MATCHING ON THE TANKER MARKET

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1. Abstract

This paper explores the economic determinants of matches (who transacts with whom) between ships and traders and the intra-allocation of the gain generated by matching using a matching model. The findings show that when ships are differentiated by only location, holding their physical characteristics constant, the ships that are matched to traders are located closest to the cargo load area, which minimizes the costs of shipping. When ships are differentiated by physical characteristics (including energy efficiency), holding location constant, the most favored ship type depends on the assumptions about cargo size. Varying location and physical characteristics shows that ships which are the most favored by physical characteristics cannot compete as strongly with ships of lesser quality which are located closer to the market. These results emphasize the importance of optimizing the efficiency of the fleet in terms of both operational efficiency and technical efficiency, especially in light of the limits on ship size that reflect the customer's preferences.

Keywords: matching; tanker shipping; linear programming; energy efficiency

2. Introduction

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. Understanding the impact of these geographical, physical, and time dimensions is especially relevant in today's market, which has been confronted with a sharp rise in fuel prices and a slump in freight rates, particularly damaging to the tanker market given ships almost always have to sail empty once they unload their cargo to another source incurring a cost that is proportional to distance travelled.

Since Koopmans' seminal work in the 1930s on the tanker shipping industry, the classical maritime economics literature has followed predominantly an aggregate modeling approach of supply and demand econometric modeling by assuming one route for simplicity, avoiding the task of modeling voyages of different duration. This simplification might have been justified by the dominance of the Arabian Gulf-Northern Europe route in past decades, but changing trade flows due to demand from Asia have increased the spatial complexity of ship movements. By excluding the geographical dimension, the aggregate approach is not equipped to model the spatial and temporal specificities in the market that lead to volatility in prices. The aggregate supply curve is also outdated, assuming that ship owners are indifferent between providing service and not (their refusal rate) at a rate equal to their marginal operating costs minus the lay-up cost. In recent years, it has been noted that there has been a tendency for idle tankers to wait fully operational in the loading area (Kennedy, 2002). Lay-up is costly because ships have 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 which is supported by the small proportion of ships in lay-up (about 5% of the fleet). Additionally, the assumption that prices reflect perfect competition is at odds with the volatility in the time series of prices, in which the spot rate frequently reaches levels that are unrelated to the marginal cost of transport, producing supernormal profit to owners.

In a market with heterogeneous buyers and sellers, who is matched with whom and the intra-allocation of the gain generated by a match is a function of the other market players. This equilibrium concept of dependency on the market environment to determine the matching outcome endogenizes the power between each pair. A matching model is a particularly applicable framework for the tanker shipping market because ships and traders are heterogenous - ships are differentiated by their location and physical characteristics and traders by their expected net oil revenue and their cargo demand requirements. The consideration of agents' outside options or the opportunity cost of matching is crucial because there are large stakes of money involved (millions of dollars) and different matching options. The location of a ship is a large factor in determining the shipment cost and time, affecting a traders' oil revenue and a ship's local market competition. The latter feature means that ships need to understand the implications of matching to a trader in terms of not only the current match-specific trading costs and benefits but also the consequences of the decision in terms of future employment from the destination. Not only are there considerations about who to match with, but an inter-temporal decision - whether to match in the current period or wait a period and match in the next period.

I use a subsample of data on VLCC shipment transactions to estimate the matching model. The methodology builds on previous work on the estimation of dynamic settings, Rust (1987) and Devanney (1971) on single agent dynamics, Chiappori, McCann and Nesheim(2009) on matching models. The model incorporates two features of the industry. First, demand for oil is inherently uncertain and volatile and is modeled as exogenous. Second, supply adjusts slowly to new entrants because of time to build constraints (one to three years) and will focus on the short-run.

3. Description of the Industry

The market for shipping oil exists because there is world demand for oil which cannot be met by domestic production or pipeline supply. The majority of tanker shipments are for crude oil, reflecting the location of refineries which are typically near consumption areas. VLCCs accounted for 38% of capacity and of 52% of the tankers that transport crude oil [1] Economies of scale make vessels in larger size categories more fuel efficient per tonne-mile, but the length of the route, port and canal constraints, and shippers' cargo size preferences leads to different optimum sizes for trade routes that differ in these parameters. The industry has around 1,750 firms, with the largest firm only accounting for 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. The industry is competitive in terms of the distribution of output shares.

Demand for shipping crude oil is rather inelastic, especially in the transportation sector, which accounts for a greater share today than the 1970s (61.5% of total consumption in 2010). Fuel substitution possibilities are far more limited, and the share has increased since 1973 as emerging economies in Asia and South America have greater income to purchase vehicles. The general shift of global oil demand to non-OECD countries is shown in figure 1 shows total consumption by region. The Asia Pacific region surpassed North America as the largest consumer of oil in 2004.

[1] Although the three largest classes of ships - VLCC, Suezmax, and Aframax - transport crude oil, the shipping industry treats them as different markets.

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, speed, and days in port. Speed is influenced by a tradeoff between revenue and costs. Costs can be divided into fixed and variable costs. Capital, periodic maintenance, and operating costs are all fixed costs because they are incurred regardless of whether a ship is employed. Variable costs include fuel, port charges, and canal dues. Fuel costs represent the largest variable cost and this proportion has risen given the 5 fold increase since 1990, averaging $645 per tonne in 2011 (Figure 2).

