If a ship is at a waiting area w, it will wait at the waiting area until it has a fixture, at which point it will sail to the load area. The value is:

$$W^x(x^w_{j,t+1}, T+1) = \sum_{a \in A} \mathbb{P}(a|w)\Big(- c^r n^x_{wait} - c^{rep}_{wa,t+1} + \beta^{x,d^{la}(x_{j,t+1},y_i)} W^x(x^a_{j,t+1}, T+1)\Big) \tag{4.33}$$

where n^x_{wait} is the number of days waiting to match with a trader.

4.5.5 The matched optimal speed

The matched speed is optimized in the case when the trader and ship bargain over the speed in the contract. In Policy 1, this speed is determined by solving for the derivative of the matching surplus under Policy 1 (Equation) with respect to speed:

$$\frac{d}{dv^{op}}(\pi(x_{jt}, y_i, t) - c^{rep}_{la,t} - c^{voy}_{ab,t} - \beta^{x,d(x_{jt},y_i)} c^{rep}_{ba,t}) = 0 \tag{4.34}$$

In Policy 2, the matched speed is optimized by solving for the derivative of the matching surplus function using the forward-looking option value:

$$\frac{d}{dv^{op}}(\pi(x_{jt}, y_i, t) - c^{rep}_{la,t} - c^{voy}_{ab,t} + \beta^x W^x(x^b_{j,t+1}, t+1)) = 0 \tag{4.35}$$

The optimal speed depends on the relative magnitude of each parameter and its effect (positive or negative). A slower speed lowers the oil revenue because the trader has to pay to store the oil cargo until the ship arrives and through the discounting. For the ship, going slower increases its opportunity costs, but decreases the fuel cost portion of shipment costs. The impact of speed on the ship's option value depends on its sign: if it is positive, then a slower speed decreases the value, while a negative value is positively impacted by a slower speed.

4.6 Specification of the surplus to remain unmatched

This section provides the specification for the surplus to remain unmatched for the trader and the ship. The section is divided into two subsections: the trader's surplus to remain unmatched and the ship's surplus to remain unmatched.

4.6.1 The trader's surplus to remain unmatched

In theory, if the model is solved repeatedly, $W^x(x_{j,t+1}, t+1)$ would be the value of the ship type $x_{j,t+1}$ in period $t+1$ from the model's output. However, prior to solving a dynamic matching model, a good guess can be estimated from data. It can be estimated as follows. The model assumes the trader has already bought the oil cargo and therefore his alternative is to store the oil at the load area until a ship can pick up his cargo. Storage costs are represented as a daily cost per barrel of oil, which could be either land or floating storage.[3] If a trader matches in the next period, they earn an average expected oil revenue based on potential matches with ships. This means that their average revenue depends on the location of ships because oil revenue is discounted by the days at sea. Then the estimated value of a null match for the trader in period T is:

$$s(\emptyset_x, y_i, T) = \mathbb{E}(\bar{\pi}(x_{jt}, y_i, T+1)) - c^{store} q^b n^y_{wait} - \mathbb{E}(P(x_{j,t+1}, y_i, T+1) \tag{4.36}$$

where:

$\bar{\pi}(x_{jt}, y_i, T+1)$	average expected oil revenue at $T+1$
c^{store}	daily storage cost per tonne
n^y_{wait}	waiting days until a trader matches to a ship
$\mathbb{E}(P(x_{j,t+1}, y_i, T+1))$	expected freight rate (\$) at $T+1$

The number of days until a trader matches with a ship n^{wait} equals the days until the next matching period plus the average days until the trader can match which depends on the probability of matching. In the model, the probability of matching is a function of the aggregate demand to supply ratio. I assume that if this ratio is less than 1, then traders can always match with a ship with probability 1.

4.6.2 The ship's surplus to remain unmatched

The value to remain unmatched for the shipowner depends on the policy. In the myopic policy, the shipowner discounts future periods heavily such that he does not consider the potential revenue earned from waiting. Thus the surplus of a dummy match is:

$$s(x_{jt}, \emptyset_y, T) = -c^{rep}_{lw,t} + -c^r n^x_{wait} \tag{4.37}$$

In policy 2, the surplus a dummy match is:

$$s(x_{jt}, \emptyset_y, T) = -c^{rep}_{lw,t} + \beta^{x,d(l,w)} W^x(x^w_{j,t+1}, T+1) \tag{4.38}$$

which is the repositioning cost from location l to w and the option value to be at w defined by equation 4.22.

[3]Floating storage is oil stored in a tanker that is anchored.

4.7 A Forward Looking Dynamic Matching Game

The static matching model requires an estimate of the ship's terminal option values, the dummy match values for each agent, the supply of ships available to match and the demand for cargoes in each location from outside the model. The endpoint values provide an initial "guess" and rely on many parameters - the freight rates in each location, probabilities of taking different routes, voyage costs, among others. In a dynamic model, the output from the linear program - $W^x(x_{jt}, t)$ and $W^y(y_i, t)$ - can be used as input for the ship's option value in the match surplus and dummy match surpluses instead of using the endpoint estimates. Although there is an implied supply of ships which is computed in the model, in this model formulation, I assume that supply and demand of ships is the same each period and exogenously provided for the one dimensional ship population. This is equivalent to assuming that the system is in a stationary equilibrium. Therefore the difference between the static and dynamic models is the option value for the ship and the dummy match surplus values, and the goal is to understand whether the earnings (and therefore option values) converge to a stationary value in each location, a so-called "fixed point" in earnings after the matching model is run for a certain amount of iterations. For example, if the option values from the model are the same as the respective terminal option values, then the model has converged in one iteration and the vector of terminal option values is the best guess. Because the model's option values are determined endogenously by the matching surplus function which depends on the model's supply and demand parameters, the values in general will not be equal to the terminal values.

The condition in which a value (point) is mapped to itself by a function (i.e., $v^n = f(v^{n-1})$) is known as a fixed point in mathematics. In the dynamic programming paradigm, solving a fixed point problem can be achieved through a numerical algorithm called value iteration by relaxing the condition that $v^n - f(v^{n-1}) = 0$ or $v^n - v^{n-1} = 0$ and assuming that the absolute value of the difference is equal to a small number specified by an error tolerance ϵ. In the model, I specify ϵ to be less than 10^{-4} which is the standard used in the literature (Powell, 2011). The model is solved forwards using value iteration. Using value iteration, the new option values input for the ship and the trader in the next iteration are a weighted average of the previous two iterations. The weights are determined by a stepsize parameter λ which generally weights the previous iteration $t-1$ more heavily than iteration $t-2$. The stepsize used in this model is .80. For the first iteration of the model, the static model is run using the terminal option values $W^x(x_{j,t+1}, T+1)$ and dummy match surpluses to obtain the first vector of option values for the ship and trader as output from the model. In iteration 2, the option values for the ship are equal to a weighted average of the terminal option values $W^x(x_{j,t+1}, T+1)$ used in the static model and iteration 1's option value, according to the stepsize weights. The output $W^y(y_i, t)$ is used to update the trader's dummy surplus. Finally, option values for iterations $t > 2$ are specified using the values from the model for iterations $t-2$ and $t-1$, where the new option values are equal to the weighted average from these model iterations.

There are certain conditions under which convergence can be met and conditions which lead to a quicker solution. For convergence, the discount factor has to be between 0 and 1. For a faster rate of convergence, it has been known that the standard value iteration algorithm suffers from slow convergence when the discount factor, in this case β, is close to unity. The stepsize value can also have an impact on the rate of convergence (Powell, 2011).

4.7.1 Time and sequence of events

Time is discrete (weekly) and the horizon is infinite. I assume a fixed supply $\mathbf{n}(x_{jt})$ of ships and demand for cargoes by traders $\mathbf{n}(y_i)$. The sequence of events is as follows:

1. At the beginning of the period, all agents have state variables known to them and other agents.

2. The economy receives an exogenous oil transportation demand shock which corresponds to $\mathbf{n}(y_i)$.

3. Ships and traders simultaneously decide to match with each other, or remain unmatched, generating a surplus (and a freight rate) to both agents. Each agent also generates beliefs about future opportunities. If a ship matches with a trader, it sails to the load port to pick up the oil, loads the oil and then drops it off in the discharge port. If a ship does not match, it sails to one of the waiting areas, optimizing over the options. It waits an expected amount of weeks based on the probability of matching in the market.

4.7.2 Solution algorithm

As discussed in section 4.6, the model is solved forwards using value iteration.

The exogenous parameters are:

$$X_{exog} = \Big(\mathbf{n}(x_{jt}), \mathbf{n}(y_i), W^x(x_{j,t+1}, 0), \tilde{s}(x_{jt}, y_i, 0), s(x_{jt}, \emptyset_y, 0), s(\emptyset_x, y_i, 0), \beta^x, \beta^y, \lambda\Big) \tag{4.39}$$

where time 0 represents input from outside the model for the first time step.

The endogenous parameters (model outputs) are:

$$X_{endog} = \Big(W^x(x_{jt}, t), W^y(y_i, t), \mathbf{m}(x_{jt}, y_i, t)\Big) \tag{4.40}$$

where $\mathbf{m}(x_{jt}, y_i, t)$ is the vector of the assignment in period t.

The dynamic model is solved in the following steps:

1. Step 1. Initialization: set $t = 1$, set max $t = 1000$
   (a) Input: $\mathbf{n}(x_{jt})$, $\mathbf{n}(y_i)$; $W^x(x_{j,t+1}, 0)$, $s(x_{jt}, \emptyset_y, 0)$, $s(\emptyset_x, y_i, 0)$
   (b) Solve the LP problem.
   (c) Save outputs $W^x(x_{jt}, 1)$, $W^y(y_i, 1)$.
2. Step 2. Set $t = 2$
   (a) Input $\mathbf{n}(x_{jt})$, $\mathbf{n}(y_i)$; set $W^x(x_{j,t+1}, t+1) = (1-\lambda)W^x(x_{jt}, 0) + \lambda W^x(x_{jt}, 1)$; use $W^y(y_i, 1)$ as input to $s(\emptyset_x, y_i, 2)$.
   (b) Solve LP problem.
   (c) Check convergence: if $|W^x(x_{jt}, t) - W^x(x_{jt}, t-1)| < \epsilon$ and $|W^y(y_i, t) - W^y(y_i, t-1)| < \epsilon$ then stop.
3. Step 3. For $t > 2$
   (a) Input $\mathbf{n}(x_{jt})$, $\mathbf{n}(y_i)$; Set $W^x(x_{j,t+1}, t+1) = (1-\lambda)W^x(x_{jt}, t-2) + \lambda W^x(x_{jt}, t-1)$; Set $W^y(y_i, t) = (1-\lambda)W^y(y_i, t-2) + \lambda W^y(y_i, t-1)$.
   (b) Solve LP problem.
   (c) Check convergence: if $|W^x(x_{jt}, t) - W^x(x_{jt}, t-1)| < \epsilon$ and $|W^y(y_i, t) - W^y(y_i, t-1)| < \epsilon$ then stop. Else go to Step 3.

4.8 Summary

In this chapter, I have described the matching model structure which will be used to compute the assignment of ships to traders and the earnings for each agent in a competitive equilibrium. The model is solved using linear programming which is a simple but large combinatorial optimization problem where the combinations are the surpluses from the pairings of agents, including dummy agents. The objective function is to maximize these surpluses subject to the agent constraints which place restrictions on both the number of resources that can be used to fulfill cargo demands and the value each agent must earn (the dummy surplus values for each agent). Associated with solving a linear programming problem are the multipliers on the constraints which indicate how valuable each type of agent is in the market. The multipliers can be used to construct equilibrium prices. One of the assumptions of the model structure was that the cost of repositioning to the load area is included in the contract price. An alternative would be for the ship to pay this cost. Either formulation does not have a significant impact on the matching results in the competitive equilibrium however. The model has been divided into two parts: a static one period matching model and a dynamic matching model. The static model uses an estimate of ship option values and dummy surplus values from data outside the model, while these values are determined endogenously in the dynamic version. The purpose of the dynamic model is to solve for a fixed point to see if earnings and matching probabilities converge, keeping the supply and demand stationary.

Chapter 5

Data and Descriptive Statistics

This chapter describes the datasets used to estimate the model described in Chapter 4. Specifically, data on the trade demand between the load and discharge areas by VLCC (the trade flow), the buy price of oil, the expected price of oil in the discharge location, the average cargo size and discount rate is required to estimate the number of trader types and their cargo demands. To estimate the number and types of ships, data is required on the supply of VLCCs in each discharge and waiting area, the technical specifications of the VLCC fleet (age, tonnes per day, design speed, and DWT), and the daily opportunity cost (or rental rate) of the ship. For the matching surplus and the surplus to remain unmatched, data on the pairwise distance of all locations, the bunker price, average operating speed, days in port, per barrel storage cost, and estimated per-tonne freight rates on specific routes is needed.

Data on oil shipments is extremely valuable data. The OPEC countries have a self interest in hiding actual production figures in order to renege against their cartel quota and physical oil traders use shipment information to inform their trading decisions (Downey, 2009). It is difficult to obtain publicly available data from one source that provides complete information on the oil shipment trade flows carried by VLCCs and the prices of fixtures. This chapter describes the five datasets used to estimate the model and documents where there is missing or censored data that presents a challenge for estimation.

The first dataset consists of a sample of world tanker fixtures of crude oil containing price and volume information on trade flows, where a trade flow in the model is defined as total crude oil shipped from load area a to discharge area b. The second dataset contains data on benchmark prices for trade flows which are used to compute prices. The third dataset provides data on the VLCC fleet which is used to create physical profiles of ships. The fourth dataset is a compilation of aggregate trade data used to compute the implied average number of ships in each area. The fifth dataset provides ship movement characteristics including speed travelled.

5.1 Fixtures dataset

The fixtures dataset (Clarkson Research, 2011) is a sample of global crude oil tanker voyage (spot) and time charter contracts for the time period between January 2, 2007 to December 13, 2011. The data contains 39,022 observations grouped into fixture contract details relating to the shipowner and charterer. Clarkson Research reports the deals for which shipping brokers are willing to record; some are withheld from the market for confidential reasons (Cridland, 2010). According to Clarkson Research (2011), "Charter rates for specific fixtures are often omitted when reported to the market for a variety of reasons. For example, it may just not have been available when the various brokering houses/the Baltic Exchange reported the fixture. However, it is safe to assume that on the whole, if the rate is not available, it is more likely than not to be for confidentiality reasons." According to the sources, between 2007-2011, approximately 8,000 fixtures or 20% were marked private and confidential and were excluded from the dataset. The dataset contains detailed information on the fixture, fleet detail, and origin and destination.

The fixture detail includes the fixture date, freight rate, laycan from and to, fixture status, charterer name, beneficial shipowner, and origin and destination information. Laycan from and to refers to the earliest and latest dates when the ship can load, respectively. There is various geographical coverage, with some entries reporting detail to the port level. Rates either reported in Worldscale (WS), lump sum, US dollars per day (for time charter contracts), or are not reported at all (reported as 0). I refer to fixtures with prices that are not reported as censored fixtures, while fixtures that were excluded from the dataset by the data source are omitted fixtures.

The majority of observations for the voyage contracts are reported in WS units and occasionally quoted in lump sum units depending on the source of the information and the specifics of the charter party. The lump sum is the gross revenue per voyage.

Fleet register detail on the ship's physical characteristics includes the vessel name, IMO number, builder, builder country, flag state, main engine manufacturer, vessel design speed, vessel daily fuel consumption, and total engine propulsion (horsepower). Table 5.1 shows there are 9 types of vessels included: Aframax, Capesize, FPSO/FSU, Handy, Offshore, Panamax, Suezmax, and VLCC. VLCCs account for the largest volume of tonnes lifted (52%) of all vessel classes. The subset of VLCC fixtures contains 4,873 observations and the remaining discussion of the fixtures dataset will focus on this subset.

Table 5.1: Cargo volume by vessel type, 2007-2011

Vessel	**Cargo Volume**	**Share of Volume**
	'000 tonnes	%
VLCC	1,139,826	51.9
Aframax	506,407	23.1
Suezmax	328,447	15.0
Capesize	120,202	5.5
FPSO/FSU	79,673	3.6
Panamax	9,810	0.4
Offshore	5,022	0.2
Combined	4,720	0.2

Source: Clarkson Research (2011)

5.1.1 Major trading regions and trade flows

In practice, a shipment is from a port in a load area to another port in a discharge area. However, industry practitioners (Clarkson Research, 2012a, Braemar Insight, 2012) commonly use the sea area rather than a specific port as the geographical entity in their market activity reports. There is also a variation in coverage at the port level; the majority of fixtures in the dataset only report the port for one area (see Tables D.1 and D.2 of the Appendix for documentation of the missing geographical values for all of the fixtures and fixtures with price data). The study focuses on trade flows at the area level in order to reduce the computational cost and added uncertainty with estimation of missing ports.

The majority of cargoes shipped by VLCC originate in the Arabian Gulf (AG), which accounts for (84%) of all the cargo volume in the fixtures dataset (Table 5.2). The dominant position of the Arabian Gulf in the tanker oil shipping market implies that there is an imbalance of ship supply across loading areas.

Two other major areas are the Caribbean (8%) and West Africa (2%). These there regions can be considered as the "Big Three" which combined accounted for 95% of export volume by VLCC. Whereas the Middle East holds a considerable lead over other oil producing regions, demand for crude oil is much more spread out amongst discharge areas, though it has largely shifted to the Far East. China imports the most crude oil of any area (28%), followed by the South Pacific Oceania area (15%), Korea (12%), and the US Gulf (9%) (Table 5.3). The only publicly available data from which to compare these figures is BP's aggregate trade dataset. This requires working down from the aggregate crude oil import and exports data by making assumptions about the share of oil by pipeline and the share of VLCCs transporting crude oil for each region. BP (BP, 2012) also classifies regions differently than Clarkson Research (Clarkson

Table 5.2: VLCC fixtures volume by load area, 2007-2011

Area	Area Name	Volume ('000 tonnes)	Share (%)
AG	Arabian Gulf	1,093,200	84.16
CAR	Caribbean	110,030	8.47
WAF	West Africa	29,520	2.27
WMED	Western Mediterranean	23,000	1.77
BRZ	Brazil	13,549	1.04
UKC	United Kingdom Continent	11,480	0.88
ECMX	East Coast Mexico	4,595	0.35
EMED	Eastern Mediterranean	3,765	0.29
REDS	Red Sea	3,200	0.25
CMED	Central Mediterranean	2,360	0.18
BALT	Baltic Sea	1,440	0.11
USG	US Gulf	815	0.06
JAP	Japan	785	0.06
KOR	Korea	650	0.05
WCSA	West Coast South Africa	280	0.02
ARG	Argentina	130	0.01
ECC	East Coast Canada	130	0.01
SPOR	South Pacific Oceania Region	80	0.01

Source: Clarkson Research (2011)

Research, 2011), for example, Central and South America is one region, whereas in Clarkson Research it is divided into the Caribbean and Brazil. Of the Big Three, AG accounted for 83% of exports, CAR/BRZ accounted for 11% and WAF for 6%, whereas the implied BP shares for these three areas are 70%, 10% and 20% respectively. The largest discrepancy with the imports data compared to the implied BP data (BP, 2012) is the underrepresentation of the US and Japan in the fixtures dataset and this might lead to an upward bias in the eastward flows, particularly China which dominates the discharge regions in the Far East.

Table 5.4 shows the regional trade flows which account for more than 1% of the total 2011 (see Appendix A Table D.4 for all trade flows). The Arabian Gulf-Far East trades dominate, with the Arabian Gulf to South China route having the largest trade flow share (28%) overall.

5.1.2 Fixture demand, cargo size, and capacity utilization

The frequency of weekly VLCC shipment transactions has risen each year between 2007 and 2011, from 15 to 26 (Table 5.5). It appears there are some major discrepancies in the number of fixtures reported in the fixtures dataset and the number reported by experts in the industry. According to the VLCC fixtures dataset, an average of 26 fixtures were made per week in 2011. Backtracking from an annual 6 voyages per year, it is unlikely that the weekly number of fixtures is 26 because that would imply a very low number of hire weeks, implying that a roundtrip voyage is 2.86 weeks which is half the time of an expected roundtrip voyage. However, industry

Table 5.3: Volume by discharge area, 2007-2011

Area	Area Name	Volume ('000 tonnes)	Share (%)
SCH	South China	362,720	27.93
SPOR	South Pacific Oceania Region	198,130	15.26
KOR	Korea	154,120	11.87
USG	US Gulf	122,600	9.44
WCI	West Coast India	122,240	9.41
THAI	Thailand	77,007	5.93
JAP	Japan	67,468	5.19
TWN	Taiwan	54,574	4.20
CALI	California	33,115	2.55
UKC	United Kingdom Continent	26,650	2.05
REDS	Red Sea	21,306	1.64
ECI	East Coast India	17,484	1.35
NCH	North China	9,308	0.72
SAF	South Africa	8,560	0.66
ECC	East Coast Canada	7,003	0.54
PHIL	Philippines	5,888	0.45
BRZ	Brazil	5,495	0.42
WMED	Western Mediteranean	1,905	0.15
SPATL	South Pacific Atlantic	830	0.06
USAC	US Atlantic	655	0.05
CMED	Central Mediteranean	540	0.04
EMED	Eastern Mediteranean	490	0.04
CAR	Caribbean	260	0.02
AG	Arabian Gulf	250	0.02
WCSA	West Coast South Africa	130	0.01

Source: Clarkson Research (2011)

Table 5.4: Top trade flows by area, 2011

Load Area	Area Name	Discharge Area	Area Name	Volume (tonnes)	Share of Total (%)
AG	Arabian Gulf	SCH	South China	95,499,000	28.69
AG	Arabian Gulf	KOR	Korea	38,294,500	11.50
AG	Arabian Gulf	WCI	West Coast India	22,573,000	6.78
CAR	Caribbean	SPOR	South Pacific Oceania Region	22,550,000	6.77
AG	Arabian Gulf	SPOR	South Pacific Oceania Region	21,622,700	6.50
AG	Arabian Gulf	JAP	Japan	21,193,000	6.37
AG	Arabian Gulf	THAI	Thailand	18,310,500	5.50
AG	Arabian Gulf	USG	US Gulf	15,910,000	4.78
AG	Arabian Gulf	TWN	Taiwan	8,755,000	2.63
CAR	Caribbean	WCI	West Coast India	7,599,000	2.28
WAF	West Africa	SCH	South China	5,980,000	1.80
AG	Arabian Gulf	UKC	United Kingdom Continent	5,555,000	1.67
WAF	West Africa	WCI	West Coast India	4,420,000	1.33
AG	Arabian Gulf	CALI	California	3,890,000	1.17
WAF	West Africa	USG	US Gulf	3,640,000	1.09
WAF	West Africa	ECI	East Coast India	3,385,000	1.02

Source: Clarkson Research (2011)

Table 5.5: Average number of fixtures per week and cargo size

Year	Fixtures	Cargo Size
		tonnes
2007	14.66	266,924
2008	15.70	267,433
2009	17.19	265,533
2010	20.10	266,892
2011	26.16	266,526

Source: Clarkson Research (2011)

experts report that there are around 50-70 fixtures per week and the model will be run with 70 fixtures per week which is more representative of the VLCC shipments required based on aggregate trade data.[1] This suggests that Clarkson Research is underestimating the amount of fixtures being omitted.

Average cargo size in the dataset has declined. In 2011, the average cargo size was 266,525 (median 265,000), slightly below the 2007 average of 266,924 (see Figures 5.1), suggesting that the parcel size places a limit on capacity.

Although parcel size has declined, ship size has increased since the 1980's (Figure 5.1 shows the relationship between DWT and capacity utilization, DWT and year of build. The negative relationship between DWT and capacity utilization shows that larger ships are not obtaining higher cargo sizes so their capacity utilization is lower compared to smaller VLCCs.

In theory, there should be a positive correlation between trade route distance and cargo size because of the extra shipment days and cost. The data does not show that preferences for size are linearly related to trade route distance (Figure (5.2)); the same cargo size serves routes of varying distances. Instead, there is some unobserved preference for routes demanding certain sizes over others, perhaps reflecting the specific customer's (refinery or trading house) inventory demand and port size restrictions.

5.1.3 Prices and other descriptive statistics

Only a subset of the VLCC fixtures (72%) reported have price data and will be referred to as the uncensored fixtures dataset and fixtures with prices that are withheld will be referred to as the censored dataset. The uncensored fixtures dataset has prices reported in Worldscale multiplier (WS) units or lump sum dollar units. The majority of observations in the uncensored dataset - 87% or 3,017 observations - have WS units as this is the most common way to report prices in

[1]Based on conversations with Lloyd's List Intelligence (Lloyd's List, 2013) and Gibson Shipbrokers (Gibson, 2013).

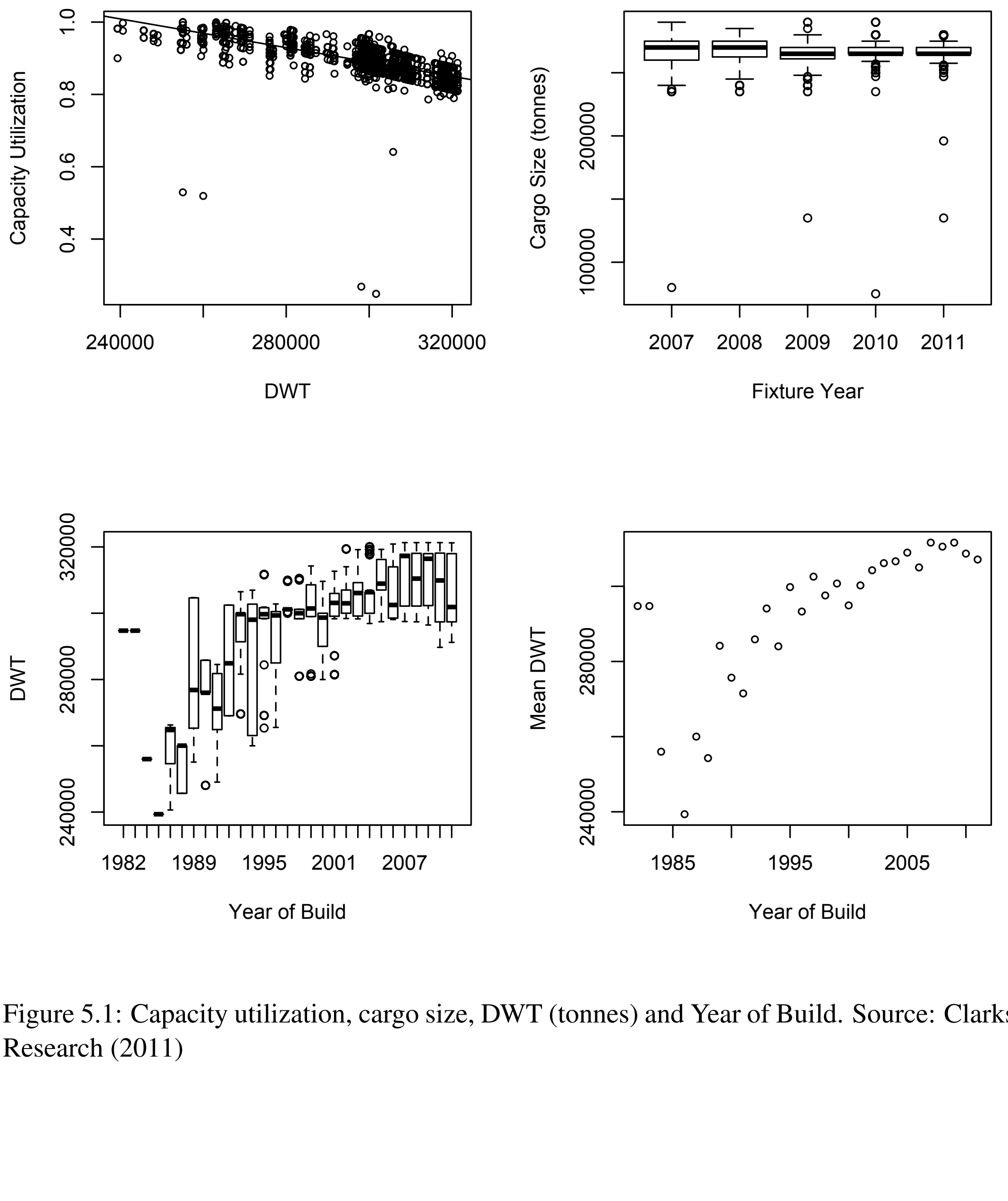


Figure 5.1: Capacity utilization, cargo size, DWT (tonnes) and Year of Build. Source: Clarkson Research (2011)

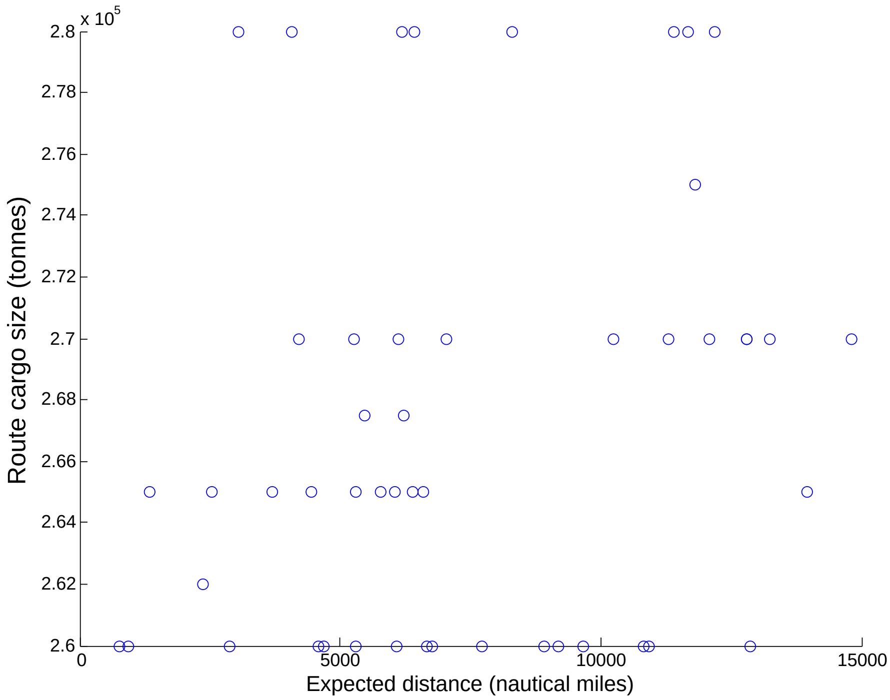


Figure 5.2: Expected route distance and cargo size (2011). Source: Clarkson Research (2012a)

Table 5.6: Share of total volume by load area (censored vs. uncensored), 2007-2011, (%)

Load Area	Area Name	All fixtures	Uncensored	Censored
AG	Arabian Gulf	84.2	93.3	96.5
ARG	Argentina	0.0	0.0	0.0
BALT	Baltic Sea	0.1	0.1	0.0
BRZ	Brazil	1.0	1.2	0.9
CAR	Caribbean	8.5	0.0	0.0
ECC	East Coast Canada	0.0	0.0	0.0
CMED	Central Mediterranean	0.2	0.0	0.0
ECMX	East Coast Mexico	0.4	0.1	0.4
EMED	Eastern Mediterranean	0.3	0.4	0.2
JAP	Japan	0.1	0.1	0.1
KOR	Korea	0.1	0.0	0.0
REDS	Red Sea	0.2	0.4	0.1
SPOR	South Pacific Oceania Region	0.0	0.0	0.0
UKC	United Kingdom Continent	0.9	0.5	0.6
USG	US Gulf	0.1	0.0	0.0
WAF	West Africa	2.3	1.9	0.6
WCSA	West Coast South Africa	0.0	0.0	0.0
WMED	Western Mediterranean	1.8	2.1	0.6

Source: Clarkson Research (2011)

crude oil shipping. For load areas in the Caribbean, Central Mediterranean, East Coast Mexico, Korea, United Kingdom, and West Coast South America - the majority of fixtures (greater than 50%) are reported as a lump sum. For the Caribbean, fixtures with prices are only reported in lump sum units.

Censoring is a potential issue if the censored dataset differs from the uncensored dataset and therefore the datasets need to be compared. Table 5.6 compares the share of cargo volume for all fixtures (lump sum, WS, and censored prices), the uncensored multiplier dataset, and the censored dataset. A greater proportion of the reported fixtures with WS units (uncensored) are from AG because the Caribbean isn't represented in these datasets. The uncensored and censored multiplier datasets have similar shares in terms of volume by load area, though the censored dataset weights the Arabian Gulf more heavily (3.14% lower in the censored dataset). In terms of volume by discharge area, there is some censoring of fixtures to the Far East (see table 5.7).

The censored dataset contains less shipowners (95 compared to 120 shipowners) and the most fixtures that were withheld in the censored dataset were from China Shipping Tankers which is associated with the censored fixtures to South China. Charterers that withheld the most fixtures (greater than 3%) were China International United Petroleum & Chemical Co.

Table 5.7: Share of total volume by discharge area (censored vs. uncensored), 2007-2011, (%)

Discharge Area	Area Name	All fixtures	Uncensored	Censored
SCH	South China	27.9	15.3	64.6
SPOR	South Pacific Oceania Region	15.3	10.9	8.7
KOR	Korea	11.9	15.8	0.0
USG	US Gulf	9.4	13.6	4.0
WCI	West Coast India	9.4	10.5	7.8
THAI	Thailand	5.9	8.3	2.6
JAP	Japan	5.2	4.6	3.1
TWN	Taiwan	4.2	6.3	1.4
CALI	California	2.6	2.7	2.3
UKC	United Kingdom Continent	2.1	3.0	1.8
REDS	Red Sea	1.6	2.7	1.2
ECI	East Coast India	1.3	1.6	1.1
NCH	North China	0.7	1.0	0.2
SAF	South Africa	0.7	1.0	0.5
ECC	East Coast Canada	0.5	0.9	0.2
PHIL	Philippines	0.5	0.5	0.2
BRZ	Brazil	0.4	0.7	0.2
WMED	Western Mediteranean	0.1	0.2	0.1
SPATL	South Pacific Atlantic	0.1	0.1	0.0
USAC	US Atlantic	0.1	0.1	0.0
CMED	Central Mediteranean	0.0	0.0	0.1
EMED	Eastern Mediteranean	0.0	0.1	0.1

Source: Clarkson Research (2011)

Table 5.8: Comparison of censored and uncensored variables (median values)

Variable	Units	Uncens.	Cens.	Uncens. China	Cens. China
DWT	tonnes	301,200	298,500	301,900	297,400
Age	years	10	7.7	8.8	6.2
Laycan Day Diff		0	0	1	0
CapUtil		0.89	0.89	0.88	0.89
k	tonnes	81.64	78.63	81.64	76.13
WS	57.5	-	57.5	-	

Source: Clarkson Research (2011)

(UNIPEC) (55%), ExxonMobil (5%), IOC (3%). UNIPEC became the world's largest charterer of oil tankers for the first time in 2012, surpassing Royal Dutch Shell Plc (RDSA), followed by Vitol Trading Group. (Bockmann, 2013), a shipbroking firm. Among all fixtures, UNIPEC chartered the most ships, but ranks 8th in the uncensored multiplier dataset. It also appears that the major charterers - Shell and Vitol Trading - are entirely omitting their fixtures. Shell ranked 8th in the total fixtures dataset and Vitol only reported 4 fixtures. These figures are for all oil tankers so they do not give precise information for VLCC charterers, but reveal that some of the major charterers are withholding fixtures.

Aside from geographical and charterer bias, other variables that explain prices (DWT, age, laycan day difference, capacity utilization, k) in the censored and uncensored datasets are very similar. Table 5.8 shows a comparison of these variables in the censored and uncensored datasets. As the majority of censored observations are from China, fixtures that had Discharge Areas in China were were also compared. The median DWT is higher in the uncensored dataset (301,200) compared to 298,500 in the censored dataset; capacity utilization is only slightly lower in the uncensored dataset (88%) compared to 89% in the censored dataset. The median difference in Laycan days is the same in both datasets. The uncensored dataset represents an older fleet (10.0 vs. 7.7 years). There are similar results for the uncensored and censored datasets filtered for fixtures discharging in China which is consistent with the fact that China represents a large proportion of the censored price data. The uncensored sample contains 721

Table 5.9: Comparison of fixtures dataset to World Fleet Register dataset (median values)

Variable	Units	Multiplier dataset	WFR dataset
Age	years	9	8
DWT	tonnes	301,428	302,159
k	tonnes	89.73	83.67
Design Speed	knots	15.7	15.68

Source: Clarkson Research (2011)

ships. Although Clarkson Research included fleet detail, tonnes per day (k) was available only when the manufacturer provided it. Additional technical specifications were obtained by linking the dataset to Dataset 3 (the fleet register dataset) which contains the entire current fleet from which k could be estimated from engineering first principles. The matching was incomplete; 12 ships did not match to an IMO number in Dataset 3. In addition, 29 ships in Dataset 3 had missing design speed so k could not be calculated. Excluding the missing observations associated with these ships reduced the sample to 2,876 (9.5% less than the uncensored sample) and 685 ships. Variables in this dataset are almost identical to the uncensored multiplier datasets and therefore can be treated as missing at random.

Table 5.10: Legend for Figure 5.3

Symbol	Route name	Cargo size (tonnes)
AG.UKC280	Arabian Gulf-United Kingdom	280,000
AG.JPN265	Arabian Gulf-Japan	265,000
AG.SPOR260	Arabian Gulf-Sout Pacific Oceania Region	260,000
AG.USG280	Arabian Gulf-US Gulf	280,000
WAF.SCH260	West Africa-South China	260,000
WAF.TWN260	West Africa-Taiwan	260,000
AG.WCI265	Arabian Gulf-West Coast India	265,000
WTI Crude Oil	West Texas Intermediate Crude Oil Price	-

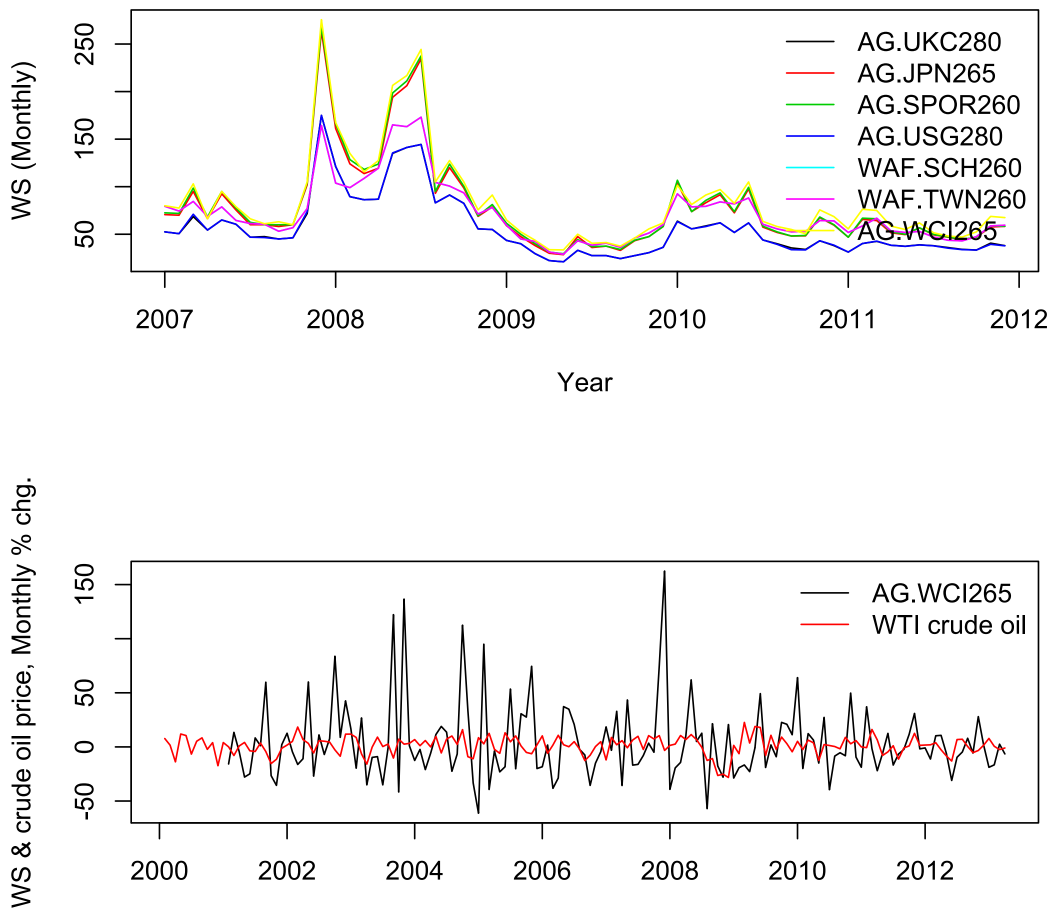


Figure 5.3: Left: WS multiplier by route; Right: WS Multiplier and Crude Oil Prices, chg. Source: Clarkson Research (2012a)

Figure 5.3 shows the monthly WS multiplier prices between 2007-2011 and the percentage change of the WS price for the AG-WCI route and the crude oil price from Clarkson Research (Clarkson Research, 2013). The monthly time series exhibits large fluctuations, reaching a high of 269 and a low of 21. Note prices are in Worldscale units which are set to a benchmark price per year. This means that freight rates are not strictly comparable across years since the benchmark is reviewed annually. Comparing prices within a year, the volatility can be attributed to changes in supply and demand, the inelastic demand for crude oil, and the time to build constraints. Two routes (AG-UKC and AG-USG) are on average 20 WS points lower, and this can be explained by their westward direction which implies they are likely to obtain a fixture in West Africa or the Caribbean as opposed to eastward routes which have to ballast back empty to AG. The right hand graph shows the percentage change in Worldscale prices for the AG-WCI route compared to the percentage change in the crude oil price. The large fluctuations cannot be explained by the crude oil price alone (which correlates closely with the bunker price), implying that these fluctuations are partially explained by supply and/or demand factors. For example, if supply becomes scarce to supply a load area, oil traders have to pay a higher freight rate in order to ship the oil quickly.

5.2 Worldscale benchmark dataset

The Worldscale benchmark dataset (Worldscale, 2012) was used to compute historical freight prices observed in the multiplier dataset. The information for the benchmark flat rate is based on the Preamble from the Worldscale Association's website and is updated annually such that there is a separate benchmark price for each port pair, route, and year. Figure 5.4 shows the distribution of prices per port pair, route, and year between 2007 and 2011 for the sample of data collected. The black line indicates the median and the box provides the upper and lower quartiles. Prices were collected for the most likely port pairs on each route in the multiplier dataset when only the area trade flow was provided in the multiplier dataset. Of the 149 known distinct year, port-pair combinations in the multiplier dataset, 89% match to a benchmark price in the benchmark dataset. Of the 59 distinct port-pair combinations represented in the multiplier dataset, 85% match to an exact benchmark port-pair and this was considered to be sufficient coverage.The benchmark dataset is an unbalanced panel dataset covering the years 2007-2011. The data was collected from Worldscale Association's website. Because the Association does not have an advanced query system, port-pairs had to be manually collected which was costly in terms of time. Prices and distances were collected for the shortest distance route and for pairs where there was more than one route (for example, the Cape of Good Hope (CGH)). The

Table 5.11: Worldscale flat rate assumptions

Year	DWT	Speed	Sailing k	Other T	T/port	Port time	Rental Rate	Bunker price
	tonnes	knots	tonnes	tonnes	tonnes	days	US \$/day	US \$/tonne
2007	75,000	14.5	55	100	5	4	12,000	318.25
2008	75,000	14.5	55	100	5	4	12,000	328.75
2009	75,000	14.5	55	100	5	4	12,000	554.05
2010	75,000	14.5	55	100	5	4	12,000	341.16
2011	75,000	14.5	55	100	5	4	12,000	467.48

T=tonnes of bunker fuel. Source: Worldscale Association (2012)

median freight rate was $9.47/tonne and mean roundtrip distance was 5352 nautical miles in 2007.

As discussed in Chapter 3, the benchmark rate represents the costs of a roundtrip voyage for a standard tanker vessel. The rate is comprised of three components: fuel, port and fixed costs. Table 5.11 shows the Association's technical assumptions for the standard vessel over the period 2007-2011. The standard vessel has a total capacity of 75,000 tonnes, fuel consumption of 55 tonnes per day while sailing, fuel consumption of 100 tonnes for purposes other than steaming, and a fuel consumption of 5 tonnes in port. In comparison, VLCCs consume 62 tonnes of fuel per day while sailing at an equivalent speed of 14.5 knots and consume 250 tonnes of fuel in port, according to the Second IMO GHG Study (IMO, 2009). The bunker price is updated annually based on the predicted price for the period. An average time of 4 days in port for a voyage from one loading port to one discharging port is assumed. The objective for port costs is to include realistic allowances for all of the port cost items which are levied against the vessel, even when the port costs are tonnage based. There are more than 20 port due items listed in the Preamble, although it is not meant to be a comprehensive list. When assessing port costs, Worldscale bases its allowances for tonnage related charges on the standard vessel, making no adjustments for any costs that would not be incurred by the standard vessel.

In addition to the flat rate, there are fixed and variable differentials for transiting certain areas such as the Suez Canal or Panama Canal. A separate flat rate is published for port pairs where there are alternative routes. Worldscale distinguishes these routes by waypoints, where major waypoints for VLCCs are the Cape of Good Hope (CGH) (tip of South Africa) and the Suez Canal (SUE).

Bunker prices are forecasted for the period January 10th to September of the benchmark's year. Table 5.11 shows that the forecasted bunker price reached its highest level in 2009 at $554.05/ tonne. There are significant differences between the forecasted bunker price and the annual average. In 2011, the margin of error was 28% too low.

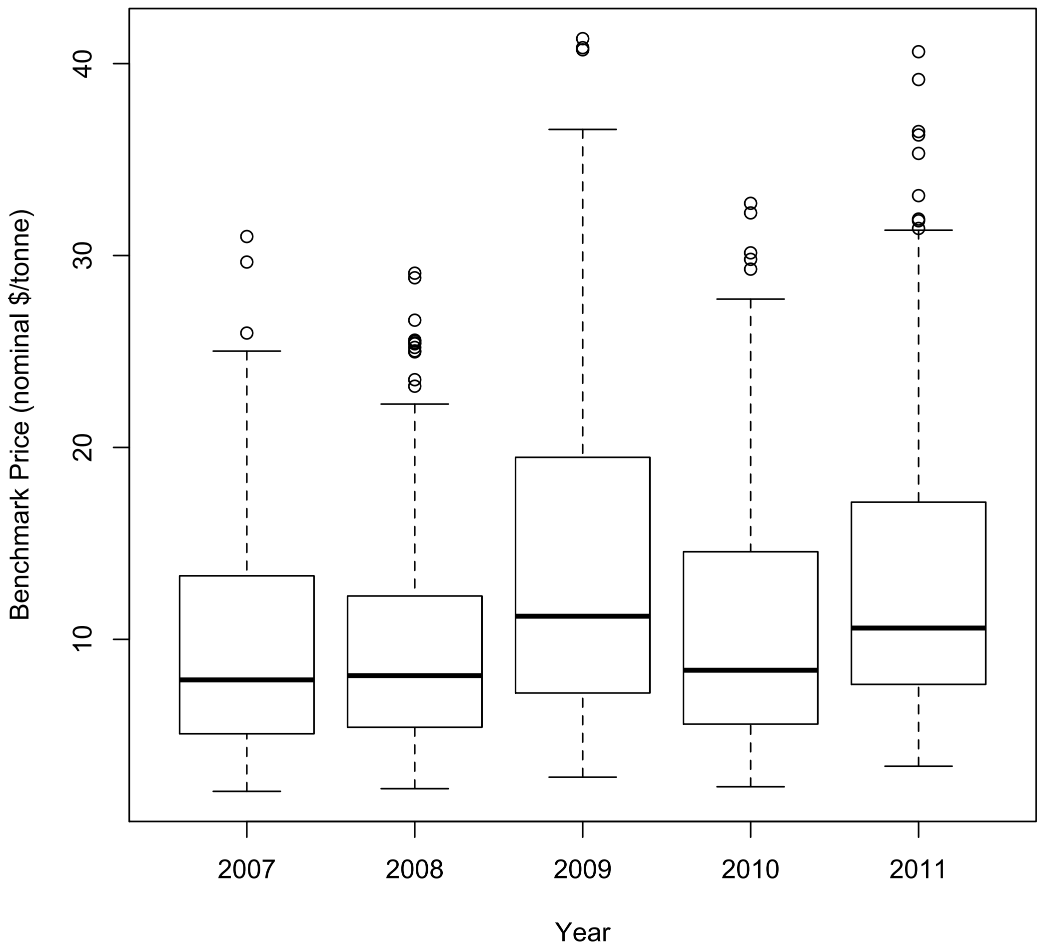


Figure 5.4: Annual Benchmark Prices (2007-2011). Source: Worldscale Association (2012).

5.3 Fleet register dataset

The fleet register dataset is a monthly dataset of the fleet's physical characteristics and ownership published by Clarkson World Fleet Register. The data was a snapshot of the fleet as of November 2012 and the VLCC fleet totaled 604 vessels. As discussed, the physical characteristics that are important determinants of contract prices are age, DWT, design speed, and daily fuel consumption. Fuel consumption on a journey can be estimated based on the "as designed" daily fuel consumption (referred to as k), the design speed and operating speed. The data for k is incomplete, with 43% of the sample missing and was computed based on a simple first principles engineering equation:

$$k = KW(MCR)(SFC) * 24/10^6 \tag{5.1}$$

where KW is the propulsion power in kilowatts or the maximum output that the main engine has been set to on board. This is multiplied by an average engine load factor (MCR) of 75%. SFC stands for specific fuel consumption, representing the grams of fuel burned per kWh. The kWh units cancel out and we are left with a tonnes per day figure. Total fuel consumption for a journey depends on k, design speed v^d, operating speed v^{op}, and the distance between the origin and destination $\phi_{ll'}$[2]:

$$k^{tot} = k(\frac{v^{op}}{v^d})^3 \frac{\phi_{ll'}}{24v^{op}} \tag{5.2}$$

Engines have different SFC values, depending on their engine size, age, and the energy density of the fuel. Typically, SFC is measured in an engine test-bed from the manufacturer. The SFC value is a function of the ship's age and the power type of the engine (2-stroke or 4-stroke). For the thirty three percent of the observations that were missing, values from the IMO were used as estimates. [3] showing that there has been improvements in efficiency of engines, which has lead to a decrease in SFC from an average of 190 (1970-1983) to 170 (2001-2007).

Observations with missing design speed values (21%) were not included in the estimation of ship types because the fuel consumption could not be calculated. This reduced the sample to 536 observations. The mean DWT of the VLCC fleet in 2012 was 304,957 tonnes. There is a distinct clustering around the median (302,159), with 75% of ships having a DWT of 311,505 or less (Figure 5.5).

[2]Fuel consumption also depends on the ship's auxiliary engine and weather conditions.

[3]The IMO estimates these values by reviewing various CIMAC papers, manufacturer's catalogues and Diesel & Gas Turbine Worldwide. The VLCC fleet contains only 2-stroke engines so the engine year of build is what determines the SFC value.

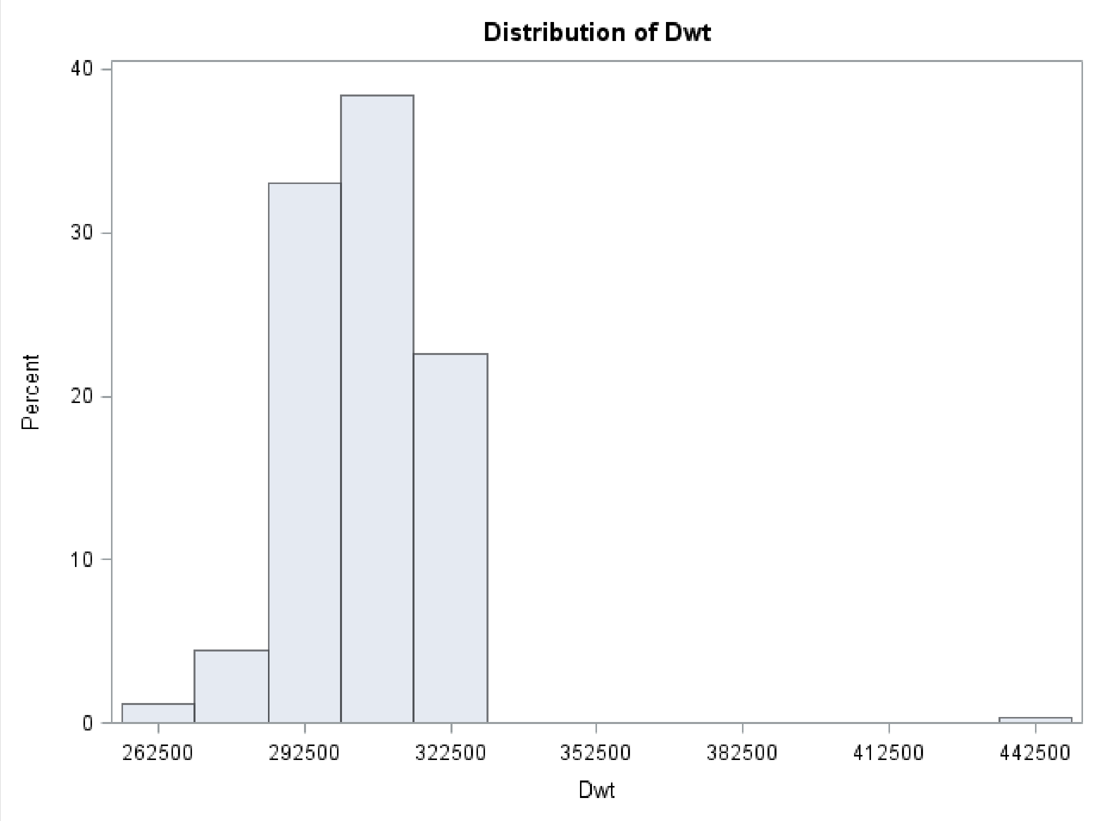


Figure 5.5: DWT Distribution of VLCC fleet (tonnes). Source: Clarkson Research (2012b).

The mean age is 8.33 years, with a median of 8 years and maximum age of 23 years. Design speeds range from 12.25 to 21.5, with a mean value of 15.68. The estimated Tpd ranged from a low of 48.95 to 113 tonnes per day, with a mean value of 83.67.

5.4 Aggregate trade statistics

No one trade source provides trade statistics at the VLCC class level; aggregate trade statistics are available for crude oil exports and imports which exists from a number of sources (BP, Energy Information Administration (EIA), International Energy Agency (IEA), and EU Commission) in various geographical detail. BP (BP, 2012) is the most comprehensive source for publicly available crude oil data, as it compiles crude imports and exports data from various government sources. The source provides inter-area total oil movements data by region and select countries, but does not break this out into oil products (which accounts for 30% of total imports) and crude oil. For the purposes of estimating seaborne trade, the aggregate data on total crude imports and exports is sufficient with some modifications. First, to obtain seaborne trade data, trade movements by pipeline were subtracted from the countries who import and export by pipeline. The US imports oil from Canada, Europe imports from Russia and the North

Sea. For the US, there is detailed information on crude oil imports and exports from the EIA (EIA, 2012) from which an estimate of seaborne imports was obtained by decoupling imports from Canada. The IEA (IEA, 2012b) has information on net exports from the Baltic Sea which can be used as an estimate for exports from the Baltic Sea. For European imports, the EU Commission's statistics on crude oil imports (EU Commission, 2012) were used to estimate its seaborne trade.

5.5 Ship movements dataset

Satellite AIS (S-AIS) is a shipboard broadcast system that is used to assist in navigation and improve maritime safety, transmitting a ship's identification, position and other critical data including its speed over ground. It is a nascent technology; companies started their service around 2010, with improved service in later years due to more satellites being launched. During the first two years of my PhD, I worked with my colleagues at the UCL Energy Institute[4] and Exact Earth, a data provider for S-AIS data, to acquire data for 2011. Analysis of the dataset was subsequently performed by my colleagues at the UCL Energy Institute for an International Council on Clean Transportation (ICCT) report (Smith et al., 2013). The analysis required converting millions of types of messages into useful data on geospatial movement characteristics which was linked to the world fleet register data. Satellite provides 88% coverage of the 2011 VLCC fleet, but ship movements near coastal areas is sparse.[5] Because of the lack of full coverage of the VLCC fleet and reliability near coastal areas, the dataset will be used for validation of speeds simulated in the model instead of as a source of ship supply in each sea area.

Time-weighted speeds were calculated for ballast and laden voyages using data on the draught (i.e., a low draught means is in ballast because it is not being weighed down by cargo) for individual VLCCs which had enough sea day coverage. The voyages include those concluded under the spot market and time-charter market as the dataset did not contain information on contract type. Not all ships had coverage for both types of voyages; 1/4th of the ships did not have ballast speed and 4% for laden speed. The median ballast speed for ships reporting a speed was 13.52 compared to 13.24 for laden, almost exactly the same. Speeds are clustered around their means, with the tails at 9.31 and 15.92 for ballast and 9.38 and 15.55 for laden voyages.

[4] Specifically, Tristan Smith and Eoin O'Keefe.

[5] The reasons for the poor coverage is the increased traffic of other ship's signals and similar transmitting devices (for example in the European Area). See Smith et al., 2013.

5.6 Summary

This chapter described the five datasets that will be used to estimate the model. Overall, despite the huge amount of dataset linking for this thesis, no one source was available that provided fully accurate port volume throughput and supply of VLCCs in each area. The fixtures dataset provides valuable data on the transactions between shipowners and charterers but there is censoring, both in terms of fixtures not reported and the censoring of prices in the sample. The censoring bias was compared to an aggregate level dataset and the implied VLCC trade shares suggest that there is an upward bias in trade share from the CAR/BRZ area (corresponding to Central and South America) for exports, and a downward bias of fixtures from the US. The limitations of the AIS data to remedy these issues was also discussed and it was concluded that it provides more useful information on speed data. These issues pose a challenge to estimating demand for VLCC shipments and the supply of ships in different areas. Aside from geographical bias, the fixtures dataset without censored prices did not differ greatly in other characteristics from the fixtures sample. Data on monthly freight rates exposed the short-run volatility in the time series, which could not be explained entirely by crude oil and bunker prices which for some routes is more than double the standard deviation of the oil price.

Chapter 6

Model Estimation

In this chapter, I specify the model estimation method and the parameters used to calibrate the matching model described in Chapter 4. The model is calibrated to 2011 data which represents the most recent year of data. The datasets described in Chapter 5 are used to estimate the following inputs:

1. Types of traders
2. Types of ships
3. Revenue from oil cargoes
4. Cost of journeys
5. Duration of journeys
6. Prices earned on journeys
7. Values of locations for ships (continuation values)

The challenge in the estimation of dynamic games results from the need to calculate the option value function explicitly. For some problems, the size of the problem increases exponentially with the number of states, making the problem intractable (Powell, 2011). Because solving a linear program yields a global maximum solution, the algorithm can sufficiently handle large systems with many dimensions. The curse of dimensionality is tackled by discretizing the agent types based on the observed finite number of ships and traders.

The empirical strategy requires two steps. The first step is to discretize the state variable. A state variable is all the information required to model the problem from any point in time onward (Powell, 2011) and will be classified into the agent state and the information state. The agent state describes the factors that classify each agent type. For the current problem, this requires discretizing the ships and traders into types as specified in Chapter 4. Ships are characterized by their location and physical characteristics (size, age, design speed, energy efficiency) and their discount rate. Traders have tasks - oil cargoes that need to be shipped - which are characterized by the load and discharge areas, the buy price, the expected sell price, and the discount rate which represents their time preference.

The information state includes information other than agent types which is needed to compute the surplus function such as the cost of bunker fuel and the storage cost of oil. These variables will be estimated as exogenous objects with a probability distribution.

After defining the state variable, the second step is to estimate the endpoint conditions (input 7). This includes the shipowner's option value at each location where ships match and the values for each agent to remain unmatched. The option value is solved by approximating Bellman's equation using information included in the state variable on ship and trader types (inputs 1 and 2) and estimating the cost, duration, and price earned on a journey (inputs 4-6). These inputs will then be used for solving the matching model in each period to determine the value of each potential matching combination.

6.1 Trader state variable

The state variable of a trader consists of its shipment location requirement (origin in load location set $\mathcal{A}_t$ and destination of cargo in discharge location set $\mathcal{B}_t$), the price the trader paid for the cargo, the expected price of oil at the destination and the discount rate which embodies the trader's time preference. Locations are sea areas defined in Appendix D. A sample of market shares on shipment routes was estimated using Dataset 1, the VLCC fixtures dataset of regional trade flows in 2011 (Table D.4).

To arrive at a demand sample, I assume the average number of fixtures are made per week is 70 based on information provided by the fixtures dataset and industry experts as described in Chapter 5. Table 6.1 is the estimated demand for fixtures on each route. In the baseline model, a fixture represents demand for a cargo of 265,900 tonnes, derived by multiplying the baseline ship's DWT (302,159 tonnes) by the estimated capacity utilization (88%). The buy price of oil varies between \$104.48 per barrel in BRZ/CAR to \$112.01 per barrel in WAF based on the crude oil spot prices in 2011 from the Energy Information Administration (EIA, 2011). Six load areas and thirteen discharge areas are represented in the sample. The Arabian Gulf (AG) which ships oil produced in the Middle East represents the largest crude oil demanded by load area (81%), followed by the Caribbean (9%), and West Africa (6%), with Brazil (BRZ), United Kingdom area (UKC) and the Red Sea (REDS) each accounting for 1%.[1] These load areas can

[1]As discussed in Chapter 5, there is some uncertainty in the trade flow shares and demand by load area due to data being censored. For example, it is possible that West Africa holds a higher share than stated in the fixtures data

Table 6.1: Imputed cargo demand

TraderID	Load	End	Distance	Oil buy price	Fixture demand
			nm	$/barrel	cargo units
1	AG	CALI	11353	105.84	1
2	AG	ECC	12885	105.84	2
3	AG	ECC	2698	105.84	1
4	AG	JPN	6358	105.84	8
5	AG	KOR	6187	105.84	6
6	AG	SCH	5729	105.84	24
7	AG	SPOR	3671	105.84	2
8	AG	THAI	4409	105.84	2
9	AG	TWN	5290	105.84	3
10	AG	UKC	6360	105.84	1
11	AG	USG	13436	105.84	4
12	AG	WCI	1358	105.84	3
13	BRZ	SCH	10766	104.48	1
14	CAR	SPOR	11179	104.48	4
15	CAR	WCI	10694	104.48	2
16	REDS	PHIL	6358	105.84	1
17	UKC	SPOR	9025	111.78	1
18	WAF	ECI	6943	112.01	1
19	WAF	SCH	9579	112.01	2
20	WAF	TWN	9118	112.01	1

Sources: Clarkson Research (2011), AXSMarine (2013), EIA (2011).

be considered as the local shipping markets which serve their respective importing countries. The cargo size is determined by multiplying a capacity utilization factor of 88% by the DWT of the ship. The utilization factor is based on the average cargo size to DWT ratio observed in the VLCC fixtures dataset (Clarkson Research, 2011).

6.1.1 Oil revenue

An oil trader's expected revenue from the sale of an oil cargo (excluding freight and storage costs) is a function of the expected oil price arbitrage, the cargo quantity, and the duration of the voyage. I assume traders have the same expectation about the oil price in each destination; there is a 10% expected increase and a 5% decrease on average from their buy price, with an 80% chance the price will increase and 20% chance of decreasing. This leads to an average $3.2 arbitrage profit which is in the range indicated by oil trading experts (Chapplow, 2013). As discussed in Chapter 4, the duration of the voyage effects revenue in two ways. The first is the inventory cost a trader has to pay between the time the oil trader buys the oil and sells it which was assumed to be 15% per annum [2]. The second way is the storage cost a trader

and sensitivity analysis will be run to consider this alternative.

[2]Estimates from McQuilling (2011).

has to pay for the days waiting for the ship to arrive (the repositioning days). Storage costs are assumed to be $10 a barrel per year which translates into 3 cents a day (Krauss, 2009). Given these simplifying assumptions across traders, the attributes that differentiate traders in the baseline model are shipment location and price at the origin and categorizing traders in this way yields 20 trader types.

6.2 Ship state variable

The state variable of a ship consists of its location, physical characteristics, and discount rate. In order to understand the spatial dimension on matching, ships vary by one dimension in their location and have the same physical characteristics in the baseline model. In the multidimensional matching model, the physical characteristics which are relevant in terms of profits are the as-designed daily fuel consumption, design speed, DWT, and age. The baseline ship *Ptype 0* has an as-designed daily fuel consumption (k) of 83 tonnes of fuel per day, a design speed of 15.8 knots, DWT of 302,159 tonnes and is 8 years old which represents the average values of the VLCC fleet. Table 6.2 shows the supply sample for the baseline model. The ShipID uniquely identifies each ship type. The following sections on the location of ships and supply, duration of journeys and cost of journeys will explain how the Supply and Rental Rate fields of the sample were estimated. In the multidimensional matching model, ships vary by their location and physical characteristics. To develop a manageable state space for the physical characteristics, I employ clustering techniques using the fleet register dataset, a method that partitions a large set of vectors into a set of groups based on the distance in the four dimensional space. Figure 6.1 shows the clustering of data for each physical type. Each group is represented by its centroid which is the center point of the cluster (Table 6.3).

The largest proportion of the sample is of *PType 2* with centroid values of 299,998 DWT, 9.3 years, 15.7 knots design speed, and a an as-designed fuel consumption (k) of 79.8 tonnes per day (see Figure 6.1). The most modern class (*PType 1*) has increased its DWT with the highest value at 317,441. It is important to consider these variables together because of the synergies that exist.

Fuel efficiency of ships is a complicated matter, influenced not only by a vessel's physical characteristics, but also by size and the speed a ship travels (among other variables). There are various ways to measure a ship's fuel efficiency, but I analyze efficiency based on the fuel consumption per output (tonne-nautical miles or t-nm). A ship which is more energy efficient consumes less fuel per t-nm and this translates into less fuel expenditure per t-nm. Economies of scale exist if the long-run average cost, defined as average variable cost plus average fixed

Table 6.2: Imputed ships available to match (baseline model)

ShipID	Start	Supply	Type	Age	DWT	k	Design speed	Rental Rate
				years	tonnes	tonnes	knots	US $/day
1	CALI	2.1	0	8	302,159	83	16	30,100
2	ECI	1.1	0	8	302,159	83	16	30,100
3	JAP	7.8	0	8	302,159	83	16	30,100
4	KOR	4	0	8	302,159	83	16	30,100
5	NCH	0.3	0	8	302,159	83	16	30,100
6	PHIL	0.2	0	8	302,159	83	16	30,100
7	SCH	10.9	0	8	302,159	83	16	30,100
8	SPOR	5.1	0	8	302,159	83	16	30,100
9	THAI	1.9	0	8	302,159	83	16	30,100
10	TWN	1.2	0	8	302,159	83	16	30,100
11	WCI	6.4	0	8	302,159	83	16	30,100
12	BRZ	0.8	0	8	302,159	83	16	30,100
13	ECC	0.5	0	8	302,159	83	16	30,100
14	SAF	0.1	0	8	302,159	83	16	30,100
15	UKC	10.3	0	8	302,159	83	16	30,100
16	USG	12.7	0	8	302,159	83	16	30,100
17	AG	30	0	8	302,159	83	16	30,100
18	WAF	5	0	8	302,159	83	16	30,100

Sources: Clarkson Research (2011), Clarkson Research (2012b), BP (2012).

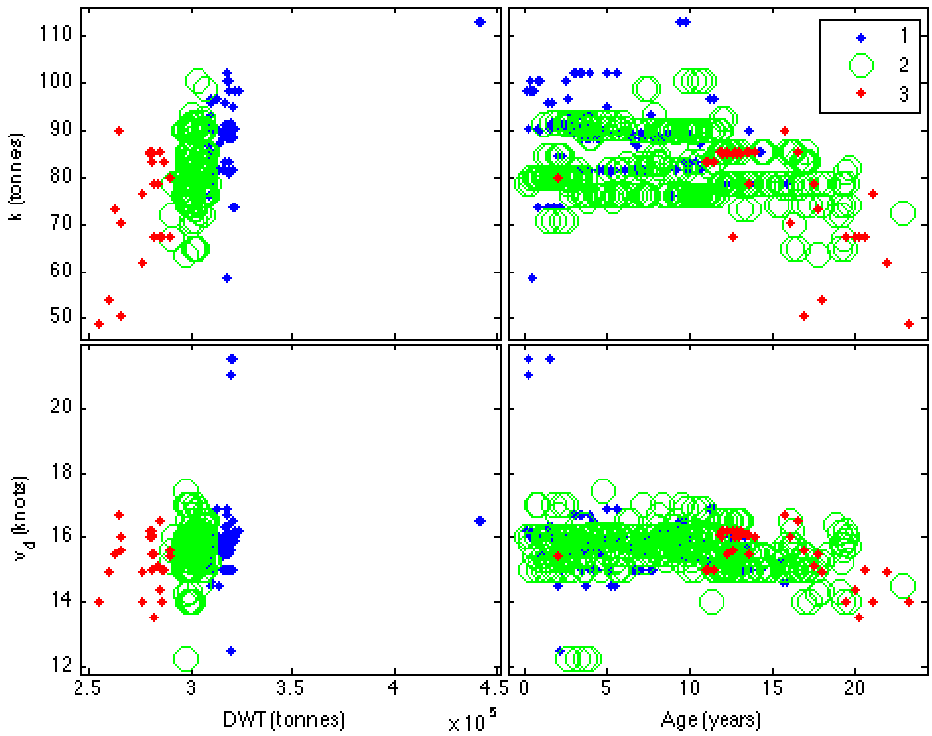


Figure 6.1: Cluster Analysis of Ship Characteristics. Source: Clarkson Research (2012b)

Table 6.3: Ship Types

PType	Fleet share	DWT	Age	Design speed	k
	%	tonnes	years	knots	tonnes/day
1	33.0	317,441	4.4	15.9	89.8
2	60.5	299,998	9.3	15.7	79.8
3	6.5	281,050	13.5	15.6	83.1

Sources: Clarkson Research (2012b).

costs, decreases with output. Due to the physical property that the water resistance on a ship's hull does not increase at the same rate as the volume of the hull, there are economies of scale in shipping. In the model, I assume daily fixed costs are the same across ship design types. Because economies of scale exist in shipping, ships in higher size class categories (i.e. VLCC compared to Suezmax tankers) can achieve a higher fuel efficiency depending on the cargo size assumption. However, the data reveals that this property does not always hold; *PType 2* has a higher fuel efficiency than *PType 1*. Assuming a constant capacity utilization factor of 88% across ship types, the average fuel cost (fuel cost per t-nm) for *PType 2* is the lowest, followed by *PType 3* and *PType 1*.[3]

The number of ships of each physical type in the model in each location is determined by multiplying the fleet share of each type by the number of ships in each location. This is equivalent to assuming that the distribution of ships of each type is randomly distributed across locations based on its representativeness in the fleet. This increases the ship type space from 18 types to 54 types $\#Locations * \#PhysicalTypes$. It is assumed that traders view ships which are older than 15 years to have a higher risk profile than younger ships because of their increased potential for an oil spill. Since the ships in the model are less than 15 years of age, I do not explicitly model risk aversion to age.

The interaction between size and fuel efficiency adds more complexity to the question of who matches with whom because these dimensions are not mutually exclusive. Size influences the trader's revenue, shipment costs and the ship's option value, but the impact depends on the assumption about the capacity utilization rate. For example, despite *PType 1*'s cost disadvantage over *PType 2*, *PType 1* can earn more revenue by achieving a higher cargo size (16,571 tonnes [4]) which would outweigh its higher shipment costs. Given the variation in ship size amongst the different physical ship types, it is likely that the matching is sensitive to the capacity utilization rate. Two different versions are run to test the sensitivity: *Bigger is Better* and

[3]For *PType 1* to be more efficient than *PType 3*, the cargo size needs to be greater than 265,360 tonnes.

[4]Assuming a maximum capacity utilization rate of .95. A ship's payload is always below its DWT because DWT is a measure of how much weight a ship can carry and includes cargo, fuel, fresh water, ballast water, provisions, passengers and crew.

Table 6.4: Multidimensional impact on model parameters

Dimension	Cargo size	Fuel cost	Freight rate
Location (l)		x	x
Capacity (ω)	x	x	x
Design speed (v^d)		x	
As-designed efficiency (k)		x	

Table 6.5: Parameters affected in *Bigger is Better* vs. *Energy Efficiency Rules*

Surplus component	*Bigger is Better*	*Energy Efficiency Rules*
Expected Oil Revenue	q^b	
Shipment Cost	v^d, k	v^d, k
Ship Option Value	$P(x_{j,t+1}, y_i, T+1), C(x_{jt}, y_i, t)$	$P(x_{j,t+1}, y_i, T+1), C(x_{jt}, y_i, t)$

Energy Efficiency Rules. In *Bigger is Better*, the cargo size is determined by the product of its capacity times constant capacity utilization rate of 88%. In contrast, *Energy Efficiency Rules* assumes a constant cargo size of 265,900 tonnes. The ways in which the different dimensions impact the primitive parameters in the model are summarized in Table 6.5.

Table 6.5 shows which surplus components vary across ship types in *Bigger is Better* and *Energy Efficiency Rules* respectively. The only difference between the scenarios is the impact on expected oil revenue through cargo size (q^b) in *Bigger is Better*.

6.2.1 Location of ships and supply

The matching model requires an estimate of the supply of ships available to match in each period. As discussed in Chapter 4, ships can only match if they are at a discharge or waiting area. This requires working down from aggregate trade data given that geospatial data was not available for this study. The supply of ships in different locations and their availability to match was estimated using the compiled aggregate trade data described in Chapter 5 and the algorithm is described in Figure 6.2.

Since ships are assumed to be only available in discharge and waiting areas, I start with the total annual crude oil imports dataset. A first pass estimate of the crude oil imported by VLCC is to multiply the aggregate import data by the share of the VLCC fleet that transports crude oil (51% in 2011). Data from Lloyd's List Intelligence (Lloyd's List, 2012), a source that provides seaborne crude movements by vessel, estimated the share was 61% in 2012, 10% higher than the fleet share. This larger share is more plausible given the dominance of VLCCs on long haul routes so this share was used in the estimates.

The aggregate data of imports and exports can be considered as a flow, because it is the import and export demand that is met per year. Weekly estimates of these flows by VLCC were

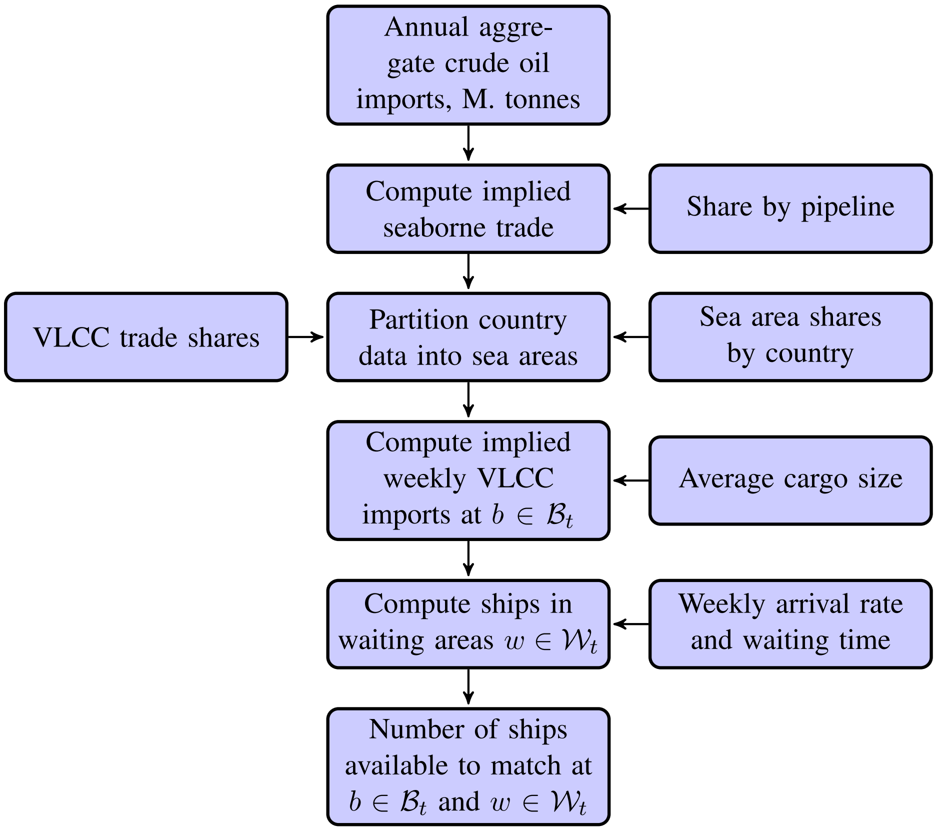


Figure 6.2: Ship availability estimation algorithm

obtained by dividing the annual figures by 52 which represents an average weekly flow and ignores seasonal fluctuations. From this number, an implied number of VLCC "import" ships was calculated by dividing by the average cargo size. This assumes that ships are not partially loading cargo, but this is a reasonable assumption because these fixtures account for only 10% and typically occur within the same area allowing us to circumvent the issue (Clarkson Research, 2011). Some areas in the aggregate trade dataset do not correspond to the shipping locations in the model. For these areas, the share of imports that comprise these higher level areas in the fixtures dataset were applied.

Estimating the number of ships in waiting areas (the Arabian Gulf and West Africa) requires knowledge of the arrival rate and the average time waiting for a fixture. If these parameters can be estimated, then Little's Law [5] can be used to calculate the stock of ships in an area. Data from Clarkson Research (Clarkson Research, 2012a) on VLCCs Due in the Gulf this Month was used to work out the average number of VLCCs arriving per week. It was assumed that the average waiting time was between 1 and 2 weeks in AG (Calderas-Mendez, 2012); an average 1.5 weeks was assumed. Applying Little's Law, the stock of ships in AG was estimated

[5] Little's Law tells us that the average number of customers in a store (the stock) is equal to the effective arrival rate times the average time a customer spends in a store. This can be similarly applied to the average number of ships in a waiting area available to match.

to be 30. There was more uncertainty estimating the supply of ships in West Africa as it was not possible to obtain data on arrivals. Data from AIS was used by zooming in on ship activity near Nigeria and Angola which suggested the number is around 5 ships.

The supply of ships available to match was estimated to be 100.4 ships [6] by summing the estimates from discharge and waiting areas. The average matching probability is 70%, computed by dividing the number of cargoes demanded by the supply of available ships. If the expected number of weeks waiting is given by a geometric distribution and there is an equal probability for each ship to match, then the expected number of weeks until a ship successfully matches is given by the expected value of a geometrically distributed random variable X is $1/p$. Then the expected waiting duration is 10 days.

6.2.2 Duration of journeys

The duration of a journey is a function of distance and the ship's speed. Distances were calculated for the trade flow and repositioning journeys. Despite the reduction in dimension by aggregating to area level, the calculation of distances is a time consuming task. Because there was no data readily available, the distances had to be collected manually for each journey. To reduce the time intensiveness of this task, a representative port (see Table D.5) was designated for each area-area pair using distances obtained from AXSMarine (AXSMarine, 2013). The majority of areas are defined narrowly enough that ports are very close to each other, with the exception of West Africa which has two major ports (Malongo Terminal, Angola and Qua Iboe, Nigeria) that are located farther away from each other than other areas. The distance assigned to WAF was a weighted distance from the origin area to the two ports. A large percentage of trade flows are between the Arabian Gulf and Asia, with the Caribbean and West Africa playing a smaller role as loading areas. The AG-Asia trade is a much shorter route; from Juaymah, Saudi Arabia to Ningbo, China it is 5729 nautical miles or about 17 days at a speed of 13.5 knots, while voyages to USG take 29 days or 12 more days at sea.

Based on the distance for each trade flow, the trade volume on each route, and an assumption about laden speed, the expected duration of a laden voyage is between on 2.73 and 3.03 weeks. The lower bound estimate is the shortest path and for east-west and northbound trips can involve the Suez canal. Ships do not always take the shortest path; this is because there is a cost to transiting the Suez, both in terms of the canal costs and the risk of sailing in a piracy zone. Because I do not have exact data on the proportion of journeys made via the Suez Canal

[6] It is acknowledged that there will be a margin of error in these estimates because some ships are domestically owned by governments, used in industrial shipping and on time-charter are not trading in the spot market, though they will at times lease their ship when they do not require it.

and Cape of Good Hope, I assumed that northbound journeys to Europe go via Suez.[7] Ships bound for the US Gulf are routed around the Cape of Good Hope. Taking these factors into consideration, the expected trip length is estimated to be an average 2.87 weeks, a weighted average of the route market share.

6.2.3 Cost of journeys

The voyage cost is a function of distance, the implicit rental rate, and the type of route. Fuel consumption is given by the cubic equation in Chapter 4 (Equation 4.26) which takes as input the ship's tonnes per day, operating speed, design speed and distance. The distance used is the representative area to area distance as described in the previous section.

Additional costs apply to the type of route - whether it involves the Suez Canal and the type of voyage (laden or ballast). By taking the Suez canal, a ship must pay for additional insurance premiums, extra fuel for faster steaming, security measures such as deployment of armed guards and Suez Canal tolls. Additional insurance premiums are for War Risk insurance and Kidnap and Ransom insurance (K&R). K&R insurance is estimated to be $15,000 per trip (Oceans Beyond Piracy, 2011). While shipowners add on the Suez canal toll costs to the final price of freight, it is not obvious whether there is pass-through of insurance costs. In the model, it is assumed that the shipowner bears the full burden of insurance costs. The size of the additional insurance depends on the level of risk perceived by the insurance underwriter. At times, these additional premiums can reach upwards of ten percent of the market value of the vessel. For example, the territorial waters of Somalia are one of the most expensive additional premium areas, with underwriters charging approximately two percent of market value of the vessel for a seven-day policy. For a $100 million VLCC, the ship would be forced to pay $2,000,000 in War Risk insurance. The combined estimated cost was $2,015,000 m. per trip.

Aside from fuel costs, port costs account for the second largest proportion of the variable costs of a voyage and depend on the port specific pair, cargo size, and ship type. These are not published separately from the flat rate and not available from one source.[8] To simplify the estimation of these costs, a fixed rate was applied.[9]

The implicit rental cost was calculated using the average of the 1-year, 3-year and 5-year time-charter rates from Clarkson (2012) in 2011 which was $30,109 per day. Interestingly, this is approximately equal to the VLCC break-even rate of Frontline, the major tanker company.

[7]The EIA estimates that the majority of fully laden ships using the Suez Canal are northbound to the Mediterranean and Northern Europe. On laden journeys, VLCCs have to partially unload their cargo in the Sumed pipeline and then transit the canal, picking up the cargo on the other side (Trench, 2010)

[8]Clarkson Research (2012d) uses a variety of sources, ranging from the ports themselves via questionnaires, owners via brokers, and the Global Ports and Intertanko websites.

[9]The Worldscale Association includes 4 days in port in their calculations.

An estimate from Intertanko (Intertanko, 2011) for the fleet was about $32,500 per day.[10] This implies that the fleet was barely breaking even in 2011. Uncertainty analysis was not undertaken to determine the probability of obtaining a time-charter contract, but companies should factor in this rate when deciding whether to continue operating or scrap their vessel.

6.3 Prices on journeys

Although freight rates are endogenous in the model, the freight rate in the terminal period is estimated outside the model using the fixtures dataset described in Chapter 5. This also serves as a way to understand the important determinants of the freight rate. In theory, the freight rate should depend on all aspects of the contract and the trade that are known to the two parties at the point when they sign the contract. The key factors include the origin, destination, distance, laycan period, the type of crude oil, ship type and trader type. The origin matters because it embodies the supply and demand characteristics at the origin and the type of crude that is bought. Different types of crude oil fetch different prices and may affect the resale value. Destination matters because it affects the profits of the trader (the selling price at the destination) and the ship option value. Distance affects the duration of the voyage which has implications for voyage and inventory costs. The laycan period should be positively correlated with the freight rate because it allows the trader a longer window when the ship can pick up if the trader wants the option of buying the oil at a later date and the option to cancel the contract if the expected freight rate in the future is lower. In the spot market, ships differentiate themselves by their location and reputation.

The total freight rate (in dollars) equals:

$$P_{ab,t} = P^{W}_{ab,YR} P^{M}_{ab,t} q \tag{6.1}$$

where $P_{ab,t}$ equals the total freight rate $P(x_{j,t+1}, y_i, t)$ for the specific port pair (ab) and route at time t. $P^{W}_{ab,YR}$ equals the Worldscale benchmark price for the year YR for the specific port pair (ab) and route in \$/tonne, $P^{M}_{ab,t}$ is the multiplier in Worldscale multiplier units for the fixture contract at time t and q is the cargo size in tonnes. The multiplier is agreed upon by both parties and is determined by the market conditions when the deal is done and the bargaining power of the two parties.

The freight rate is estimated using an econometric regression. Ideally, if data were available on benchmark prices for all years and port combinations, the estimated freight rate would equal the benchmark price times the multiplier. However, because the benchmark sample was

[10] Number was read from a bar chart.

Table 6.6: Analysis of variance table of benchmark regression

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
$log(Dist\_short)$	1	378.91	378.91	30933.00	0.0000
$log(p^{hfo})$	1	17.14	17.14	1398.91	0.0000
λ_{ab}	130	32.94	0.25	20.69	0.0000
Residuals	1085	13.29	0.01		

incomplete, it was necessary to perform separate regressions for estimating the benchmark price and multiplier. Assuming that the error terms in both equations are independent of each other, this will produce an unbiased estimate of the price.

As mentioned in Chapter 5, variation in the benchmark price over time can be attributed to changes in the forecasted bunker price, distance, and the port costs. In the data, we do not observe port costs. Aside from fuel costs, port costs are the second largest factor in these calculations and they represent the most subjective portion of forecasting new flat rates (McQuilling, 2010). Since the model is regional, these need to be estimated as a route (area-area) fixed effect which makes the assumption that areas have similar port costs. This is reasonable because ports want to be competitive with ports within their area. The dataset did not contain a sufficient amount of data for 2011 to include time effects, such that variation in port costs per year could not be estimated. Therefore the regression will estimate an average port cost over 2007-2011.

Port pairs were selected based on the pairs observed in the fixtures dataset. The benchmark price for the shortest route was regressed on the distance provided in the Worldscale book, the benchmark bunker price and dummy variables for the area pair (defined as the route) associated with the port pair. The following linear regression model was estimated for the benchmark price:

$$log(P^W_{ab,YR}) = \lambda_{ab} + \beta_1 log(\phi_{ab,YR}) + \beta_2 log(p^{hfo}_{YR}) + \varepsilon_{ab,YR} \tag{6.2}$$

where λ_{ab} is the route fixed effect, ϕ_{ab} is the distance on route ab for the shortest distance between load port a and discharge port b, and p^{hfo}_{YR} is the bunker price in year YR. Appendix D, Tables D.5-7 shows the results of the regression and the fitted values against the residuals. The model fits the data well with an R-squared of .97. A 1% increase in distance increases the benchmark price by .4%, while the elasticity for the bunker fuel price is .53%. The route fixed effects are generally negative and significant. The analysis of variance for the benchmark regression is displayed in Table 6.6. Distance explains 86% of the variation in the data, followed by the area fixed effect (7%), bunker price (4%) and the remaining unobserved (residuals) (3%).