4. Model Structure

The assumption that the tanker market is competitive lays the foundation for modeling the agents in the tanker shipping industry as behaving competitively in a matching game. In this section, a matching model is constructed for allocating charterers to ships (shipowners) which can be used to simulate the market. To simplify the number of market players on the demand side, the buyer in this model is referred to as an oil trader and demand for cargoes will be modeled as exogenous.

In a competitive equilibrium, each agent is assigned the object that maximizes his utility given the current prices (the surplus) such that the supply is equal to demand. In a matching economy, an alternative way to compute an equilibrium is to find the allocation that maximizes social surplus subject to constraints on resources (ships) and cargo demands (from traders). 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. The simplest way to compute the competitive equilibrium is to solve a linear programming program, which is a simple but large combinatorial optimization problem where the combinations to be optimized are the surpluses from the pairings of agents.

4.1. **Environment.** The model consists of a set $\mathcal{Z}$ of N^z shipping contracts, a finite set $\mathcal{Y}$ of N^y potential buyers and a finite set $\mathcal{X}$ of N^x sellers, where buyers are oil traders and sellers are firms who own ships. A ship is a firm and the terms will be used interchangeably. Time is discrete and the unit is one week.[2] Agents are characterized by a vector of attributes that define the type space of each.

A trader i at time t has a type vector y_{ti} embodying its characteristics and likewise a ship j has a type vector x_{tj}. Each oil trader owns a quantity of oil ($> 200,000$ tons) that needs to be shipped. Profits are determined by the expected oil price arbitrage between locations, the freight cost, and the estimated time of shipment arrival. He also has the option to store the oil at a cost and ship it next period and therefore remain unmatched. Ships are located in different locations at the start of the period; locations include load (source) areas, discharge (sink) areas, and waiting areas. Waiting locations are sea located near sources where ships can sit idle until they match with trader that has a cargo that needs lifting. 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. Associated with each unmatched agent is a "dummy" agent from the other side of the market. For example, if a trader decides to remain unmatched, he matches with a dummy ship. There is a value to remaining unmatched for both agent groups, which differs from most of the matching literature.

[2]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.

[3] 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.

A trader's type has 6 dimensions that affect profits and costs:

$$y_{ti} = \begin{pmatrix} \mathcal{A}_t \\ \mathcal{B}_t \\ p_t^a \\ p_t^b \\ \beta^y \end{pmatrix} = \begin{pmatrix} \text{Load location set } \mathcal{A}_t \\ \text{Discharge location set } \mathcal{B}_t \\ \text{Price of oil at } a_t \in \mathcal{A}_t \\ \text{Expected price of oil sold at } b_t \in \mathcal{B}_t \\ \text{Discount factor} \end{pmatrix}$$

Ships are characterised by 8 dimensions that affect profits and costs:

$$x_{tj} = \begin{pmatrix} \mathcal{L}_t \\ \omega \\ \alpha \\ v^d \\ k \\ c^f \\ \beta^x \end{pmatrix} = \begin{pmatrix} \text{Current location of ship} \\ \text{Deadweight tonnage of ship} \\ \text{Age} \\ \text{Design speed} \\ \text{Daily fuel consumption (tons)} \\ \text{Daily fixed costs} \\ \text{Discount factor} \end{pmatrix}$$

The current location of a ship is a vector of all location sets $\mathcal{A}_t, \mathcal{B}_t, \mathcal{W}_t$, where $\mathcal{W}_t$ is a vector of waiting locations.

4.2. **Payoffs in the matching game.** The ship's payoff is comprised of three components:

(1) $P(x_j, y_i, t)$ is the freight rate.
(2) $C(x_j, y_i, t)$ is the shipment cost which equals the repositioning cost, $c^{rep}_{t,la}$, and the voyage cost, $c^{voy}_{t,ab}$.[4]
(3) $\beta^x W^x(b, t+1)$ is the expected net present value of being in the discharge location.

A trader receives a payoff $W^y(y,t)$ equal to $\pi(x_j, y_i, t) - P(x_j, y_i, t)$ if it matches with a ship where $\pi(x_j, y_i, t)$ equals the expected profits from the sale of oil. If they match, their combined payoffs (also known as the economic surplus) are:

$$\begin{aligned} s(x_j, y_i, t) &= [\pi(x_j, y_i, t) - P(x_j, y_i, t)] + [P(x_j, y_i, t) - C(x_j, y_i, t) + \beta^x W^x(b, t+1)] \\ &= W^x(x,t) + W^y(y,t) \end{aligned}$$

(1)

Because the payoffs include a transfer of $P(x_j, y_i, t)$ (the freight rate) from the trader to the ship, the freight rate cancels out.

The continuation value for a ship that matches with a trader represents the value for the ship to be at a discharge location once it drops off the cargo. If a ship is at a discharge location b, it has the following options:

(1) Go to a load area $a \in A$
(2) Go to a waiting area $w \in W$

[3] See Shapley and Shubik (1972) and Chiappori, McCann and Nesheim (2009)) that assigns a value of 0 to null matches.

[4] See Appendix for a more detailed cost equation.