Whereas the benchmark price is a forecasted cost of shipment between two port pairs in a given year for a standard vessel, the multiplier price depends on the economic conditions in the local markets of a particular trade route ab and the characteristics of the ship. A hedonic price function can be used to describe the equilibrium relationship between the characteristics of a product and its price. For example, in the housing market, the price of a house might be described by its geographical location, size, number of bedrooms, proximity to parks, and quality. Similarly, the multiplier price can be described by geographical location (the trade route consisting of a load and discharge area), the physical characteristics of the ship (safety, age, DWT, capacity utilization, technical efficiency), fuel cost, trader type, and the lagged effect of prices in the market.

When a trader and shipowner sign a contract, they agree to terms such as the technical specifications of the ship, speed, trade route and the time period under which the ship must arrive (known as laydays). Safety is a major priority for traders because of the sums of money and reputation that is at stake if there is an oil spill. Three variables serve as a proxy for safety in the dataset - classification society, age, and hull type. A ships' classification society, which checks the ship against safety and other requirements, gives an indication of its rating. For example, societies which are members of IACS (International Association of Classified Societies), an association which ensures certain safety and regulation standards are met, would be considered as low risk ships. This variable is also used as a proxy for reputation. Age is also a risk factor, where older ships, especially those older than 15 years, are considered to bear significantly more risk due to deterioration of the hull (Shipbroker, 2011). In addition, ships which have a double hull also reduces the risk of an oil spill and some countries require double hulls.

Another possible factor affecting prices is capacity utilization. Because shipowners get paid per-tonne, shipowners might be willing to marginally discount the multiplier price if the trader is willing to ship a greater size of cargo. As discussed in Chapter 3, typically the shipowner proposes an "ask" price first, using yesterday's average freight rate for the specific trade route a trader is requesting. Traders then submit their bid, and the negotiation process continues until both parties agree on a price (could be settled in one minute or two weeks according to industry practitioners). This suggests that the lagged multiplier price is an influencing factor. Aggregate multiplier data was not available for all routes however, so a price index called the Baltic Dirty Tanker Index was used (Baltic Exchange, 2012) which represents prices for crude oil shipments by tankers. Although this includes other ship classes (Suezmax and Aframax), prices are highly correlated in these markets so it is a good proxy for the VLCC market. Another variable that may impact prices is the difference between the fuel price included in the benchmark price and the fuel price at the time when the ship is fixed. Because the fuel price is a large component of voyage costs, this could significantly impact costs. While the benchmark fuel price was \$467 (per tonne) in 2011, the average fuel price in Singapore (a major refueling location) was \$648 in 2011, and varied between \$526 and \$705 (a standard deviation of \$38).

I use a log linear regression model to estimate the hedonic price function. A time dummy is used to isolate the effect of supply and demand variation once controlling for other characteristics affecting price (see Triplett, 2004 and Nesheim, 2008 for a detailed discussion). Given these factors, the multiplier prices were regressed against the physical characteristics of the ship (age, DWT, technical efficiency) and fixed effects for time and route. The model specification for the multiplier is:

$$log(P^M_{ab,t}) = \lambda_{ab} + \beta_1\omega_j + \beta_2\omega_j^2 + \beta_3\alpha_j + \beta_4 HT_j + \beta_5 BDTI_{t-1} + \beta_6 log(p_t^{hfo}) + \beta_7 YR + \varepsilon_{ab,t} \tag{6.3}$$

where λ_{ab} is a route fixed effect, ω_j is the age of ship j, α_j is the capacity, HT_j is a dummy variable for the hull type (single or double hull), p^{hfo} is fuel price (\$/tonne) during the week of the fixture date, $BDTI_{t-1}$ is the lagged Baltic Dirty Tanker Index and YR controls for annual time effects. The Baltic Dirty Tanker Index is a price index of time charter equivalent earnings (\$/day) of the major crude oil routes weighted by the volume of trade for each route (Baltic Exchange, 2012).

Tables D.8-9 in Appendix D shows the regression results. Of the 52 routes in the sample, 32 were statistically significant at or below the 5% level. Of these, 4 routes were negative - AG-ECC, AG-SPATL, AG-UKC and AG-USG. This was also observed in Alizadeh and Talley (2011); the westward direction implies that ships can obtain a backhaul in the Caribbean or West Africa such that they can discount the price relative to other routes like those from the AG to Far East.

Of the physical characteristics, age, DWT and hull type were significant. The signs of the coefficients for Age and Age-squared suggest a quadratic relationship and this can be explained by the fact that ships which are greater than 15 years are viewed as more risky. The log of the lagged BDTI price was also statistically significant ($p < .0001$) and was approximately unit elastic; a 1% percent increase in the lagged BDTI price leads to an average increase of 1.2% in the multiplier price. Because the index includes Suezmax and Aframax vessels which also transport crude oil, this finding could be picking up the substitution effects between the overall dirty tanker market and VLCCs. The price elasticity with respect to fuel cost (HFO) was less than unit elastic, increasing by an average .244% for a 1% increase in the fuel price. This estimate falls within the range that other studies have found. Table 6.7 shows a comparison of studies that have particularly focused on the relationship between oil/bunker prices. They range from -.31 to 1.7. Economic theory implies that there should be a positive relationship between the bunker fuel price and the freight rate, as higher costs typically induce a partial pass-through when the supply curve is upward sloping. Therefore the negative relationship found in Beenstock and Vergottis (1993) is erroneous.

Yearly time dummies were all significant and accounted for the variation in the data not explained by the other regressors. They were also used to control for the changing yearly benchmark rate which means that the rates are not strictly comparable across years (Vivid Economics, 2010). The year 2009 had the largest impact on prices relative to the 2007 reference year, while 2011 had a negative impact. These findings are consistent with the market, which peaked in 2008 and then plunged to a low in 2011.

The analysis of variance for the multiplier regression is displayed in Table 6.8. The variables together explain 84% of the variation with the lagged BDTI explaining the largest percentage of variation (69%), followed by the HFO price (6%), and the route fixed effect (5%).

Because the dataset is a panel dataset with observations of the same ship and shipowner across days in a particular year, the assumption that the standard errors are homoskedastic is questionable (Angrist and Pischke, 2009). I therefore relax the Gauss-Markov homoskedasticity assumption, and account for the fact that there may be several different covariance structures within the dataset that vary by a shipowner but are homoskedastic within each cluster of transactions by shipowner. Figure D.2 in Appendix D shows the residuals are normally distributed around 0.

The hedonic price regression is used to estimate prices in 2011 for each physical ship type per route using each type's age and DWT, holding design speed and k fixed (representing average values for 2011). *PType 1* had the highest average price, followed by *PType 2* and *PType 3*. Compared to the baseline, *PType 1* was .36% higher, *PType 2* was .05% higher and *PType 3* was 2.14% lower.

6.4 Second step: estimate the endpoint conditions

In the second step, the continuation values for the agents are estimated outside the model for period $T+1$. The requirement that $W^x(x_{j,t+1}, T+1)$ take a prescribed value is known as an endpoint condition. If a ship is at a destination, it has two options. If it matches with a trader, it will reposition to one of the loading areas a given an average matching probability which

Table 6.7: Elasticity of freight rates with respect to fuel

Study	Independent Variables	Type of model	Elasticity
Hawdon (1978)	Trade, bunker oil price, world tanker fleet, crisis events, dry cargo index	R. form	1.7
Beenstock and Vergottis (1993)	Operating tonnage, bunker oil price, average haul	Structural	-0.31
Lundgren (1996)	Lay-up, bunker prices, capacity, change in main bulk trade, crisis events	R. form	0.39
Hummels (2007)	Weight/value, fuel costs, dist., containerized share of trade	R. form	.232-0.327
Mirza and Zitouna (2009)	Quantity, unit value, dist., time, dist.*oil price, contiguity,mode, contiguity*oil price	R. form	.088-.103
Beverelli (2010)	Brent oil price, volatility of Brent oil price, trade	R. form	0.281-.446

R. Form=Reduced Form; dist=distance.

Table 6.8: Analysis of variance table of benchmark regression

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
λ_{ab}	53	30.53	0.58	16.57	0.0000
ω_j	1	4.61	4.61	132.64	0.0000
ω_j^2	1	5.88	5.88	169.27	0.0000
α_j	1	0.67	0.67	19.15	0.0000
$log(p^{hfo})$	1	32.99	32.99	949.04	0.0000
HT_j	1	3.41	3.41	98.09	0.0000
$log(BDTI_{t-1})$	1	417.21	417.21	12000.92	0.0000
YR	4	10.68	2.67	76.84	0.0000
Residuals	2812	97.76	0.03		

measures the market's strength. It only considers repositioning to loading locations which are not too far away, set according to a threshold distance in the model, and then obtains the value to be at the loading area. If it doesn't match with a trader, then it repositions to a waiting area w until there is sufficient demand for cargo and obtains the value of being at the waiting location. The option value to be at b is given by 6.4 from Chapter 4:

$$\begin{aligned} W^x(x^b_{j,t+1}, T+1) = \sum_{a \in A} \mathbb{P}(a|b)\Big(- c^{rep}_{ba,t+1} + \beta^{x,d^{ba}(x_{j,t+1},y_i)} W^x(x^a_{j,t+1}, T+1)\Big) + \\ \sum_{w \in W} \mathbb{P}(w|b)\Big(- c^{rep}_{bw,t+1} + \beta^{x,d^{la}(x_{j,t+1},\emptyset_y)} W^x(x^w_{j,t+1}, T+1)\Big) \end{aligned} \tag{6.4}$$

From equation 6.5 in Chapter 4, the value to be at a loading area is:

$$\begin{aligned} W^x(x^a_{j,t+1}, T+1) = \sum_{b \in B} \mathbb{P}(b|a)\Big(P(x_{j,t+1}, y_i, T+1) \\ - c^{voy}_{ab,t+1} + \beta^{x,d^{ba}(x_{j,t+1},y_i)} W^x(x^b_{j,t+1}, T+1)\Big) \end{aligned} \tag{6.5}$$

The value to be at a loading area equals the expected revenue from the loading area minus the expected shipment costs plus the option value to be at the destination. Each possible destination a ship can travel to from the origin area is weighted by the probability of going to the destination, based on the trade with that area. In the model, ships located at a loading area do not have the option to go to a waiting area.

As discussed in Chapter 4 (equation 6.6), the value to be at a waiting area is :

$$W^x(x^w_{j,t+1}, T+1) = \sum_{a \in A} \mathbb{P}(a|w)\Big(- c^r n^x_{wait} - c^{rep}_{wa,t+1} + \beta^{x,d^{la}(x_{j,t+1},y_i)} W^x(x^a_{j,t+1}, T+1)\Big) \tag{6.6}$$

which reflects the model's specification that ships located at waiting areas are waiting to serve demand at a nearby loading area. Therefore, the value to be at a waiting area is the expected repositioning cost to a loading area plus the value to be at the loading area.

The main data inputs for the value functions are:

1. Transition potentials $\mathbb{P}(l'|l)$: the probability of going from one location l to another location l': $\mathbb{P}(b|a)$, $\mathbb{P}(w|a)$, $\mathbb{P}(a|b)$, $\mathbb{P}(w|b)$, $\mathbb{P}(a|w)$

2. Ship revenue: $P(x_{j,t+1}, y_i, T+1)$

3. Voyage cost: $c^{voy}_{ab,t+1}$

4. Repositioning cost: $c^{rep}_{ll',t+1}$

5. Discount factor: $\beta^{x,d(x_{j,t+1},y_i)}$

Given these inputs, the unknowns that need to be computed are $W^x(x^b_{j,t+1}, T+1)$, $W^x(x^a_{j,t+1}, T+1)$, and $W^x(x^w_{j,t+1}, T+1)$. The problem is solved by solving a system of linear equations. This is a deterministic solution representing the expected present value of all future periods. There are some obvious differences among the value functions; $W^x(x^a_{j,t+1}, T+1)$ is the only function which contains no discounted revenues so intuitively the value should be higher than $W^x(x^b_{j,t+1}, T+1)$ and $W^x(x^w_{j,t+1}, T+1)$ which discount $W^x(x^a_{j,t+1}, T+1)$ by the voyage duration from b to a and w to a, respectively. The repositioning costs included in $W^x(x^b_{j,t+1}, T+1)$ and $W^x(x^w_{j,t+1}, T+1)$ have more prominence because they are not discounted.

From equations 6.4, 6.5, and 6.6, it is clear that:

$$\begin{aligned}
\sum_{a\in A}\mathbb{P}(a|b) + \sum_{w\in W}\mathbb{P}(w|b) &= 1\\
\sum_{b\in B}\mathbb{P}(b|a) &= 1\\
\sum_{a\in A}\mathbb{P}(a|w) &= 1
\end{aligned}$$

The probability of going from a load port to a discharge port, $\mathbb{P}(b|a)$, was calculated using the estimated trade flow matrix from step 1. The model does not consider strategic locational games that predict individual ship movements as a function of other ships' relocation strategies. Instead, the probability that a ship moves to a load area compared to a waiting area is based on the demand to supply ratio of the overall market. The probability of matching with a trader at a discharge location ($\sum_{a\in A}\mathbb{P}(a|b)$) is estimated to be 70%, based on the demand to supply ratio (fixture demand to available ships). That means the probability of going to any waiting location from b ($\sum_{w \in W} \mathbb{P}(w|b)$) is $1 - \sum_{a \in A} \mathbb{P}(a|b)$ or 30%. There are two reasons to believe ships will not relocate to all load areas from a given discharge area. If a ship is located far away from a load area market, it has to pay the repositioning costs of getting to the load area. In addition, the trader has to wait for the ship to arrive at a rate proportional to distance. Ships compete with other ships which may be located closer to the trader's preferred market (load area). Therefore the matching probability in a discharge location should decrease the farther away a ship is.

Ideally, $\mathbb{P}(a|b)$ should be taken from the dataset on ship movements. A first pass approximation used a distance threshold of 9720 nautical miles (equivalent to traversing from Ulsan, Korea to Malongo Terminal, Angola) based on correspondence with Tanker Operator (2012) of observed voyages from discharge ports to load ports. Once distances greater than this are eliminated, the smaller subset serves as the possible loading areas from b. Using the fixture cargo volume in each of these areas, I calculate the new trade shares which provides a measure of the probability of a fixture. This probability is then weighted by the matching probability to obtain the joint probability of choosing to match with a trader and matching in each load location.

The freight rate was estimated using the estimated freight rate from section 6.5. The cargo size is calculated by multiplying the DWT times an average capacity utilization factor of 88% which is estimated from the fixtures dataset.

Voyage and repositioning costs were calculated using the route distances. The bunker price was set to a constant \$645 per tonne representing the average bunker price for 2011. Discount factors were the most subjective calculation. The discount factor was calibrated to represent how much shipowners should value future earnings. Bellman's equation includes all future periods for the remaining lifetime of the asset. In shipping, this corresponds to the second hand (resale) price of the ship. In the data, prices for second hand ships are highly volatile. Figure 6.3 shows the prices of Time-Charter Equivalent earnings and second hand values between 2001 and 2011.

There are large fluctuations in both time series, reflecting the volatile nature of the industry due to the features of the market: aggregate demand for oil is inelastic and supply is lumpy due to the long lag between the order-book and delivery for ships. Given this uncertainty, the model only looks ahead one voyage. The values are therefore discounted to the magnitude of one period profits. This short-term perspective is justified by the literature (Devanney, 2010; Ronen, 1982) and a statement from Maersk (2012) that "There are alot of cargoes out there from different customers. It's all about optimizing over a number of voyages...If I want to take this cargo from point A to point B, then I want to be able to get a cargo from there onto the next

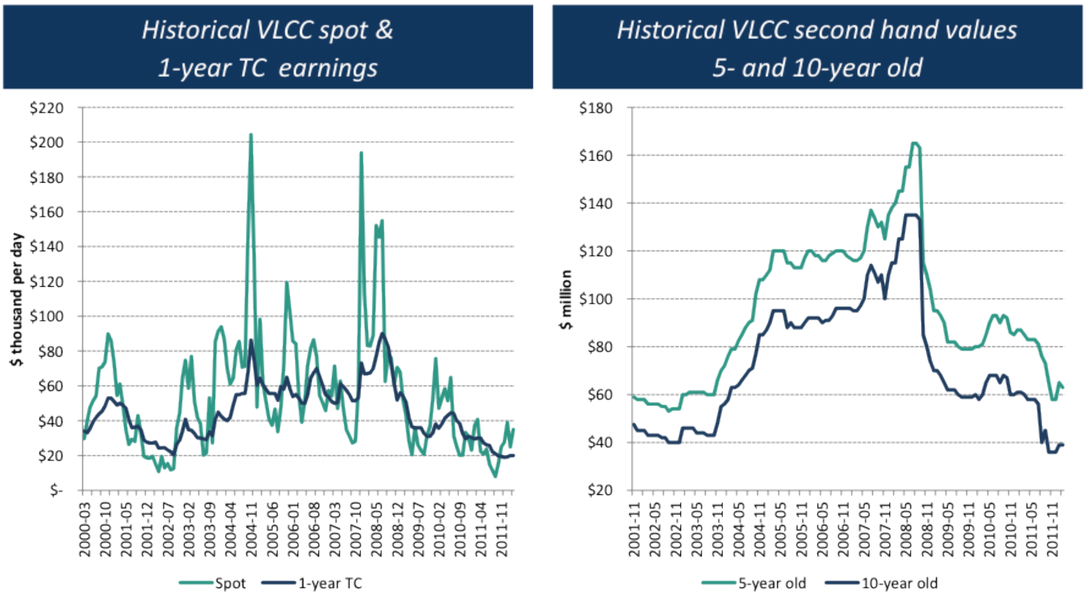


Figure 6.3: Historical prices of VLCC freight rates and second hand values. Source: Clarkson Research, 2012c.

one."

6.4.1 Numerical computation of continuation values

The equations for $W^x(x^a_{j,t+1}, T+1)$, $W^x(x^b_{j,t+1}, T+1)$ and $W^x(x^w_{j,t+1}, T+1)$ combine to form a system of linear equations. In matrix form this is:

$$\mathbf{A}\mathbf{w} = \mathbf{b} \tag{6.7}$$

where $\mathbf{A}$ is a a square matrix containing all of the coefficients of the unknowns in $\mathbf{w}$ and $\mathbf{b}$ is a vector of the constants. In linear algebra, it is required that an equation like (1) has a unique solution if the rank of $\mathbf{A}$ and the rank of the matrix $[\mathbf{A}\ \mathbf{b}]$ are both equal to size($\mathbf{w}$), i.e., the number of unknowns. This condition was satisfied. The solution (computed in Matlab) to equation (1) is:

$$\mathbf{w} = \mathbf{A}^{-1}\,\mathbf{b} \tag{6.8}$$

6.4.2 Numerical results: continuation values for ships

Under the assumption of a large number of identical shipowners, the second hand sale price of a ship must equal its expected option value. Given volatility in freight rates, average second hand sale prices for ships also exhibit variation; Figure (6.3) shows that for a ship aged 10 years, the value ranged between \$60 million and \$165. The estimated option value of a ship in the previous section is deterministic; it assumes that all of the parameters - including price - are the same for all future periods. This approach will not therefore capture uncertainty in these parameters, which can cause prices to change dramatically in the short run. For this reason, the model will lookahead over a much shorter time horizon - sufficient to capture the expected value of one journey ahead - by applying a hyperbolic discount rate to the option value. Although the aforementioned parameters have been estimated for 2011, the year 2011 was considered to be one of the toughest, though the tanker market is still struggling. Average Worldscale prices dropped to 51, compared to the longer term average (2000-2012) of 83. These two states - times of great prosperity and depression - are the defining features of the industry (Serghiou and Zannetos, 1978).

For this reason, I will generate two freight rate scenarios. The first price scenario simulates option values using a multiplier calibrated to 2011 price data, and the second scenario is an average multiplier price over the long-run (representing 2008-2011) holding all other parameters constant. The multiplier in 2011 was estimated using the price regression from section 6.3 and takes into account the variation in levels among routes using the geographical fixed effects for each area. The long-run price scenario is generated by multiplying the estimated prices by the percentage difference in the average multipliers (61% higher than the 2011 multiplier price). It was not possible to estimate prices using the hedonic price regression before 2007 because the larger dataset used to construct this regression was only available for 2007-2011. For the purposes of the model, it suffices to compare the same shock across routes.

Considering two scenarios is important because a change in the multiplier price can lead to significant changes in profits which can have implications for the assignment and changes in speed. In 2011, the market experienced an overcapacity of ships, caused by weak demand and ships ordered in the 2008 boom which flooded the market.

In the long-run scenario, average profits per voyage excluding the repositioning cost are an estimated \$3.7 million, compared to \$1.6 million in the 2011 case, a difference of over \$2 million. Voyage costs range from \$.3 million to \$3.4 million dollars. Given that ships have to reposition back to a loading area, some routes were loss making as discussed in Chapter 3. In theory, the expected discounted profits of all future should be close to the value of a second hand ship to reflect the future expected discounted profits of operating a VLCC. Using a discount rate of 7% per annum, this value is \$145 million, which corresponds to prices during the boom years of 2000-2011. Figures 6.4 and 6.5 show the distribution of the discounted expected value of one voyage ahead for the high and low scenarios broken out by type of location: $W^x(x^a_{j,t+1}, T+1)$,

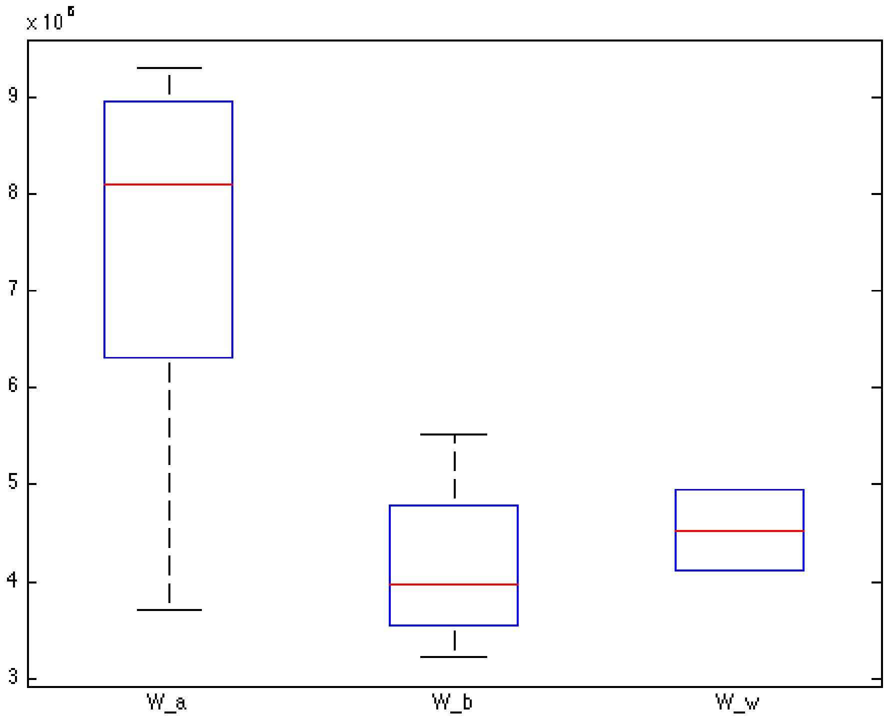


Figure 6.4: Terminal Option Values in long-run scenario (\$ m.): $W_a = W^x(x^a_{j,t+1}, T+1)$; $W_b = W^x(x^b_{j,t+1}, T+1)$; $W_w = W^x(x^w_{j,t+1}, T+1)$

$W^x(x^b_{j,t+1}, T+1)$ and $W^x(x^w_{j,t+1}, T+1)$ for the baseline. The values to be at the loading area a are the highest because profits (excluding the repositioning cost) are not discounted, whereas the values to be at b and w discount these profits.

Table 6.9 shows the values for discharge areas discounted to represent the profits of one voyage for both scenarios where $W_b = W^x(x^b_{j,t+1}, T+1)$. This represents a weighted average of the expected repositioning cost and net revenue from one voyage at the load area plus the expected repositioning cost to a waiting area and the value to be at the waiting area ($W^x(x^w_{j,t+1}, T+1)$), weighted by the probability of choosing the option which is determined by the aggregate market conditions. East Coast Canada, United Kingdom Area and the US Gulf have the highest values while North China, Korea and Japan rank the lowest. The areas with the highest option values all have similar characteristics - they are located relatively close to load areas (Caribbean and West Africa) with high option values (Table 6.10), whereas the lower ranking option values are in the Far East and California, locations which are more isolated from load areas. These findings are also consistent with the multiplier regression results, which show that shipowners discount prices on westward routes because they can obtain a backhaul.

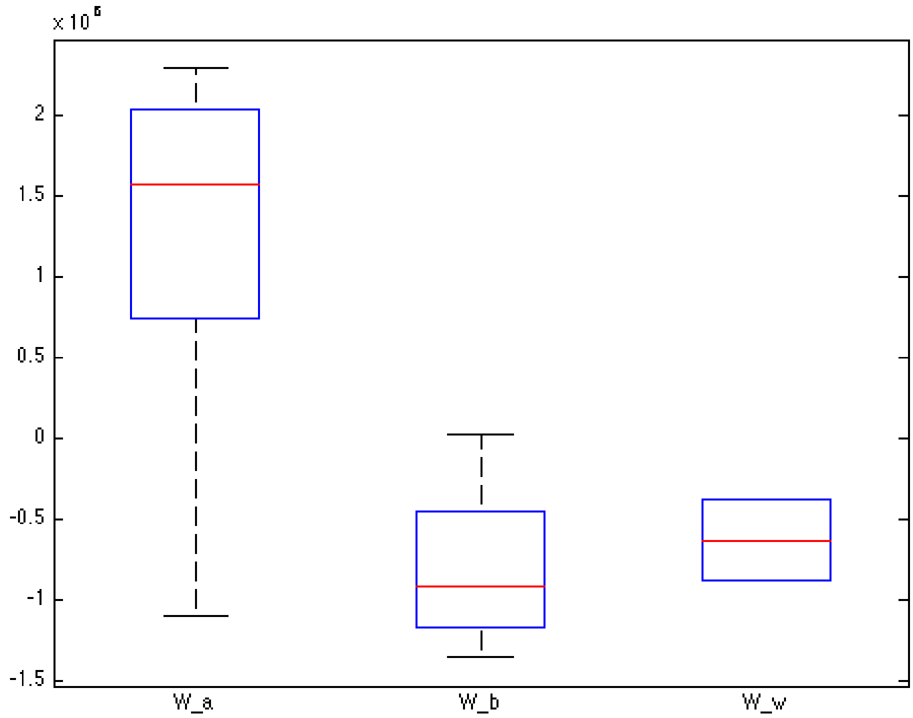


Figure 6.5: Terminal Option Values in 2011 ($ m.): $W_a = W^x(x^a_{j,t+1}, T+1)$; $W_b = W^x(x^b_{j,t+1}, T+1)$; $W_w = W^x(x^w_{j,t+1}, T+1)$

Table 6.9: Option values for discharge areas (million dollars, $W_b = W^x(x^b_{j,t+1}, T+1)$)

Area Acronym	Area Name	W_b	W_b
		Long-run	2011
ECC	East Coast Canada	5.52	0.02
USG	US Gulf	5.41	-0.05
UKC	United Kingdom Area	5.34	-0.09
CMED	Central Mediterranean	5.27	-0.13
WCI	West Coast India	4.79	-0.45
ECI	East Coast India	4.51	-0.61
SAF	South Africa	4.41	-0.66
REDS	Red Sea	4.38	-0.68
SPOR	South Pacific Oceania Region	4.1	-0.84
THAI	Thailand	3.85	-0.98
CALI	California	3.66	-1.08
PHIL	Philippines	3.61	-1.12
TWN	Taiwan	3.58	-1.14
BRZ	Brazil	3.54	-1.17
SCH	South China	3.42	-1.23
NCH	North China	3.31	-1.3
KOR	Korea	3.28	-1.32
JAP	Japan	3.23	-1.35

In other words, their option value is higher, and controlling for other effects, this lowers the price. For the Far East, there is a high probability they will relocate to the Arabian Gulf which has a relatively lower option value than the Caribbean and West Africa. In the formulation of $W^x(x^b_{j,t+1}, T+1)$, repositioning costs are not discounted, whereas for each load area that a ship chooses to relocate to with a probability greater than 0, $W^x(x^a_{j,t+1}, T+1)$ is discounted by the number of repositioning days. Whereas in the long-run scenario, all values are positive and represent at least \$1.7 million in profits, 2011 shows a stark contrast with all negative values. Discounted profits in load areas are not large enough to offset the expected repositioning costs.

6.5 Summary

In this chapter, the datasets described in Chapter 5 were used to estimate the matching model. This required estimating the types of traders, oil revenue, types of ships, cost of journeys, duration of journeys, price earned on journeys, and the ship option values. The first step of the model estimation was to estimate trader and ship types (state variable) and the information state required to estimate the surplus function in the model. Twenty trader types were estimated for the demand sample, differentiated by their trade demand and oil buy price. A sample of ship types in the baseline model was estimated using a combination of aggregate trade data and waiting area information which added up to 18 ship types. Cluster analysis showed that there

Table 6.10: Option values for load areas (million dollars, $W_a = W^x(x^a_{j,t+1}, T+1)$

Area Acronym	Area Name	W_a	W_a
		Long-run	2011
WMED	West Mediterranean	9.29	2.28
UKC	United Kingdom	9.28	2.26
USG	US Gulf	9.18	2.19
ECMX	East Coast Mexico	8.95	2.04
CAR	Caribbean	8.87	2.02
BRZ	Brazil	8.7	1.94
BALT	Baltic Sea	8.39	1.74
WAF	West Africa	7.82	1.4
EMED	East Mediterranean	7.67	1.31
CMED	Central Mediteranean	6.82	0.74
REDS	Red Sea	6.3	0.77
AG	Arabian Gulf	6.07	0.33
KOR	Korea	3.94	-0.96
JAP	Japan	3.71	-1.1

are three distinct groups of ships differentiated by their physical type which will be used in a separate multidimensional matching simulation. A number of uncertainties in the data estimation were discussed; on the demand side the greatest uncertainty was estimating the number of fixtures per week and the expected sell price of oil. On the supply side, the supply of available ships to match and port costs were the most uncertain parameters. A regression was run to explain the determinants of the Worldscale flat rate and multiplier price, revealing that distance accounts for the largest variance in the flat rate with a much smaller proportion attributed to port costs and the bunker price. The multiplier regression showed a good fit to the data, with the area-area route, fuel price, lagged Baltic Dirty Tanker Index explaining the most variation in the data. Of the physical characteristics tested, age, size and hull type were statistically significant, with double-hulled, larger and younger aged ships obtaining a higher price on average. Routes that were westward to the Americas had a negative sign for the route fixed effect, meaning that prices were lower on average, and this can be explained by the opportunity to obtain a backhaul as compared to eastward routes. In the second step of the model estimation, the parameters in the information state were used to estimate the ship option values. These values were consistent with the finding that values to be in westward locations (i.e., ECC and USG) were higher than values in the Far East, influenced by the lower repositioning costs to West Africa from westward destinations. Two scenarios were run - a long-run and 2011 scenario - to characterize the industry's cyclical behavior of oscillating between boom and bust periods.

Chapter 7

Results

7.1 Introduction

The solution of the matching model yields an assignment of ships to shippers, earnings and prices that clear the market for these assignments, the valuations of different locations for shipowners, and the implied supply of ships in future periods. I first provide provide a simple market example in Section 7.1.1 to illustrate how the model works using data from Chapter 6. In Sections 7.2 and 7.3, I discuss the baseline model results of the static matching model with option values that reflect different characterizations of agent beliefs where ships are differentiated by location (holding physical characteristics constant). The results are compared to historical data in sections 7.4 and 7.6. Section 7.7 investigates the first order effects and sensitivity in the static model to a transitory shock to fuel prices, demand for oil cargoes, supply, and a simultaneous demand and fuel price shock. I then extend the model in Section 7.7.5 to consider ships which are differentiated by location and physical characteristics. Section 7.8 explores the dynamic version of the baseline matching model by simulating the model until it converges in matching probabilities and earnings in each location. Finally, Section 7.9 simulates the impact of a permanent demand shock and a carbon tax.

The different model variants and simulations are described in Table 7.1. An x in the table indicates which features are varied for each simulation. I denote the quasi-myopic[1] static model as Model 1 (*M1*), the forward-looking static model as Model 2 (*M2*) and the dynamic forward-looking model Model 3 (*M3*). The ship's option value to be in a discharge location $\beta^{x,d(x_{jt},y_i)}W^x(x^b_{j,t+1}, T+1)$ will be denoted as V_b. The quasi-myopic model ($M1$) and forward-looking models are run with two scenarios reflecting different freight rates. The 2011 scenario uses the econometric equations in Chapter 6 and data in 2011 to estimate a price $P_{2011} = P(x_{jt}, y_i, t)$ for each ship type and trade route. Similarly, the long-run price scenario

[1] Also referred to as myopic as an abbreviation.

is estimated ($P_{lr} = P(x_{jt}, y_i, t)$) to represent average prices over 2008-2011 for each ship type and route. Both price scenarios are used as inputs to the trader's dummy surplus value and the ship's option value V_b. Model 2 uses $W^x_{2011} = W^x(x_{j,t+1}, T+1)$ for the 2011 scenario and $W^x_{lr} = W^x(x_{j,t+1}, T+1)$ for the long-run scenario, estimated in Chapter 6 as inputs to the surplus function and ship's dummy match value. Model 3 uses W^x_{2011}, P_{2011} and $s(\emptyset_x, y_i, t)$ as inputs and then updates these values using a smoothed version of the previous two time steps' estimates of $W^x(x_{jt}, t)$ and $W^y = W^y(y_i, t)$ as input in the next iteration (see Chapter 4 section 4.6.2). Each model is run assuming either a constant or optimal speed.

7.1.1 What determines the intra-allocation of the surplus?

To illustrate the results, I take the data used to calibrate the model in Chapter 6 and focus on a simple market where there is one location, one set of ships and one set of traders. Suppose the market is located in Brazil (BRZ) and ships are located in the Brazilian discharge area. In addition, the outside option for the trader is \$0.4 million and the ship's outside option is \$-1.1 million. If they match, the surplus is \$2.3 m. The way they split the surplus is determined by the demand to supply ratio in the market. As discussed in Chapter 4, when there are fewer ships than traders demanding cargo in the local market ships are short (Figure 7.1), whereas ships which are in excess supply are on the long side of the market (Figure 7.2). A symmetric condition holds for traders. A ship (trader) which is long earns his outside option which in this example is the dummy match surplus and this has the interpretation that the agent is indifferent between matching or not matching. In this simple market, the lowest earnings a ship is willing to accept is the ship's outside option (in this case, $s(x_{jt}, \emptyset_y, t)$).

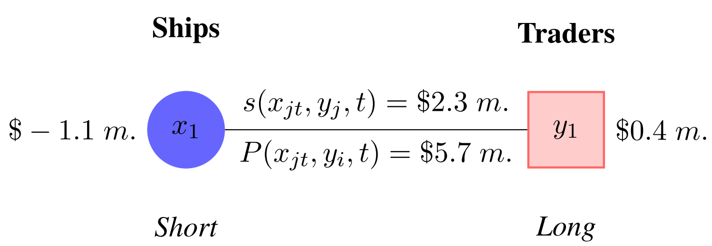


Figure 7.1: Short ship scenario

Figure 7.1 and Table 7.2 show how prices are determined when ships are on the short side of the market. I denote the ship's option value from the discharge area as V_b. In this simple example, when ships are short the price they obtain is determined by equation 4.14 or the difference between the trader's willingness to pay (\$6.0 m.) and his outside option (\$.4 m.) which equals \$5.7 m. The utilization of ships in Brazil is 100% which is equivalent to having an $ExtraRatio$ of 1 and the $locDSR$ as discussed in Chapter 4, is above 1 such that there are

Table 7.1: Static model simulations

	Model									
	$M1cs2011$	$M1os2011$	$M1cslr$	$M1oslr$	$M2cs2011$	$M2os2011$	$M2cslr$	$M2oslr$	$M3cs2011$	$M3os2011$
time	static	static	static	static	static	static	static	static	dynamic	dynamic
V_b	myopic	myopic	myopic	myopic	W^x_{2011}	W^x_{2011}	W^x_{lr}	W^x_{lr}	W^x_{2011}	W^x_{2011}
$s(\emptyset_x, y_i, t)$ input	P_{2011}	P_{2011}	P_{lr}	P_{lr}	P_{2011}	P_{2011}	P_{lr}	P_{lr}	P_{2011}	P_{2011}
v_{op}	cs	os	cs	os	cs	os	cs	os	cs	os
Variations										
fuel					x	x				
supply						x				
demand						x				x
fuel & demand						x				
multidim.						x				
carbon tax									x	x

M=Model; cs=constant speed, os=optimal speed; lr=long run
V_b=ship option value at the discharge location; $s(\emptyset_x, y_i, t)$ is the trader's value to remain unmatched

Table 7.2: Determinants of price (short scenario, one ship and trader type), million (m.) dollars

	Outside option	Costs/Revenue	V_b	Price	Earnings
	\$ m.	\$ m.	\$ m.	\$ m.	\$ m.
Ships	-1.1	2.5	-1.2	5.7	1.9
Traders	0.4	6.0	-	-5.7	0.4

more traders than ships. In contrast, when ships are on the long side of the market (Figure 7.2 and Table 7.3), competition amongst ships of the same type drives the ship's earnings to his outside option and the price drops to \$2.7 m. or 52%. At this price he is indifferent between matching and remaining unmatched. In the long scenario, ships are not fully utilized such that $ExtraRatio < 1$ and $locDSR < 1$.[2]

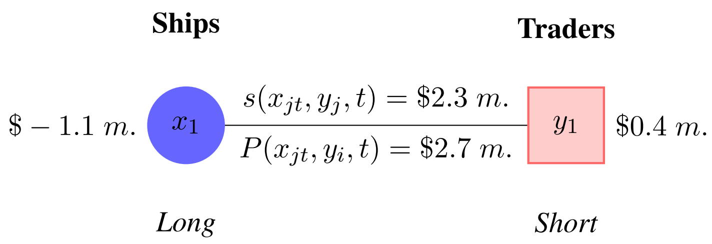


Figure 7.2: Long ship scenario

Table 7.3: Determinants of price (long scenario, one ship and trader type), m. \$

	Outside option	Costs/Revenue	V_b	Price	Earnings
	\$ m.	\$ m.	\$ m.	\$ m.	\$ m.
Ships	-1.1	2.5	-1.2	2.7	-1.1
Traders	0.4	6.0	-	-2.7	3.3

Having described how the intra-allocation is divided between one set of ships and trader types, I now look at what happens to prices and the intra-allocation of surplus when I differentiate ships across locations keeping demand constant in one location in Brazil. I use the estimated supply of ships in different locations (Table 6.2) as the ship types in the market. In the baseline model, there are .80 ships in BRZ and 1 cargo demand for oil in BRZ [3] (on the route BRZ-SCH). When there is more than one ship type, ships have to compete with other ship types but can still be short if their service is more desirable than other ship types and they are fully utilized. In this example, ships in BRZ are short and traders have to consider ships from other locations to meet their remaining .20 demand. The best alternative for a trader is to match with

[2]A special case is when supply equals demand in the local market. In this case, the linear program in Matlab chooses the trader as the receiver of the entire residual pie, as if the trader has all of the bargaining power. A more realistic outcome would be for them to split the pie which is the Nash Bargaining Solution.

[3]Load and discharge area definitions are provided in Table D.5 of the Appendix.

Table 7.4: Determinants of price (multiple ship types, one trader type)

Ships	Match	$W^x(x_{jt},t)$	$s(x_{jt},\emptyset_y,t)$	$W^y(y_i,t)$	$s(\emptyset_x,y_i,t)$	Rev.	Cost	V_b	Price
		\$ m.	\$ m.	\$ m.	\$ m.	\$ m.	\$ m.	\$ m.	\$ m.
BRZ	0.8	0.3	-1.1	2.0	-0.9	6.0	2.5	-1.2	4.1
USG	0.2	-1.6	-1.6	2.0	-0.9	5.2	3.5	-1.2	3.2

a ship in the US Gulf. Note that this is not the ship that is located closest to the BRZ market (excluding the ship in BRZ). Ships in WAF are closer but are not allocated to this route because the value to remain unmatched is higher for the ship in WAF. This is consistent with the social welfare maximizing solution and has the economic interpretation that the ship in USG is willing to provide its service for a lower price in order not to have to sail empty to a waiting location. I will refer to this ship as the marginal ship used to meet demand. The presence of ships in USG increases the competition for the cargo in Brazil, lowering the economic rent that the ship in Brazil can extract. Figure 7.3 depicts this graphically and Table 7.4 shows the relevant factors determining prices for each trade.

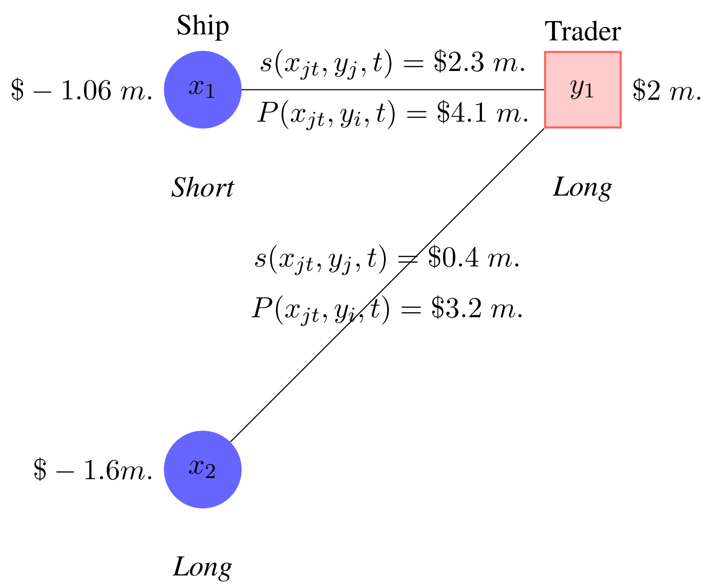


Figure 7.3: Impact of a competitor

Ships in BRZ are denoted as type x_1 and ships in USG are type x_2. Ship x_2 serves as a price threat to x_1, sabotaging its ability to extract the maximum economic rent obtained when there is only one ship type. Ship x_1 should receive a premium equal to the difference in the trader's willingness to pay which is given by the difference in the trader's oil revenue in the match with x_1 over x_2 (\$.85 M). Because there is an excess supply of x_2, ship x_2 is only able to obtain its dummy outside option (\$-1.06) so the price is determined by equation 4.15 where $W^x(x_{jt},t)$ equals $s(x_{jt},\emptyset_y,t)$ and the trader receives earnings of \$2 m. if he matches with

x_2. Now the trader must obtain at least this outside option (its threat point) to match with x_1 which significantly improves the trader's bargaining position. Ship x_1 must also get at least the price that x_2 receives ($3.2 m.) but it also knows that there is a gain of $.85 m. to the trader to matching with x_1 over x_2. Since ships are short in BRZ, the price must equal the price of x_2 plus the trader's economic benefit of matching with x_1 over x_2 so the price the ship can charge is $4.1 m. which exactly equals the sum of the price to match with x_2 plus the economic benefit of matching with x_1 over x_2. At this price, the trader earns the same amount in both trades, but the cargo arrives more quickly with ship x_1 so he prefers to match with x_1. The price ship x_1 can charge has dropped from $5.7 m. to $4.1 m., a 28% decrease or more than three times the largest change in fuel prices in 2011. This example illustrates the model's ability to capture the impact of the presence of a competitor, leading to vastly different prices depending on the balance between local supply and demand and the competition from other ships in other locations. Although prices are not unique, the difference in prices when there is only one ship type and multiple ship types illustrates the model's capability to model volatility in prices that characterizes the time series data of tanker freight rates as described in Chapter 5. It also provides a range of prices we should expect to observe in this market example is given by {$2.70 m., $5.66 m.} for the BRZ-BRZ-SCH match.

7.2 Quasi-myopic matching

The quasi-myopic model with the 2011 version of the trader's dummy surplus ($M1cs2011$) results in 64 matches between ships and traders. Although there is an oversupply of ships in the market, two trader types representing 6 cargoes choose not to match. Table 7.5 shows the matches between ships and traders, the surplus of each match, and the intra-allocation of surplus between each ship and trader type. The ShipID and TraderID fields denote their type which in the baseline model varies by location and trade route respectively.

Thirteen out of eighteen ship types match to traders. These ships can be partitioned into groups serving the local markets AG, BRZ, CAR, REDS, UKC and WAF. Of the traders demanding cargo to be lifted in AG, 59% is served by ships in AG, the maximum amount given the supply of ships in AG. To meet this excess demand, ships are allocated from the Far East (ECI, KOR, NCH, PHIL, SCH, THAI, TWN, WCI) which are located relatively closer than other locations in the supply sample. Ships in WAF serve the WAF market because there is enough supply of ships to meet demand ($locDSR = 80\%$). Ships located in USG serve the CAR market, while ships in SAF and SPOR serve REDS. Ships which are fully utilized (all match to traders) are located in AG, ECI, WCI, PHIL, SPOR, THAI, TWN, BRZ, SAF, the ma-

Table 7.5: Matching with myopic policy ($M1cs2011$)

ShipID	TraderID	Start	Load	End	Match	Supply	Surplus	$W^x(x_{jt}, t)$	$W^y(y_i, t)$
							$ m.	$ m.	$ m.
2	5	ECI	AG	KOR	1.1	1.1	2.47	0.04	2.43
6	4	PHIL	AG	JAP	0.2	0.2	1.34	-1.03	2.36
7	1	SCH	AG	CALI	1	10.9	-0.82	-1.22	0.39
7	4	SCH	AG	JAP	4	10.9	1.14	-1.22	2.36
7	10	SCH	AG	UKC	1	10.9	1.14	-1.22	2.36
8	4	SPOR	AG	JAP	0.7	5.1	1.91	-0.45	2.36
8	5	SPOR	AG	KOR	3.5	5.1	1.98	-0.45	2.43
8	16	SPOR	REDS	PHIL	0.9	5.1	1.75	-0.45	2.20
9	4	THAI	AG	JAP	1.9	1.9	1.64	-0.73	2.36
10	4	TWN	AG	JAP	1.2	1.2	1.32	-1.04	2.36
11	5	WCI	AG	KOR	1.4	6.4	2.84	0.40	2.43
11	6	WCI	AG	SCH	5	6.4	3.01	0.40	2.61
12	13	BRZ	BRZ	SCH	0.8	0.8	1.39	0.49	0.91
14	16	SAF	REDS	PHIL	0.1	0.1	1.91	-0.29	2.20
15	17	UKC	UKC	SPOR	1	10.3	1.14	-1.06	2.21
16	13	USG	BRZ	SCH	0.2	12.7	-0.44	-1.35	0.91
16	14	USG	CAR	SPOR	4	12.7	0.65	-1.35	2.00
16	15	USG	CAR	WCI	2	12.7	1.06	-1.35	2.42
17	3	AG	AG	ECI	1	30	4.70	0.74	3.96
17	6	AG	AG	SCH	19	30	3.35	0.74	2.61
17	7	AG	AG	SPOR	2	30	4.18	0.74	3.43
17	8	AG	AG	THAI	2	30	3.88	0.74	3.14
17	9	AG	AG	TWN	3	30	3.54	0.74	2.80
17	12	AG	AG	WCI	3	30	5.10	0.74	4.36
18	18	WAF	WAF	ECI	1	5	3.47	-0.17	3.65
18	19	WAF	WAF	SCH	2	5	2.33	-0.17	2.51
18	20	WAF	WAF	TWN	1	5	2.52	-0.17	2.70

See Table D.5 for geographical area definitions jority of which serve the AG market. Ship types which are completely unmatched are located in areas farther away from the local markets (NCH, ECC, CALI, KOR and JAP) and have to relocate to a waiting area. Partially utilized ships are located in UKC, SCH and WAF and ships which do not match from these areas also relocate to waiting areas. The myopic model allocates 17 ships (47%) to AG and 19.4 (53%) ships to WAF and the waiting area that is chosen depends on the cost of relocating to each waiting area, a function of the repositioning distance. Ships which are located in the Far East relocate to AG and ships in the Americas relocate to WAF.

Figure 7.4 shows the relationship between the number of matches and the surplus and surplus components (expected oil revenue, shipment cost, and V_b, the ship's option value to be at the discharge area) for all possible matching combinations. Each dot represents a potential match; positive matches belong to group 1 whereas combinations that result in 0 matches belong to group 0. Group 1 matches have a surplus in the higher end of the distribution of surplus and this is primarily driven by the higher oil revenue and lower cost of these pairings compared to other possible combinations. The ship's option value has a smaller impact, although the majority of matches occur where V_b is less negative given the positive impact on the surplus. Matches which are low cost but are in the no match group occur because the resource constraints restrict the number of ships which can be allocated to routes when ships are short and are rationed to the matches with the highest surplus.

Traders demanding cargo on the AG-USG and AG-ECC routes do not match to ships. This is because the surplus of these matches is not large enough to satisfy the stability conditions (Model definition 2) that each agent must receive at least their dummy surplus values. For example, trader type 11 which demands cargo on the AG-USG route has to obtain at least $1.05 m. in order to match, but the surplus to match with ships not already allocated to other traders is not large enough. Figure 7.5 shows the relationship between the number of matches and surplus, ship dummy surplus and trader dummy surplus. The reason that the higher (less negative) surplus values for the ship's dummy option are not chosen is because the surplus to match relative to not matching is higher for the majority of these matches. Earnings for ships in the quasi-myopic model range from $-1.35 m. to $.74 m., while traders' earnings are significantly more, ranging from $.39 m. to $4.36 m. The majority of the traders' share of the surplus is above 1 because most ships earn negative profits. Trader shares which are under 1 are on routes loading in AG and BRZ and ships serving these routes are located close to these markets (AG, BRZ, ECI and WCI) and are on the short side of the market. There is a larger surplus because the repositioning cost is lower given proximity to the market. Table 7.6 shows the ship's earnings compared to the estimated terminal option values for the long-run and

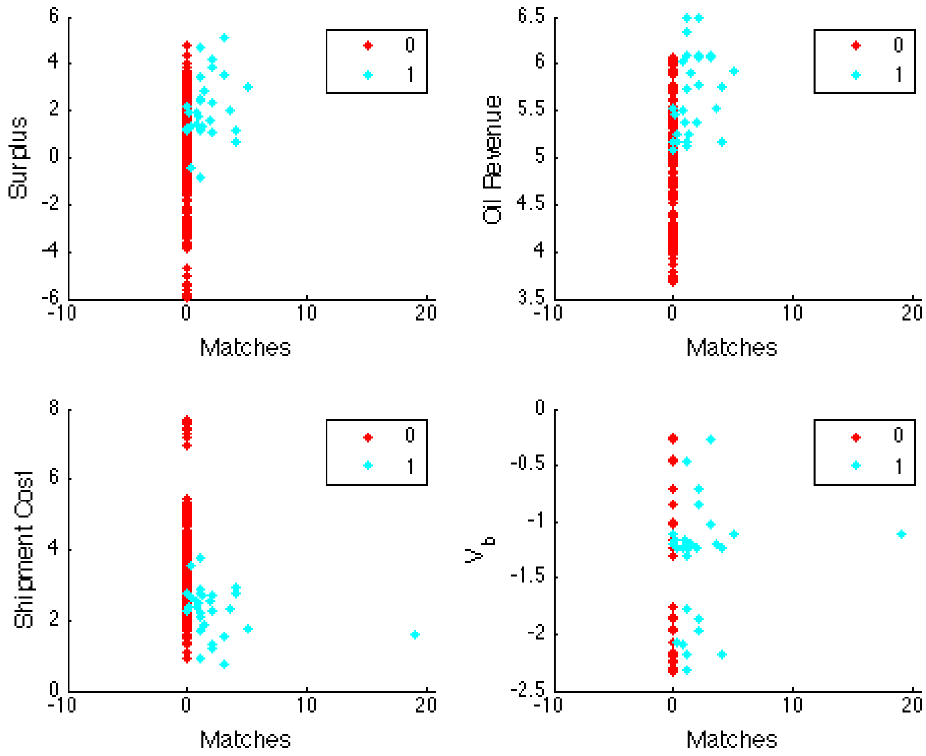


Figure 7.4: Matches and surplus factors ($M1cs2011$; 0=No Match, 1=Match), \$ m.

2011 scenarios. The model's output ($W^x(x_{jt}, t)$) is higher on average compared to the 2011 estimates but lower than the long-run estimates given that the model is calibrated to 2011 data. Values are significantly higher in AG, BRZ, WCI and ECI because these ship types are able to extract an economic rent in the AG and BRZ markets. Table 7.7 shows the factors affecting earnings and prices.

There is a negative correlation between a ship's distance to the load area and the oil trader's revenue due to the storage costs a trader has to pay and the days that the revenue is discounted. The table shows the outside options for traders and ships. Since traders are short in the aggregate market, they always have a ship to substitute for. For example, Trader 6 which demands cargo on the AG-SCH route matches with 19 ships of type 17 located in AG and 5 ships of type 11 located in WCI so the trader's substitute for ship type 17 is ship type 11. In comparison, ships are long in the aggregate market, and therefore ship types which are not fully utilized receive their dummy surplus value $s(x_{jt}, \emptyset_y, t)$. For example, ships in WAF have a 80% utilization rate so they receive \$-.17 m. which equals $s(x_{jt}, \emptyset_y, t)$. Ship option values which are more negative decrease a ship's earnings and therefore matches with more negative V_b values lead overall to lower earnings holding all other parameters constant. Prices are above costs for all matches.

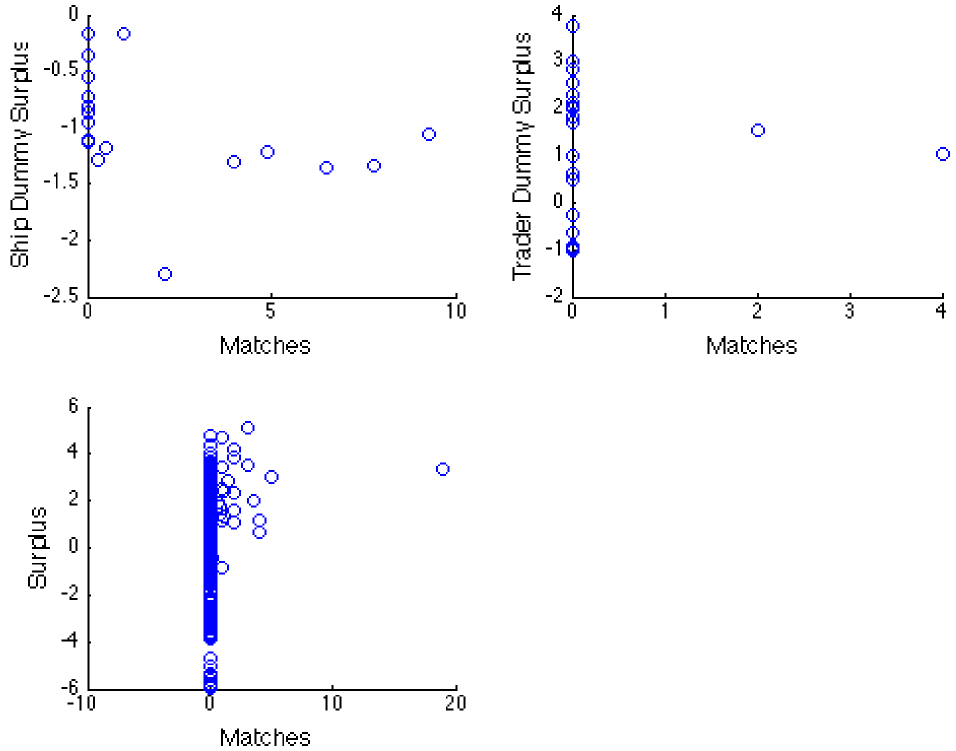


Figure 7.5: Number of matches and surplus (million \$) factors (Model 1; 0=No Match, 1=Match)

Table 7.6: Ship earnings: results from $M1cs2011$ compared to $W^x(x_{j,t+1}, T+1)$

ShipID	Area	PTypeID	W^x_{lr}	W^x_{2011}	$W^x(x_{jt}, t)$
			\$ m.	\$ m.	\$ m.
17	AG	0	4.11	-0.89	0.74
12	BRZ	0	3.54	-1.17	0.49
11	WCI	0	4.79	-0.45	0.4
2	ECI	0	4.51	-0.61	0.04
18	WAF	0	4.95	-0.38	-0.17
14	SAF	0	4.41	-0.66	-0.29
8	SPOR	0	4.1	-0.84	-0.45
9	THAI	0	3.85	-0.98	-0.73
6	PHIL	0	3.61	-1.12	-1.03
10	TWN	0	3.58	-1.14	-1.04
15	UKC	0	5.34	-0.09	-1.06
13	ECC	0	5.52	0.02	-1.18
7	SCH	0	3.42	-1.23	-1.22
5	NCH	0	3.31	-1.3	-1.29
4	KOR	0	3.28	-1.32	-1.3
3	JAP	0	3.23	-1.35	-1.34
16	USG	0	5.41	-0.05	-1.35
1	CALI	0	3.66	-1.08	-2.3

Table 7.7: Factors affecting earnings and prices ($M1cs2011$)

Start	Load	End	Match	$P(x_{jt}, y_i, t)$	$W^x(x_{jt}, t)$	$s(x_{jt}, \emptyset_y, t)$	$W^y(y_i, t)$	$s(\emptyset_x, y_i, t)$	Extra	$\pi(x_{jt}, y_i, t)$	$C(x_{jt}, y_i, t)$	V_b
				\$ m.	\$ m.	\$ m.	\$ m.	\$ m.		\$ m.	\$ m.	\$ m.
AG	AG	SCH	19	3.46	0.74	-0.17	2.61	1.99	0	6.07	1.61	-1.11
AG	AG	TWN	3	3.28	0.74	-0.17	2.80	2.31	0	6.07	1.51	-1.02
AG	AG	THAI	2	2.94	0.74	-0.17	3.14	2.55	0	6.08	1.34	-0.86
AG	AG	SPOR	2	2.65	0.74	-0.17	3.43	2.83	0	6.08	1.19	-0.71
AG	AG	ECI	1	2.13	0.74	-0.17	3.96	3.03	0	6.09	0.93	-0.46
AG	AG	WCI	3	1.74	0.74	-0.17	4.36	3.76	0	6.09	0.73	-0.26
BRZ	BRZ	SCH	0.8	5.11	0.49	-0.86	0.91	-0.92	0	6.02	2.54	-2.08
WCI	AG	KOR	1.4	3.48	0.40	-0.37	2.43	2.12	0	5.91	1.88	-1.20
WCI	AG	SCH	5	3.31	0.40	-0.37	2.61	1.99	0	5.91	1.79	-1.11
ECI	AG	KOR	1.1	3.31	0.04	-0.56	2.43	2.12	0	5.74	2.08	-1.20
WAF	WAF	SCH	2	3.97	-0.17	-0.17	2.51	0.51	1	6.48	2.29	-1.86
WAF	WAF	TWN	1	3.79	-0.17	-0.17	2.70	0.62	1	6.48	2.19	-1.77
WAF	WAF	ECI	1	2.85	-0.17	-0.17	3.65	1.01	1	6.50	1.72	-1.31
SAF	REDS	PHIL	0.1	3.26	-0.29	-0.73	2.20	1.86	0	5.45	2.38	-1.17
SPOR	REDS	PHIL	0.9	3.18	-0.45	-0.81	2.20	1.86	0	5.38	2.47	-1.17
SPOR	AG	JAP	0.7	3.15	-0.45	-0.81	2.36	1.73	0	5.51	2.37	-1.23
SPOR	AG	KOR	3.5	3.08	-0.45	-0.81	2.43	2.12	0	5.51	2.34	-1.20
THAI	AG	JAP	1.9	3.03	-0.73	-0.96	2.36	1.73	0	5.39	2.52	-1.23
PHIL	AG	JAP	0.2	2.89	-1.03	-1.12	2.36	1.73	0	5.25	2.68	-1.23
TWN	AG	JAP	1.2	2.88	-1.04	-1.12	2.36	1.73	0	5.24	2.69	-1.23
UKC	UKC	SPOR	1	4.15	-1.06	-1.06	2.21	-1.03	1	6.35	2.89	-2.32
SCH	AG	CALI	1	4.74	-1.22	-1.22	0.39	-0.28	1	5.13	3.78	-2.18
SCH	AG	UKC	1	2.80	-1.22	-1.22	2.36	2.06	1	5.16	2.79	-1.23
SCH	AG	JAP	4	2.80	-1.22	-1.22	2.36	1.73	1	5.16	2.79	-1.23
USG	BRZ	SCH	0.2	4.26	-1.35	-1.35	0.91	-0.92	1	5.17	3.54	-2.08
USG	CAR	SPOR	4	3.76	-1.35	-1.35	2.00	-0.99	1	5.76	2.94	-2.17
USG	CAR	WCI	2	3.35	-1.35	-1.35	2.42	-0.64	1	5.77	2.73	-1.97

By comparison, when the quasi-myopic model is run using the long-run freight rates as input to the trader's dummy surplus ($M1cslr$), all traders types decide to match with ships. This is because freight rates are much higher in the long-run scenario (63% higher) and these higher freight rates make it more economical for all traders to match in the current period because the trader's dummy surplus is lower. In $M1cslr$, traders demanding cargo on routes AG-ECC and AG-USG match to ships from SCH on the AG-ECC route and ships from KOR, NCH, and SCH on the AG-USG route.

7.3 Forward-looking matching

In this section, I discuss the forward-looking matching results of models $M2cslr$ and $M2cs2011$. Model ($M2cslr$) results in all trader types matching to ships. Table 7.8 shows the matches between ships and traders, the surplus of each match, and the intra-allocation of surplus between each ship and trader type. Fourteen out of eighteen ship types match to traders. Of the traders demanding cargo to be lifted in AG, 53% is served by the supply of ships in AG. The remaining demand is met by ships from the Far East (ECI, KOR, NCH, PHIL, SCH, SPOR, THAI, TWN, WCI) which are located relatively closer than other locations in the supply sample. Because there are enough ships to meet demand in WAF ($locDSR = 80\%$), ships from other areas are not required. Ships located in USG serve the CAR market, while ships in SPOR serve REDS. Ships which are fully utilized (all match to traders) are located in AG, BRZ, ECI, NCH, PHIL, SCH, SPOR, THAI, TWN, and WCI, the majority of which serve the AG market. Ships which are not utilized at all are located in ECC, CALI, and SAF and have to relocate to a waiting area. Partially utilized ships are located in KOR, UKC, USG and WAF and ships which do not match from these areas also relocate to waiting areas. The forward-looking model allocates all of the ships (30.4) to WAF. This can be explained by the higher option value in WAF compared to AG in the forward-looking model, which offsets the higher costs for ships which are located closer to the AG market (ships in the Far East) which would relocate to AG in the quasi-myopic model. All traders match to a ship because their earnings are larger than the dummy surplus values which are impacted by the long-run freight cost. Figure 7.6 shows the relationship between the number of matches and the surplus and surplus components for all possible matching combinations. Similar to model $M1cs2011$ and $M1cslr$, the matches in Group 1 can be explained by higher than average oil revenue and lower than average cost compared to matches in Group 0 where zero matches occur. The magnitude of surplus is due to the long-run ship option values, and this leads to a much higher share of the surplus allocated to the ship compared to the quasi-myopic matching model. The ship's earnings are higher in this scenario

Table 7.8: Forward-looking matching with long-run option values ($M2cslr$)

ShipID	TraderID	Start	Load	End	Match	Supply	Surplus	$W^x(x_{jt}, t)$	$W^y(y_i, t)$
							\$ m.	\$ m.	\$ m.
2	6	ECI	AG	SCH	1.1	1.1	7.16	4.49	2.67
4	4	KOR	AG	JAP	0.9	4	5.41	3.06	2.35
5	4	NCH	AG	JAP	0.3	0.3	5.44	3.09	2.35
6	5	PHIL	AG	KOR	0.2	0.2	5.86	3.42	2.44
7	4	SCH	AG	JAP	6.8	10.9	5.57	3.23	2.35
7	5	SCH	AG	KOR	4.1	10.9	5.66	3.23	2.44
8	6	SPOR	AG	SCH	4.1	5.1	6.67	4.00	2.67
8	16	SPOR	REDS	PHIL	1	5.1	6.50	4.00	2.50
9	5	THAI	AG	KOR	0.5	1.9	6.16	3.72	2.44
9	6	THAI	AG	SCH	1.4	1.9	6.39	3.72	2.67
10	5	TWN	AG	KOR	1.2	1.2	5.84	3.41	2.44
11	6	WCI	AG	SCH	6.4	6.4	7.53	4.86	2.67
12	13	BRZ	BRZ	SCH	0.8	0.8	6.88	5.67	1.21
15	17	UKC	UKC	SPOR	1	10.3	7.52	4.09	3.43
16	13	USG	BRZ	SCH	0.2	12.7	5.02	3.81	1.21
16	14	USG	CAR	SPOR	4	12.7	6.88	3.81	3.07
16	15	USG	CAR	WCI	2	12.7	7.78	3.81	3.97
17	1	AG	AG	CALI	1	30	6.95	5.20	1.75
17	2	AG	AG	ECC	2	30	8.75	5.20	3.54
17	3	AG	AG	ECI	1	30	9.66	5.20	4.45
17	6	AG	AG	SCH	11	30	7.87	5.20	2.67
17	7	AG	AG	SPOR	2	30	8.97	5.20	3.77
17	8	AG	AG	THAI	2	30	8.57	5.20	3.37
17	9	AG	AG	TWN	3	30	8.13	5.20	2.92
17	10	AG	AG	UKC	1	30	9.65	5.20	4.45
17	11	AG	AG	USG	4	30	8.53	5.20	3.33
17	12	AG	AG	WCI	3	30	10.14	5.20	4.94
18	18	WAF	WAF	ECI	1	5	9.27	4.77	4.49
18	19	WAF	WAF	SCH	2	5	7.60	4.77	2.82
18	20	WAF	WAF	TWN	1	5	7.85	4.77	3.07

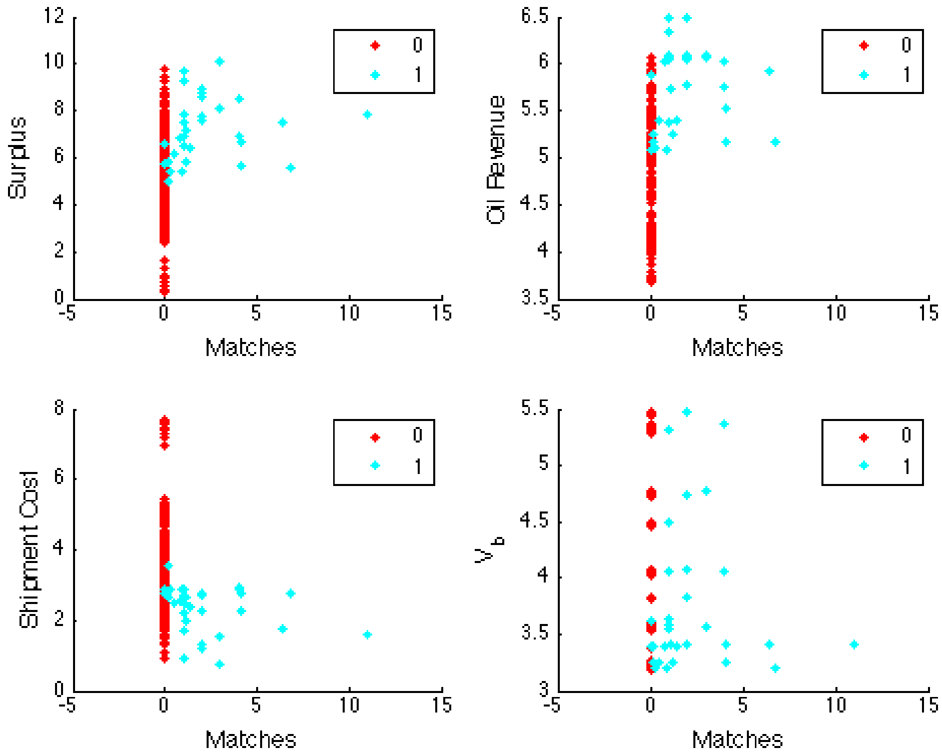


Figure 7.6: Number of matches and surplus (million \$) factors ($M2cslr$; 0=No Match, 1=Match)

because they include the current and one voyage ahead earnings which have a positive value (\$4.45 m. on average). The trader obtains a considerably smaller share, which averages 40% because the trader's average earnings are \$2.96 m. Table 7.9 shows the differences in ship allocation to routes between models $M1cslr$ and $M2cslr$. Because the only difference between the models is the ship's option value, a difference in the allocation of ships to routes occurs when the relative difference in ship option values is different. For example, the table shows that in $M1cslr$ a ship in SCH matches on the AG-CALI route over a ship from AG because V_b is less negative and this has the effect of increasing the surplus. In $M2cslr$, V_b is greater for the ship located in AG compared to SCH. The reason that the ship's option value is less negative for a ship located farther away is because the option value to be in CALI is discounted by the days at sea from the ship's starting location to the ending location which is greater for ships which are farther away. This reveals that the effect of discounting on the surplus is different depending on the sign of the ship's option value: a negative value that is more heavily discounted leads to a greater surplus but a positive option value which is more heavily discounted leads to a smaller surplus value. However, this does not adversely affect the matching results in $M1cslr$. For

Table 7.9: Differences in matches (M1=$M1cslr$ vs. M2=$M2cslr$)

Start	Load	End	Match	Match	Surplus	Surplus	V_b	V_b
			M1	M2	M1	M2	M1	M2
					$ m.	$ m.	$ m.	$ m.
AG	AG	CALI	0.0	1.0	1.14	6.95	-2.19	3.63
SCH	AG	CALI	1.0	0.0	-0.82	4.98	-2.18	3.62
AG	AG	ECC	0.0	2.0	1.02	8.75	-2.24	5.48
SCH	AG	ECC	2.0	0.0	-0.94	6.76	-2.24	5.46
KOR	AG	JAP	0.0	0.9	0.98	5.41	-1.23	3.20
NCH	AG	JAP	0.0	0.3	1.01	5.44	-1.23	3.20
PHIL	AG	JAP	0.2	0.0	1.34	5.77	-1.23	3.20
SPOR	AG	JAP	0.7	0.0	1.91	6.34	-1.23	3.20
THAI	AG	JAP	1.9	0.0	1.64	6.07	-1.23	3.20
TWN	AG	JAP	1.2	0.0	1.32	5.75	-1.23	3.20
ECI	AG	KOR	1.1	0.0	2.47	6.93	-1.20	3.26
PHIL	AG	KOR	0.0	0.2	1.41	5.86	-1.20	3.26
SCH	AG	KOR	0.0	4.1	1.21	5.66	-1.20	3.26
SPOR	AG	KOR	3.5	0.0	1.98	6.43	-1.20	3.26
THAI	AG	KOR	0.0	0.5	1.71	6.16	-1.20	3.26
TWN	AG	KOR	0.0	1.2	1.39	5.84	-1.20	3.26
WCI	AG	KOR	1.4	0.0	2.84	7.30	-1.20	3.26
ECI	AG	SCH	0.0	1.1	2.64	7.16	-1.11	3.41
SPOR	AG	SCH	0.0	4.1	2.15	6.67	-1.11	3.40
THAI	AG	SCH	0.0	1.4	1.88	6.39	-1.11	3.40
AG	AG	UKC	0.0	1.0	3.10	9.65	-1.24	5.32
SCH	AG	UKC	1.0	0.0	1.14	7.67	-1.23	5.30
AG	AG	USG	0.0	4.0	0.83	8.53	-2.34	5.37
KOR	AG	USG	0.8	0.0	-1.29	6.38	-2.33	5.35
NCH	AG	USG	0.3	0.0	-1.26	6.41	-2.33	5.35
SCH	AG	USG	2.9	0.0	-1.13	6.55	-2.33	5.35
SAF	REDS	PHIL	0.1	0.0	1.91	6.66	-1.17	3.59

example, ships in AG are fully utilized and allocated to the AG market. Furthermore, as shown by Figure 7.6, the matching is influenced more by the oil revenue and cost components than by V_b.

Table 7.10 compares earnings from models $M2cslr$ and $M2cs2011$ to the estimated terminal option values. Comparing W^x_{lr} to W^x_{M2cslr} where W^x_{M2cslr} is the ship's earnings $W^x(x_{jt}, t)$

Table 7.10: Ship earnings: results from $M2cslr$ and $M2cs2011$ compared to $W^x(x_{j,t+1}, T+1)$

ShipID	Area	PTypeID	W^x_{lr}	W^x_{2011}	W^x_{m2cslr}	$W^x_{m2cs2011}$
			$ m.	$ m.	$ m.	$ m.
12	BRZ	0	3.54	-1.17	5.67	0.28
17	AG	0	4.11	-0.89	5.2	0.11
11	WCI	0	4.79	-0.45	4.86	-0.23
18	WAF	0	4.95	-0.38	4.77	-0.56
2	ECI	0	4.51	-0.61	4.49	-0.6
14	SAF	0	4.41	-0.66	4.41	-0.92
15	UKC	0	5.34	-0.09	4.09	-1.27
8	SPOR	0	4.1	-0.84	4	-1.08
13	ECC	0	5.52	0.02	3.98	-1.38
16	USG	0	5.41	-0.05	3.81	-1.56
9	THAI	0	3.85	-0.98	3.72	-1.36
6	PHIL	0	3.61	-1.12	3.42	-1.66
10	TWN	0	3.58	-1.14	3.41	-1.67
7	SCH	0	3.42	-1.23	3.23	-1.85
5	NCH	0	3.31	-1.3	3.09	-1.98
4	KOR	0	3.28	-1.32	3.06	-2.01
3	JAP	0	3.23	-1.35	3.04	-2.05
1	CALI	0	3.66	-1.08	2.88	-2.52

from model scenario $M2cslr$, earnings are lower overall in the model compared to the estimated option values with the exception of BRZ, AG, and WCI which are higher. In $M2cs2011$, earnings are lower than W^x_{2011} except for BRZ, AG and ECI. Table 7.11 shows the factors that explain earnings in model $M2cslr$. Take for instance the price that a ship in BRZ obtains from matching to a trader demanding cargo from BRZ-SCH. The model output W^x_{M2cslr} is a function of the trader's willingness to pay for the service (\$6.02 m.) and his outside option (\$1.21 m.), which in this case is determined by the earnings if he were to match with a ship in USG, his next best alternative. Earnings for ships in USG are equal to the dummy surplus value (\$3.81 m.) because ships in this market are long so the price that a trader has to pay for the USG ship can be directly calculated using equation 4.15, a function of the shipment cost, earnings, and option value V_b where earnings equal $s(x, \emptyset_y, t)$ and the price equals \$3.96 m. Traders match with the USG ship because there is a shortage of ships in BRZ. The economic rent that the ship in BRZ can extract for the BRZ-SCH match is equal to the price of the ship in USG plus the marginal

Table 7.11: Factors affecting earnings and prices ($M2cslr$)

Start	Load	End	Match	$P(x_{jt}, y_i, t)$	$W^x(x_{jt}, t)$	$s(x_{jt}, \emptyset_y, t)$	$W^y(y_i, t)$	$s(\emptyset_x, y_i, t)$	Extra	$\pi(x_{jt}, y_i, t)$	$C(x_{jt}, y_i, t)$	V_b
				\$ m.	\$ m.	\$ m.	\$ m.	\$ m.		\$ m.	\$ m.	\$ m.
AG	AG	CALI	1	4.29	5.2	3.93	1.75	-3.37	0	6.04	2.72	3.63
AG	AG	ECC	2	2.5	5.2	3.93	3.54	-0.39	0	6.04	2.77	5.48
AG	AG	ECI	1	1.64	5.2	3.93	4.45	1.97	0	6.09	0.93	4.5
AG	AG	SCH	11	3.4	5.2	3.93	2.67	0.3	0	6.07	1.61	3.41
AG	AG	SPOR	2	2.32	5.2	3.93	3.77	1.67	0	6.08	1.19	4.08
AG	AG	THAI	2	2.71	5.2	3.93	3.37	1.21	0	6.08	1.34	3.84
AG	AG	TWN	3	3.15	5.2	3.93	2.92	0.83	0	6.07	1.51	3.57
AG	AG	UKC	1	1.62	5.2	3.93	4.45	0.42	0	6.07	1.73	5.32
AG	AG	USG	4	2.71	5.2	3.93	3.33	-1.21	0	6.04	2.87	5.37
AG	AG	WCI	3	1.16	5.2	3.93	4.94	3.17	0	6.09	0.73	4.78
BRZ	BRZ	SCH	0.8	4.81	5.67	4.29	1.21	-4.21	0	6.02	2.54	3.4
ECI	AG	SCH	1.1	3.07	4.49	3.74	2.67	0.3	0	5.74	1.99	3.41
KOR	AG	JAP	0.9	2.74	3.06	3.06	2.35	-0.13	1	5.08	2.87	3.2
NCH	AG	JAP	0.3	2.75	3.09	3.08	2.35	-0.13	0	5.1	2.86	3.2
PHIL	AG	KOR	0.2	2.81	3.42	3.3	2.44	0.52	0	5.25	2.65	3.26
SCH	AG	JAP	6.8	2.81	3.23	3.14	2.35	-0.13	0	5.16	2.79	3.2
SCH	AG	KOR	4.1	2.72	3.23	3.14	2.44	0.52	0	5.16	2.75	3.26
SPOR	AG	SCH	4.1	2.85	4	3.51	2.67	0.3	0	5.52	2.25	3.4
SPOR	REDS	PHIL	1	2.88	4	3.51	2.5	0.14	0	5.38	2.47	3.59
THAI	AG	KOR	0.5	2.95	3.72	3.37	2.44	0.52	0	5.39	2.49	3.26
THAI	AG	SCH	1.4	2.72	3.72	3.37	2.67	0.3	0	5.39	2.4	3.4
TWN	AG	KOR	1.2	2.81	3.41	3.23	2.44	0.52	0	5.24	2.66	3.26
UKC	UKC	SPOR	1	2.92	4.09	4.09	3.43	-4.4	1	6.35	2.89	4.06
USG	BRZ	SCH	0.2	3.96	3.81	3.81	1.21	-4.21	1	5.17	3.54	3.39
USG	CAR	SPOR	4	2.69	3.81	3.81	3.07	-4.12	1	5.76	2.94	4.06
USG	CAR	WCI	2	1.8	3.81	3.81	3.97	-3.56	1	5.77	2.73	4.75
WAF	WAF	ECI	1	2	4.77	4.77	4.49	-1.42	1	6.5	1.72	4.49
WAF	WAF	SCH	2	3.66	4.77	4.77	2.82	-2.24	1	6.48	2.29	3.4
WAF	WAF	TWN	1	3.41	4.77	4.77	3.07	-2.06	1	6.48	2.19	3.56
WCI	AG	SCH	6.4	3.24	4.86	3.93	2.67	0.3	0	5.91	1.79	3.41

willingness to pay for the ship in BRZ over the marginal ship. Earnings in the model reflect the relevant substitutes in the market, a function of location and the availability of other ships in the market. In comparison, the earnings from the terminal period are a function of trade flow shares, probabilities of matching, freight rates and a discount factor which are annual averages and are estimated with a degree of uncertainty as discussed in Chapter 6.

In the second version of Model 2 ($M2cs2011$), the 2011 data used to calibrate V_b has a downward impact compared to $M2cslr$. This still results in all traders matching to ships because the surplus is high enough (see Figure 7.7) that the agents can obtain at least their dummy surplus values in contrast to $M1cs2011$ where the surplus was not high enough for two trader types to match. The matching between $M2cs2011$ and $M2cslr$ is the same except

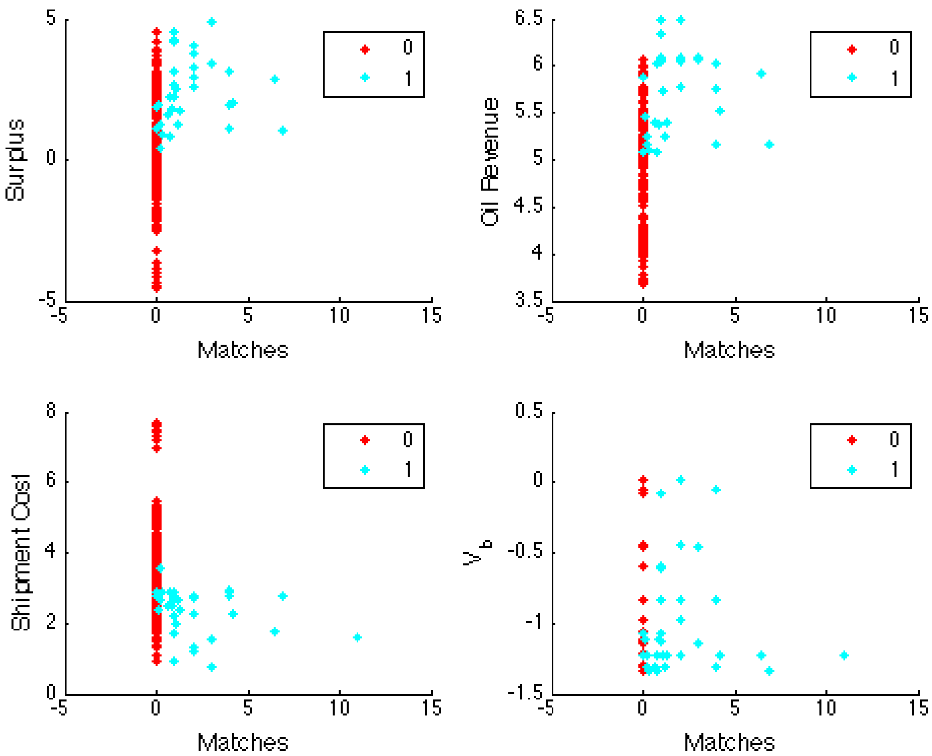


Figure 7.7: Number of matches and surplus (million \$) factors ($M2cs2011$; 0=No Match, 1=Match)

for the REDS-PHIL route. In $M2cs2011$, two ship types from SAF and SPOR match on the REDS-PHIL route. The supply in SAF is fully utilized (.10) because the surplus is higher than matching with a ship from SPOR and the remainder of the demand (.90) is satisfied by the ship in SPOR. The rest of the supply in SPOR is allocated to the AG-SCH route. In contrast, model $M2cslr$ allocates the entire demand on REDS-PHIL route to the ship in SPOR, and the

Table 7.12: Factors determining matches on REDS-PHIL route ($M2cslr$)

Start	Load	End	Match	Supply	$s(x_{jt}, y_i, t)$	$s(x_{jt}, \emptyset_y, t)$
					\$ m.	\$ m.
SPOR	REDS	PHIL	1	5.1	6.498	3.505
SAF	REDS	PHIL	0	0.1	6.663	4.410
SPOR	AG	SCH	4.1	5.1	6.668	3.505

ship in SAF remains unmatched. To understand why ships in SPOR are chosen over ships in SAF, it is necessary to know the surplus values of the potential matches and dummy matches for the ships $s(x_{jt}, \emptyset_y, t)$.[4] Table 7.12 shows the factors determining matches on REDS-PHIL route in $M2cslr$. Although the surplus of matching with a ship in SAF is higher (\$6.66 m. vs. \$6.49 m.), the value of not matching $s(x_{jt}, \emptyset_y, t)$ for the ship in SAF is relatively higher than $s(x_{jt}, \emptyset_y, t)$ in SPOR. Both ships would relocate to WAF because the option value is higher in the waiting area compared to AG.

In $M2cs2011$, ships which don't match relocate to WAF (19.4 ships or 64%) and AG (11 ships or 36%) compared to $M2cslr$ which allocated all ships to WAF. The difference can be explained by the larger weight on repositioning costs in $M2cs2011$. While the laden speed is constant in all models, the ballast speed to a waiting area (the unmatched speed) is optimized. The quasi-myopic model minimizes the cost of the ballast unmatched journey because there is no incentive to speed up. Ships travel at their minimum speed (8 knots). In Model 2, the ballast speed depends on future earnings. Ships sail at their minimum speed of 8 knots in the 2011 scenario because V_b values are negative, but travel at a faster average speed of 10.4 knots in the long-run scenario given significantly higher and positive future profits.

7.4 Prices in the model compared to historical data

Table 7.13 shows prices in models $M1cs2011$ and $M2cs2011$ compared to data on freight rates in 2011 in multiplier units. This was calculated using equation 7.1 and weighted by the number of matches of each ship type on each route. In model $M1cs2011$, prices are higher on average than historical prices (18.3%) whereas prices are lower on average in model $M2cs2011$ compared to historical data (-5.4%). The forward-looking model $M2cs2011$ outperforms the myopic model $M1cs2011$ by a wide margin. The residual sum of squares for $M1cs2011$ is 249 compared to 56 for $M2cs2011$.

Differences in prices between the two model versions can be explained by two reasons. First, the option values are more negative in $M1cs2011$. If a ship's option value is negative,

[4] Since all traders match, we can ignore the traders' dummy surplus values, though they would be required if traders did not match.

the price increases because there are negative profits earned from the discharge area holding all else constant. Secondly, the differences in the AG market reflect the prices of different marginal ships in each model. In the quasi-myopic model, the marginal ship is SCH whereas the marginal ship in the forward-looking model is in KOR. Since each ship is extra, their dummy earnings determine the price. The dummy earnings for the ship in KOR is lower because it is located farther away than the ship in SCH and therefore it is willing to accept a lower price in the market.

Table 7.13: Comparison of multiplier prices in baseline models (Model 1 and 2) to historical data

Load	End	WS_{2011}	$WS_{M1cs2011}$	$WS_{M2cs2011}$	pct_diff	lvl_diff	pct_diff	lvl_diff
			$M1$	$M2$	$M1$	$M1$	$M2$	$M2$
		WS	WS	WS	%	WS	%	WS
AG	CALI	50	52	43	4	2.1	-16.6	-7.1
AG	ECC	39	43	35	9	4	-11.5	-4
AG	ECI	54	79	61	31.5	24.8	11.5	7
AG	JAP	53	51	40	-3.5	-1.8	-32.2	-12.9
AG	KOR	50	64	45	21.8	13.9	-11.7	-5.2
AG	SCH	53	67	54	21	14.1	1.7	0.9
AG	SPOR	53	76	61	30	22.7	13.6	8.3
AG	THAI	54	73	60	26	19	10.6	6.4
AG	TWN	51	70	59	26.9	18.8	13.3	7.8
AG	UKC	38	46	32	17.3	7.9	-20.2	-6.4
AG	USG	37	44	34	19.1	7.1	-10.3	-3.4
AG	WCI	56	98	73	42.8	41.9	23.3	17
BRZ	SCH	51	67	40	21	14.1	-26.2	-10.6
REDS	PHIL	48	62	49	22.3	13.8	1.3	0.6
WAF	SCH	50	67	39	21	14.1	-28.5	-11.1
WAF	TWN	47	70	36	26.9	18.8	-30.8	-11.1
Total					18.3	13.0	-5.4	-1.30

WS=Worldscale units

Other reasons that prices differ from historical prices is the demand to supply ratio could be different from the historical data. As mentioned previously, for a finite number of agents, these prices are not unique; rather there is a lower and upper bound on the allocation of surplus which can lead to different prices. Another level of uncertainty is the estimated benchmark price used to compute the multiplier. As mentioned in Chapter 6, aside from fuel costs, port costs are the second largest factor in these calculations and they represent the most subjective portion of forecasting new flat rates (McQuilling, 2010). Port costs are also estimated in the model and are assumed to be uniform across routes but in practice vary according to the port authority. The forward-looking model is able to capture the almost 15 point level difference in westward routes (AG-UKC and AG-USG) compared to eastward routes which was seen in the data which are lower because of the backhaul opportunity in WAF, whereas the myopic model's prices are higher because it assumes the ship will relocate to AG.