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

$$W^x(b,t+1) = \sum_{a\in A} \mathbb{P}(a|b)\Big(- c^{rep}_{ba} + \beta^{x,d(b,a)} W^x(a,t+1)\Big) + \sum_{w\in W} \mathbb{P}(w|b)\Big(- c^{rep}_{bw} + \beta^{x,d(b,w)} W^x(w,t+1)\Big) \quad (2)$$

It is apparent from this equation that the value to be at b depends on the values of locations $a \in A$ and $w \in W$. These values are estimated using a system of linear equations containing data that parameterizes these values, namely revenue and costs for the trade flows from the load areas and the costs to be in a waiting area.

4.3. **Values to remain unmatched.** The value to remain unmatched (the dummy match) for the trader is:

$$s(\emptyset_x, y_i, t+1) = \bar{\pi}(x_j, y_i, t) - C^{store} - \mathbb{E}(P(a,b,t+1)q^t \quad (3)$$

where:

$\bar{\pi}(x_j, y_i, t)$	average expected oil revenue at $t+1$
C^{store}	oil storage cost
$\mathbb{E}(P_{t+1})$	expected freight rate for route $a-b$ at $t+1$
q^t	cargo size (tonnes)

If the ship doesn't match, it has to go to one of the waiting areas $w \in W$. The model considers two waiting areas: Fujairah in the Arabian Gulf and the other in West Africa. The value to remain unmatched for the ship is:

$$s(x_j, \emptyset_y, t+1) = -c^{rep}_{lw} + \beta^{x,d(l,w)} W^x(w,t+1) \quad (4)$$

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

4.4. **A competitive equilibrium associated with a linear programming problem.** It is well known that the solution to the assignment problem using linear programming can be used to compute a competitive equilibrium (Koopmans and Beckman, 1957). Specifically, the solution provides a unique allocation of buyers to sellers in a decentralized profit-maximizing economy. Appendix C provides the formulation for the assignment problem.

There are two outputs from solving the linear program:

(1) $m(x_j, y_i, t)$: the assignment or matching probability
(2) The marginal values for ships and traders: $W^x(x_{t+1}, t+1)$, $W^y(y, t+1)$

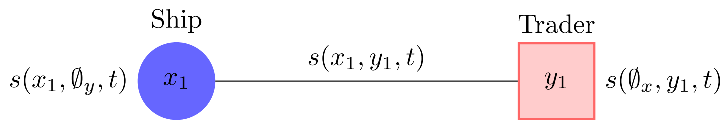
Prices can be found by utilizing the accounting relationship with either marginal value of ship or trader:

$$P(x_j, y_i, t) = \pi(x_j, y_i, t) - W^y(y,t) \quad (5)$$

Similarly, the price can also be derived from the ship's payoff equation:

$$P(x_j, y_i, t) = C(x_j, y_i, t) + W^x(x,t) - \beta^x W^x(b, t+1) \quad (6)$$

The matching between two agents is graphically depicted in the figure below for a ship x_1 and a trader y_1. Suppose the ship and the trader are bargaining about how to split the surplus and 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 $s(\emptyset_x, y_1, t)$ and consequently, each agent can leave the negotiations if they each do not get at least these outside options respectively. If $s(x_1, \emptyset_y, t) + s(\emptyset_x, y_1, t) > s(x_j, y_i, t)$, 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, $s(x_1, \emptyset_y, t) + s(\emptyset_x, y_1, t) \leq s(x_1, y_1, t)$. In the model, it can be shown that this property holds for all the trades that occur.



When a ship and trader match, they have to decide how to split the rest of the pie once their minimum requirements (in this case, dummy match values) are met. This is given by:

$$R_{pie} = s(x_j, y_i, t) - s(x_j, \emptyset_y, t) - s(\emptyset_x, y, t)$$

where R_{pie} stands for residual pie. With a finite number of agents, the equilibrium conditions (demand to supply ratio) 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 none of the pie. 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, there is no explicit bargaining power, but the ability for each agent in a match to eat away at the leftover pie is impacted by the market tightness in the local market (defined as $locDSR$, the number of traders demanding cargo in the load area over the number of ships in the load area) and the relevant substitution possibilities outside the local market which depends on the location of other ships and their other opportunities determined by the aggregate demand to supply ratio ($aggDSR$). In the baseline model where ships are differentiated by their location, if $locDSR$ is greater than 1 such that demand is greater than supply, traders have to consider ships from other areas and the price they can get from matching with these ships lowers the economic rent a ship in the local market can obtain. I vary the supply of ships across locations which allows me to define the relevant submarket describing the set of ship types which constrain a ship type's pricing decisions. I refer to ships and traders in the model as being either on the short or long side of the market. A ship on the short side of the market has the ability to raise prices above his dummy match value, while a ship on the long side of the market faces substitutes for his products and therefore his market power will be limited. Ships on the short side of the market do not face pricing constraints except to the extent that buyers (traders) decide not to purchase at all. In the model, a traders' decision to not purchase (not match) is a decision between the relevant matches in the market and his dummy match option (the expected earnings next period). A ship on the long side of the market gets his dummy match value in a match with a trader and this has the economic interpretation that he is indifferent between matching with a trader or matching with a dummy trader (relocating to a waiting location). His indifference is caused by the excess supply of ships which increases competition and drives down the ship's earnings to his dummy value.

5. Data and Model Estimation

The model requires the following data inputs, which are calibrated using 2011 data:

(1) Types of ships

(2) Types of traders
(3) Cost of journeys
(4) Duration of journeys
(5) Price earned on journeys
(6) Values of locations for ships

The table below shows the parameters required and sources used for the model inputs.

TABLE 1. Data Inputs and Sources

Model Input	Parameters	Sources
Types of ships	location, physical characteristics	BP, Clarksons Research
Types of traders	oil revenue, cargo demand	EIA, Clarksons Research
Duration of journeys	distance, route	AXS Marine, Suez Canal Authority
Cost of journeys	fuel price, fixed costs, piracy costs	Clarksons, Frontline, Univ. of Austin Texas
Freight prices on journeys	benchmark prices, WS prices	Worldscale Association, Clarksons, Baltic Exchange
Value of locations for ships	ship revenue, costs	Inputs 4) and 5)

The supply of ships in each location was determined using a top-down approach of crude oil imports and exports and an assumption about waiting time in port as there was not sufficient data available on the number of ships in each sea area (Table 7). Given this information, the baseline ships available to match is given in Table 9. To differentiate ships by physical characteristics, I use cluster analysis based on DWT, age, design speed, and as-designed daily fuel consumption (Figure 3) which classifies the fleet into three types (Table 8) .

To estimate types of traders, I collected data on oil prices in different load areas. I assume traders have the same expectation about the oil price in each destination; there is an average $7.3 per barrel arbitrage profit, calibrated from observed variance in oil prices. Given these simplifying assumptions across traders, the attributes that differentiate traders in the baseline model are shipment location and and price at the origin (Table 10).

I estimate the benchmark and WS prices per route using a hedonic price regression (contained in the appendix) which depends on the load and discharge areas, fuel price, age, the Baltic Dirty Index, DWT and a year time dummy.

The results for the estimation of continuation values are given in Figure 4 for 2011 due to the overcapacity of ships. The values to be at discharge locations are negative because the discounted freight revenue is not high enough to outweigh the repositioning costs. It is not unusual to operate under losses in tanker shipping, especially given the depressed state of the market in 2011. 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."

6. Results

6.1. **One dimensional matching.** In the baseline model, I consider ships which are differentiated by their location, holding physical characteristics and speed constant during "matched" [5] voyages.

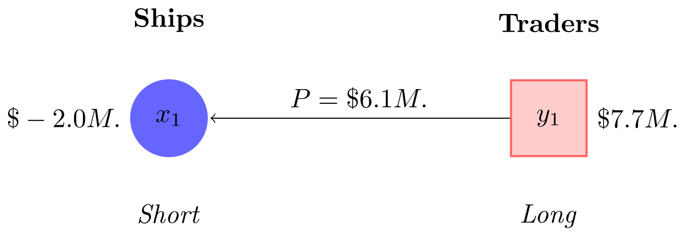
[5]Matched voyages can include both repositioning and voyage legs, the former occurs when the ship is not located in the same load area where the cargo is demanded.

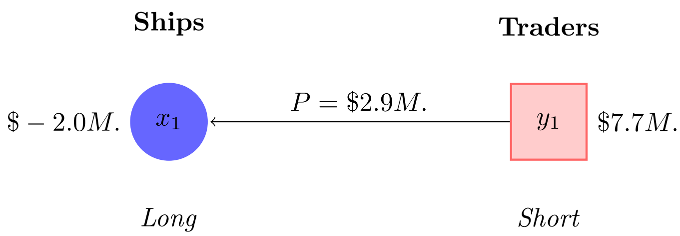
Speed is a parameter that is negotiated between the trader and the shipowner but in practice can be slow to adjust to changing conditions (though it is a parameter that can be optimized in the model). Given high fuel prices and low freight rates, many shipping companies are trying to negotiate slower speeds; according a statement from the chief of Frontline in 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."

The simplest situation to illustrate how the model splits the surplus is to consider the situation where there is only one ship and trader type. The figure below shows two scenarios in which ships are on the short side (top graph) and long side of the market (bottom graph) for a ship located in the Brazilian discharge area and demand for cargoes in the Brazilian load area. The equilibrium (stability) condition requires that the trader must receive at least its outside (dummy match) option of \$7.7 million to stay in the match while the ship must receive at least \$-2.0 million in order to match. A ship earning a negative amount means he incurs a loss if he doesn't match, implying he is indifferent between matching or not when his earnings in a match equals his dummy option value. The price he is willing to accept is therefore derived as $P(x_j, y_i, t) >= s(x_j, \emptyset_y, t) + C(x_j, y_i, t) - \beta^x W^x(b, t+1)$.