Unfortunately, there was no publicly available data for this study on the trajectories of ships which could validate the matching.

7.5 Optimal speed simulations

In this model comparison run, the constant matched speed assumption which was analyzed in the previous sections is relaxed in order to understand how the factors (oil revenue, cost, and option values) affect speed in the matched state and investigate whether the average matched speed from the model is close to observed average speeds in 2011. As discussed in Chapter 4, the optimal matched speed is the speed that maximizes the match surplus (the combined payoff to the trader and ship) which is equivalent to solving for the match surplus equation's derivative with respect to speed. The optimal matched speed applies to the speed the ship sails from its starting location to its discharge location when it is matched to a trader. Different discount rates are applied to the oil revenue and ship's option value to reflect heterogeneity in trader and ship time preferences. Ships which are not located in the load area market are penalized. In the model, this is implemented by the storage costs a trader has to pay for the days until a ship arrives to pick up his cargo and the inventory cost which discounts the oil revenue. Figure 7.8 shows density plots of the matched speeds in Models 1 and 2 with different ship option value scenarios. They were generated using a kernel density plot which estimates the distribution of the data based on a histogram of the data rather than a priori distribution assumptions.

In $M2os2011$, the average matched speed (weighted by the total days spent in the matched state) is 11.25 compared to 11.19 in $M1os2011$. The long-run scenario $M2oslr$ has slightly higher matched speeds because of the higher ship option values (11.34 knots compared to 11.24 in $M1oslr$). Ballast speeds are broken into matched and unmatched speeds. The matched ballast speed in $M2os2011$ is 12.46 compared to the unmatched ballast speed of 8 knots, with a total weighted average ballast speed of 9.53 knots. This reflects the fact that a larger proportion of time is spent in the unmatched ballast state. For model $M2oslr$, ballast speeds are higher - 12.56 compared to 10.39 - because the ship option values are positive, and this results in a higher average ballast speed of 11.15. Figure 7.9 shows the influence of voyage cost, repositioning cost, and option values on speed.

The figure shows that the distinct cluster of ships with the highest speed results from a combination of relatively higher repositioning costs, lower voyage costs, and higher option values. These matches correspond to ships located in SCH matching on the AG-ECI and AG-WCI routes, which have relatively higher option values for WCI and ECI. In contrast, the speeds

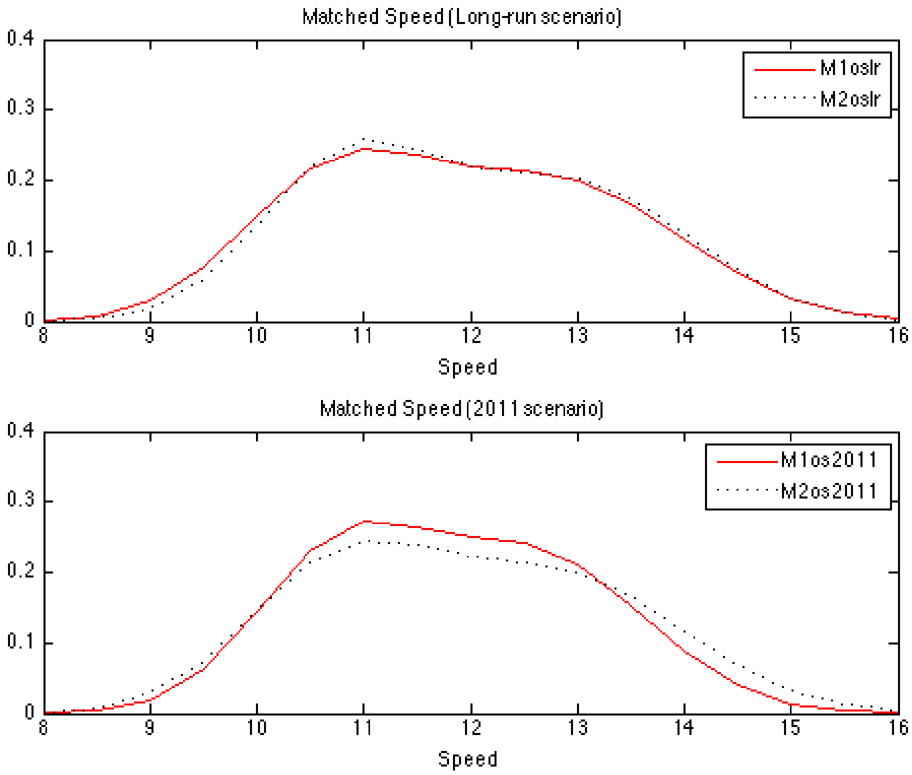


Figure 7.8: Matched speeds (knots) in M1oslr vs. M2oslr

which rank the lowest correspond to matches that have zero repositioning costs, high voyage costs and low option values.

7.6 Social welfare, speed and emissions

Table 7.14 compares the total surplus (social welfare), speed and emissions among the different baseline models. The long-run forward looking models $M1cslr$ and $M1oslr$ have the highest social welfare because of the higher option values for the ships. The model with the lowest social welfare is model $M1cs2011$ because of the ship's option value assumptions and constant speed assumption. The optimal speed variant leads to a higher surplus compared to the constant speed version in all models because the reduction in cost outweighs the decreased oil revenue to the trader. This also leads to a reduction in emissions compared to the constant speed models. The highest total emissions occur in $M2cslr$ which is explained by its high ranking in total speed. The model with the lowest emissions is $M1os2011$ because in this model not all traders match and therefore the tonne-miles is less than the other models. To provide context to speeds in the model, data from AIS in 2011 shows that the average ballast speed was 13.52 and 13.24 in laden. Data was not available to decipher whether ships were matched or unmatched. The

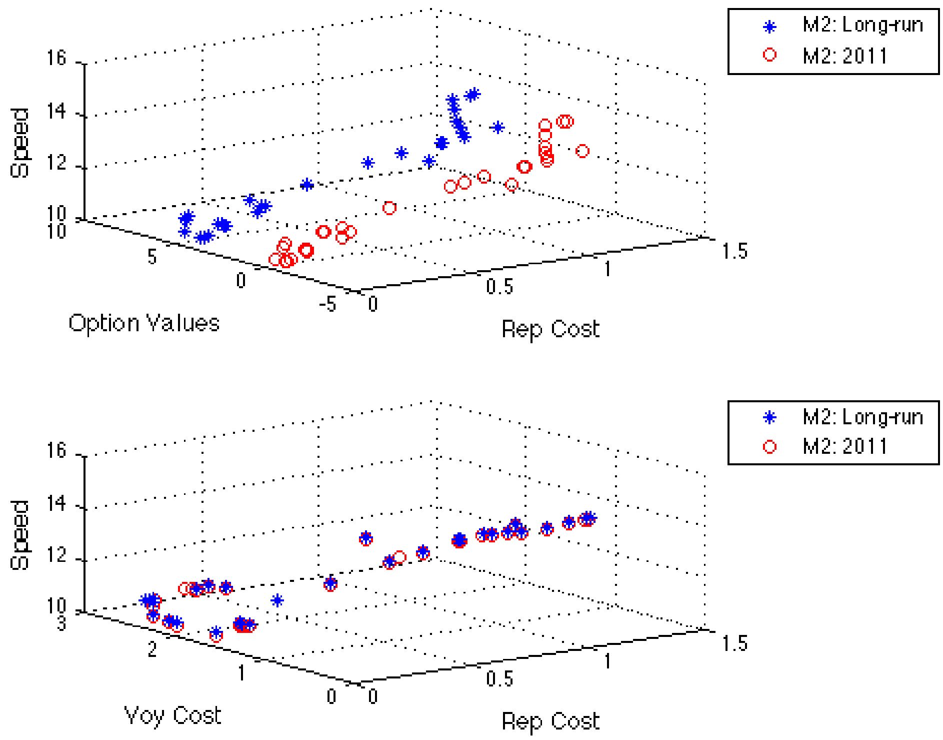


Figure 7.9: Factors affecting matched speed (knots) Cost/Option Values in million $

model that is closest to these speeds is $M2cslr$, where 13.5 is the equivalent laden speed and 10.4 is the ballast speed, which averages to a total speed of 12.6.

7.7 Static Model Counterfactuals

This section considers the impact of transitory shocks on the static matching model. A transitory shock assumes that the shock lasts one period. An example of a transitory shock is a temporary supply disruption to oil supplies which causes demand to increase in the current period but returns to normal in the next period. In the model, this means that expectations (the ship option value and trader's dummy match surplus) remain unchanged. I consider changes in fuel prices, supply, demand, and a simultaneous demand and fuel price shock using the 2011 scenario.

7.7.1 Simulation 1: impact of higher fuel prices

I consider a transitory 5% fuel price shock in models $M2cs2011$ and $M2os2011$ by simulating an increase in the heavy fuel oil price (HFO) above the baseline HFO price of $645/tonne which translates into $677.25 per tonne. This is a reasonable assumption given the weekly fluctuations in HFO prices ranged between -5.1% and 9.3% in 2011 for the reference Singapore 380cst bunker price. In the short-run, the impact of an increase in the HFO price increases

Table 7.14: Social welfare, speed and emissions

Model	TSurplus	MSpeed	UMSpeed	TSpeed	MCO2	UMCO2	TCO2
	\$ m.	knots	knots	knots	m. grams	m. grams	m. grams
$M1cs2011$	130.6	13.5	8	11.5	311,214	37,402	348,616
$M1os2011$	137.3	11.4	8	10.3	220,827	37402	258,229
$M1cslr$	124.1	13.5	8	11.9	370,567	31,451	402,018
$M1oslr$	132.2	11.5	8	10.6	268,041	31,451	299,492
$M2cs2011$	135.6	13.5	8	11.9	370,567	31,469	402,036
$M2os2011$	143.6	11.5	8	10.6	268,466	31,469	299,935
$M2cslr$	630.8	13.5	10.4	12.6	370,721	67,139	437,859
$M2oslr$	638.4	11.6	10.4	11.3	272,810	67,139	339,948

T=Total; L=laden; BM=ballast matched; M=matched; UM=unmatched

the repositioning and voyage cost because shipowners cannot substitute away from using this input. A transitory shock increases the price of HFO in the current period but does not impact future periods. This has the effect of increasing the price of matching in the current period through the increase in fuel cost for ships who match to traders and who are unmatched and have to sail empty to a waiting area but does not impact the traders' option value to remain unmatched because fuel prices are expected to return to the baseline price in the next period. The sensitivity of price to cost increases can be measured in terms of the price elasticity and the cost pass-through rate.

The price elasticity with respect to cost is defined as:

$$\epsilon_P = \frac{\Delta P(x_{jt}, y_i, t)}{P(x_{jt}, y_i, t)} / \frac{\Delta C(x_{jt}, y_i, t)}{C(x_{jt}, y_i, t)}$$

A unit elastic price change ($\epsilon_P = 1$) means that the percentage change in cost leads to an equal percentage change in price, while less than unit elasticity occurs when the percentage change in price does not increase by as much as the percentage change in cost, and greater than unit elasticities occur when the the percentage change in price increases by more than the percentage change in cost.

The cost pass-through rate is defined as:

$$CPR = \frac{\Delta P(x_{jt}, y_i, t)}{\Delta C(x_{jt}, y_i, t)} * 100$$

where $\Delta P(x_{jt}, y_i, t)$ and $\Delta C(x_{jt}, y_i, t)$ are the change in prices and costs respectively. The price elasticity provides a unit-less measure whereas cost-pass through is used to compare the level difference in cost compared to price. The extent to which the shipowner can pass the fuel price increase on to the freight rate depends on the market tightness for the particular ship type (measured by its *ExtraRatio*), the agents' dummy surplus values, and the speed assumptions in the contract. For ships which are long, the price change is a function of the change in the cost, the ship's dummy surplus value and V_b which is represented mathematically as:

$$\Delta P(x_{jt}, y_i, t) = \Delta C(x_{jt}, y_i, t) + \Delta s(x_{jt}, \emptyset_y, t) + \Delta V_b \tag{7.1}$$

For ships which are not located at a waiting area, $s(x_{jt}, \emptyset_y, t)$ will decrease, so the sign is negative. The impact on V_b depends on the assumption about speed; in the constant speed case it stays the same. Assuming a constant speed, the change in cost will be greater than the change in price because $\Delta s(x_{jt}, \emptyset_y, t)$ offsets the price increase. In the cases where ships are already located in the waiting area (ships in AG and WAF), $\Delta s(x_{jt}, \emptyset_y, t) = 0$ such that for ships which are long, $\Delta C(x_{jt}, y_i, t)$ exactly equals the $\Delta P(x_{jt}, y_i, t)$ so the cost pass-through is 100%. Changes in prices for ships on the short side of the market reflect the change in the price of the ship type's substitute and the change in the trader's willingness to pay for the ship type over its substitute. Mathematically, this is represented as:

$$\Delta P(x_{jt}, y_i, t) = \Delta P(x_{j\prime t}, y_i, t) + (\Delta\prime\pi(x_{jt}, x_{j\prime t}, y_i, t) - \Delta\pi(x_{jt}, x_{j\prime t}, y_i, t)) \tag{7.2}$$

The first term, $\Delta P(x_{j\prime t}, y_i, t)$ represents the change in the substitute's price and the second term is the difference between the change in the willingness to pay (oil trader's revenue) between the fuel shock scenario ($\Delta\prime\pi(x_j, x_{j\prime t}, y_i, t)$ and the baseline scenario.

Table 7.15 shows that VLCC freight rates are sensitive to fuel price changes, generally increasing by 2-3.6% (price elasticity .8-1.4) if fuel prices increase by 5% given a constant matched speed ($M2cs2011$) in 2011. Cost pass-through rates are between 84 and 221%, averaging 124% (weighted by number of matches per route). Cost-pass through for ship types in AG, BRZ, ECI, SAF, SPOR, WAF and WCI is greater than or equal to 100%, while cost-pass through is less than 100% for ship types in KOR, NCH, PHIL, SCH, USG, UKC and TWN. For ships on the long side of the market, the extent to which ships can pass through the cost depends on their dummy surplus value. In the WAF market, *CPR* is 100% because $\Delta s(x_{jt}, \emptyset_y, t) = 0$ since the ship is already located in the waiting area. Ships in AG are also located in a waiting area, but their cost pass-through rate is above 100% because they are on the short side of the market and therefore the change in price is determined by equation 7.2, a function of the trader's next best (and feasible) substitute service and the relative WTP for matching with AG over the substitute service.

Table 7.15: Price elasticities for a 5% transitory fuel shock ($M2cs2011$)

Start	Load	End	Cost_pct	Price_pct	ϵ_P	CPR (%)	Diff(Speed)	Diff(Match)	ExtraRatio	Diff($s(x_{jt}, \emptyset_y, t)$)	Diff($s(\emptyset_x, y_i, t)$)
			%	%		%	knots			\$ m.	\$ m.
USG	CAR	WCI	2.54	3.58	1.41	84	0	0	0.49	-0.01	0
USG	CAR	SPOR	2.54	2.87	1.13	85	0	0	0.49	-0.01	0
KOR	AG	JAP	2.54	2.83	1.11	85	0	0	0.2	-0.01	0
NCH	AG	JAP	2.54	2.81	1.11	86	0	0	1	-0.01	0
USG	BRZ	SCH	2.56	2.48	0.97	88	0	0	0.49	-0.01	0
SCH	AG	KOR	2.54	2.78	1.09	88	0	0	1	-0.01	0
SCH	AG	JAP	2.54	2.73	1.08	88	0	0	1	-0.01	0
UKC	UKC	SPOR	2.54	2.65	1.04	88	0	0	0.1	-0.01	0
TWN	AG	KOR	2.53	2.68	1.06	91	0	0	1	-0.01	0
PHIL	AG	KOR	2.53	2.67	1.05	92	0	0	1	-0.01	0
THAI	AG	SCH	2.52	2.61	1.03	98	0	0	1	-0.01	0
THAI	AG	KOR	2.52	2.52	1	98	0	0	1	-0.01	0
WAF	WAF	ECI	2.47	2.4	0.97	100	0	0	0.8	0	0
WAF	WAF	SCH	2.51	1.95	0.77	100	0	0	0.8	0	0
WAF	WAF	TWN	2.51	1.99	0.79	100	0	0	0.8	0	0
SPOR	REDS	PHIL	2.52	2.59	1.03	104	0	0	1	-0.01	0
SPOR	AG	SCH	2.51	2.47	0.98	104	0	0	1	-0.01	0
SAF	REDS	PHIL	2.52	2.52	1	108	0	0	1	-0.01	0
ECI	AG	SCH	2.49	2.25	0.9	119	0	0	1	0	0
BRZ	BRZ	SCH	2.53	1.96	0.78	123	0	0	1	-0.01	0
AG	AG	USG	2.54	3.05	1.2	127	0	0	1	0	0
AG	AG	ECC	2.54	3.14	1.24	128	0	0	1	0	0
AG	AG	CALI	2.54	2.27	0.89	128	0	0	1	0	0
WCI	AG	SCH	2.47	2.12	0.86	133	0	0	1	0	0
AG	AG	UKC	2.47	3.23	1.31	146	0	0	1	0	0
AG	AG	SCH	2.45	2	0.82	150	0	0	1	0	0
AG	AG	TWN	2.44	2.05	0.84	153	0	0	1	0	0
AG	AG	THAI	2.42	2.14	0.88	161	0	0	1	0	0
AG	AG	SPOR	2.39	2.24	0.94	169	0	0	1	0	0
AG	AG	ECI	2.31	2.49	1.08	191	0	0	1	0	0
AG	AG	WCI	2.22	2.76	1.25	221	0	0	1	0	0

Table 7.16 shows that a fuel price increase of 5% results in price increases of 1.1-4.0% when speed is optimized ($M2os2011$), which translates into a price elasticity of .77 to 1.41. Cost pass-through rates are between 57-233%, averaging 153% (weighted by number of matches per route). The variation reflects the impact of speed on cost, dummy surplus values and option values. The fuel price increase reduces speed by an average .19 knots reduction (11.48 to 11.29) compared to the baseline $M2os2011$. In order to understand the factors that influence prices, I consider changes in prices for the BRZ-SCH route in the constant and optimal speed cases. Table 7.17 examines the reason for the difference in prices between the ship in BRZ and USG matching to a trader type on the BRZ-SCH route in the constant and optimal speed baseline and fuel price simulation. The change in the price to match with a ship in BRZ reflects the change in the price of the ship's substitute (USG). When speed is constant, the change in USG's price reflects the change in the shipment cost and $s(x_{jt}, \emptyset_y, t)$ (the ship's option value to be in SCH remains unchanged because the voyage duration is the same). After the fuel price increase, the ship's dummy surplus value decreases (becomes more negative) because of the increased cost to relocate to a waiting area (in this case, WAF) and the ship's bargaining power is now worse. Because of this weaker position, the ship cannot fully pass through the increase in shipment cost, and the change in price reflects the sum of the change in shipment cost and the change in its dummy surplus value is \$.08 m. giving a price elasticity of .97. Prices increase by the same amount in BRZ as in USG (\$.08 m.) which reflects the change in earnings of the trader as his willingness to pay is unchanged. This leads to a lower price elasticity (.78 compared to .97 for USG) and exemplifies how changes in prices in one market (USG) can ripple through to changes in prices in another market (BRZ).

In the optimal speed version, a higher fuel price negatively impacts the speed at which ships are willing to supply the transportation service. Because there is a non-linear relationship between speed and fuel cost, there are diminishing returns to fuel savings and this leads to non-linear changes in prices. Continuing with the example of ships in BRZ and USG, Table 7.17 shows that speed changes from 10.5 to 10.33 (.17 knots) on the BRZ-BRZ-SCH route compared to 12.07 to 11.88 (.19 knots) on the USG-BRZ-SCH route. A variation in speed impacts not only costs and the ship's dummy surplus value but also the ship's option value and the oil trader's revenue because the duration of the voyage is now longer. This lowers the trader's oil revenue and increases the ship's option value (since it is a negative amount). The change in the price on the USG-BRZ-SCH route is lower compared to the constant speed case because the slower speed lowers costs. But this also lowers the trader's revenue, so its earnings on this route decrease by \$.05 m. The price on the BRZ-BRZ-SCH route is determined by the combination of

Table 7.16: Price elasticities for fuel shock ($M2os2011$)

Start	Load	End	Cost_pct	Price_pct	ϵ_P	CPR (%)	Diff(Speed)	Diff(Match)	ExtraRatio	Diff($s(x_{jt}, \emptyset_y, t)$)	Diff($s(\emptyset_x, y_i, t)$)
			%	%		%	knots			$ m.	$ m.
ECI	AG	SCH	1.34	1.49	1.11	151	-0.19	0	1	0	0
KOR	AG	WCI	1.31	3.94	3.02	57	-0.23	0	0.2	-0.01	0
NCH	AG	WCI	1.3	3.86	2.96	59	-0.23	0	1	-0.01	0
PHIL	AG	SCH	1.4	1.45	1.03	85	-0.21	0	1	-0.01	0
SCH	AG	ECI	1.33	2.44	1.84	69	-0.22	0	1	-0.01	0
SCH	AG	SCH	1.41	1.44	1.02	77	-0.21	0	1	-0.01	0
SCH	AG	SPOR	1.37	1.83	1.34	73	-0.21	0	1	-0.01	0
SCH	AG	THAI	1.39	1.65	1.19	75	-0.21	0	1	-0.01	0
SCH	AG	TWN	1.4	1.5	1.07	77	-0.21	0	1	-0.01	0
SCH	AG	WCI	1.29	3.57	2.77	66	-0.22	0	1	-0.01	0
SCH	REDS	PHIL	1.43	1.54	1.08	79	-0.21	0	1	-0.01	0
SPOR	AG	SCH	1.37	1.47	1.07	115	-0.2	0	1	-0.01	0
THAI	AG	SCH	1.39	1.46	1.05	100	-0.2	0	1	-0.01	0
TWN	AG	SCH	1.4	1.45	1.03	85	-0.21	0	1	-0.01	0
WCI	AG	CALI	1.45	1.6	1.11	149	-0.18	0	1	0	0
WCI	AG	ECC	1.45	2.3	1.58	148	-0.18	-1.4	1	0	0
WCI	AG	JAP	1.34	1.44	1.08	181	-0.18	1.4	1	0	0
WCI	AG	USG	1.46	2.22	1.52	147	-0.18	0	1	0	0
BRZ	BRZ	SCH	1.42	1.35	0.95	162	-0.17	0	1	-0.01	0
SAF	REDS	PHIL	1.39	1.55	1.12	123	-0.2	0	1	-0.01	0
UKC	UKC	SPOR	1.45	1.34	0.93	77	-0.17	0	0.1	-0.01	0
USG	BRZ	SCH	1.47	1.26	0.85	77	-0.19	0	0.49	-0.01	0
USG	CAR	SPOR	1.45	1.4	0.97	71	-0.18	0	0.49	-0.01	0
USG	CAR	WCI	1.43	1.76	1.23	69	-0.18	0	0.49	-0.01	0
AG	AG	ECC	1.44	2.25	1.56	169	-0.17	1.4	1	0	0
AG	AG	JAP	1.31	1.45	1.11	221	-0.17	-1.4	1	0	0
AG	AG	KOR	1.31	1.47	1.12	224	-0.17	0	1	0	0
AG	AG	SCH	1.29	1.51	1.17	233	-0.17	0	1	0	0
AG	AG	UKC	1.31	2.44	1.86	221	-0.17	0	1	0	0
WAF	WAF	ECI	1.32	1.28	0.97	100	-0.17	0	0.8	0	0
WAF	WAF	SCH	1.4	1.05	0.75	99	-0.17	0	0.8	0	0
WAF	WAF	TWN	1.39	1.07	0.77	100	-0.17	0	0.8	0	0

Table 7.17: Factors affecting price changes in 5% fuel shock compared to the baseline ($M2cs2011$ and $M2os2011$)

Start	Load	End	$\Delta C(x_{jt}, y_i, t)$	Δv_{op}	$\Delta s(x_{jt}, \emptyset_y, t)$	ΔV_b	$\Delta \pi(x_{jt}, x_{j\prime t}, y_i, t)$	$\Delta W^y(y_i, t)$	$\Delta s(\emptyset_x, y_i, t)$	$\Delta P(x_{jt}, y_i, t)$
			\$ m.		\$ m.	\$ m.	\$ m.	\$ m.	\$ m.	\$ m.
Constant speed										
BRZ	BRZ	SCH	0.064	0	-0.007	0	0	-0.08	0	0.08
USG	BRZ	SCH	0.091	0	-0.011	0	0	-0.08	0	0.08
Optimal speed										
BRZ	BRZ	SCH	0.03	-0.17	-0.01	0.00	0.94	-0.05	0.00	0.05
USG	BRZ	SCH	0.05	-0.19	-0.01	0.00	0.96	-0.05	0.00	0.04

the decreased oil revenue and oil trader's outside option, which leads to a higher price elasticity (.95) over the constant speed version. Overall, the matched speed decreases from 11.48 to 11.29 (.19 knots).

7.7.2 Simulation 2: increase in supply in one location

The simple market example from section 7.1.1 in which demand is fixed for one location (Brazil) and ships are short in BRZ resulted in ships from Brazil and the US Gulf matching in the BRZ market, while all other ship types remained unmatched. In other words, ships located in Brazil and the US Gulf were relevant for determining equilibrium prices in the BRZ market. This result is useful for predicting changes in prices when the supply of ships is increased in one location and demand is given by Table 6.1, the market demand for all markets. Continuing with the example of Brazil, when the supply of ships is increased in Brazil and held constant across other locations, the only prices that change are prices for the matches BRZ-BRZ-SCH. Prices drop in Brazil when its ExtraRatio switches to 0 and the price is the price that equates earnings to the ship's dummy surplus value.

7.7.3 Simulation 3: demand shock

The demand sample was estimated using trade flow shares from the VLCC fixtures data. As discussed in Chapter 5, there is a margin of error in these estimates because of censoring bias as identified in Chapter 5. One of the biases is for Chinese imports from West Africa. The VLCC fixtures data suggests that China imports 89% of its oil from AG, 7% from WAF, and 4% from BRZ. Using an implied share from the aggregate trade data on oil inter-area movements from BP (2012) suggests that these trade flow shares could be lower for AG (70%) and higher for WAF (20%) and BRZ (10%). In order to test the sensitivity of the model to changes in demand shares on routes to China, I simulate this alternative trade flow scenario. Applying the BP shares to total demand for shipments in China in the demand sample, trade on the AG-SCH route decreases by 5.10 cargoes, increases in the WAF market by 3.40 cargoes and 1.7 cargoes in BRZ compared to the baseline model.

Table 7.18 shows the change in matches between the baseline and the change in Chinese trade flow shares. A decrease in demand on the AG-SCH route leads price decreases for matches in the AG market ranging from -2.3 to -21.4%, while an increase in demand on the WAF-SCH route increases prices for matches in the WAF market by 68.5 to 145.2%. There is no change in price for the BRZ, UKC and CAR markets. The previous analysis suggested that prices are affected by a change in demand when the price of a trader's substitute changes. In the model, this occurs when a ship type's position moves from long (short) to short (long) or equivalently its $ExtraRatio$ switches from < 1 to 1 or 1 to < 1. Starting with the BRZ-SCH route, prices remain the same because there is still an excess supply of ships located in USG to absorb the shock ($ExtraRatio$ increases from .49 to .83) which had previously matched on the BRZ-SCH route. Thus the demand shock is localized because it can be absorbed by the excess supply of ships in the local market. In contrast, a shock to demand on the AG-SCH and WAF-SCH routes should alter prices given the market tightness in the AG market and the increased demand for ships in WAF. Before the demand shock, the extra ships which matched were located in KOR, WAF and USG. Ships from AG, ECI, PHIL, SCH, SPOR, THAI, and TWN served the AG-SCH route. After the demand shock however, the decrease in demand for ships on the AG-SCH route causes a reallocation of ships from AG-SCH to other routes. Ships from TWN, THAI, SCH and PHIL drop out, but AG, ECI and SPOR continue to serve the AG-SCH route. Prior to the demand decrease, all ships serving the AG-SCH route were in a short position and the marginal ship was SCH. The best substitute for this ship before the decrease in demand was determined by the price of KOR. After the shock, the marginal vessel changes to SPOR. The price of this match is determined by a new substitute, the price to match with a ship in SCH. Prices decrease because the price of this substitute is lower. The decrease in demand also affects other routes from AG, reflecting the new prices of substitute ships.

A similar logic can be applied to the demand shock on the WAF-SCH route. The shock tips this ship type's position from long to short. Ships from SAF and UKC are allocated to the WAF-SCH route to meet demand. The difference in how prices are affected in the BRZ-SCH demand shock compared to the AG-SCH and WAF-SCH demand shock illustrate the conditions under which a shock to one market will cascade through to prices. Despite demand remaining the same at 70 cargoes, the overall surplus decreases from \$143.58 m. to \$138.87 m. because the surplus generated from the additional matches on the USG-BRZ-SCH and WAF-WAF-SCH routes is less than the change in total surplus from the decrease in ships that match on the AG-SCH route.

7.7.4 Simulation 4: simultaneous demand and higher fuel price shock

The impact of a simultaneous demand shock to Chinese imports on the AG-SCH, WAF-SCH and BRZ-SCH route of 10% [5] and a 5% fuel prices increase on all routes is simulated. In order to understand whether the simultaneous shock will have an additive [6] or non-additive impact on the results, I first simulate the demand shock and then compare the results from the demand

[5]China increased its total demand for oil imports (in thousand barrels per day) by 10.4% between 2009 and 2010 (BP, 2012).

[6]An additive impact means that the sum of the change in prices due to the demand shock and fuel price equals the change in prices due to the simultaneous shock.

Table 7.18: Difference in matches and prices ($M2os2011$ vs. change in Chinese trade flow shares)

Start	Load	End	PriceDiff	Price_pct
			$ m.	%
ECI	AG	SCH	-0.081	-3.2
PHIL	AG	SCH	-0.081	-3.9
SCH	AG	SCH	-0.081	-4.1
SPOR	AG	SCH	-0.081	-3.5
THAI	AG	SCH	-0.081	-3.7
TWN	AG	SCH	-0.081	-4.0
WCI	AG	USG	-0.081	-3.0
AG	AG	SCH	-0.081	-2.8
WCI	AG	CALI	-0.081	-2.3
WCI	AG	ECC	-0.081	-3.2
AG	AG	ECC	-0.081	-3.0
AG	AG	JAP	-0.081	-2.6
AG	AG	KOR	-0.081	-2.6
AG	AG	UKC	-0.081	-4.3
SCH	AG	TWN	-0.079	-4.4
SPOR	AG	TWN	-0.079	-3.7
THAI	AG	TWN	-0.079	-4.0
PHIL	AG	THAI	-0.078	-5.0
SCH	AG	THAI	-0.078	-5.3
THAI	AG	THAI	-0.078	-4.6
TWN	AG	THAI	-0.078	-5.0
KOR	AG	WCI	-0.078	-21.4
NCH	AG	WCI	-0.078	-20.6
SCH	AG	ECI	-0.078	-10.3
SCH	AG	WCI	-0.078	-17.9
SCH	AG	SPOR	-0.078	-6.4
SCH	REDS	PHIL	-0.078	-3.8
SAF	REDS	PHIL	-0.078	-3.1
BRZ	BRZ	SCH	0.000	0.0
UKC	UKC	SPOR	0.000	0.0
USG	BRZ	SCH	0.000	0.0
USG	CAR	SPOR	0.000	0.0
USG	CAR	WCI	0.000	0.0
UKC	WAF	ECI	1.090	145.2
WAF	WAF	ECI	1.090	68.5
UKC	WAF	TWN	1.093	64.3
WAF	WAF	TWN	1.093	42.7
UKC	WAF	SCH	1.094	58.4
WAF	WAF	SCH	1.094	40.0

Table 7.19: Difference in matching ($M2os2011$ vs. 10% Chinese demand shock)

Start	Load	End	Match Diff.
KOR	AG	ECI	0.2
KOR	AG	WCI	2.2
NCH	AG	ECI	0.3
NCH	AG	WCI	-0.3
SCH	AG	ECI	-0.5
SCH	AG	SCH	2.4
SCH	AG	WCI	-1.9
USG	BRZ	SCH	0.1
WAF	WAF	SCH	0.2

shock, fuel shock, and simultaneous shock. Table 7.19 shows that the 10% Chinese demand shock causes a reallocation of ships in NCH from the AG-WCI route to AG-ECI and SCH ships move from AG-ECI and AG-WCI to meet the increased demand on the AG-SCH route. Ships in SCH which previously served the AG-ECI and AG-WCI routes are replaced by ships in KOR. Ships in WAF and USG meet demand on the WAF-SCH and BRZ-SCH routes, which they were previously serving respectively before the demand shock. Prices change for ships serving most routes that load in AG and REDS. The change in price can be explained by the marginal vessel (KOR) which is added to the AG-ECI route as a result of the increase in demand on the AG-SCH route. Before the demand shock, the marginal vessel on the AG-ECI route was SCH; the demand shock reallocates some of these ships to the AG-SCH route because the surplus is higher for this matching combination. The marginal ship (KOR) is more expensive because it is located farther away and this bids up the price on the routes that the other ships serving the AG and REDS markets must obtain. Note however, that the AG-WCI route is unaffected. This is because ships from KOR were already serving this route. Prices for the SCH-REDS-PHIL and SAF-REDS-PHIL matches increase because ships in SCH and SAF are on the short side of the market and must now obtain a higher price. The change in the price can be explained by the difference in the oil trader's earnings between the SCH-AG-ECI and KOR-AG-ECI routes. The matched speed also increases from 11.48 to 11.53 because the new routes - KOR-AG-ECI and NCH-AG-ECI - increase the weighted average.

Table 7.20 shows that the difference in cost is the same between the fuel shock and fuel and demand shock simulations, but the price elasticities differ on the routes where prices also change due to the demand shock. There is no difference in price elasticities compared to the fuel shock simulation on routes where prices did not change due to the Chinese demand shock. On routes where prices change due to the demand shock, the increase in prices is not additive; prices increase by less than the additive result. This is because speed adjusts to 11.34 compared to 11.29 in the fuel shock simulation. However, if the same simulation is run using a constant speed, the increase is additive.

7.7.5 Simulation 5: Multidimensional matching

In this simulation, ships vary by their location and physical characteristics. As described in Chapter 6, the model has three distinct physical character types (*PType*), differentiated by age, DWT, design speed, and the ship's as-designed daily fuel consumption (k). This increases the ship type space from 18 to 54 types ($\#Locations * \#PhysicalTypes$). The simulation considers two scenarios which have different assumptions about cargo size. In *Bigger is Better*, the cargo size is determined by a constant capacity utilization rate times the DWT of the ship whereas scenario *Energy Efficiency Rules* holds the cargo size constant.

Because ships are dispersed across locations according to their fleet share, with *PType* 2 having the greatest share (60%) compared to *PType* 1 (33%) and *PType* 3 (7%), there is an interaction between location and physical ship types. It is therefore important to first understand how the surplus differs across physical type holding location constant. I perform a decomposition analysis in order to pin down each of the primitive parameters' impact on the surplus components. Starting with the ship's option values, Figure 7.10 shows that the option values in *Bigger is Better* are the highest for *PType* 1, followed by *PType* 2 and 3. This is due to a combination of price and quantity effects which outweigh the increased cost. For example, the difference in average option values due to the change in q^t is \$.42 m. between Type 1 and Type 2 while the price difference is \$.02 m. all else constant. On the other hand, costs are higher for *PType* 1 (\$.301 m.) than *PType* 2. The net effect is a \$.14 m. higher earnings in favor of *PType* 1 over *PType* 2. Figure 7.11 shows the option values when cargo size is held constant. In this case, the cost is the most important determinant of earnings and therefore *PType* 2, the most energy efficient ship, has the highest values. Table 7.21 shows the difference between surplus values, surplus components and prices across physical ship types for matches with Trader 13 demanding cargo on the BRZ-SCH route in both scenarios.

In each scenario, ships of all three physical types which are located in BRZ are utilized first because they command the highest surplus over ship types located in other areas, but the

Table 7.20: Price elasticities (fuel shock vs. fuel and demand shock)

Start	Load	End	Cost_pct	Price_pct	ϵ_P	Price_pct	ϵ_P	$\Delta\epsilon_P$
			fuel	fuel	fuel	fuel & dem.	fuel & dem.	
			%	%		%		
ECI	AG	SCH	1.3	1.5	1.106	1.5	1.129	0.023
KOR	AG	SCH	1.4	1.4	1.010	1.5	1.040	0.029
KOR	AG	WCI	1.3	3.9	3.016	3.9	3.016	0.000
NCH	AG	WCI	1.3	3.9	2.960	3.9	2.960	0.000
PHIL	AG	SCH	1.4	1.5	1.033	1.5	1.060	0.027
SCH	AG	ECI	1.3	2.4	1.837	2.5	1.915	0.078
SCH	AG	KOR	1.4	1.4	0.979	1.4	1.005	0.026
SCH	AG	SCH	1.4	1.4	1.021	1.5	1.049	0.028
SCH	AG	SPOR	1.4	1.8	1.340	1.9	1.387	0.047
SCH	AG	THAI	1.4	1.6	1.189	1.7	1.227	0.038
SCH	AG	TWN	1.4	1.5	1.072	1.5	1.103	0.031
SCH	AG	WCI	1.3	3.6	2.766	3.6	2.766	0.000
SCH	REDS	PHIL	1.4	1.5	1.076	1.6	1.102	0.026
SPOR	AG	SCH	1.4	1.5	1.070	1.5	1.095	0.025
THAI	AG	SCH	1.4	1.5	1.052	1.5	1.078	0.026
TWN	AG	SCH	1.4	1.4	1.032	1.5	1.059	0.027
WCI	AG	CALI	1.4	1.6	1.110	1.6	1.126	0.015
WCI	AG	ECC	1.4	2.3	1.585	2.3	1.606	0.021
WCI	AG	JAP	1.3	1.4	1.078	1.5	1.098	0.020
WCI	AG	USG	1.5	2.2	1.523	2.2	1.543	0.020
BRZ	BRZ	SCH	1.4	1.3	0.948	1.3	0.948	0.000
SAF	REDS	PHIL	1.4	1.6	1.120	1.6	1.142	0.023
UKC	UKC	SPOR	1.4	1.3	0.928	1.3	0.928	0.000
USG	BRZ	SCH	1.5	1.3	0.854	1.3	0.854	0.000
USG	CAR	SPOR	1.4	1.4	0.970	1.4	0.970	0.000
USG	CAR	WCI	1.4	1.8	1.230	1.8	1.230	0.000
AG	AG	ECC	1.4	2.3	1.564	2.3	1.584	0.020
AG	AG	JAP	1.3	1.5	1.107	1.5	1.126	0.019
AG	AG	KOR	1.3	1.5	1.123	1.5	1.143	0.020
AG	AG	SCH	1.3	1.5	1.169	1.5	1.190	0.021
AG	AG	UKC	1.3	2.4	1.857	2.5	1.889	0.032
WAF	WAF	ECI	1.3	1.3	0.969	1.3	0.969	0.000
WAF	WAF	SCH	1.4	1.1	0.753	1.1	0.753	0.000
WAF	WAF	TWN	1.4	1.1	0.771	1.1	0.771	0.000

Table 7.21: Surplus components and prices for the BRZ-SCH route (top: *Bigger is Better*, bottom: *Energy Efficiency Rules*)

ShipID	Ptype	TraderID	Start	Load	End	Match	$P(x_{jt}, y_i, t)$	$s(x_{jt}, \emptyset_y, t)$	$\pi(x_{jt}, y_i, t)$	$C(x_{jt}, y_i, t)$	V_b	Speed	Extra
							\$ m.	\$ m.	\$ m.	\$ m.	\$ m.	knots	
12	1	13	BRZ	BRZ	SCH	0.27	4.23	2.99	6.30	2.34	-0.97	10.38	0
30	2	13	BRZ	BRZ	SCH	0.5	3.89	2.55	5.96	2.28	-1.13	10.64	0
48	3	13	BRZ	BRZ	SCH	0.05	3.51	1.30	5.58	2.32	-1.96	10.40	0
13	1	13	ECC	BRZ	SCH	0.17	3.30	1.09	5.37	3.31	-0.97	11.92	0
34	2	13	USG	BRZ	SCH	4.41	2.96	0.61	5.04	3.30	-1.13	12.22	1
30	2	13	BRZ	BRZ	SCH	0.5	3.949	2.64	6.001	2.28	-1.07	10.65	0
48	3	13	BRZ	BRZ	SCH	0.05	3.947	2.23	5.999	2.32	-1.45	10.43	0
12	1	13	BRZ	BRZ	SCH	0.27	3.946	2.31	5.999	2.34	-1.35	10.36	0
31	2	13	ECC	BRZ	SCH	0.31	3.082	0.84	5.135	3.23	-1.07	12.16	0
34	2	13	USG	BRZ	SCH	4.27	3.021	0.70	5.074	3.30	-1.07	12.23	0

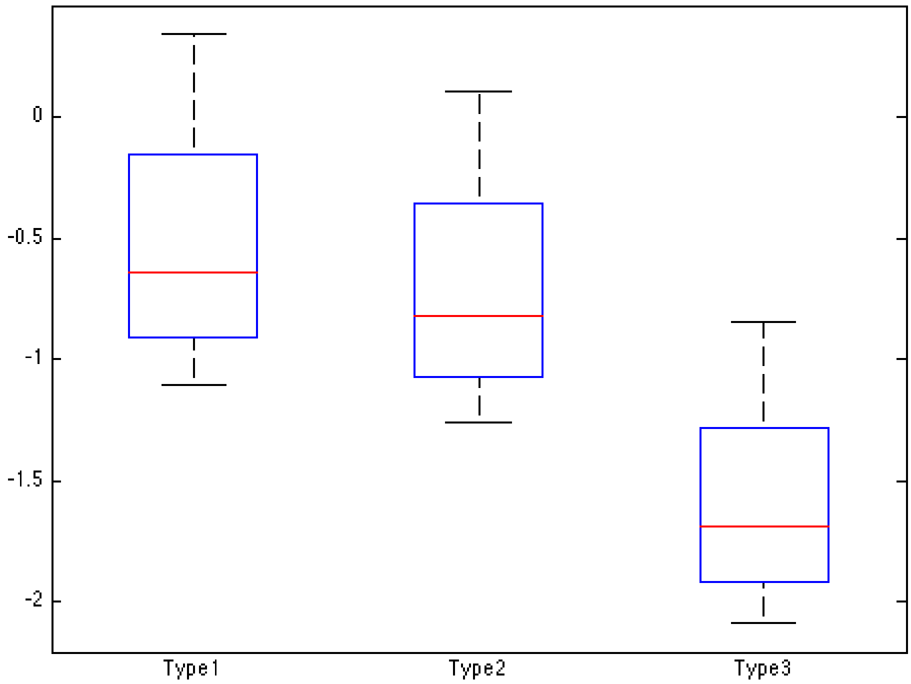


Figure 7.10: Ship Option Values ($ m.) where Type refers to its *Ptype* (*Bigger is Better*)

ranking of physical ship types within BRZ differs. In *Bigger is Better*, *PType* 1 has the highest surplus values, followed by *PType* 2 and 3 because the additional cargo quantity that *PType* 1 can carry increases the oil revenue and V_b and this outweighs the higher shipment cost; *PType* 1 earns $.44 m. more than *PType* 2 and $ 1.7 m. over *PType* 3. However, in the *Energy Efficiency Rules* scenario, shipment cost explains differences in surplus values; *PType* 2 ranks the highest in surplus as oil revenue and V_b influence the matching to a lesser degree due to the constant cargo size. This leads to a premium in earnings on the BRZ-BRZ-SCH match for *PType* 2 of $ .33 m. over Type 1 and $.42 m. over Type 3. The differences in prices amongst the three types (12, 30, 48) located in BRZ reflects the difference in the oil trader's willingness to pay between each ship and its best feasible substitute. For example, in the *Bigger is Better* scenario, the difference in oil revenue between $PType$ 1 and 2 reflects the additional oil revenue from a higher cargo size ($ .34 m.). This outweighs the additional shipment cost that $PType$ 1 incurs, which leads to a lower contract speed than $PType$ 2. Ships of $PType$ 1 in ECC compete with a $PType$ 2 ship in USG because the surplus is higher. This can be attributed to the higher oil revenue and ship option value which outweighs the greater shipment cost compared to ship 34. However, when cargo size is constant in *Energy Efficiency Rules*, this advantage disappears and

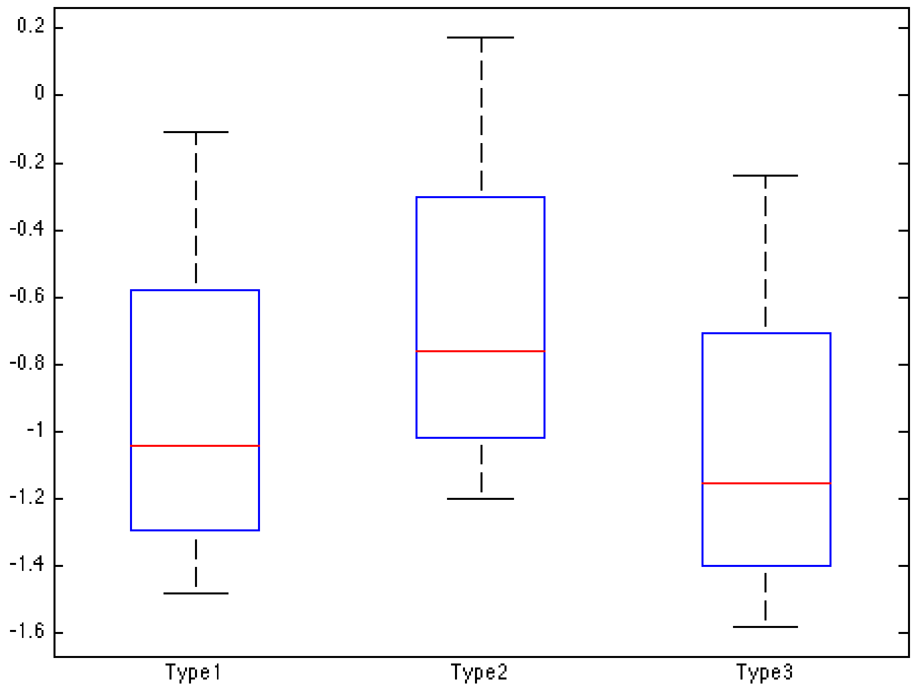


Figure 7.11: Ship Option Values ($ m.) where Type refers to its *Ptype* (*Energy Efficiency Rules*), $ m.