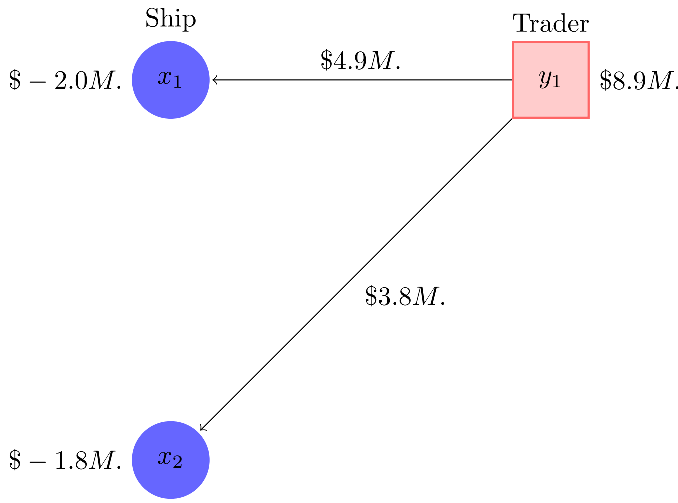
After the stability conditions are met, the residual pie (money leftover to split) is \$3.2 million. When ships are on the short side of the market (supply is less than demand), they are able to extract the entire residual pie. The Lumpsum price [6] is \$6.1 million and the ship earns \$1.2 million. In contrast, when ships are on the long side of the market and the *locDSR* is below 1, the price drops to \$2.9 M. in which he is indifferent between matching and remaining unmatched. Now the trader obtains the residual pie. This example demonstrates that as long as supply is equal to or greater than demand ($locDSR <= 1$, the trader is allocated all of the residual pie, leading to a large drop in price. A special case is when supply equals demand in the local market. In this case, the LP program in Matlab chooses the trader to gain 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.

[6] This analysis reports prices generated from the model in both Lumpsum (gross shipment price) rather than WS prices for transparency of model results, though a WS price can be derived using Worldscale benchmark prices.





Keeping demand fixed at one cargo in Brazil, I then simulate the impact of including all the ships in the population (Table 9). The model matches the residual demand to a ship located in West Africa (WAF). This reveals the relevant substitution of ships in Brazil is ships located in West Africa. The presence of ships in WAF increases the competition for the cargo in Brazil, lowering the economic rent that the ship in Brazil can extract. Because there is an excess supply of ships in WAF, the ship is only able to obtain its dummy outside option ($-1.8) and the trader receives earnings of $8.9 M. Now the trader must obtain at least this outside option to match with the ship in Brazil, lowering the ship's earnings to -$.003 M. at a Lumpsum price of $4.9. When the ship supply is incrementally increased by an additional 10% in each location over the baseline, prices drop when the local DSR in Brazil is <= 1, the same result as when ships were on the long side of the market when there was one ship and trader type. 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. Although prices are not unique, the change in price when there is only one ship type and multiple ship types introduces the kind of volatility in prices that characterizes the time series data, unlike an aggregate modeling approach which assumes price equals marginal cost or a refusal rate.



The one dimensional model results show that the optimal allocation minimizes the shipment costs. This is equivalent to minimizing the repositioning cost to the load areas where the cargo is demanded. Figure 5 shows the impact of cost on matches (where an optimal match is in group 1) by plotting all of the possible match combinations; Figure 6 shows the resulting surplus from these matches. Matches occur at the lower end of the cost spectrum and surplus is at the higher end of the spectrum which is the expected result. Matches which are low cost but are in the no match group occur because of the resource constraints. The ships that do not match are located farther away from the load areas in California and the Far East and have to relocate to a waiting area.

6.2. **Multidimensional matching.** In the baseline model, ships varied by one dimension in their location. In this simulation, ships vary by their location and physical characteristics. As described section 5, the model has three distinct physical character types, differentiated by age, DWT, design speed, and the ship's as-designed daily fuel consumption (k). 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 to $\#Locations * \#PhysicalTypes$ (54 types).

Fuel efficiency of ships is a complicated matter, influenced not only by a vessels 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 fuel cost per output (ton-nautical miles or t-nm) which in the model is equivalent to its average variable costs. Economies of scale exist if the long-run average cost, defined as average variable cost plus average fixed costs, decreases with output. 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; Type 2 which is a smaller ship than Type 1 has a higher fuel efficiency. Given a cargo size of 260,000 tons, the average fuel cost (fuel cost per t-nm) for Type 2 is the lowest, followed by Type 3 and Type 1. The cargo size needs to be greater than 265,360 tonnes for Type 1 to be more efficient than Type 3.

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 except in the ship's option value through its effect on the estimated multiplier price.

From an economic perspective, it is interesting to understand how the matching changes when capacity utilization is varied. Two different versions are run to understand how ships of each type are chosen: *Bigger is Better* and *Energy Efficiency Rules.* In *Bigger is Better*, a ship obtains a constant capacity utilization rate such that $q^t = DWT * caputil$, using a capacity utilization rate of 88%. In contrast, *Energy Efficiency Rules* assumes a constant cargo size of 265,900. The ways in which the different dimensions impact the primitive parameters in the model are summarized below:

TABLE 2. Multidimensional impact on model parameters

Dimension	Cargo size (q^t)	Fuel cost ($c^f_{ll'}$)	Freight rate ($P(a, b, t+1)$)
Location (l)		x	x
Age (α)			x
DWT (ω)	x	x	x
Design speed (v^d)		x	
Tonnes per day (k)		x	

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. When ships are differentiated by one dimension (location) holding design characteristics constant, the problem is an assortative matching problem; ships were chosen based on their minimum cost (proximity to load area) which is equivalent to maximizing profits for a given level of output. However, size influences both revenue and costs; whether a ship within the VLCC fleet is more profitable depends on the assumption about its capacity utilization. For example, despite Type 1's cost disadvantage over Type 2, Type 1 can potentially earn more revenue by achieving a higher cargo size (16,571 tons [7]) which would outweigh its relatively higher shipment costs.