PType 2 dominates the matching of ship types from other areas outside of BRZ.

Figures 7.12 and 7.13 show the probability densities of the surplus and surplus components for the multidimensional ship types which match to traders compared to the baseline $M2os2011$ model. The mean of the density surplus function is greater in the *Bigger is Better* simulation compared to *Energy Efficiency Rules*; the total social welfare in *Bigger is Better* is \$154 m. compared to \$143 m. in *Energy Efficiency Rules*. In both scenarios, oil revenue is greater than the baseline and shipment cost is less than the baseline mean of the density function for cost. However, the mean of the density for V_b is lower for both scenarios compared to the baseline due to the influence of *PType* 3.

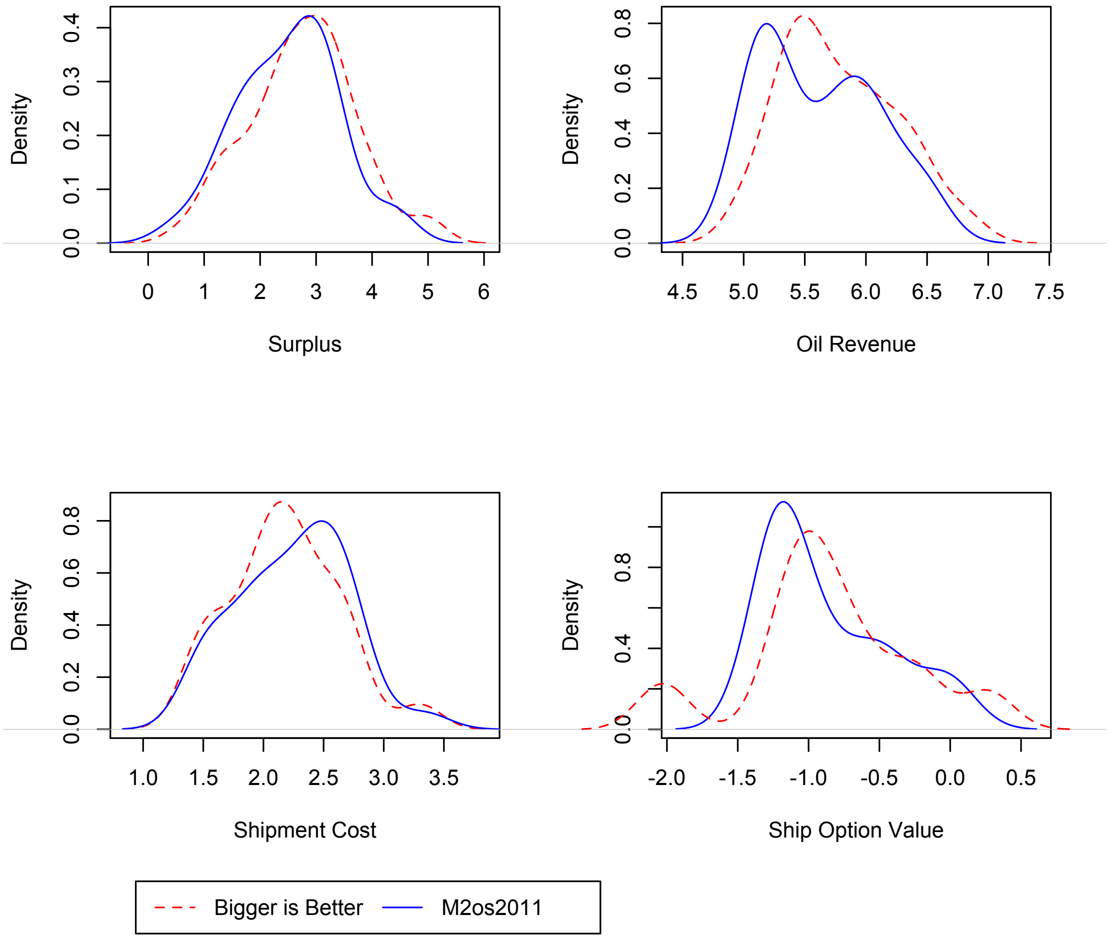


Figure 7.12: Kernel density of match surplus and its components (\$ m.) (*Bigger is Better*)

In *Bigger is Better*, ships of all physical types match but in varying quantities. *PType* 1

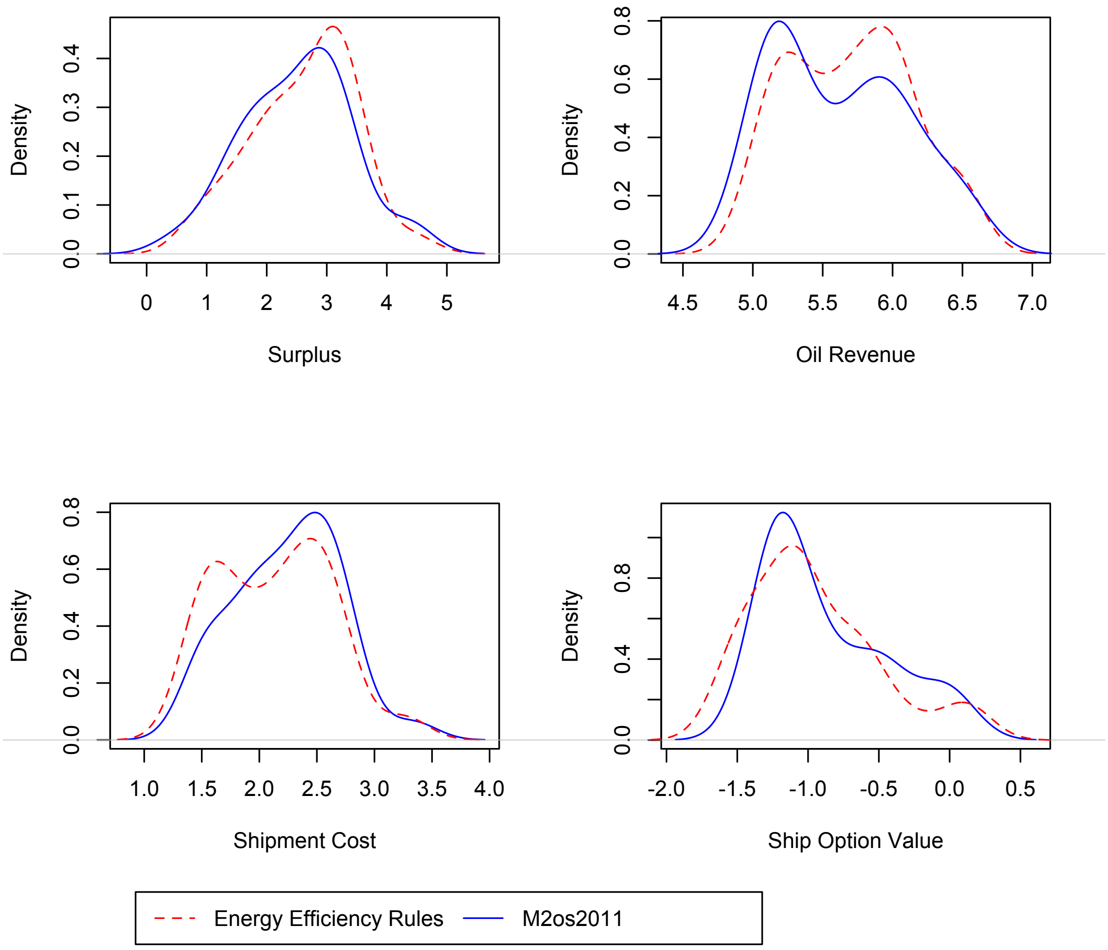


Figure 7.13: Kernel density of match surplus and its components ($ m.) (*Energy Efficiency Rules*)

is the most utilized [7] (90%), followed by *PType* 2 (62%) and *PType* 3 (39%). The interaction between location and physical type is evidenced by the fact that ships of *PType* 1 which are located in close proximity to the local market where they match have the highest surplus. In contrast, ships of *PType* 1 which are located farther away (in California and the Far East) are at a disadvantage to ships of other physical types located closer to the market. The results show a significant change in matching in *Energy Efficiency Rules* with *PType* 2 utilized at a higher rate (77% compared to 62% in *Bigger is Better*), 70% for *PType* 3, and 56% for *PType* 1. The difference demonstrates the impact of changes in cargo size. With equal payload, energy efficiency plays a more important role in the matching.

[7] The utilization rate is defined as the total matches of its type as a percentage of its total supply to the market

The distribution of the surplus components for the *Bigger is Better* scenario (Figure 7.14) shows the contribution of oil revenue, shipment cost and ship option values to the surplus and explains the influence of each ship type on the density of the match surplus. Although *PType* 1 has a lower energy efficiency compared to *PType* 2, its location in these matches makes it competitive with the other physical ship types and the higher oil revenue and ship option values tilt the matching in its favor. In contrast, in *Energy Efficiency Rules*, the distribution and mean of shipment costs for *PType* 1 (Figure 7.15) is lower than the other types because the proximity to the load area is much more important for these ships to remain competitive. Specifically, the close proximity to the load area has a positive impact on the oil revenue and ship option values and a negative impact on the shipment cost. However, due to the distribution of *PType* 1 across locations with a variety of distances to the load area, the locational advantage is not enough to offset the higher shipment costs, leading to a lower matching probabilities compared to the *Bigger is Better* scenario.

The analysis of multidimensional matching did not consider radical changes in energy efficiency because it was calibrated to the current fleet and focused on the short-run. One speculative long-run question is how much the results would change in the *Bigger is Better* scenario if *PType* 2 had zero fuel costs, holding other costs constant. This is a simplifying assumption because current technologies for low carbon ships are more expensive and no zero-carbon technology exists except sailing ships which have to be sailed at a much slower speed than diesel-run ships. Hence the question posed refers to a what-if scenario in which a zero carbon ship was available at the same fixed costs as the other ship types. The introduction of such a ship significantly changes the matching results in *Bigger is Better*, greatly increasing the utilization rate of *PType* 2 from 62% to 87%, and reducing shares in *PType* 1 from 90% to 45%, and *PType* 3 from 39% to 30%.

7.8 Dynamic Matching: Solving for a fixed point

In this section, the baseline model is extended to a dynamic model, $M3os2011$, using 2011 option values. As discussed in Chapter 4, the difference between the static and dynamic models is the time horizon and how the ship option values and dummy surplus values are computed. As discussed in Chapter 4, the static version required an estimate of these values outside the model, whereas the dynamic version uses the earnings derived from the output of the model as input for the next time step. The dynamic version assumes that the supply and demand is stationary in each period and is provided as an exogenous input. The goal is to understand whether the earnings converge to a stationary value in each location, a so-called “fixed point”

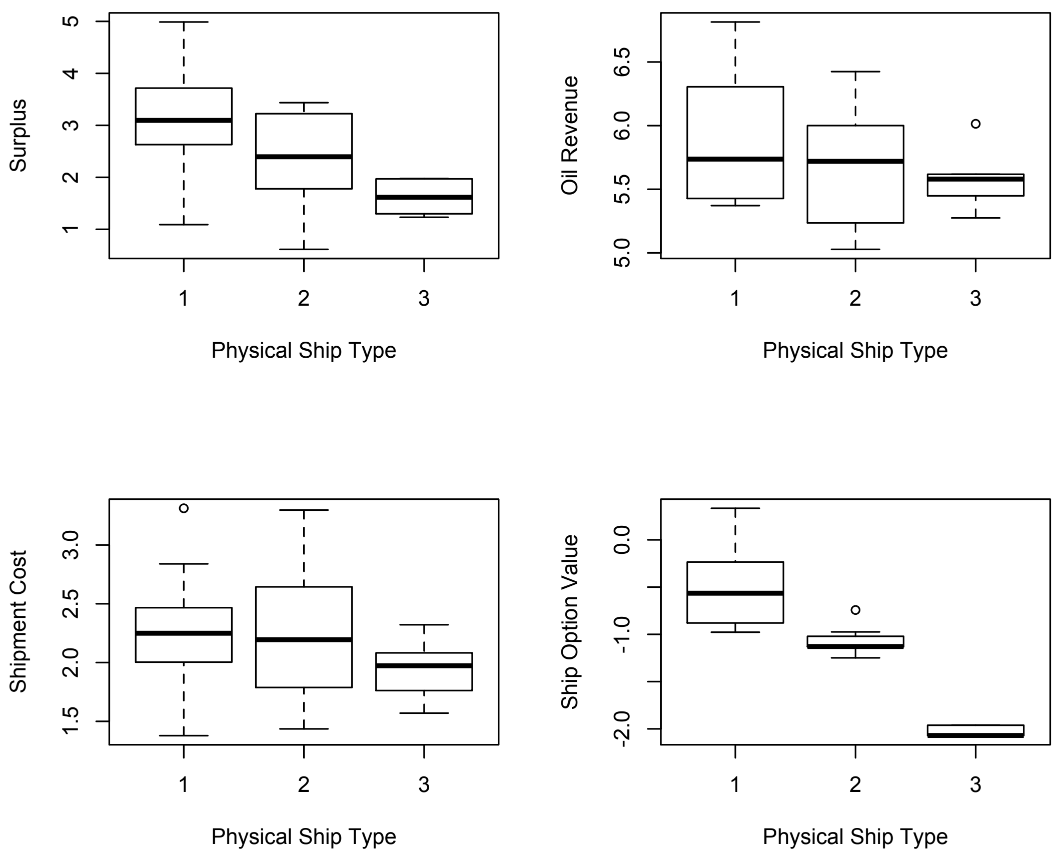


Figure 7.14: Match surplus distribution and its components ($ m.) by physical type and location (*Bigger is Better*)

in option values after the matching model is run for a certain amount of iterations. One of the ways to reach convergence more quickly is to increase the discount rate of the ship. To reach convergence, this rate has to be increased to 1000% per annum (2.7% per day) or a .51 discount factor such that the model converges in 46 iterations. A high discount rate implies that ships heavily discount the future much more than in the static model. A drawback of this approach is its affect on V_b, which is lowered by an average $ .77 m. compared to $M2os2011$.

The fixed point solution of the model (the final iteration) yields a matching of all traders to ships because earnings are better than the values to remain unmatched. Table 7.22 shows the difference in matches between the static ($M2os2011$) and dynamic models. The difference is due to the surplus values between the models which is affected by the V_b values and the dummy

Table 7.22: Differences between static and dynamic matching ($M2os2011$ and $M3$)

Start	Load	End	Match	Match	Surplus	Surplus	V_b	V_b
			M1	M2	M1	M2	M1	M2
					$ m.	$ m.	$ m.	$ m.
AG	AG	ECC	0.6	0.0	3.50	3.10	0.02	-0.36
AG	AG	ECI	0.0	1.0	4.63	5.72	-0.60	0.52
AG	AG	JAP	8.0	0.0	3.13	4.19	-1.34	-0.29
AG	AG	KOR	6.0	0.0	3.20	4.24	-1.31	-0.28
AG	AG	SPOR	0.0	2.0	4.15	5.13	-0.84	0.15
AG	AG	THAI	0.0	2.0	3.87	4.84	-0.98	-0.01
AG	AG	TWN	0.0	3.0	3.55	4.53	-1.14	-0.16
AG	AG	UKC	1.0	0.0	4.39	3.84	-0.08	-0.61
AG	AG	WCI	0.0	3.0	4.97	6.24	-0.45	0.87
ECC	BRZ	SCH	0.0	0.2	0.64	1.76	-1.22	-0.10
ECI	AG	SCH	1.1	0.0	2.60	3.63	-1.23	-0.20
ECI	AG	USG	0.0	1.1	2.56	2.27	-0.05	-0.34
KOR	AG	WCI	0.8	0.0	2.77	3.75	-0.45	0.57
NCH	AG	UKC	0.0	0.1	2.19	1.83	-0.08	-0.44
NCH	AG	WCI	0.3	0.0	2.80	3.79	-0.45	0.57
PHIL	AG	KOR	0.0	0.2	1.33	2.44	-1.31	-0.20
PHIL	AG	SCH	0.2	0.0	1.50	2.56	-1.22	-0.17
SCH	AG	CALI	0.0	1.0	0.38	1.13	-1.07	-0.31
SCH	AG	ECI	1.0	0.0	2.59	3.52	-0.60	0.35
SCH	AG	JAP	0.0	8.0	1.07	2.21	-1.34	-0.21
SCH	AG	KOR	0.0	1.1	1.13	2.25	-1.31	-0.20
SCH	AG	SCH	0.1	0.0	1.30	2.37	-1.22	-0.16
SCH	AG	SPOR	2.0	0.0	2.09	3.03	-0.84	0.10
SCH	AG	THAI	2.0	0.0	1.81	2.78	-0.98	-0.01
SCH	AG	TWN	3.0	0.0	1.49	2.52	-1.13	-0.11
SCH	AG	UKC	0.0	0.8	2.32	1.95	-0.08	-0.45
SCH	AG	WCI	1.9	0.0	2.93	3.93	-0.45	0.59
SCH	REDS	PHIL	0.9	0.0	1.06	2.08	-1.11	-0.09
SPOR	AG	ECC	0.0	2.0	2.21	1.88	0.02	-0.31
SPOR	AG	KOR	0.0	1.6	1.92	3.01	-1.31	-0.23
SPOR	AG	SCH	5.1	0.0	2.09	3.14	-1.22	-0.18
SPOR	AG	USG	0.0	1.5	2.04	1.78	-0.05	-0.32
THAI	AG	KOR	0.0	1.9	1.64	2.74	-1.31	-0.21
THAI	AG	SCH	1.9	0.0	1.81	2.86	-1.22	-0.18
TWN	AG	KOR	0.0	1.2	1.32	2.43	-1.31	-0.20
TWN	AG	SCH	1.2	0.0	1.49	2.55	-1.22	-0.16
USG	BRZ	SCH	0.2	0.0	0.50	1.63	-1.22	-0.10
WAF	AG	UKC	0.0	0.1	1.84	1.51	-0.08	-0.42
WAF	REDS	PHIL	0.0	0.9	0.92	1.95	-1.11	-0.09
WCI	AG	CALI	1.0	0.0	2.09	2.75	-1.07	-0.40
WCI	AG	ECC	1.4	0.0	3.12	2.75	0.02	-0.35
WCI	AG	SCH	0.0	5.0	3.00	4.01	-1.23	-0.22

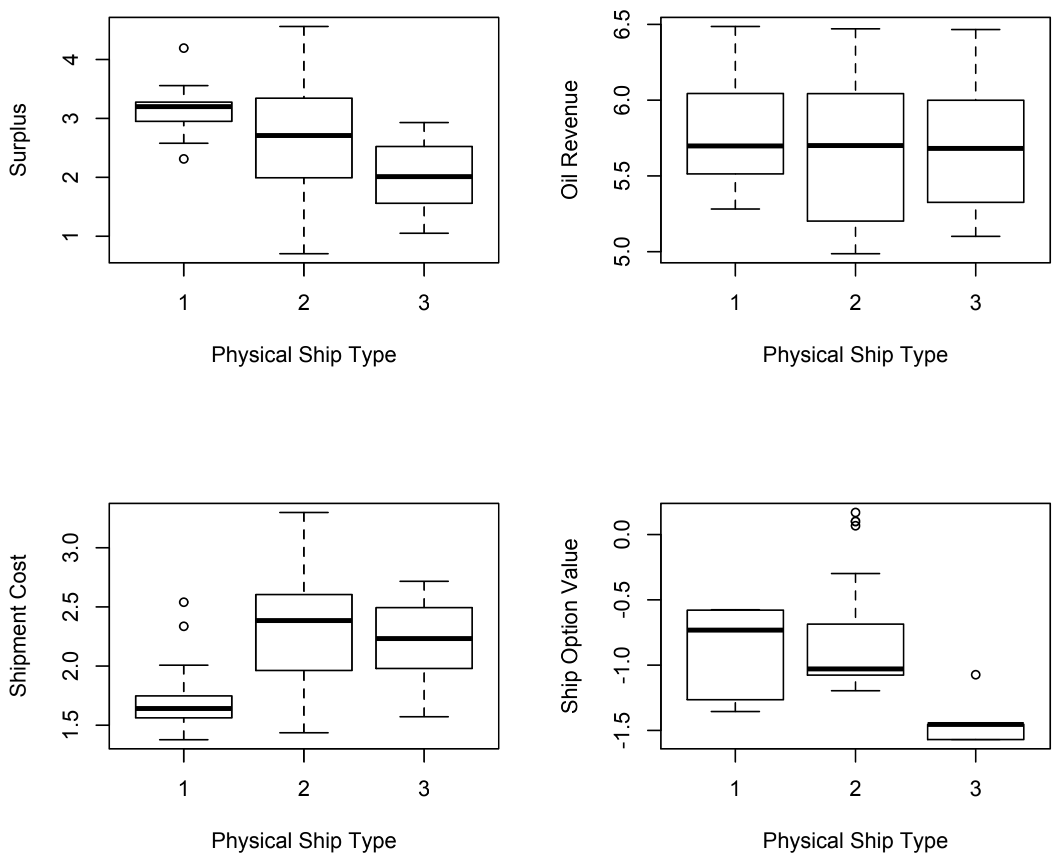


Figure 7.15: Match surplus distribution and its components ($ m.) by physical type and location (*Energy Efficiency Rules*)

surplus values which change the stability requirements. The same ships serve the AG, CAR and WAF markets but there are different ship types serving the REDS and BRZ markets. Ships in SAF and SCH serve the REDS market in the static model whereas SAF and WAF serve REDS in the dynamic model. For the BRZ market, both models allocate ships from BRZ but the remaining demand is served by USG in the static model and ECC in the dynamic model. The reason is that the difference in the ship's dummy surplus between USG and ECC decreases as earnings in ECC erode given the ship's long position, and this eventually leads to a higher difference in surplus relative to the difference in dummy surplus. Of the unmatched ships, 14.10 ships relocate to AG and 16.30 ships relocate to WAF.

Figure 7.16 shows the simulation of earnings and dummy earnings for ships and traders, where $Dummy_y$ is the earnings if the ship doesn't match and $Dummy_x$ for the trader.

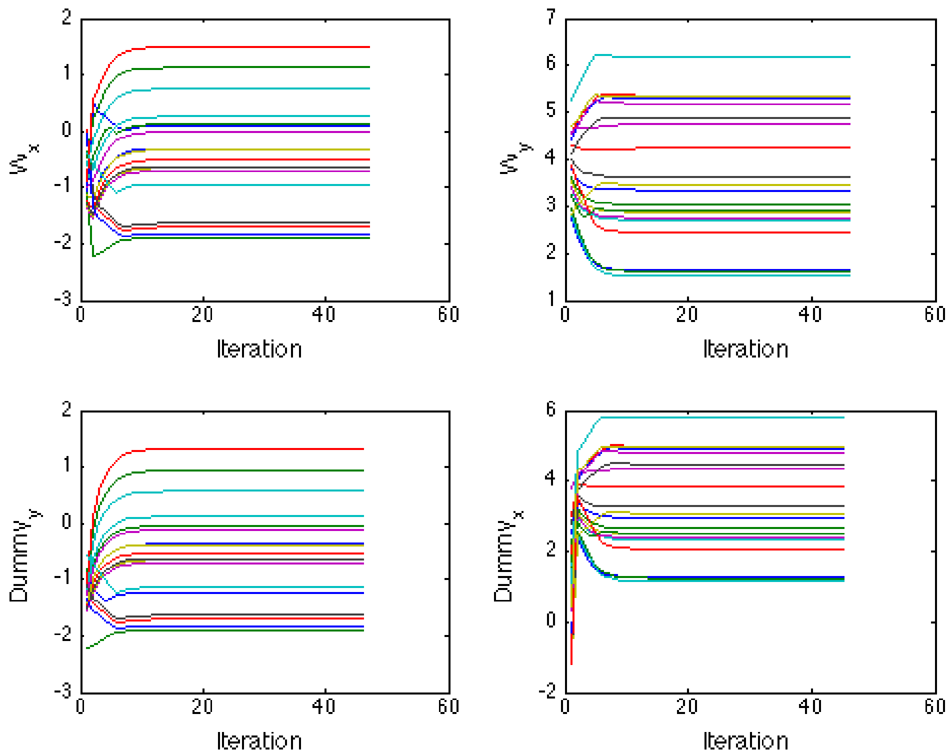


Figure 7.16: Dynamic simulation of earnings under $M3$ (Baseline, \$ m.)

In the first iteration, all traders match to ships, and the solution is equal to $M2os2011$. The algorithm then updates the dummy surplus values according to the Step 2 of the dynamic solution algorithm using the terminal option values and the earnings from the first iteration's model output. Earnings increase for ships which are on the short side of the market and decrease for those on the long side relative to iteration 1 of the model. The trader and ships' earnings from iteration 1 of the model are used to compute the new dummy surplus values in the next model iteration which is discounted by the time waiting until each agent can match in the next period. The increase can be explained by the traders' higher earnings compared to the estimated earnings given that these earnings are now determined by the intra-allocation of surplus within the model. This increase causes some traders to remain unmatched in the 2nd iteration because the surplus is not large enough to satisfy these higher dummy surplus values. Traders on the routes AG-CALI, AG-ECC, AG-UKC and AG-USG do not match until their dummy surplus values decline over the next few iterations. The reason $Dummy_x$ declines is due to the discounting and their position in the market (which is long in the AG market). For example, Trader 1 which demands cargo on the AG-CALI route has a dummy surplus value of \$ -.46 m. in the first

Table 7.23: Ship earnings: initial guess, static, and dynamic values

AreaName	W^x_{2011}	$W^x_{M2os2011}$	$W^x_{M3os2011}$	$Dummy\_y\_M3$	Extra
	\$ m.	\$ m.	\$ m.	\$ m.	
AG	-0.89	0.22	1.49	1.32	0
WCI	-0.45	-0.16	1.13	0.93	0
ECI	-0.61	-0.55	0.75	0.57	0
SPOR	-0.84	-1.06	0.26	0.12	0
SAF	-0.66	-0.89	0.12	-0.04	0
BRZ	-1.17	0.41	0.10	-1.22	0
THAI	-0.98	-1.34	-0.01	-0.12	0
PHIL	-1.12	-1.65	-0.31	-0.37	0
TWN	-1.14	-1.67	-0.33	-0.38	0
SCH	-1.23	-1.85	-0.50	-0.52	0
NCH	-1.30	-1.98	-0.62	-0.62	1
KOR	-1.32	-2.01	-0.65	-0.65	1
JAP	-1.35	-2.05	-0.70	-0.70	1
WAF	-0.38	-0.56	-0.94	-1.12	0
UKC	-0.09	-1.27	-1.63	-1.63	1
ECC	0.02	-1.38	-1.70	-1.70	1
USG	-0.05	-1.56	-1.82	-1.82	1
CALI	-1.08	-2.52	-1.89	-1.89	1

iteration. It matches with a ship in AG and earns 2.73. At the start of the second period, its new dummy value is 2.35 which equals the discounted earnings in the previous iteration. This value is too much to satisfy the stability conditions, so the trader continues to remain unmatched until iteration 5 when the trader's dummy surplus has declined enough to be able to match to a ship in WCI and the trader earns \$1.76 m. In iteration 6, the matching changes to SCH-AG-CALI because the trader's dummy surplus value is low enough to satisfy a matching combination with a lower surplus. A similar process occurs for other trades, and this has the effect of changing the matching compared to $M2os2011$. The surplus differs from the static model because V_b and the dummy surplus values are different.

Tables 7.23 and 7.24 show the starting guess for earnings for the ship and trader, the static model solution, the fixed point solution for earnings and dummy surplus values. For ships, the top five largest values are AG, WCI, ECI, SPOR, and SAF. The reason for higher (and positive) values for the ship types in these areas is because these ships are on the short side of the market ($Extra = 0$). Consequently, these locations also command higher prices and the trader earns less in these markets compared to markets where ships are on the long side of the market, as evidenced by traders' lower earnings in the AG, REDS and BRZ markets. One exception to this trend is for ships in WAF which are not extra. The reason these ships' earnings are lower is because ships in WAF start off being on the long side of the market. In iterations 1-3, Traders

Table 7.24: Trader earnings: initial guess, static, and dynamic values

Load	End	W^y_{2011}	$W^y_{M2os2011}$	W^y_{M3}	$Dummy\_x\_M3$
		\$ m.	\$ m.	\$ m.	\$ m.
WAF	ECI	5.26	4.90	6.20	5.81
UKC	SPOR	4.58	4.11	5.36	4.98
WAF	TWN	4.70	3.91	5.33	4.94
CAR	WCI	4.41	4.30	5.31	4.92
WAF	SCH	4.60	3.73	5.19	4.81
CAR	SPOR	4.14	3.71	4.87	4.48
AG	WCI	4.55	4.78	4.74	4.36
AG	ECI	4.30	4.43	4.23	3.85
AG	SPOR	3.98	3.94	3.64	3.26
BRZ	SCH	2.83	2.06	3.46	3.08
AG	THAI	3.81	3.66	3.35	2.97
AG	TWN	3.63	3.34	3.04	2.66
REDS	PHIL	3.23	2.90	2.90	2.52
AG	SCH	3.52	3.15	2.88	2.50
AG	KOR	3.43	2.98	2.75	2.38
AG	JAP	3.40	2.92	2.71	2.33
AG	UKC	3.89	4.17	2.45	2.08
AG	CALI	2.73	2.25	1.63	1.26
AG	ECC	2.94	3.28	1.62	1.24
AG	USG	2.82	3.12	1.52	1.14

18-20 who demand cargo to be shipped from WAF match to ships in WAF. This leaves 1 ship left and therefore ships are long. In iteration 4, it becomes profitable to allocate .90 ships to the REDS-PHIL route because the earnings have lowered the stability conditions required to match. These ships are still long but are close to switching to being short at a utilization ratio of 98%. In the next iteration as the trader's dummy surplus value continues to increase on this route, Trader 10 on the AG-UKC route decides to trade (.10) with WAF so the ship in WAF is no longer extra. This tips the balance in favor of the ship, and ships in WAF start to earn more than their dummy surplus value. This process continues until both the ships' and traders' earnings have converged.

Table 7.25 shows a comparison of prices in $M3os2011$, $M2os2011$ and historical 2011 multiplier prices. Prices are lower overall in the models compared to historical data and this can be explained by lower speeds in the optimal speed case. The dynamic model does a better job overall at predicting prices on routes from AG compared to $M2os2011$, but a poor job on routes from BRZ and WAF. Prices on these routes are significantly lower and this reflects the erosion of ship earnings over the model iterations. For the BRZ-SCH route, earnings decrease over the model simulation because the substitute's (ECC) prices decrease due to the fact that the

Table 7.25: Comparison of historical, $M2os2011$ and $M3os2011$ prices

Load	End	WS_{2011}	$WS_{M2os2011}$	$WS_{M3os2011}$	pct_diff	lvl_diff	pct_diff	lvl_diff
					M2	M2	M3	M3
		WS	WS	WS	%	WS	%	WS
AG	CALI	50	39	36	-27.3	-10.7	-37.4	-13.6
AG	ECC	39	32	45	-23.3	-7.4	13.7	6.2
AG	ECI	54	28	68	-93.8	-26.1	21.1	14.4
AG	JAP	53	55	42	4	2.2	-27.5	-11.4
AG	KOR	50	61	50	17.7	10.8	-0.8	-0.4
AG	SCH	53	52	61	-2.6	-1.3	13	7.9
AG	SPOR	53	35	69	-53.1	-18.4	23.4	16.2
AG	THAI	54	37	67	-47.2	-17.3	19.6	13.1
AG	TWN	51	38	64	-34.2	-13	20.2	12.9
AG	UKC	38	31	41	-24.2	-7.4	8.2	3.4
AG	USG	37	30	44	-24.1	-7.2	16.9	7.5
AG	WCI	56	23	76	-142.7	-32.9	26.3	20
BRZ	SCH	51	39	25	-30.6	-12	-108	-26.5
REDS	PHIL	48	41	40	-17.4	-7.1	-20.7	-8.2
WAF	SCH	50	36	17	-38.8	-14	-198.2	-33.2
WAF	TWN	47	33	15	-41.6	-13.8	-217.5	-32.2

ship is on the long side of the market. A similar process occurs for ships in WAF as previously described.

The average matched speed is 11.14 in $M3os2011$ compared to 11.48 in $M2os2011$. Although the average repositioning cost is greater in $M3$ and V_b is less in $M3$, the ship's higher discount rate penalizes going faster because V_b is negative and this is consistent with the ship's greater impatience over the future compared to the static baseline model.

7.9 Dynamic Counterfactuals

In this section, I consider the impact of a permanent shock on the dynamic matching model. I consider shocks to demand and the fuel price. A permanent shock impacts every period, which affects the dummy surplus and V_b values. These values change over the time horizon due to changes in the matching and discounting.

7.9.1 Dynamic Simulation 1: Permanent demand shock

This simulation considers the impact of a permanent 10% increase in demand for Chinese oil imports which is the same demand shock considered in the static simulation of a simultaneous demand and fuel price shock.

The matching results are similar to the dynamic baseline in terms of the types of ships that serve each route, except for the REDS market which is served by three types of ships (SAF, SPOR and WAF) compared to the baseline which sources ships from SAF and WAF. The routes

Table 7.26: Ship earnings: dynamic demand shock compared to static and dynamic baseline models

AreaName	W^x_{2011}	$W^x_{M2os2011}$	$W^x_{M3os2011}$	$W^x_{M3os2011}$	$Dummy\_y\_M3$	Extra
				demand	demand	
	\$ m.	\$ m.	\$ m.	\$ m.	\$ m.	
AG	-0.89	0.22	1.49	1.53	1.35	0
WCI	-0.45	-0.16	1.13	1.17	-1.64	0
ECI	-0.61	-0.55	0.75	0.78	-0.63	0
SAF	-0.66	-0.89	0.12	0.46	-0.1	0
BRZ	-1.17	0.41	0.1	0.3	-1.88	0
SPOR	-0.84	-1.06	0.26	0.29	0.96	0
THAI	-0.98	-1.34	-0.01	0.02	-1.21	0
PHIL	-1.12	-1.65	-0.31	-0.28	0.14	0
TWN	-1.14	-1.67	-0.33	-0.3	-1.51	0
SCH	-1.23	-1.85	-0.5	-0.47	-0.36	0
NCH	-1.3	-1.98	-0.62	-0.6	-0.5	0
WAF	-0.38	-0.56	-0.94	-0.61	-0.79	0
KOR	-1.32	-2.01	-0.65	-0.63	-0.35	1
JAP	-1.35	-2.05	-0.7	-0.68	-0.61	1
UKC	-0.09	-1.27	-1.63	-1.42	-0.02	1
ECC	0.02	-1.38	-1.7	-1.51	-0.68	1
USG	-0.05	-1.56	-1.82	-1.64	-1.42	1
CALI	-1.08	-2.52	-1.89	-1.88	0.6	1

with different allocations are associated with the AG and REDS markets (AG-CALI, AG-ECC, AG-JPN, AG-KOR, AG-SCH, AG-UKC, AG-USG, and REDS-PHIL). To meet the increase in demand on the AG-SCH route, ships from WCI are reallocated from the AG-USG route and ships from ECI are assigned to the AG-SCH route. Additional ships from ECC and WAF serve the BRZ-SCH route and WAF-SCH routes respectively.

Table 7.26 shows the earnings in the demand shock compared to the static model and dynamic baseline.

Earnings are higher for all locations relative to the dynamic baseline but increase in varying amounts. The earnings for ships in SAF and WAF increase by the most (\$.33 m.), followed by the UKC (\$.21 m.), and BRZ/ECC (\$.20). The earnings' increase is bundled into ship types which are substitutes for each other, for example SAF and WAF serve the REDS market, so when demand increases in WAF the price increases in the substitute market in SAF. The magnitude of the increase reflects the degree of market differentiation, which in this case is a function of distance.

7.9.2 Dynamic Simulation 2: Permanent carbon tax

In this simulation, I consider the impact of a permanent carbon tax. According to the IMO MEPC Report (2010), four carbon tax amounts have been proposed, ranging from $20 per tonne of carbon to $100. Using a carbon factor of 3.17, this translates into a $63.4 increase the fuel price up to a $317 increase in the fuel price. In this simulation, I choose to use a $40 carbon tax which is the third highest carbon tax, equivalent to a 20% increase in the fuel price to $771.80 per tonne fuel price.

Table 7.27 shows the price elasticities and cost pass-through rates for a 20% fuel price increase when the matched speed is held constant compared to the baseline $M3cs2011$ model. Price increases range between 9.0-30.8% (a price elasticity .94-3.2) if fuel prices increase by 20% given a constant matched speed ($M3cs2011$) using the 2011 scenario. Cost pass-through rates are between 51 and 186%, averaging 141% (weighted by number of matches per route). Cost pass-through rates are higher in $M3$ compared to $M2$ because now the trader's dummy surplus changes given that the shock is permanent. Cost-pass through for ship types in AG, BRZ, ECI, PHIL, SAF, SCH, SPOR, THAI, WAF and WCI are greater than 100%, while cost-pass through is less than 100% for ship types in ECC, UKC, USG and WAF. Continuing with the example of matching on the BRZ-SCH route, the cost pass-through rate for the match BRZ-BRZ-SCH is greater than 100% compared to 75% for the ECC-BRZ-SCH match. The price of the ECC-BRZ-SCH match is determined by the shipment cost, the ship's dummy surplus value and V_b; the dummy surplus value decreases such that cost cannot be fully passed through. The change in the price of the BRZ-BRZ-SCH match reflects the change in prices for the ECC-BRZ-SCH match and the change in price is greater than the change in the cost of shipping for the BRZ-BRZ-SCH match because costs increase by less than the ECC-BRZ-SCH match. This leads to a greater than 100% *CPR*.

Table 7.28 shows the price elasticities and cost pass-through rates for a 20% fuel price increase when the matched speed is optimized. Price increases range between 4.8-18.3% (a price elasticity .86-3.51) if fuel prices increase by 20% given an optimal matched speed using the 2011 scenario ($M3os2011$). These findings are similar to the static model results in that speed flexibility negates some of the carbon tax impacts. Cost pass-through rates are between 19 and 328%, averaging 201% (weighted by number of matches per route). Speed reductions range from .52-.71 knots (average of .42 knots).

Table 7.27: Price elasticities for \$40 carbon tax ($M3cs2011$)

Start	Load	End	Cost_pct	Price_pct	ϵ_P	CPR (%)	Diff(Speed)	Diff(Match)	ExtraRatio	Diff($s(x_{jt}, \emptyset_y, t)$)	Diff($s(\emptyset_x, y_i, t)$)
			%	%		%	knots			\$ m.	\$ m.
USG	CAR	WCI	9.97	24.22	2.43	51	0.00	0.00	0.47	-0.09	-0.14
USG	CAR	SPOR	10.01	17.14	1.71	61	0.00	0.00	0.47	-0.09	-0.18
UKC	UKC	SPOR	10.00	16.56	1.66	67	0.00	0.00	0.10	-0.07	-0.19
WAF	WAF	ECI	9.70	30.78	3.17	72	0.00	0.00	1.00	0.00	-0.12
ECC	BRZ	SCH	10.07	14.07	1.40	75	0.00	0.00	0.40	-0.08	-0.26
WAF	WAF	TWN	9.86	15.40	1.56	95	0.00	0.00	1.00	0.00	-0.20
WAF	WAF	SCH	9.88	14.79	1.50	97	0.00	0.00	1.00	0.00	-0.22
WAF	REDS	PHIL	10.01	14.20	1.42	97	0.00	0.00	1.00	0.00	-0.29
BRZ	BRZ	SCH	9.94	9.88	0.99	104	0.00	0.00	1.00	-0.01	-0.26
SCH	AG	JAP	9.98	12.51	1.25	108	0.00	0.00	1.00	0.03	-0.30
WAF	AG	UKC	10.02	13.37	1.33	108	0.00	0.00	1.00	0.00	-0.33
SCH	AG	CALI	10.10	11.94	1.18	111	0.00	0.00	1.00	0.03	-0.42
SCH	AG	ECC	10.10	12.19	1.21	112	0.00	0.00	1.00	0.03	-0.43
SCH	AG	USG	10.11	12.17	1.20	112	0.00	0.00	1.00	0.03	-0.44
TWN	AG	JAP	9.97	12.10	1.21	112	0.00	0.00	1.00	0.04	-0.30
PHIL	AG	JAP	9.96	12.06	1.21	113	0.00	0.00	1.00	0.04	-0.30
SCH	AG	UKC	9.98	12.29	1.23	119	0.00	0.00	1.00	0.03	-0.33
THAI	AG	JAP	9.93	11.43	1.15	120	0.00	0.00	1.00	0.05	-0.30
SAF	REDS	PHIL	9.90	11.44	1.15	122	0.00	0.00	1.00	0.06	-0.29
SPOR	AG	KOR	9.90	10.92	1.10	128	0.00	0.00	1.00	0.07	-0.30
SPOR	AG	JAP	9.90	10.90	1.10	128	0.00	0.00	1.00	0.07	-0.30
ECI	AG	KOR	9.83	10.08	1.03	145	0.00	0.00	1.00	0.09	-0.30
WCI	AG	KOR	9.76	9.53	0.98	162	0.00	0.00	1.00	0.12	-0.30
WCI	AG	SCH	9.73	9.53	0.98	162	0.00	0.00	1.00	0.12	-0.28
AG	AG	WCI	8.72	9.02	1.03	175	0.00	0.00	1.00	0.14	-0.11
AG	AG	SCH	9.65	9.05	0.94	182	0.00	0.00	1.00	0.14	-0.28
AG	AG	TWN	9.60	9.03	0.94	184	0.00	0.00	1.00	0.14	-0.27
AG	AG	ECI	9.08	8.97	0.99	184	0.00	0.00	1.00	0.14	-0.16
AG	AG	THAI	9.50	9.00	0.95	185	0.00	0.00	1.00	0.14	-0.24
AG	AG	SPOR	9.38	8.98	0.96	186	0.00	0.00	1.00	0.14	-0.21

Table 7.28: Price elasticities for $40 carbon tax ($M2os2011$ vs. $M3os2011$)

Start	Load	End	Cost_pct	Price_pct	ϵ_P	CPR (%)	Diff(Speed)	Diff(Match)	ExtraRatio	Diff($s(x_{jt}, \emptyset_y, t)$)	Diff($s(\emptyset_x, y_i, t)$)
			%	%		%	knots			$ m.	$ m.
USG	CAR	WCI	5.51	6.66	1.21	20	-0.66	0.00	0.47	-0.09	-0.05
USG	CAR	SPOR	5.54	4.78	0.86	26	-0.62	0.00	0.47	-0.09	-0.06
UKC	UKC	SPOR	5.51	6.08	1.10	40	-0.59	0.00	0.10	-0.07	-0.07
ECC	BRZ	SCH	5.65	5.24	0.93	47	-0.65	0.00	0.40	-0.08	-0.14
WAF	WAF	ECI	5.22	18.33	3.51	65	-0.57	0.00	1.00	0.01	-0.06
WAF	WAF	TWN	5.28	8.38	1.59	92	-0.53	0.00	1.00	0.01	-0.10
WAF	WAF	SCH	5.31	8.00	1.51	93	-0.52	0.00	1.00	0.01	-0.11
WAF	REDS	PHIL	5.57	7.59	1.36	96	-0.71	0.00	1.00	0.01	-0.23
WAF	AG	UKC	5.54	6.79	1.23	100	-0.67	0.00	1.00	0.01	-0.24
SCH	AG	CALI	5.72	6.68	1.17	110	-0.62	0.00	1.00	0.04	-0.29
BRZ	BRZ	SCH	5.40	5.46	1.01	111	-0.53	0.00	1.00	0.00	-0.14
SCH	AG	ECC	5.69	6.90	1.21	113	-0.63	1.10	1.00	0.04	-0.30
SCH	AG	KOR	5.53	7.12	1.29	114	-0.68	-1.10	1.00	0.04	-0.23
SCH	AG	JAP	5.54	7.09	1.28	114	-0.67	0.00	1.00	0.04	-0.23
NCH	AG	UKC	5.49	6.74	1.23	114	-0.66	0.00	0.33	0.03	-0.24
TWN	AG	ECC	5.68	6.87	1.21	120	-0.63	0.90	1.00	0.05	-0.30
SCH	AG	UKC	5.47	6.72	1.23	121	-0.66	0.00	1.00	0.04	-0.24
TWN	AG	KOR	5.50	7.08	1.29	122	-0.67	-0.90	1.00	0.05	-0.23
PHIL	AG	KOR	5.50	7.08	1.29	123	-0.67	0.00	1.00	0.05	-0.23
THAI	AG	KOR	5.45	7.02	1.29	140	-0.65	0.00	1.00	0.07	-0.23
SPOR	AG	USG	5.63	6.79	1.21	142	-0.60	1.40	1.00	0.08	-0.31
SPOR	AG	ECC	5.62	6.80	1.21	143	-0.60	-2.00	1.00	0.08	-0.30
SAF	REDS	PHIL	5.42	7.29	1.34	148	-0.66	0.00	1.00	0.07	-0.23
SPOR	AG	KOR	5.40	6.96	1.29	158	-0.64	0.60	1.00	0.08	-0.23
ECI	AG	USG	5.57	6.73	1.21	165	-0.57	0.00	1.00	0.11	-0.31
WCI	AG	USG	5.51	6.69	1.21	186	-0.54	-1.40	1.00	0.14	-0.31
WCI	AG	KOR	5.17	6.81	1.32	240	-0.56	1.40	1.00	0.14	-0.23
WCI	AG	SCH	5.13	6.84	1.33	244	-0.57	0.00	1.00	0.14	-0.22
AG	AG	SCH	4.97	6.77	1.36	299	-0.52	0.00	1.00	0.17	-0.22
AG	AG	WCI	4.19	6.92	1.65	304	-0.61	0.00	1.00	0.17	-0.10
AG	AG	TWN	4.92	6.84	1.39	308	-0.52	0.00	1.00	0.17	-0.21
AG	AG	THAI	4.84	6.94	1.43	321	-0.54	0.00	1.00	0.17	-0.19
AG	AG	ECI	4.55	7.08	1.56	326	-0.58	0.00	1.00	0.17	-0.14
AG	AG	SPOR	4.76	7.02	1.47	328	-0.55	0.00	1.00	0.17	-0.18

7.10 Summary of Results

The outputs of the matching model can analyzed around three areas: the allocation of ship types to routes (the matching) determining the trading pattern of ships, the earnings to each agent and hence equilibrium prices, and the speed of ships which match and those who remain unmatched.

7.10.1 Matching results

The model results show that when ships are differentiated by location, there is a higher probability that a ship will match to a trader when it is located in close proximity to the local market relative to ships located farther away. However, the model is sensitive to the relative values of agents' options to remain unmatched (dummy surplus values) and this leads to certain instances of ships being matched from farther away relative to other ships. An initial scenario in which ships have quasi-myopic beliefs about future earnings from the cargo's destination leads to lower market shares on some routes and low average speeds. Alternative models were run with forward-looking ship beliefs, and these models resulted in all traders matching to ships and higher average speeds compared to the models with quasi-myopic beliefs. For the matches between ships and traders, the assignment was influenced the most by the oil revenue and the shipment cost and to a lesser degree by the ship's option value to be in the destination.

Overall, ships which are unmatched are located farther away from the local markets and have to relocate to one of two waiting areas - West Africa or Fujairah in the Arabian Gulf. The allocation of ships to these areas is determined by the dummy surplus values, which reflects the agents' future beliefs. In the quasi-myopic model, the assignment of ships to each waiting area was divided almost evenly, with 47% relocating to AG and 53% to WAF. Ships in this model base their relocation decision on the minimum distance to each area which determines the cost; ships which are located in the Americas will relocate to WAF and those in the Far East and California relocate to AG and therefore the shares reflect the supply of ships that were not required to meet demand in the current period in the local markets. In contrast, the forward-looking model is sensitive to the values of the waiting areas and the sensitivity depends on the magnitude of the value of the waiting area. When the value is calibrated to the long-run average, this leads to all ships relocating to WAF. A much lower share was estimated from the data to be in WAF compared to AG, and this might suggest that the estimated value to be in WAF is too high. In contrast the results of $M2$ using the 2011 option value result in 64% of ships relocating to WAF compared to 36% to AG because the the value to be in each waiting area is less such that the repositioning costs influence the decision to relocate in WAF.

A 10% increase in demand for Chinese imports from AG, BRZ and WAF leads to a reallocation of ships in NCH from the AG-WCI route to AG-ECI and SCH ships move from AG-ECI and AG-WCI to meet the increased demand on the AG-SCH route. Ships in SCH which previously served the AG-ECI and AG-WCI routes are replaced by ships in KOR and this reallocation is driven by the higher surplus that can be achieved with with this reallocation. Ships in WAF and USG meet demand on the WAF-SCH and BRZ-SCH routes, which they were previously serving respectively before the demand shock.

In the multidimensional matching model, there is an interaction effect between location and physical characteristics. This means that ships can differentiate themselves within a location and this leads to a different assignment within a location. The impact of capacity utilization was tested using two scenarios, one that varies cargo size using a constant capacity utilization rate (*Bigger is Better*) and the other which holds cargo size constant (*Energy Efficiency Rules*). The estimation of the physical characteristics resulted in the largest ship having a lower fuel efficiency (fuel burned per tonne-mile) even when using the cargo size assumptions in (*Bigger is Better*) so there is a trade-off between cargo size and energy efficiency in this case. The matching results showed that when cargo size is allowed to vary, the largest ship was utilized the most compared to more energy efficient ships, but location matters in the probability of matching. Ships which are the most favored in terms of their physical characteristics but are located farther away from a local market have a much lower probability of matching compared to ships which are located closer but have less desirable physical characteristics. In comparison, when cargo size is held constant in *Energy Efficiency Rules*, the utilization of ships of the most energy efficient class is higher.

In the dynamic matching model, matching is driven by the endogenous changes in earnings which updates the dummy surplus and ship option values. The dynamic model introduces memory of previous earnings (prices) which is a function of the supply and demand from within the model compared to the static model which relies on a number of exogenous parameters that are annual averages of statistics. The evolution of surplus values and dummy surplus values leads to different results in the dynamic model. For example, in the static model, the dummy surplus for the ship in WAF and ECC was relatively higher than for ships in USG, and this lead to an allocation of ships from USG to the BRZ-SCH route. In the dynamic model, these dummy surplus values decrease such that it makes it viable to allocate ships from ECC to the BRZ-SCH route and ships from WAF to additional routes which causes WAF ships to be fully utilized.

7.10.2 Agent earnings and prices results

Taking the data used to calibrate the model in Chapter 6, a simple market in which there is one location (BRZ), one set of ships (ships in BRZ) and one set of traders demanding cargo on the BRZ-SCH was simulated in order to demonstrate how the surplus is divided and hence earnings and prices are determined. It was shown that when ships are on the short side of the market and there is only one set of ships of the same type, ships obtain the entire residual pie as defined in Chapter 4. In other words, after the trader receives its dummy surplus value, the ship earns the rest of the surplus. At the opposite extreme, when ships are on the long side of this market, they receive only their dummy surplus. Finally, when ships are differentiated across locations according to the model's demand sample and keeping demand constant for the one market in BRZ, ships are short in BRZ and long in other markets, and this increases competition for the trader's cargo. This leads to a drop in the short ship's price from \$5.66 m. to \$2.70 m. This example, while simple, illustrates the model's ability to capture volatility in prices due to the spatial dimension of the model and provides a range of prices according to the type of competition a ship faces.

In all model variants, earnings and prices are determined precisely by agents' position in the market (short, long). If the agent is short, then the price a ship obtains reflects the price of the trader's best feasible substitute and the difference in the willingness to pay for the favored ship over the substitute. In the baseline model where ships are differentiated by location, these substitutes reflect the location of other ships, whereas in the multidimensional model, prices differ within the same location reflecting preferences over one ship type that has more favorable physical characteristics. Earnings were also compared to the estimated option values which were calibrated to 2011 and long-run freight rate data. In the quasi-myopic model ($M1cs2011$), the model's output of ship earnings is higher than the 2011 estimates and lower than the long-run estimates which was to be expected given that the model's option values are the discounted repositioning costs to the original load area which increases the price that a ship must obtain to match compared to the 2011 estimates which include the discounted profits of one voyage ahead. In the forward-looking model, a comparison of the long-run model $M2cslr$ to earnings from the long-run terminal period estimates shows that on average, earnings are lower in the model than the estimates with the exception of several ship types which are on the short side of the market and the same resulted in a comparison of $M2cs2011$ results to the 2011 estimates. This suggests that the estimated values outside the model overestimate the ship's option values.

Prices were also compared to historical Worldscale multiplier rates for selected routes where data was available in 2011. Prices are higher on average than historical rates in $M1cs2011$ and lower in model $M2cs2011$. The reason for these differences is that the option values are more negative in $M1cs2011$, which has a positive impact on prices but also reflects differences in the marginal ships in the two models. Several reasons were discussed as to why prices differ, including the uncertainty in the demand to supply ratio, the fact that prices are not unique in the model and are a function of the finiteness of the agents which provides bounds on prices rather than exact numbers.

A number of counterfactual simulations were run on $M2cs2011$ and $M2os2011$ to understand the impact on earnings and prices due to changes in demand, the fuel price, changes in trade flow shares and the impact of variation in location and physical characteristics in the static model under the assumption that it is a transitory shock. It was shown that the extent to which the shipowner can pass the fuel cost on to the freight rate depends on the ship's position in the local markets (if it is short or long) and whether a ship can adjust its speed in the match. When ships are long, the cost pass through depends on the relative changes between costs, dummy surplus and option value. Long ships located in the waiting area could pass cost on by 100% whereas ships which were not had less than 100% cost pass-through. When ships are short, the change in price reflected the change in the substitute's price and the change in the difference between the trader's willingness to pay for the ship and its substitute. This generally lead to a more than 100% cost pass-through. In the 5% transitory fuel shock scenario with constant speed, prices are moderately sensitive to fuel price changes, generally increasing by 2-3.6%. In the optimal speed case, the price variation increased, ranging from 1.1-4.0% and this greater variation reflects the impact of the matched speed on the price of the substitute and the willingness to pay. For a permanent shock of 20% to fuel prices given a carbon tax of $40, prices are expected to increase between 9.0-30.8% for the constant speed case, and 4.8-18.3% for the optimal speed case.

The extent to which a demand shock affected prices depended on whether the shock could be localized or rippled through to other trade routes. A shock of 10% to Chinese imports affecting the AG-SCH, BRZ-SCH and WAF-SCH routes showed that supply from WAF and USG ship types were able to absorb the demand. Prices did not change on these routes or affect prices in other markets because these ships were still not fully utilized. In contrast, the demand shock to the AG-SCH route caused prices to increase for ship types serving the AG and REDS markets, with the exception of ships serving the AG-WCI route. The price increase can be explained by the last marginal vessel (KOR) which was added to the AG-ECI route after ships from SCH serving this route were allocated to the AG-SCH route. Similarly, the change in trade flow share simulation which caused demand to decrease for SCH ships lead to a drop in prices on routes previously served by SCH. The price decrease can be explained by the fact that SCH ships were on the short side of the market prior to the demand shock and changed to a long position.

The multidimensional matching illustrated how prices are differentiated not only for ships located in different locations but also for those in the same location which have different physical characteristics. Demand rationing for these ships occurred when the ships were on the short side of the market and prices reflected differing willingness to pay for each physical ship type. Two scenarios were considered that affected willingness to pay and caused prices to differ across physical ship types. For example, the *Bigger is Better* scenario, the willingness to pay for a larger ship size increased prices over smaller sized ships.

7.10.3 Speed results

A number of model variants of the baseline model with different values of parameters affecting speed (oil revenue, shipment cost, and ship option values) in the matched state were tested to understand the sensitivities. The model that resulted in the highest speeds, $M2oslr$ was associated with the highest ship option values, while the model with the lowest average matched speeds was the quasi-myopic model reflecting the fact that when there are profits to be made on future journeys, it pays to go faster. However, ship option values are only one component determining the matched speed. The matches with the highest speeds resulted from a combination of relatively higher repositioning costs, lower voyage costs and higher option values. In contrast, the speeds which rank the lowest correspond to matches that have zero repositioning costs, high voyage costs and low option values. In the unmatched state, ships are expected to go their minimum speed (8 knots in the model) when option values are negative, but speeds increase to 10.4 when the long-run scenario is run.

Speed clearly has an impact on carbon emissions. In the baseline scenarios, carbon emissions were the highest with the long-run ship option values and the lowest in $M1os2011$ because in this model not all traders match (and hence less miles are travelled in the matched state) and ship option values are low which leads to lower speeds. The fuel price simulations for the optimal speed case had varying impacts on speed and emissions depending on the level of the increase. For a 5% increase in the fuel price, speed reduces by an average .13 knots (10.57 to 10.44) compared to the $M2os2011$ baseline. This translates into a 3.0% reduction in emissions. For a 20% increase in the fuel price, the average speed reduction was .42 (10.75 to 10.33), leading to a reduction in emissions by 8.7%.

Chapter 8

Discussion and Conclusions

8.1 Introduction

This chapter discusses the insights that can be gained from the model results, their implications for the existing literature in maritime economics and their limitations. The aim of this study is to understand the economic determinants of transactions or matches, between traders and ships in order to simulate the impact of changes in the system. The scope of the study is the short-run VLCC tanker market within a spatially explicit market for crude oil. The discussion is organized around answering the research questions which were structured to achieve the stated aim:

- What determines the assignment of ships to traders (who matches with whom) given the spatial distribution of ships across different locations in the oil tanker shipping industry?
- What determines the division of surplus in the matches between ships and traders and therefore equilibrium prices?
- What are the influencing factors of the contract (matched) speed and ballast (unmatched) speed?
- What are the impacts of supply side and demand side changes on the market in terms of matching outcome, earnings, prices and speed?

8.1.1 Economic determinants of matches between ships and traders in a spatially explicit tanker model

Previous modeling approaches in maritime economics have largely ignored the inherently spatial nature of the tanker market and its impact on the determinants of the types of ships and traders that match in the marketplace. The study showed that the spatial dimension is critical for understanding decision making and the equilibrium formation of transactions (called matches) between ships and oil traders. A matching model provided the capability to incorporate the spatial distribution of demand and supply by classifying ships and traders into types. Ship types were defined in the baseline model by their location in order to identify the impact of the spatial dimension on the problem. In theory, ships available to match could be located anywhere in the sea, but to make the model manageable, these locations were a set of discharge and waiting areas. Traders were characterized by the load and discharge pair (the trade route) they demanded and their willingness to pay, captured by the profits from selling the oil cargo. In order to understand who matches with whom, including the decision to remain unmatched, it was important to value the decisions that the agents - oil traders and ships - could make. An investigation of the modern tanker industry uncovered that shipowners and traders do make inter-temporal choices. The model simplified these decisions into two periods, the current period and the decision to wait and match in the next period. For oil traders, the choice is a function of the value of the oil commodity in the future, the storage costs, and the expected freight rate. This contrasts with the majority of structural modeling approaches in maritime economics which assume that demand for crude oil is inelastic: there is a quantity of oil that needs to be shipped immediately. Instead, the approach to estimating demand was inelastic as demand was exogenously provided but could be shipped one period ahead. For shipowners, a new approach was taken to value the decision to match or wait one period. The valuation of a match to a trader required a valuation of the cost of the current match and a quantification of the implications of being in the discharge area (known as the ship's option value) once the ship has fulfilled the current voyage shipment obligations. Two different approaches were taken to value the option value: a quasi-myopic and forward-looking approach. The conclusions from this analysis showed that shipowners have forward-looking beliefs. It was concluded from speaking with shipping industry experts and current shipping newsletters that ships who do not match with traders or have no employment prospects in the spot market generally relocate to a waiting area near a major demand market (in the Arabian Gulf and West Africa). Existing structural modeling approaches in maritime economics do not take into account these location-specific tactical repositioning decisions.

Results described in this thesis show that the contracts that form in equilibrium depend on the demand for oil cargoes in each load area market and the supply of available ships within proximity to the market. Additionally, agents' opportunity costs and future expectations has also been found to influence the matching. The location of ships was shown to influence both the trader's willingness to pay and the shipment cost, with ship option values playing a smaller role in determining the matching with traders. The matching was also shown to be endogenously determined by the relative supply and demand in the local markets; too few ships in the local market lead to ships being sourced from other locations. Ships which were located relatively closer to the local market had a greater probability of matching with traders over ships in more distant locations, but this was not a rule of thumb. In some matches, the model results showed that the matching was sensitive to the values placed on the ships' option to wait (the dummy surplus). The determination of whether this would occur was due to the relative difference between the surplus of two contending matches and their dummy surpluses. If the difference in dummy surpluses was larger, then the ship was chosen that had a lower dummy surplus because this would lead to a higher social welfare. The economic interpretation is that the ship that is worse off in terms of its value to remain unmatched would be willing to accept a lower price in order to match with a trader over not matching. The benefit of this approach is its ability to incorporate the large stakes, or opportunity costs, involved in shipping due to the geographical dispersion between the discharge and load areas. As described in Chapter 6, taking into account the implications of being in the destination is important for some tanker operators. According to a leading tanker company (Maersk Tankers, 2012),"There are alot of cargoes out there from different customers. It's all about optimizing over a number of voyages...If I want to take this cargo from point A to point B, then I want to be able to get a cargo from there onto the next one."

8.1.2 Determinants of the division of surplus in matches between ships and traders

The conclusions from Chapter 3 confirmed that given the large number of shipowners and a sufficient quantity of oil traders, the market continues to be very competitive as characterized by the existing literature. However, as discussed in Chapter 2, the notion that the market is perfectly competitive is too strong an assumption given the large short-run fluctuations in prices which do not closely resemble the costs of the last marginal vessel used. It was therefore necessary to drill down to the micro-level determinants of these transactions to explore whether the short-run volatility could in part be explained by the spatial distribution of supply and the nature of demand.

A large determinant in the fluctuations in prices and therefore how the surplus is divided was found to be a function of the bargaining power of each agent in a match, a feature absent from most of the previous modeling of tanker rates. The matching model is one way of generating endogenously the power to each agent in the match, and this power depends on the relative demand to supply in both the aggregate and local markets and the inter-temporal choices (dummy surplus values) of each agent. This required a new terminology for the global tanker market. The existing theory (since Tinbergen, 1934) classified tanker rates into two regimes: a regime in which ships are fully employed, and one in which some are unemployed. In the matching model, this is known as the aggregate market conditions and was defined as the total demand for cargoes to the available transport supply. This indicator determines whether traders have any bargaining power or a threat point; in other words whether they have a ship to substitute for that serves as a threat to the ship they would like to match with depends on other traders' demand in all crude oil markets relative to the supply of available ships. The model setup was one in which traders do have a threat point (the aggregate demand is less than the aggregate supply), such that they can always match with a ship. If traders do have a threat point, then it was termed that traders are on the short side of the aggregate market.

However, it is the local demand to supply in the load area that determines the strength of this threat point. It was found that ship types which were in scarce supply (more ships than trader types demanding them as the best option) received a higher share of the surplus than ships which were in excess supply. Scarcity was defined as the utilization rate of the ship type or the number of ships of type that were matched to a trader divided by the total ships of that type. This share of the pie was determined by the trader's threat point or best substitute ship which depended on the location of other ships and the demand for those ship types. The price was equal to the threat point plus the difference in marginal willingness to pay between the two types of ships. This contrasts with existing maritime structural models, which do not model the demand side in any detail so there is no understanding of the willingness to pay for different ship types. On the other hand, when ships were long in the market and therefore in excess supply, and the price they receive is the price that gives them their dummy surplus, or the earnings if they remained unmatched. The economic interpretation is that prices would be lowered until they were indifferent between matching or remaining unmatched.

The uncertainty of the input parameters and the non-uniqueness of prices given the finiteness of the ships in the model means that there will be a margin of error in predicting prices. When modeling under conditions of considerable uncertainty, there is therefore more value in examining broad trends rather than fixating on absolute values. The uncertainty surrounding the estimates of prices is discussed in the Limitations Section 8.2.

8.1.3 Factors influencing speed

Chapter 2 discussed the different views about modeling speed in the literature. Vessel speed optimization plays an important role in earlier maritime economics models, while later structural models assume a constant speed given charter party clauses stating a fixed speed, weather conditions or the small margin that it was believed a ship should be operated under. In the matching model, the extent to which speed can be optimized depends on whether the ship is employed or not. It was therefore necessary to distinguish between a "matched" speed and an "unmatched" speed. The conclusions drawn from the literature, data and interviews with industry is that speed optimization is important but the extent to which it is being optimized in the matched state depends on the oil trader. Rather there appears to be some stickiness in changing the speed in contracts, especially for oil majors which have speed clauses. In recent years, the simultaneous downturn of freight rates and higher bunker fuel prices relative to the bunker price priced into the benchmark flat rate has meant that it would be in shipowners best interest to have more flexibility over the contract speed. An optimal speed and constant speed were simulated for the model's matched state. The optimal speed in the matched state was specified as a function of the trader's oil revenue, the shipment cost, and the ship's option value. The sensitivity of speed to this parameter was a function of the specification of the equation, and therefore the speeds from the model reflect this. The optimal speed is sensitive to the assumption that the oil trader has already purchased the oil cargo and therefore has to store the cargo until the ship arrives, thus imposing a cost for the days it has to wait until the ship arrives. In some cases however, oil traders make a simultaneous decision to purchase oil provided there is a ship available to hire. This would have the effect of lowering the ship's speed. For the ship, it was important to include not only the impact of speed on the current voyage in terms of cost, but also the opportunity cost of time. This opportunity cost was quantified by including the ship's option value. The optimal speed equation for the matched state contains some opposing forces; a slower speed lowers the trader's oil revenue and the potential rental revenue to the ship while at the same time lowering the shipment costs. The impact of the ship's option value depends on its sign; a negative ship option value would mean that it is better to go slower since there are negative profits to be made from the discharge area, while a positive option value would be negatively affected by a slower speed. Ultimately, the results showed that the optimal speed depended on the relative magnitude and the effect of speed on these parameters.

In the unmatched state, ships are unemployed and have to decide what speed to travel in their repositioning voyage to a waiting area. In this case, the optimal speed depends on the shipowner's decision. This decision is a tradeoff between the repositioning costs (a function of distance, the fuel price, and the fuel efficiency) and the ship's option value to be in the waiting area. When this option value is negative, it makes sense to go as slow as possible, whereas a positive value will offset the benefits of minimizing costs to relocate.

Anecdotal evidence points to some ships operating at slow-steaming speeds in 2011; according to Lloyd's List (2011), "Maersk's fleet of 11 VLCCs are traveling at speeds as slow as

8.5 knots when transiting without cargo to the next load port." In practice, ships have a time window to arrive at a load area once they match, which is not included in the model. It would not be difficult however to extend the model to include an average time window. In addition, a charter party will provide a speed range rather than one speed (common for oil majors) and can contain an "utmost dispatch clause" requiring the ship to sail at full speed. According to Lloyd's List (Lloyd's List, 2011), one major London broker of VLCCs said, "Certainly owners try to have low and high speeds in the charterers' options of 14.5-15.5 knots and I know a lot of owners say 'we're not going to do that' [when higher speeds are asked for] and say "we're not going to give you the upside on speed because we don't get compensated for it."

Aside from just anecdotal evidence, average speed for the 2011 option value scenario was validated using AIS data as described in Chapter 5. The AIS sample data (Smith et. al., 2013) shows that VLCC ships sailed at an average of 13.24 (9.38-15.55) knots in laden and slightly higher in ballast at 13.52 (9.31-15.92 range) knots in 2011. This contrasts with evidence from Maersk stating super-slow speeds of 8.5 knots in ballast. Both speeds are higher than what the model predicts should be the optimal speed. There are a few plausible reasons why the observed speeds are closer to 13 knots in ballast and not 8. It is well-known that the tanker and bulk shipping companies have expressed concerns about super-slow steaming due to the belief that operating a ship well below its as-designed speed (around 15 knots) might damage a ship's engine. According to Maersk Tankers, "What we have found out is that during times of difficulties owners have gone down to the most economical speed, which is about 13 knots," said Maersk Tankers head of crude Claus Gronborg (Lloyd's List, 2011). "If you go below that speed there are some precautions your crew need to take onboard the vessel but in contrast to common beliefs, no engine modifications as such have to be made," which Mr. Gronborg said were technical lessons learned from super-slowing steaming within its Maersk-Line container ship fleet. The practice was introduced 18 months prior to 2011 and the company "now decides on a case-to-case basis at what speed each VLCC will travel in ballast to potential crude loading ports in search of employment." Another explanation for the difference in economical sailing speeds among shipowners is that ships have different engine efficiencies which deliver different savings from slow steaming. This "case-by-case" speed determination by some of the leading companies is however consistent with the model's forward-looking optimal speed scenario. From a modeling perspective, it is important to understand the implications of both the constant and optimal speed case. The fact that the model predicts slower speeds suggests that traders have the bargaining power and this is justified by the fact that the aggregate market is in their favor. In other words, ships have to consider that a higher a speed is better than no fixture.

8.1.4 Impact of supply side (fuel price increase, physical ship characteristics) and demand side changes (demand shock) on the market in terms of the matching, earnings and prices and speeds

A common belief by some industry practitioners is that fuel costs will be fully passed through to freight prices. The results of this study showed that cost pass-through is not uniform across all matches and depends on the ship's position in the market, which in turn determines how much cost pass-through will result. The variation in cost-pass through for ships on the long side of their local markets reflected the impact of the fuel price increase on the cost of relocating to a waiting area (the dummy surplus value). In the 5% transitory fuel price shock, full cost pass-through resulted when there was no change in relocation cost since they were strategically located in a waiting area. On the other hand, ships which were located in a discharge area faced a greater cost to relocate and this decreased their bargaining power through the decrease in the dummy surplus and less than 100% cost-pass through resulted. For ships on the short-side of the market, cost pass-through was over 100%, reflecting the change in the price of the ship type's substitute and the difference in the change in the trader's willingness to pay between the baseline and fuel price increase. In the 5% transitory fuel shock scenario with constant speed, prices are sensitive to fuel price changes, generally increasing by 2-3.6%. These estimates are higher than the average price increases suggested by the econometric freight rate regression which predicted that a 5% increase would increase the price by 1.22%. In the optimal speed case, the price variation increased, ranging from 1.1-4.0%. This greater variation reflected the impact of the matched speed on the price of the substitute and the willingness to pay. For a permanent shock of 20% to fuel prices given a carbon tax of $40, prices were expected to increase between 9.0-30.8% for the constant speed case, and 4.8-18.3% for the optimal speed case.

The baseline model provided new insights into the spatial relationship between different crude oil shipping markets but it was acknowledged that this represents a simplified version of the tanker market given ships also differ by their physical characteristics (defined in the model by their size, age, energy efficiency and design speed). Simulating ship types that are differentiated by both location and physical characteristics provided a better understanding of the interaction effect of location and physical characteristics and the impact on matching probabilities. Existing structural models use data from a fleet register to construct the voyage cost and assume that the 95th or most energy inefficient ship provides an upper bound on the freight rate. In contrast, the multidimensional matching model incorporates the impact of physical characteristics not only on cost but also the trader's willingness to pay and ship option values which combined determine prices. This illustrated how prices are differentiated not only for ships located in different locations but also for those in the same location which have different physical characteristics. Demand rationing for these ships occurred when the ships were on the short side of the market and prices reflected differing willingness to pay for each physical ship type. Varying location and physical characteristics shows that ships which are the most favored by physical characteristics cannot compete as strongly with less preferred ships located closer to the market.

It is a common assumption that bigger ships are more energy efficient given a sufficient capacity utilization rate. However, the data revealed that this assumption does not always hold; larger ships can be less energy efficient than smaller ones even accounting for the larger cargo size. Anecdotal evidence from Cameron (2013), a tanker company, suggests that ships which were built in recent years (which corresponds to the age group of the largest size category) were designed to go fast, reflecting the booming market at the time they were ordered. Ships that have higher design speeds also require a larger engine which can explain the higher energy requirement. Ships which are bigger can carry more cargo however, and as a consequence this study showed they are favored over smaller sized ships when the payload is higher. The data revealed the trend of larger ships being built, but the increase in a ship's size is limited by the trader's cargo size preferences due to land inventory storage costs and the port size restrictions. Given that the average cargo size for fixtures is 265,000 and the speed of ships has decreased, the higher matching probability of the more energy efficient ship should send a signal to shipowners to invest in these ships over larger ships which are less fuel efficient. In fact, there is evidence that tanker companies (Scorpio, 2013) are beginning to see the payback to investing in more energy efficient ships because it also provides a premium in the time charter (rental) market.

The uncertainty in trade flow shares was tested using an alternative demand scenario for Chinese imports and illustrated the conditions under which a demand shock could be localized or whether it would ripple through to prices on other trade routes. For instance, a change in demand to the BRZ-SCH route was localized because it could be absorbed by the existing excess supply of the ship type already allocated to serve the trader's demand. In contrast, the decrease in demand on the AG-SCH route and increase in demand on the WAF-SCH route lead to a decrease and increase in prices respectively on routes with the AG and WAF load area. Price changes were caused by a change in the position of the last marginal ship's substitute. The decrease in demand for AG-SCH cargoes caused a decrease in price because SCH switched from being short to long, while the change in position of the WAF ship from long to short caused an increase in price.

8.2 Limitations

The new insights that can be gained from the tanker matching model do not come without some limitations. This section discusses these limitations in terms of data and method. The data limitations can be attributed mostly to incomplete information on VLCC trade flows and the supply of available ships to match. There are clear trade-offs between model tractability and model completeness and these trade-offs are discussed in the method section.

8.2.1 Data

An overarching limitation in the estimation of the model was the reliability of the data. In some cases, this was because data did not exist, in others because it was not publicly available. As explained in the relevant chapters, approaches were taken in this study to lessen the impact, but a full uncertainty analysis was beyond the scope of this study. In addition, the assumption that ships can only match in discharge and waiting areas is a simplifying assumption to avoid the complications of modeling ships located anywhere in the sea and the limitations of the datasets used to estimate supply. In theory, if ship brokers were willing to share this information then it could provide a better understanding of their availability. Shore-based and satellite-based AIS data could provide information on the geographical location of ships and could greatly enhance the supply estimates. Another source of uncertainty in the estimates of supply were ships owned by governments like China and oil majors which do not trade in the spot market. There has been a growing trend for government-owned ships to trade only with Chinese oil traders and this poses as a threat to independent shipowners.

In the multidimensional matching simulation, the matching results clearly depend on the assumptions made about the distribution of physical ship types across locations. The distribution was based on the ship type's fleet share; no assumptions were made about whether specific physical ship types serve specific routes. The analysis could be enhanced by further understanding of port size restrictions which could be added to the model. The interpretation of these results therefore was to highlight a "what-if" scenario for understanding the influence of energy efficiency in the matching model rather than calibration to existing data.

8.2.2 Method

As discussed in the data limitations section, there are a number of uncertainties in the data that required inferences to be made. Second, to make the model tractable, a number of abstractions were made about the market:

1. There was uncertainty in the purchasing decision of oil caused in part by the lack of access to oil trading experts given that this information is confidential and would be a breach of

the company's policies. The approach taken to modeling demand contains a number of simplifications. The first simplification was the modeling of the trader's profits, which depend on the type of oil trader (oil major, trading house) and the specific contract they agree to with the purchaser of the oil cargo. The volatility of future oil prices could affect their inter-temporal decision making about when to purchase and sell the oil and therefore the period in which they fix a ship and terminate a contract. It is known that some traders will pay the ship a fee for any extra days that are not included in the contract when the ship arrives at the port in order to secure a better selling price. Oil cargoes are also sold on board and this was not included. The timing of the sale could affect the route that is agreed in the contract (the Suez or Cape of Good Hope). Second, the model assumed that the oil trader has already bought the oil cargo before a ship is fixed, incurring a cost to store the oil at the loading area. An alternative is that the timing of the oil purchase coincides with the fixture date, thus impacting the speed that a ship is required to travel in the optimal speed version.

2. Another simplification was the modeling of agents in the tanker market. There were a number of agents not included that play a role in the shipping market, including ship brokers, charterers and the wholesale purchaser (refineries). These agents could have an impact on the dissemination of information, and the model did not discuss the process that leads to equilibrium prices, including an oil traders' access to different brokers which could be linked to different shipowners. The bargaining power was also assumed to be solely a function of the market conditions, which abstracts from the individual agents' ability to bargain.

3. The model calibration focused on the VLCC sector and therefore limits the equilibrium prices to be a function of only other VLCC ships in the market. In reality, there could be substitution effects with other ships that ship crude oil (Suezmax, Aframax), although this is likely to be less influential on the long-haul routes where VLCCs dominate. The model could however be extended to include other ship types and this would represented as another possible match combination.

4. The geographical complexity of ship and weather routing was also not included in the model. To collect average distances between each of the possible route combinations was highly data intensive, and the routes included in the model reflect the most travelled path between the origin and destination. Therefore any changes in the cost of the Suez Canal or of piracy could alter the routing decisions, impacting the implications for carbon

emissions and the supply of available ships.

5. The model also focused on the short-run, which was defined as under one year such that there was no modeling of investment decisions. Clearly, there could be some market entrants and the increase in supply was instead modeled as a counterfactual. The fact that investment was not modeled however does not mean that there are no implications for investment decisions. Investment decisions are a function of observing the profitability and utilization of types of ships, and this analysis can be used to inform these decisions.

6. Although the time-charter market is linked with the spot market, the decision to time-charter was not explicitly represented in the model, although a daily average time-charter rate was included as the rental rate of capital.

7. Agents took account of the market conditions, but did not consider the locational decisions of individual ships.

8.2.3 Static modeling

The limitations can also be analyzed according to the static and dynamic models. The static model required the estimation of the dummy surplus and ship option values that rely on specifying parameters outside of the model, and the greatest uncertainty was estimating the freight rate, the probability of matching, the discount rate, and the assumptions about the trader's oil purchasing decision which are the most influential factors. The freight rate estimation was a reduced form approach rather than a structural approach, and this meant that modeling a permanent shock in the static framework was not possible because the freight rate did not specify structural demand and supply side parameters, such as GDP and available supply of ships. The demand and supply balance was encapsulated in the trade flow and yearly time fixed effects but these represent annual averages. Panel data methods could also explored in estimating the freight rate to detect variables unobserved by the econometrician, though an OLS model (corrected for clustering) is efficient when there is sufficient data available. Second, it was not possible to forecast the matching probability in a static framework which was used to calculate the estimated waiting days and the type of ship a trader was matched to. Instead, an average matching probability had to be estimated based on the aggregate demand to supply ratio. Third, the approach to estimating the ship's option value was deterministic, and therefore it was acknowledged that forecasting the profits of one voyage ahead would be sufficient. The method to solving for these values using a linear system of equations produced a value of all future periods, which was then discounted to obtain an estimate of the profits of one voyage and it was important that the magnitude was appropriate. It was subsequently learned from the static matching model that these values overall were slightly higher than the model's output.

8.2.4 Dynamic modeling

The dynamic modeling approach improved upon some of the limitations of the static model by using the output from the model to update the estimated dummy surplus and ship option values. A nice feature of this approach is that it incorporates the fact that ships and traders use the previous freight rate as a starting point in their negotiations, which is an equilibrium outcome of the previous trading game. Nevertheless, there are a number of limitations of the dynamic modeling approach. The first is the assumption of stationary supply and demand which was made in order to concentrate on searching for a fixed point in earnings. This assumption means that we lose the richness of using the implied supply of ships in different locations in the next periods which is commonly deployed in transportation models. Solving a matching model with an endogenous supply of ships introduces a number of complexities into the analysis. The first complexity arises from the modeling of ships at sea arriving into areas which started at different times and different voyage lengths. The voyages are dependent on the route and speed they travel. As a journey can be up to 8 weeks long, this information needs to be input from outside the model for up to 8 weeks. The second complexity of using an endogenous supply estimate is the forecast of the ship option value and dummy surplus values because these values are dependent on the demand to supply ratio in the aggregate and local markets. The assumption of stationary supply and demand allows the algorithm to use the previous time step's values as input for the next time step's earnings. Dynamic economic models are typically run backwards from the last period of the model in order to obtain a forecast of earnings as input to the current period. In transportation modeling however, this approach loses the ability to use the matching model's output of the implied supply of ships arriving into each area in future periods. One approach to make supply endogenous is to update the supply of ships in each matching area with the matching from the previous time step. The assumption is that the same matching game that was played in the current period occurred in the previous periods. The problem with this approach is if the demand to supply ratio rises in subsequent periods due to a decrease in the supply of ships in one or more areas. If the earnings in the previous time step is used as the dummy surplus for the trader, traders will decide to remain unmatched, and in some cases this could cause no traders to match with a ship. Since the model requires option values for all locations as input for the next period, if no ships match to traders then there is no value to update the V_b values. A workaround would be to smooth the supply of ships from the previous time step with the implied supply from the current period which might be a smoother transition.

8.3 Future Work

As the limitations outlined, there were a number of simplifications that were made in order to create a tractable matching model. There are three main priorities for future work to improve upon which would address some of the limitations of the model. The first would be to focus on modeling of demand. Specifically, this requires interviewing oil traders (or those who have left the profession) and refineries and their purchasing decisions in greater detail. This would enhance the estimates of the willingness to pay and the opportunity costs of trading. It might require greater complexity in modeling inter-temporal decision making, possibly extending the decision to match in the current period to be a function of not only the next period but several periods ahead.

The second extension would be to perform an uncertainty analysis of the model inputs since they were modeled as deterministic. This requires a quantification of the joint distribution of the model parameters. Monte Carlo techniques could be used to generate a range of values for the model outputs. As outlined in the Limitations section, a large uncertainty in the input data was the supply of ships in each area. These estimates could be enhanced using shore-based and satellite AIS data. This data is now being used to track ships in different areas and would be useful not only for inferring the supply distributions in locations but also to verify the model's allocation of ships to routes. It could also be useful for working out trajectories of ship movements across a year. However, it is still necessary to infer the availability of ships to match which is not provided by the AIS data. This data could also be used to analyze the physical types of ships in each area and possibly their average waiting times.

Thirdly, the matching model could be extended to include other ships that carry crude oil (Suezmax and Aframax) and investment decisions about whether to enter or exit the market and the type of ship to invest in using the implied earnings from the model as input into this decision. Short-term decisions to time-charter a ship or go into lay-up could also be included in this framework.

Finally, aside from addressing the limitations, future work could apply the existing model to the tanker industry by engaging with tanker companies to improve their matching and tactical repositioning strategies using real-time ship movements and companies' financial and ship engineering data.

Appendix A

Glossary of shipping terms

Aframax

A vessel of 70,000 to 119,000 DWT capacity.

Automated Identification System (AIS)

A system used by ships and Vessel Traffic Service (VTS) principally for the identification and the locating of vessels. AIS provides a means for ships to electronically exchange ship data including: identification, position, course, and speed, with other nearby ships and VTS stations.

Backhaul

To haul a shipment back over part of a route it has traveled.

Barrel

A term of measure referring to 42 gallons of liquid at 600 degrees.

Discharge Area

The sea area where cargo is discharged from for means of transport.

Broker

A person who arranges for transportation of loads for a percentage of the revenue from the load.

Bunker Fuel

A maritime term referring to fuel used aboard the ship. In the past, fuel coal stowage areas aboard a vessel were in bins or bunkers.

Cargo

Freight loaded into a ship.

Carrier

Any person or entity who, in a contract of carriage, undertakes to perform or to procure the perfor- mance of carriage by rail, road, sea, air, inland waterway or by a combination of such modes.

Charter Party

A written contract between the owner of a vessel and the person desiring to employ the vessel (char- terer); sets forth the terms of the arrangement, such as duration of agreement, freight rate and ports involved in the trip.

Charterer

A person who charters something.

Classification Society

An organization maintained for the surveying and classing of ships so that insurance underwriters and others may know the quality and condition of the vessels offered for insurance or employment. See also ABS, BV, DNV, LR and NK.

Contract of Affreightment

An agreement by an ocean carrier to provide cargo space on a vessel at a specified time and for a specified price to accommodate an exporter or importer.

Deadweight Tonnage

The number of tons of 2,240 pounds that a vessel can transport of cargo, stores and bunker fuel. It is the difference between the number of tons of water a vessel displaces light and the number of tons it displaces when submerged to the load line. An approximate conversion ratio is 1NT = 1.7GT and 1GT = 1.5DWT.

Demurrage

A penalty charge against shippers or consignees for delaying the carriers equipment or vessel beyond the allowed free time. The free time and demurrage charges are set forth in the charter party or freight tariff.

Destination

A penalty charge against shippers or consignees for delaying the carriers equipment or vessel beyond the allowed free time. The free time and demurrage charges are set forth in the charter party or freight tariff.