The table below shows which of the physical characteristics affect the match surplus function ($s(x_j, y_i, t)$) components in *Bigger is Better*:

TABLE 3. Parameters affected in *Bigger is Better*

Surplus component ($s(x_j, y_i, t)$)	Primitive parameters affected
Expected Oil Revenue ($\pi(x_j, y_i, t)$)	q^t
Shipment Cost ($C(x_j, y_i, t)$)	v^d, k
Ship Option Value ($\beta^x W^x(b, t+1)$)	$P(a, b, t+1), q^t, C(x_j, y_i, t)$

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 in *Bigger is Better*, Figure 7 shows the decomposition of the ship's option value by each of the three primitive parameters which are impacted by varying the ship's physical characteristics: price, quantity, and cost. The figure

[7]Assuming a .95 capacity utilization rate. 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.

shows the option values are highest for Type 1 due to a combination of price and quantity effects which outweigh the increased cost. For example, the difference in average option values due to a change in q^t is \$.42 M. between Type 1 and Type 2 while the price difference \$.02 M. for Type 1 all else constant. On the other hand, costs are higher for Type 1 (\$.301 M.) than Type 2. The net effect is \$.14 M. in favor of Type 1.

By comparison, in *Energy Efficiency Rules* where the cargo size is the same across ship types, the only advantage of having a larger ship is the impact of DWT on $P(a, b, t+1)$ which is not enough to outweigh the increased costs so Type 2 ranks highest as shown by Figure 8.

Table 4. Parameters affected in *Energy Efficiency Rules*

Surplus component ($s(x_j, y_i, t)$)	Primitive parameters affected
Expected Oil Revenue ($\pi(x_j, y_i, t)$)	
Shipment Cost ($C(x_j, y_i, t)$)	v^d, k
Ship Option Value ($\beta^x W^x(b, t+1)$)	$P(a, b, t+1), C(x_j, y_i, t)$

Figure 9 shows a comparison of the surplus components by ship type for the two model versions when location is fixed and ships go a constant speed of 13.5 knots (ships of each type are located in Brazil and match to trader demanding BRZ-SCH cargo shipment). It is clear that the additional oil revenue has the most positive influence on the match surplus in *Bigger is Better*, while there is no difference among types for the *Energy Efficiency Rules* version.

The results of the *Bigger is Better* simulation show that ships in the largest size class (Type 1) earn the most, followed by Type 2 and 3. Traders match with all three ship types but in varying quantities. Type 1 is the most utilized [8] (70%), Type 2 has a 45% utilization rate and Type 1 only 1%. Ships of Type 1 which are located in close proximity to the local market are associated with the highest surplus. In contrast, ships of Type 1 which are located farther away from the local market at a disadvantage to ships located closer to the market. This is evidenced by the ships of Type 1 who do not match; they are all located farther away from load area markets, the majority in California and the Far East. The results reveal an intuitive result: ships which are not strategically located are not as competitive compared to ships located near the local market despite their comparative advantage in other dimensions.

The results show a significant change in matching in *Energy Efficiency Rules* with Type 2 utilized at a higher rate (56% compared to 45% in *Bigger is Better*) and an equivalent utilization rate for Type 1 and Type 3 (43%). The difference demonstrates the impact of changes in cargo size. With equal payload, the most energy efficient ships have a greater probability of matching.

7. Conclusion

This paper has explored the economic determinants of matches (who matches with whom) between ships and traders and the intra-allocation of the gain generated by matching using a matching model. The findings show that when ships are differentiated by only location, holding their physical characteristics constant, the ships that are matched to traders are located closest to the cargo load area, which minimizes the costs of shipping. By varying the supply of ships in different areas, the model is able to produce volatility in prices which is characteristic of the market. When ships are differentiated by physical characteristics (including size), holding location constant, the most

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

favored ship type depends on the assumptions about cargo size. When the capacity utilization rate is the same across ship types, bigger ships are better. However, when the cargo size is the same across types, the most energy efficient but slightly smaller ship is utilized the most. Varying location and physical characteristics shows that ships which are the most favored by physical characteristics cannot compete as strongly with ships located closer to the market, implying that there is a tradeoff between physical characteristics and location. Overall, the results of the matching model emphasize the importance of optimizing the efficiency of the fleet in terms of both operational efficiency and technical efficiency, especially in light of the limits on ship size that reflect the customer's preferences.