Handymax Vessel

A penalty charge against shippers or consignees for delaying the carriers equipment or vessel beyond the allowed free time. The free time and demurrage charges are set forth in the charter party or freight tariff.

Laden

Loaded aboard a vessel.

Laycan

Range of dates within the hire contract must start.

Load Area

The sea area where cargo is loaded from for means of transport.

Tonne

A metric tonne, 2,204.6 pounds or 1,000 kilograms.

Nautical Mile

Distance of one minute of longitude at the equator, approximately 6,076.115. The metric equivalent is 1852.

Route

A way or course taken from a starting point to a destination.

Ship

A vessel of considerable size for deep-water navigation.

Shipment

The tender of one lot of cargo at one time from one shipper to one consignee on one bill of lading.

Shipper

The person or company who is usually the supplier or owner of commodities shipped. Also called Consignor.

Tankers

Ships fitted with tanks to carry liquid bulk cargo such as crude petroleum and petroleum products, chemicals, Liquefied gasses (LNG and LPG), wine, molasses, and similar product tankers.

Bulk Carriers

All vessels designed to carry bulk homogeneous cargo without mark and count such as grain, fertilizers, ore, and oil.

Suezmax Tanker

A tanker of 120,000 to 199,000 DWT.

Tender

The offer of goods for transportation or the offer to place cars or containers for loading or unloading.

Time Charter

The hiring of a vessel for a specific period of time; the shipowner still manages the vessel but the charterer selects the ports and directs the vessel where to go. The charterer pays for all fuel the vessel consumes, port charges, commissions, and a daily hire to the owner of the vessel.

Time Charter Equivalent

A shipping industry standard used to calculate the average daily revenue performance of a vessel. Time charter equivalent is calculated by taking voyage revenues, subtracting voyage expense and then dividing the entire total by the round-trip voyage duration in days. It gives shipping companies a tool to measure period-to-period changes.

Tonne-Mile

The movement of a tonne of freight one mile.

VLCC

Very Large Crude Carrier. A tanker of 200,000 to 319,000 DWT. It can carry about 2 million barrels of crude oil.

War Risk

Insurance coverage for loss of goods resulting from any act of war.

Worldscale

A unified system of establishing payment of freight rate in nominal $/tonne for a given oil tanker's cargo produced by the Worldscale Association (NYC) Inc. The scale comprises a flat rate representing the average total cost of shipping oil from one port to another by a standard 75,000 tanker ship for various routes where there are multiple waypoints available.

Worldscale Multiplier

The spot rate, represented as a percentage of the Worldscale flat rate. A Worldscale multiplier of 100 equals the Worldscale flat rate, whereas a Worldscale of 50 equals 50% of the flat rate for a particular port pair and route.

Oil Major

The ”majors” are a group of multinational oil companies given the name due to their size, age or market position. The majors are typically ”integrated” companies, with divisions in exploration, production, marketing, refining, transportation and distribution.

Dry Dock

A dock that can be kept dry and that is used for building or repairing boats or ships.

Voyage Charter

The hiring of a vessel and crew for a voyage between a load port and a discharge port. The charterer pays the vessel owner on a per-ton or lump-sum basis. The owner pays the port costs (excluding stevedoring), fuel costs and crew costs. The payment for the use of the vessel is known as freight. A voyage charter specifies a period, known as laytime, for loading and unloading the cargo. If laytime is exceeded, the charterer must pay demurrage. If laytime is saved, the charter party may require the shipowner to pay despatch to the charterer.

Fixture

A fixture is a completed negotiation that results in a Charter Party between an Owner and a Charterer.

Lay-up

To put (a ship) in dock, as for repairs.

Appendix B

Table of Symbols

Table B.1: Table of symbols

Symbol	Description	Units
$\mathcal{A}$	Set of load locations	
a	Load location	
$aggDSR$	The ratio of total demand to total supply in the aggregate market	
$\mathcal{B}$	Set of discharge locations	
b	Discharge location	
α	Age of ship	Years
$beta_x$	A ship's discount factor	
$beta_y$	A trader's discount factor	
$c^f_{ll',t}$	A ship's fuel cost	Dollars
c^r	A ship's daily opportunity costs	Dollars per day
$C(x_{jt}, y_i, t)$	Total shipment cost	Dollars
c^{store}	Daily oil storage cost.	Dollars per barrel
$c^{rep}_{ll',t}$	A ship's repositioning cost	Dollars
$c^{voy}_{ab,t}$	A ship's voyage cost	Dollars
$d^{la}(x_{jt}, y_i)$	The duration to sail from the ship's current location l to a load location a	Days
$d^{lb}(x_{jt}, y_i)$	The duration to sail from the ship's current location l to a discharge location b	Days
d^p	Total number of days in port	Days
$d(x_{jt}, y_i)$	Voyage duration	Days
$\emptyset_x$	Dummy ship type	
$\emptyset_y$	Dummy trader type	
$\mathbb{E}(p^b_{tl'}\|x_{jt}, y_i, t)$	Expected average price of oil bought at location a and sold at location b at time $t+d$	\$ per barrel
$\mathbb{E}(\bar{\pi}(x_{jt}, y_i, T+1))$	The expected freight rate in period $T+1$	
$g(x_{jt}, y_i, t)$	The function that determines a ship's type in period $t+1$	
$g(x_{jt}, \emptyset_y)$	The function determining a ship's state when it remains unmatched	
i	A trader	
j	A ship	
k	As-designed fuel consumption	Tonnes per day
l	Current location of a ship	
λ	The stepsize or parameter used to weight the importance of payoff values	
$locDSR$	The demand to supply ratio in a local demand market	

Table B.2: Table of symbols (continued)

Symbol	Description	Units
$m(x_{jt}, y_i, t)$	The number of ships of type x_{jt} matched to a trader of type y_i, t at time t	
$m(\emptyset_x, y_i, t)$	The number of unmatched traders of type y_i at time t	
$m(x_{jt}, \emptyset_y, t)$	The number of unmatched traders of type x_j at time t	
$\mathbf{n}(x_{jt}, t)$	Vector of quantity of each ship type at time t	
$\mathbf{n}(y_i, t)$	Vector of quantity of each trader type at time t	
$n_{x_{wait}}$	The number of days a ship waits to match with a trader	Days
N^x	Number of ships	
N^y	Number of traders	
N^z	Number of contracts	
ω	The deadweight tonnage of a ship	Tonnes
$\mathbb{P}(a\|b)$	The probability of a ship going to a load location given it's located at a discharge l location	
$\mathbb{P}(b\|a)$	The probability of a ship going to a waiting location given it's located at a discharge location	
$\mathbb{P}(w\|b)$	The probability of a ship going to a load location given it's located at a waiting location	
$\mathbb{P}(w\|a)$	The probability of a ship going to a load location given it's located at a waiting location	
p^a	Price of oil at a	
$P(x_{jt}, y_i, t)$	The total freight rate	Dollars
$\pi(x_{jt}, y_i, t)$	Oil trader's profits from the sale of oil	Dollars
q^b	Cargo size	Barrels
q^t	Cargo size	Tonnes
r^x	A ship's discount rate	
R_{pie}	The amount of surplus that is leftover once the dummy surplus of each agent is satisfied	Dollars
$\mathbb{R}$	Real number	
s	Surplus function	
$s(x_{jt}, y_i, t)$	Surplus of a match between a trader and a ship	Dollars
$\tilde{s}(x_{jt}, y_i, t)$	Current period's surplus for a match between a trader and a ship	Dollars
$s(\emptyset_x, y_i, t)$	Trader's surplus for remaining unmatched	Dollars
$\tilde{s}(\emptyset_x, y_i, t)$	Trader's current period surplus for remaining unmatched	Dollars
$\tilde{s}(x_{jt}, \emptyset_y, t)$	Ship's current period surplus for remaining unmatched	Dollars
$s(x_{jt}, \emptyset_y, t)$	Ship's total surplus for remaining unmatched	Dollars
T	The terminal period	

Table B.3: Table of symbols (continued)

Symbol	Description	Units
θ_t	Assignment pair	
Θ_t	Set of possible assignment pairs	
v_d	Design speed of a ship	Knots
v_{op}	Operating speed of a ship	Knots
$W^x(x_{jt}, t)$	A ship's payoff in a match	Dollars
$W^x(g(x_{jt}, \emptyset_y), t+1)$	A ship's future payoff at a waiting location	Dollars
$W^x(x^b_{j,t+1}, t+1)$	A ship's payoff to be at a discharge location	Dollars
$W^x(x^a_{j,t+1}, T+1)$	A ship's payoff to be in a load location in period $T+1$	Dollars
$W^x(x^w_{j,t+1}, T+1)$	A ship's payoff to be in a waiting location in period $T+1$	Dollars
$W^y(y_i, t)$	A trader's payoff in a match in period t	Dollars
$W^y(y_i, t+1)$	A trader's future period payoff	Dollars
$\Delta WTP(x_{jt}, x_{j't}, y_i, t)$	The willingness to pay for ship x_{jt} over the substitute ship x_{jt}	Dollars
$x_{j't}$	The substitute to ship x_{jt}	
x_{jt}	A ship type	
$\mathcal{X}_t$	Set of ship types	
$\mathcal{Y}$	Set of trader types	
y_i	A trader type	
$\emptyset_{y_1}$	A dummy trader in the Arabian Gulf	
$\emptyset_{y_2}$	A dummy trader in the West Africa	

Appendix C

Chapter 3

Interviews were conducted with the commercial and operations team tanker team at a major tanker shipping company (Tanker Operator, 2012) and a shipbroker (Shipbroker, 2011). Names were withheld for confidentiality reasons and are paraphrased.

C.1 Tanker shipping company

The notation Q refers to the interviewer question (asked by me) and A refers to the interviewee's answer.

C.1.1 Spot fixing process (Aframax division)

Q: Could you describe a typical spot fixture process, i.e., communication between oil trader/charterer, ship operators, broker?

A: Typically work through brokers (in Asia and London) but have a number of contacts in the oil industry, sometimes will try to pre-empt the spot market by approaching traders/charterers directly if I think I know there is a stem (80,000 lots). I don't work with some companies because they don't pay me on time.

Q: Describe how you advertise your available ships to the market: how many days in advance of unloading current voyage's cargo?

A: I am constantly advertising on a daily basis. Theres some predictability in the market, Shell works with Statoil, Shell buys a number of contracts which they use for themselves at their refineries. Out of these, they might be using some of their own ships to trade oil, with the remaining amount chartered. Once they've supplied their refineries they might have leftover oil which the oil traders play in the spot market which is speculative.

Q: Freight rate: what factors influence the rate you will offer the charterer? How does the bunker price factor into the WS multiplier?

A: I use the previous day's Worldscale rate as a starting point. Use the daily bunker price as a proxy.

Q: Bargaining process: how many counter offers and average days till a deal is reached?

A: It can take between 5 minutes to two weeks.

Q: And do the oil traders wait until they have a ship secured before buying oil?

A: As long as they can see from the broker list that there are enough ships in the market, they will buy the cargo even if they dont have a ship.

Q: Do you ever choose to wait for another charterer prospect if you aren't happy with the deal?

A: Yes, I would rather wait than make a bad decision. Some ports are really expensive like Le Havre. There are some shipowners who really stupid and decide to do a deal and it doesn't make economic sense. Others know they will lose money but they have to pay the bank so they do the deal anyway.

Q: Do you take into account future voyage prospects in loading regions when you decide to designate a ship to a particular route? What information do you use to anticipate the market?

A: Yes, I run a voyage calculation of what we make, taking into account where I would ballast to next. Use today's bunker prices. Finding a bottleneck to exploit and put the prices up is the name of the game.

Q: When does speed get negotiated, and what is the speed you negotiate for?

A: The speed is calculated based on the type of ship and the cost. On average, it's about 13 knots. The relationship between speed and fuel consumption is non-linear, so moving from 14 to 13 knots makes a big difference; from 13 to 11.5 knots is not so much. I always say "about" 13 knots in the charter party so that there is no dispute at the end about exact speed. There is a negotiation on speed, but its often the shipowner who is setting the price (does the calculation at a number of different prices and tries to pick what is looking attractive for the other commercial drivers e.g. when the next voyage is going to be picked up and which way prices are going). The broker is not intelligent, doesnt understand the price/fuel efficiency anyway and also is not-incentivised because their commission is related to the price of the fixture.

Q: How do you factor in piracy risk?

A: We have a map of the piracy zones we can show you. Piracy is a big deal, if you get captured, then you lose the cargo and the crew gets taken hostage.

Q: I've heard many VLCC's use the SUMED pipeline to offload cargo and transit the Suez in order to avoid transiting around the Cape of Hope. Is this a typical practice? How is it priced with Worldscale?

A: Yes this is common practice, but usually it doesn't make sense for the VLCC to transit through the Suez once you've dropped off cargo at Ain Sukna because these cargoes are normally serving Mediterranean and VLCC's can only serve Rotterdam. So an Aframax picks up the cargo at Sidi Kerir.

C.1.2 Voyage Optimization

Q: Do you always choose the shortest route?

A: Not necessarily. We have to factor in piracy and port dues, which are high in the Suez. Sometimes there is a time imperative and so we go via Suez, even if it is better value to go around the Cape (e.g. the oil majors).

Q: If you still haven't sold the ship once at berth, how many days on average will the ship typically wait? The waiting time can be between 2 and 15 days, depending on the market. We never go to a berth unless you have a cargo. Sometimes waiting for a couple of days or sometimes waiting for a couple of weeks. We wait in Fujairah in the Arabian Gulf or West Africa which is a waiting hub where we look for the next fix if we don't forward contract. Shipowners are tracking each other to see where the ships are and decide where to wait for loading. Use AIS data for this.

Q: I've often heard people in the industry say that the ship will set sail to a discharge area but not know the exact port. If so, how many days in advance does the charterer tell you which port to unload at?

A: We almost never know the exact destination until getting close to the destination area. It could be 2 days or even 5 hours before. This depends also on the customer; the oil majors like Shell or BP know where they're going versus the oil traders. Deviation claims on a demurrage rate so wouldnt represent the number of miles. CoA (Contract of Afreightment) cargoes are more obvious in terms of their destination. Its a holding game rather than a dumping and getting out game for the oil traders. They like there to be volatility in the prices because that gives him the chance to make money.

Q: Your company has been a leader in extreme slow steaming not only in containers but also tankers. What factors influence your decision to slow steam in ballast?

A: It is a trade-off between fuel costs and time costs. If we know the next fixture, then we optimise for the laycan period, i.e., if laycan allows 2 days to arrive then we'll use these days to go slower. We also adjust the speed during the laden voyage, for example you can only berth in Japan in daylight, and in Singapore to get over the 1 fathom bank. It's also influenced by demurrage rates. If we get paid to sit around then we'll do that instead of slow steaming.

Q: What percentage of contracts use Virtual Arrival?

A: 1 out of every 25 cargoes. On the shorter voyages it just doesn't make sense. Oil traders aren't interested in Virtual Arrival; if they aren't ready to unload the cargo, they'll either pay the demurrage rate or a storage rate (this could be floating storage).

Q: How do you hedge against volatility in bunker fuel prices?

A: We use swap agreements. Sometimes our container shipping subsidiary has a contract purchase so we'll use some of this bunker fuel. Otherwise, we use Fujarah and Singapore for 95% of fuel sales. This is subject to whatever prices you can find for fuel as on the spot charter.

C.1.3 Other

Q: How do you decide when to lay-up a ship?

A: Lay-up, very rare, but has been done so on the Handymaxes. Today we're making 8-9k per day on a ship (need to make 27k).

C.2 Interview with a tanker shipbroker

Q: Who do you work on behalf of, the owner, charterer or both?

A: Both, it's an independent brokerage firm. The business before was to have multiple brokers representing both, but these days it's just one intermediary i.e., Exxon - shipbroker - Greece though sometimes have one broker providing info to owner, another to the charterer. Some oil majors have their own transportation company like Saudi Aramco has Vela. On charterer side, it's oil companies (Exxon, Shell etc) and traders (Vittal, Glencore). They have brokers for all types of oil - crude, clean, gas, palm oil.

Q: How do you keep track of all the vessels and what vessels do you consider for a fixture in say, the AG?

A: The brokers are in constant contact with the shipowners. It's very much a relationship business, where you're on the phone and email hence over-the-counter trading. Owners advertise their vessel by sending out an email and may deal with multiple brokers. They've got a ship that's available to ship from AG to Rotterdam for example arriving between 5th Sept to 10th. They're responsible therefore for all of the logistics of estimating when they'll be there (i.e., speed) - the shipbroker doesn't estimate this though uses AIS to check.

Q: So the shipowner has to make alot of decisions about repositioning their vessels?

A: Yes, and the oil market has changed to their advantage due to new areas of oil opening up and new demands from China/India and historical relationships changing - i.e., Chavez fell out with USA so now it's shipping to China. Traditionally it was AG to USA and back and now new areas - shipowner has to make alot of decisions about which direction to go based on the market. Since Worldscale is based on a roundtrip cost, they can profit from making smart repositions. To have most options, it'll sail to areas where it can make a split decision to go in two different directions. Often times they'll go around Cape Hope more slowly and avoid the expensive Suez. They also have to fix ships before they reach a port of discharge in order to ensure they get another job. The ship has to be precise about the Laycan dates or else it has to go on the ”spot prompt” - fix on the spot market and wait around.

Q: How do you choose the right ship for the charterer?

A: Since we know where all the ships are, we draw up a candidate list and then cross out the ones that aren't suitable, say if it's too small, or if it's too unreliable (going to India and port is really inefficient). The specs of the ship are vetted by the oil companies who have internal records.

Q: How do you know what price to bargain for?

A: We use the previous freight rate as a base, and then look at the demand/supply to tell them what they should do. There isn't always correlation between oil price and demand to ship stuff, but they need to move it anyway. The owner offers in first, and if the buyer doesn't want it, then goes to next person. Sometimes can take 2-3 days. It's a very sentimental market, sometimes freight rate goes up for no particular reason!

Q: Are speeds always put in the contract?

A: Yes, it's typically 13.5-14 with an option to speed up, though this option is getting less popular due to high bunker prices. It's in the ballast leg where you see a lot of differences between owners, with Maersk running at 9 knots bc they have newer ships and others who are forced to go faster, at 13 or so due to design speed/safety restrictions.

Q: And are there many options for loading cargo, this depends on the size?

A: VLCC is easiest to model because only certain ports let them in due to port constraints, harder for other sizes. You can get the VLCC routes from Clarksons Research data.

Q: Do you work on the spot market and Time Charter? How important is energy efficiency in Time Charter?

A: Energy efficiency is becoming important in Time Charter, getting latest economical engines, though there aren't many ships to buy which are energy efficient.

Q: How do charterers view age of vessel?

A: After 15 years, risk goes up by a lot.

Q: How is your trading desk organized?

A: We have a dirty oil team which is VLCC, Panamax, Afra, and Suez and a clean team (LR2 (coated Afra), LR1, Handy, MR). The LR2 has to be cleaned out if it's just been filled with dirty.

Q: Are inventory costs important in determining quantity demanded per shipment?

A: Not really sure, trader doesn't provide this info. Its most likely related to port restrictions.

Appendix D

Chapter 5 and 6

Table D.1: Missing geographical data for all VLCC fixtures

Load Port	Discharge Port	Load Country	Discharge Country	Frequency	Percent
0	0	0	0	712	14.61
0	1	0	1	42	0.86
1	0	1	0	3842	78.84
1	1	1	1	277	5.68

Source: Clarkson Research (2011)

Table D.2: Missing geographical data for all VLCC fixtures with prices

Load Port	Discharge Port	Load Country	Discharge Country	Frequency	Percent
0	0	0	0	604	17.21
0	1	0	1	33	0.94
1	0	1	0	2689	76.61
1	1	1	1	184	5.24

Source: Clarkson Research (2011)

Table D.3: Trade flows by Area, 2011

Load Area	Discharge Area	Volume	Share (%)
AG	SCH	95,499,000	28.69
AG	KOR	38,294,500	11.50
AG	WCI	22,573,000	6.78
CAR	SPOR	22,550,000	6.77
AG	SPOR	21,622,700	6.50
AG	JAP	21,193,000	6.37
AG	THAI	18,310,500	5.50
AG	USG	15,910,000	4.78
AG	TWN	8,755,000	2.63
CAR	WCI	7,599,000	2.28
WAF	SCH	5,980,000	1.80
AG	UKC	5,555,000	1.67
WAF	WCI	4,420,000	1.33
AG	CALI	3,890,000	1.17
WAF	USG	3,640,000	1.09
WAF	ECI	3,385,000	1.02
AG	NCH	2,948,000	0.89
BRZ	SCH	2,890,000	0.87
WAF	TWN	2,605,000	0.78
AG	ECI	2,588,000	0.78
UKC	SPOR	2,150,000	0.65
AG	SAF	2,145,000	0.64
AG	PHIL	1,612,500	0.48
WMED	SCH	1,590,000	0.48
CAR	SCH	1,360,000	0.41
REDS	SCH	1,325,000	0.40
BRZ	SPOR	1,319,000	0.40
AG	ECC	1,120,000	0.34
AG	REDS	1,105,000	0.33
AG	BRZ	830,000	0.25
ECMX	WCI	820,000	0.25
USG	SPOR	815,000	0.24
WMED	USG	780,000	0.23
KOR	TWN	650,000	0.20

Source: Clarkson Research (2011)

Table D.4: Trade flows by Area, 2011 (continued)

Load Area	Discharge Area	Volume	Share (%)
BALT	USG	535,000	0.16
CMED	SCH	530,000	0.16
REDS	WCI	530,000	0.16
WMED	SPOR	520,000	0.16
AG	CMED	280,000	0.08
EMED	USG	280,000	0.08
BALT	SPOR	270,000	0.08
ECMX	SCH	270,000	0.08
REDS	KOR	270,000	0.08
REDS	PHIL	265,000	0.08
BRZ	UKC	260,000	0.08
JAP	SCH	260,000	0.08
WAF	SAF	260,000	0.08
WAF	SPOR	260,000	0.08
WAF	UKC	260,000	0.08

Source: Clarkson Research (2011)

Table D.5: Representative load, discharge and waiting areas

Area	Country	Representative Port	Area Type
AG	Saudi Arabia	Juaymah	Load
BALT	Estonia	Tallin	Load
BRZ	Brazil	Angra dos Reis	Load
BRZ	Brazil	Sao Sebastiao	Discharge
CALI	USA	Los Angeles	Discharge
CAR	Bonaire	Bonaire	Load
CMED	Libya	Es Sider	Load
CMED	Italy	Augusta	Discharge
ECC	Canada	Canaport	Discharge
ECI	India	Chennai	Discharge
ECMX	Mexico	Cayo de Arcas	Load
EMED	Egypt	Sidi Kerir	Load
JAP	Japan	Sakai	Load & Discharge
KOR	Korea	Ulsan	Discharge
NCH	China	Qingdao	Discharge
PHIL	Phillippines	Davao	Discharge
REDS	Saudi Arabia	Yanbu	Load
REDS	Egypt	Ain Sukhna	Discharge
SAF	South Africa	Durban	Discharge
SCH	China	Ningbo	Discharge
SPOR	Singapore	Singapore	Discharge
THAI	Thailand	Rayong	Discharge
TWN	Taiwan	Kaohsiung	Discharge
UKC	United Kingdom	Sullom Voe	Load
UKC	United Kingdom	Rotterdam	Discharge
USG	USA	LOOP Terminal	Load
WAF	Angola/Nigeria	WAF Centroid	Load
WCI	India	Mumbai	Discharge
WMED	India	Arzew	Load
AG	UAE	Fujairah	Wait
WAF	Angola/Nigeria	WAF Centroid	Wait

D.1 Chapter 6 Regression Results

Table D.6: Benchmark regression results

Coefficients:					
	Estimate	Std.Error	t-value	$Pr(> \|t\|)$	significance
(Intercept)	-3.8392	0.144665	-26.539	2.00E-16	***
log(Dist_short)	0.396768	0.008386	47.313	2.00E-16	***
log(Pbunker)	0.534163	0.015414	34.655	2.00E-16	***
AG-CALI	0.107869	0.086543	1.246	0.212881	
AG-CMED	-0.190146	0.083499	-2.277	0.022967	*
AG-ECC	-0.005138	0.135573	-0.038	0.969774	
AG-ECI	-0.481874	0.081509	-5.912	4.52E-09	***
AG-EMED	-0.30417	0.096144	-3.164	0.001601	**
AG-KOR	-0.244241	0.086618	-2.82	0.004894	**
AG-NCH	-0.164823	0.135588	-1.216	0.224397	
AG-PHIL	-0.274183	0.13564	-2.021	0.043484	*
AG-REDS	-0.491192	0.089117	-5.512	4.44E-08	***
AG-SAF	-0.250945	0.101198	-2.48	0.013299	*
AG-SCH	-0.198636	0.08339	-2.382	0.017391	*
AG-SPATL	-0.191341	0.084635	-2.261	0.023971	*
AG-SPOR	-0.399888	0.083923	-4.765	2.15E-06	***
AG-THAI	-0.332474	0.101172	-3.286	0.001048	**
AG-TWN	-0.250032	0.088815	-2.815	0.004963	**
AG-UKC	-0.063676	0.08456	-0.753	0.451592	
AG-USG	0.076435	0.084075	0.909	0.363483	
AG-WCI	-0.682618	0.080667	-8.462	2.00E-16	***
AG-WMED	-0.093503	0.092743	-1.008	0.313587	
BALT-SPOR	0.129792	0.092606	1.402	0.161335	
BALT-UKC	-0.429717	0.08674	-4.954	8.43E-07	***
BALT-USAC	-0.246365	0.101228	-2.434	0.015104	*
BALT-USG	-0.136223	0.090427	-1.506	0.132245	
BALT-WMED	-0.322078	0.135807	-2.372	0.017886	*
BRZ-BRZ	-0.559367	0.13797	-4.054	5.39E-05	***
BRZ-CALI	-0.013858	0.085732	-0.162	0.871613	
BRZ-ECC	-0.239757	0.135657	-1.767	0.077447	.
BRZ-SCH	0.1817	0.101073	1.798	0.072501	.
BRZ-SPATL	-0.277796	0.135685	-2.047	0.040863	*
BRZ-UKC	-0.162265	0.092687	-1.751	0.080284	.
BRZ-USG	-0.240176	0.092689	-2.591	0.009692	**
BRZ-WCI	0.001626	0.101049	0.016	0.987167	
CAR-CAR	-0.769481	0.098046	-7.848	1.01E-14	***
CAR-ECC	-0.635305	0.111462	-5.7	1.55E-08	***
CAR-SCH	0.080191	0.110712	0.724	0.469023	
CAR-SPATL	-0.241727	0.135669	-1.782	0.075071	.
CAR-SPOR	0.186925	0.092673	2.017	0.043937	*
CAR-UKC	-0.309886	0.135686	-2.284	0.022573	*
CAR-USAC	-0.609709	0.093568	-6.516	1.10E-10	***
CAR-USG	-0.762275	0.087425	-8.719	2.00E-16	***
CAR-WCI	0.154418	0.13559	1.139	0.255013	

p-value: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

Table D.7: Benchmark regression results (continued)

Coefficients:					
	Estimate	Std.Error	t-value	$Pr(>\|t\|)$	significance
CMED-BRZ	-0.233512	0.110776	-2.108	0.035264	*
CMED-CAR	-0.34626	0.135683	-2.552	0.010847	*
CMED-CMED	-0.710944	0.084418	-8.422	2.00E-16	***
CMED-ECI	-0.222441	0.101172	-2.199	0.028114	*
CMED-EMED	-0.838972	0.103624	-8.096	1.51E-15	***
CMED-SCH	-0.006461	0.092601	-0.07	0.944391	
CMED-SPATL	-0.702566	0.087829	-7.999	3.19E-15	***
CMED-SPOR	-0.183321	0.090423	-2.027	0.042869	*
CMED-THAI	-0.13521	0.135588	-0.997	0.318884	
CMED-UKC	-0.465124	0.087034	-5.344	1.11E-07	***
CMED-USAC	-0.32886	0.09053	-3.633	0.000294	***
CMED-USG	-0.220327	0.090421	-2.437	0.014982	*
CMED-WCI	-0.326446	0.087752	-3.72	0.000209	***
CMED-WMED	-0.611157	0.097464	-6.271	5.18E-10	***
ECMX-CAR	-0.705058	0.136246	-5.175	2.72E-07	***
ECMX-CMED	-0.194238	0.135618	-1.432	0.152361	
ECMX-SPATL	-0.247179	0.087611	-2.821	0.00487	**
ECMX-UKC	-0.27924	0.13566	-2.058	0.039792	*
ECMX-USG	-0.883341	0.093022	-9.496	2.00E-16	***
ECMX-WCI	0.101322	0.092609	1.094	0.27416	
EMED-CMED	-0.708279	0.082579	-8.577	2.00E-16	***
EMED-EMED	-0.876659	0.08818	-9.942	2.00E-16	***
EMED-SCH	-0.043486	0.135578	-0.321	0.748464	
EMED-SPATL	-0.664236	0.085001	-7.814	1.30E-14	***
EMED-SPOR	-0.193784	0.090462	-2.142	0.032404	*
EMED-UKC	-0.416348	0.086109	-4.835	1.52E-06	***
EMED-USAC	-0.264903	0.101132	-2.619	0.008932	**
EMED-USG	-0.206513	0.09589	-2.154	0.031488	*
EMED-WMED	-0.54135	0.088405	-6.124	1.28E-09	***
JAP-CALI	-0.253069	0.110808	-2.284	0.022573	*
JAP-KOR	-0.868355	0.113505	-7.65	4.41E-14	***
JAP-SPOR	-0.500314	0.09085	-5.507	4.56E-08	***
JAP-TWN	-0.775115	0.103192	-7.511	1.22E-13	***

p-value: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

Table D.8: Benchmark regression results (continued)

Coefficients:					
	Estimate	Std.Error	t-value	$Pr(>\|t\|)$	significance
KOR-CALI	-0.337177	0.110898	-3.04	0.002419	**
REDS-CAR	-0.193346	0.135628	-1.426	0.154281	
REDS-ECI	-0.568812	0.135966	-4.183	3.10E-05	***
REDS-NCH	-0.108083	0.135588	-0.797	0.425544	
REDS-SCH	-0.086992	0.135581	-0.642	0.521254	
REDS-SPATL	-0.508665	0.136204	-3.735	0.000198	***
REDS-UKC	-0.316202	0.135777	-2.329	0.020051	*
REDS-WCI	-0.552168	0.084251	-6.554	8.65E-11	***
SPOR-CALI	-0.234194	0.092686	-2.527	0.011653	*
SPOR-ECI	-0.577126	0.08128	-7.101	2.24E-12	***
SPOR-JAP	-0.560514	0.081665	-6.864	1.13E-11	***
SPOR-KOR	-0.604362	0.08005	-7.55	9.22E-14	***
SPOR-NCH	-0.542382	0.082036	-6.612	5.96E-11	***
SPOR-PHIL	-0.792355	0.088388	-8.965	2.00E-16	***
SPOR-SCH	-0.604872	0.081392	-7.432	2.17E-13	***
SPOR-SPOR	-0.808916	0.081828	-9.886	2.00E-16	***
SPOR-THAI	-0.806268	0.083567	-9.648	2.00E-16	***
SPOR-TWN	-0.343062	0.091121	-3.765	0.000176	***
SPOR-USG	0.217259	0.11078	1.961	0.050114	.
SPOR-WCI	-0.444888	0.081525	-5.457	6.00E-08	***
UKC-ECC	-0.394949	0.096326	-4.1	4.44E-05	***
UKC-UKC	-0.330547	0.086672	-3.814	0.000145	***
UKC-USAC	-0.367337	0.089101	-4.123	4.03E-05	***
UKC-USG	-0.199717	0.135709	-1.472	0.141405	
WAF-BRZ	-0.391727	0.10135	-3.865	0.000118	***
WAF-CALI	0.062838	0.095859	0.656	0.512265	
WAF-CAR	-0.272293	0.085903	-3.17	0.001568	**

p-value: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

Table D.9: Benchmark regression results (continued)

Coefficients:					
	Estimate	Std.Error	t-value	$Pr(>\|t\|)$	significance
WAF-CMED	-0.494448	0.08219	-6.016	2.44E-09	***
WAF-ECI	-0.150892	0.084594	-1.784	0.07475	.
WAF-EMED	-0.757239	0.095396	-7.938	5.11E-15	***
WAF-SAF	-0.554872	0.088102	-6.298	4.37E-10	***
WAF-SCH	-0.007301	0.135597	-0.054	0.957069	
WAF-SPATL	-0.429913	0.081244	-5.292	1.47E-07	***
WAF-SPOR	-0.094136	0.095903	-0.982	0.326527	
WAF-TWN	0.02846	0.09586	0.297	0.766602	
WAF-UKC	-0.273631	0.080947	-3.38	0.00075	***
WAF-USAC	-0.292384	0.085938	-3.402	0.000693	***
WAF-USG	-0.188464	0.081161	-2.322	0.020412	*
WAF-WCI	-0.161732	0.084126	-1.922	0.054805	.
WAF-WMED	-0.58204	0.09714	-5.992	2.82E-09	***
WCSA-CALI	-0.373684	0.110907	-3.369	0.00078	***
WCSA-SPOR	0.093781	0.135588	0.692	0.489295	
WMED-BRZ	-0.216888	0.110807	-1.957	0.050562	.
WMED-CAR	-0.257634	0.110859	-2.324	0.02031	*
WMED-CMED	-0.4328	0.102989	-4.202	2.86E-05	***
WMED-ECC	-0.349354	0.08909	-3.921	9.36E-05	***
WMED-ECI	-0.080347	0.110785	-0.725	0.468451	
WMED-KOR	0.092239	0.092611	0.996	0.319478	
WMED-SCH	0.10199	0.101043	1.009	0.313023	
WMED-SPATL	-0.418574	0.090458	-4.627	4.15E-06	***
WMED-SPOR	-0.027702	0.092615	-0.299	0.764916	
WMED-UKC	-0.442446	0.086779	-5.099	4.04E-07	***
WMED-USAC	-0.301188	0.086071	-3.499	0.000485	***
WMED-USG	-0.237446	0.092715	-2.561	0.010571	*
WMED-WCI	-0.166057	0.08468	-1.961	0.050135	.
WMED-WMED	-0.389654	0.098681	-3.949	8.37E-05	***

p-value: 0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

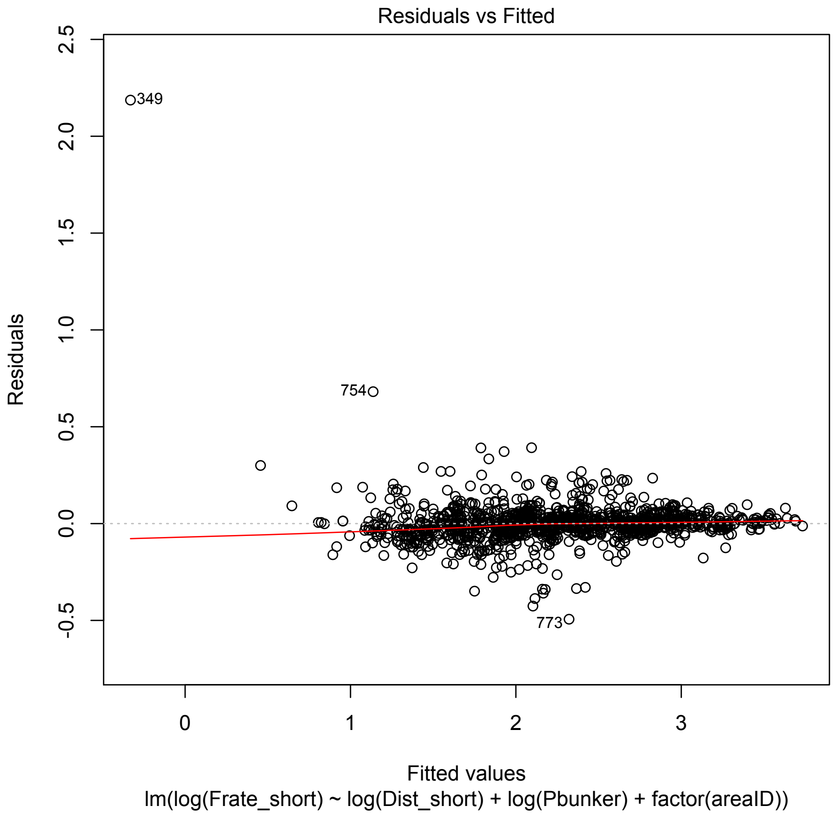


Figure D.1: Benchmark Residuals vs. Fitted

Table D.10: Multiplier regression results

Coefficients:					
	Estimate	Std. Error	t value	$Pr(>\|t\|)$	significance
(Intercept)	-5.979	1.95E-01	-30.695	2.00E-16	***
AG-CALI	0.204	4.82E-02	4.233	2.38E-05	***
AG-ECC	-0.172	6.22E-02	-2.756	0.005882	**
AG-ECI	0.341	5.84E-02	5.851	5.47E-09	***
AG-JAP	0.170	4.60E-02	3.695	0.000224	***
AG-KOR	0.147	4.49E-02	3.28	0.001051	**
AG-NCH	0.145	5.57E-02	2.597	0.009446	**
AG-PHIL	0.111	6.15E-02	1.797	0.072431	.
AG-REDS	0.225	5.10E-02	4.408	1.08E-05	***
AG-SAF	0.176	5.93E-02	2.969	0.003012	**
AG-SCH	0.190	4.50E-02	4.216	2.57E-05	***
AG-SPATL	-0.256	1.16E-01	-2.202	0.027742	*
AG-SPOR	0.194	4.53E-02	4.288	1.86E-05	***
AG-THAI	0.188	4.58E-02	4.11	4.07E-05	***
AG-TWN	0.146	4.65E-02	3.132	0.001757	**
AG-UKC	-0.031	4.98E-02	-0.613	0.539924	
AG-USAC	0.232	1.92E-01	1.206	0.228008	
AG-USG	-0.134	4.54E-02	-2.951	0.003195	**
AG-WCI	0.196	4.60E-02	4.255	2.16E-05	***
AG-WMED	-0.037	9.44E-02	-0.389	0.69745	
BALT-USG	0.045	1.39E-01	0.32	0.748637	
BRZ-CMED	0.166	1.92E-01	0.864	0.387888	
BRZ-SCH	0.185	5.95E-02	3.105	0.001924	**
BRZ-SPOR	0.111	9.45E-02	1.171	0.241517	
BRZ-UKC	0.320	1.92E-01	1.668	0.095492	.
BRZ-USG	0.303	1.03E-01	2.938	0.003331	**
BRZ-WCI	0.046	1.17E-01	0.398	0.690929	
CMED-SCH	0.210	1.92E-01	1.095	0.273754	
ECMX-USG	0.320	1.17E-01	2.743	0.006123	**
EMED-EMED	0.286	1.92E-01	1.489	0.136664	
EMED-UKC	0.226	8.83E-02	2.558	0.010577	*
EMED-USG	0.208	1.03E-01	2.01	0.044569	*

p-value: 0 *** 0.001 ** 0.01 * 0.05 . 0.1   1
One-way clustered standard errors, clustered variable on shipowner

Table D.11: Multiplier regression results (continued)

Coefficients:					
	Estimate	Std. Error	t value	$Pr(>\|t\|)$	significance
JAP-SCH	0.024	1.92E-01	0.126	0.89977	
JAP-TWN	0.103	1.92E-01	0.536	0.591838	
REDS-KOR	0.146	1.39E-01	1.046	0.295453	
REDS-NCH	0.503	1.92E-01	2.624	0.00874	**
REDS-PHIL	0.096	1.92E-01	0.498	0.618585	
REDS-SCH	0.247	1.04E-01	2.383	0.017227	*
REDS-USG	-0.096	1.92E-01	-0.502	0.615482	
REDS-WCI	0.285	1.39E-01	2.044	0.041004	*
SPOR-JAP	0.812	1.92E-01	4.235	2.36E-05	***
UKC-ECC	0.331	1.17E-01	2.844	0.004492	**
UKC-USG	0.226	7.16E-02	3.152	0.001636	**
WAF-SAF	0.290	1.39E-01	2.083	0.037342	*
WAF-SCH	0.147	6.04E-02	2.431	0.015126	*
WAF-SPOR	0.150	1.92E-01	0.781	0.435155	
WAF-TWN	0.074	7.64E-02	0.966	0.334273	
WAF-UKC	0.032	1.39E-01	0.227	0.820589	
WAF-USAC	0.170	1.92E-01	0.886	0.375789	
WAF-USG	0.169	5.94E-02	2.84	0.004549	**
WMED-KOR	0.150	8.81E-02	1.699	0.089343	.
WMED-SCH	-0.001	1.16E-01	-0.006	0.995013	
WMED-SPOR	0.061	1.39E-01	0.437	0.662197	
WMED-USG	0.202	5.11E-02	3.948	8.06E-05	***
Age	0.009	2.77E-03	3.228	0.001259	**
I(Age$\hat{2}$)	-0.0004	1.24E-04	-3.053	0.002289	**
DWT	0.000	3.60E-07	3.471	0.000526	***
log(p(hfo))	0.244	1.77E-02	13.829	2.00E-16	***
(Flag_HT)1	0.066	2.19E-02	2.99	0.002812	**
log(lag_BDTI)	1.171	2.16E-02	54.339	2.00E-16	***
(YR)2008	0.034	1.39E-02	2.47	0.013558	*
(YR)2009	0.128	1.79E-02	7.144	1.15E-12	***
(YR)2010	0.055	1.35E-02	4.074	4.74E-05	***
(YR)2011	-0.098	1.81E-02	-5.4	7.20E-08	***

p-value: 0 *** 0.001 ** 0.01 * 0.05 . 0.1   1
Age=ω; Age$\hat{2}$=ω^2; DWT=α
One-way clustered standard errors, clustered variable on shipowner

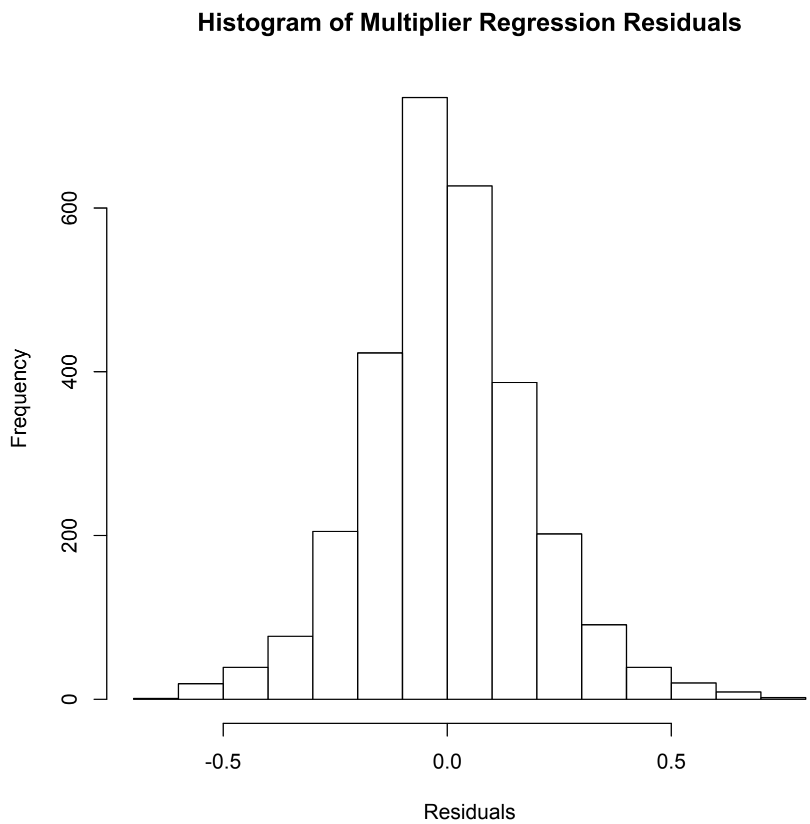


Figure D.2: Histogram of Residuals (Multiplier Regression)

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