8. Acknowledgements

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Appendices

A. Introduction

B. Input into payoff functions

The total shipment cost from the ship's current location l to destination b is:

$$C(x_j, y_i, t) = c_{la}^{rep} + c_{ab}^{voy} \tag{7}$$

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

$$c_{ll'}^{rep} = c^c(\frac{\phi_{ll'}}{24v^{op}}) + c_{ll'}^f \tag{8}$$

where c_{la}^{rep} is the repositioning costs where c^c are the daily fixed costs, including capital and $c_{ll'}^f$ equals the fuel cost:

$$c_{ll'}^f = p^{hfo}k(\frac{v^{op}}{v^d})^3\frac{\phi_{ll'}}{24v^{op}}$$

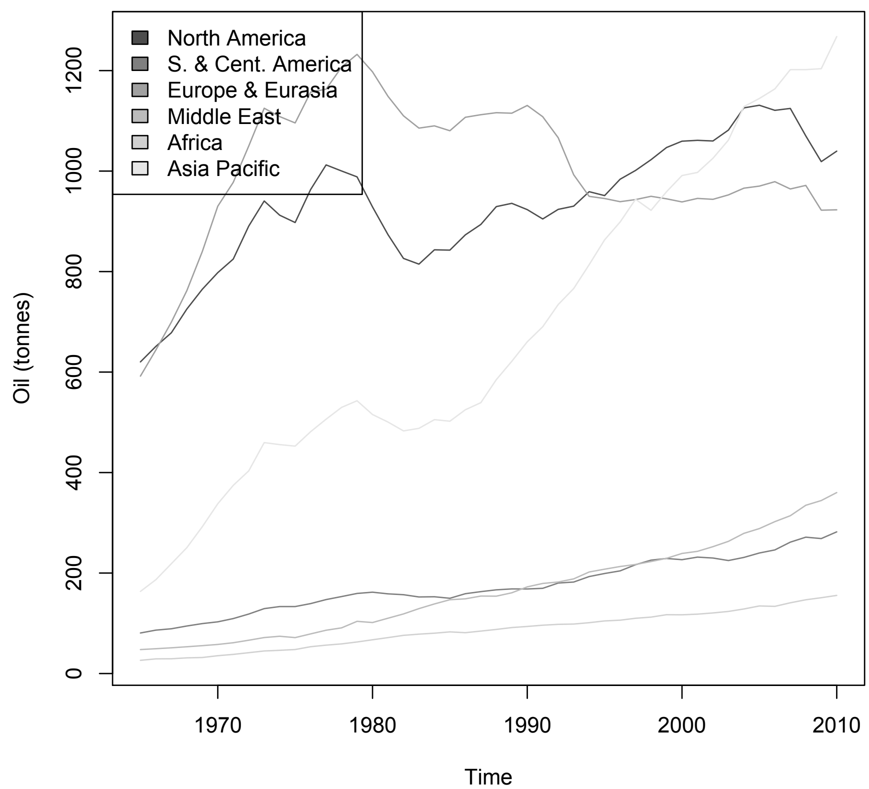

FIGURE 1. Oil Consumption by Region (2011)

$\phi_{ll'}$	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 (tons)

The voyage cost from a to b is:

$$c^{voy}_{ab} = c^c(\frac{\phi_{ab}}{24v^{op}}) + c^f_{ab} + d^p c^p \tag{9}$$

where d^p equals days in port and c^p are the daily port costs.

The trader's oil revenue is the expected present value of the revenue of selling the cargo at date $t + d$ is:

$$\pi(x_j, y_i, t) = \beta^y_{rep}\beta^y_{voy}(\mathbb{E}^b(\bar{p}^a_{t+d(x_j,y_i)}) - p^a_t)q^b) \tag{10}$$

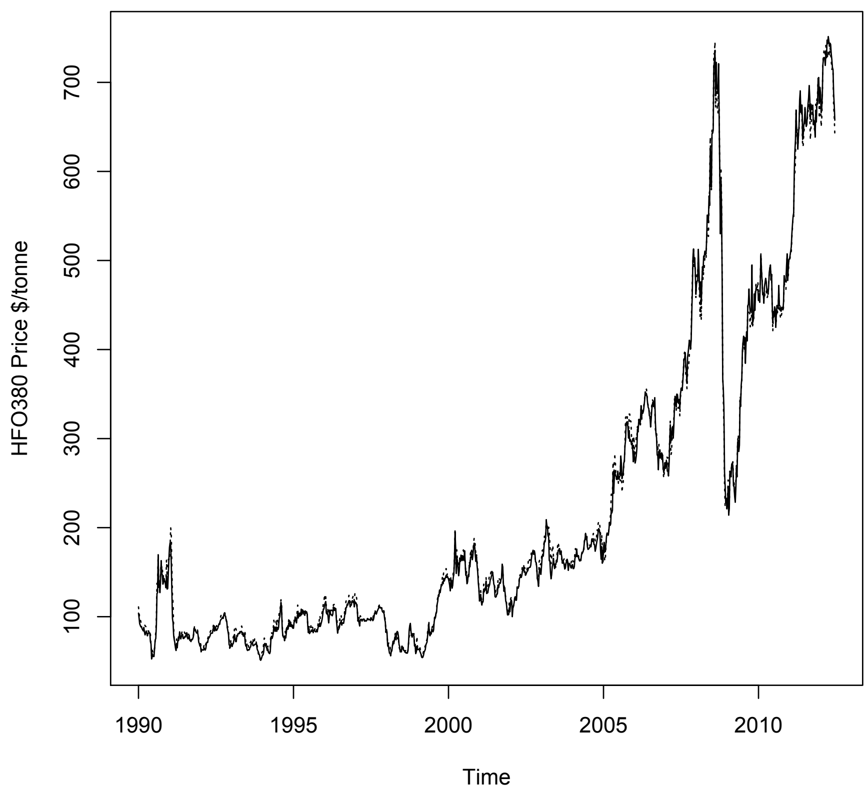

FIGURE 2. Heavy Fuel Prices

where:

$\mathbb{E}^b(p^a_{t+d})$	expected price of oil bought at location a and sold at location b at time $t+d$
p^a_t	the price of oil paid at location a at time t
q^b	cargo size (barrels)
β^y_{rep}	far away ship discount factor
β^y	voyage discount factor

C. Solving the assignment problem using linear programming

The assignment problem from section can be written as a linear programming (LP) problem where the objective is to maximize:

$$\sum_{(x_j,y_i)\in\Theta_t} s(x_j,y_i,t)m(x_j,y_i,t) + \sum_{y\in\mathcal{Y}_t} s(\emptyset_x,y_i,t)m(\emptyset_x,y_i,t) + \sum_{x\in\mathcal{X}_t} s(x_j,\emptyset_y,t)m(x_j,\emptyset_y,t)$$

$$\text{subject to:} \quad \sum_{x_j\in\mathcal{X}_t}[m(x_j,y_i,t)+m(\emptyset_x,y_i,t)] = \mathbf{n}(y,t) \quad \sum_{y_i\in\mathcal{Y}_t}[m(x_j,y_i,t)+m(x_j,\emptyset_y,t)] = \mathbf{n}(x,t) \tag{11}$$

where $m(x_j, y_i, t)$ is defined as the measure between a ship and a trader; $m(\emptyset_x, y_i, t)$ the measure of matching with a dummy ship; $m(x_j, \emptyset_y, t)$ the measure of a ship matching with a dummy trader.

D. Model estimation

Table 5. 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's Research

Price regression equations 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 associated with the port pair. The following log-log OLS model was estimated for the benchmark price:

Table 6. 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's Research

$$ln(P_t^W(a,b)) = \lambda_i + \beta_1 ln(\phi_i) + \beta_2 ln(p^{hfo})$$

where λ_i is the area fixed effect, ϕ_i is distance, and p^{hfo} is the bunker price. A 1% increase in distance increases the benchmark price by .4%, while the elasticity for the bunker fuel price is .53%. The sign on the fixed effects is negative and significant, around -4% on average. Figure plots the fitted values against the residuals.

The model specification for the multiplier price is:

$$P_t^M(a,b) = \lambda_a + \lambda_b + \beta_1\omega + \beta_2\omega^2 + \beta_3\alpha + \beta_4 HT + \beta_5 BDTI_{t-1} + \beta_6 HFODIFF + \beta_7 YR$$

where λ_a is a dummy factor for the load area, λ_b is a dummy factor for the discharge area, ω is age, α is DWT, HT is Hull Type (single or double hull), $HFODIFF$ is the difference between the fuel price in the benchmark price and the actual price during the week of the fixture date, $BDTI_{t-1}$ is the lagged Baltic Dirty Tanker Index and YR controls for time effects.

TABLE 7. Estimated ships in areas

		Flow	Flow	Flow	Available	Stock
Sea Area	Type	Import ships	Export Ships	Ships	Ships	Ships
AG	Load	-	38.6	38.6	-	38.6
BALT	Load	-	0.9	0.9	-	2.2
BRZ	Load & Discharge	0.8	0.7	1.6	0.8	3.9
CALI	Discharge	2.1	-	2.1	2.1	5.3
CAR	Load	-	5.4	5.4	-	13.5
CMED	Load	-	0.4	0.4	-	1.1
ECC	Load & Discharge	0.5	4.3	4.8	0.5	12.0
ECI	Discharge	1.1	-	1.1	1.1	2.7
ECMX	Load	-	3.0	3.0	-	7.5
EMED	Load	-	0.2	0.2	-	0.6
JAP	Discharge	7.8	0.0	7.9	7.8	19.6
KOR	Discharge	4.0	-	4.0	4.0	9.9
NCH	Discharge	0.3	-	0.3	0.3	0.8
PHIL	Discharge	0.2	-	0.2	0.2	0.5
REDS	Load	0.5	0.3	0.8	0.5	2.0
SAF	Load & Discharge	0.1	0.7	0.8	0.1	2.1
SCH	Discharge	10.9	-	10.9	10.9	27.2
SPOR	Discharge	5.1	-	5.1	5.1	12.7
THAI	Discharge	1.9	-	1.9	1.9	4.7
TWN	Discharge	1.2	-	1.2	1.2	3.1
UKC	Load & Discharge	10.3	0.6	10.8	10.3	27.1
USG	Load & Discharge	12.7	0.1	12.8	12.7	31.9
WAF	Load	-	9.9	9.9	-	9.9
WCI	Discharge	6.4	-	6.4	6.4	16.1
WMED	Load	-	2.5	2.5	-	6.4
AG - Wait	Wait	-	-	57.9	57.9	57.9
WAF - Wait	Wait	-	-	14.9	14.9	14.9
Total Ships		66	68	206	139	334

TABLE 8. Ship Types

Type	Fleet share	Dwt	Age	Design speed	Tpd
1	33.02%	317,000	4.4	15.9	89.8
2	60.45%	300,000	9.3	15.7	79.8
3	6.53%	281,000	13.5	15.6	83.1

E. RESULTS

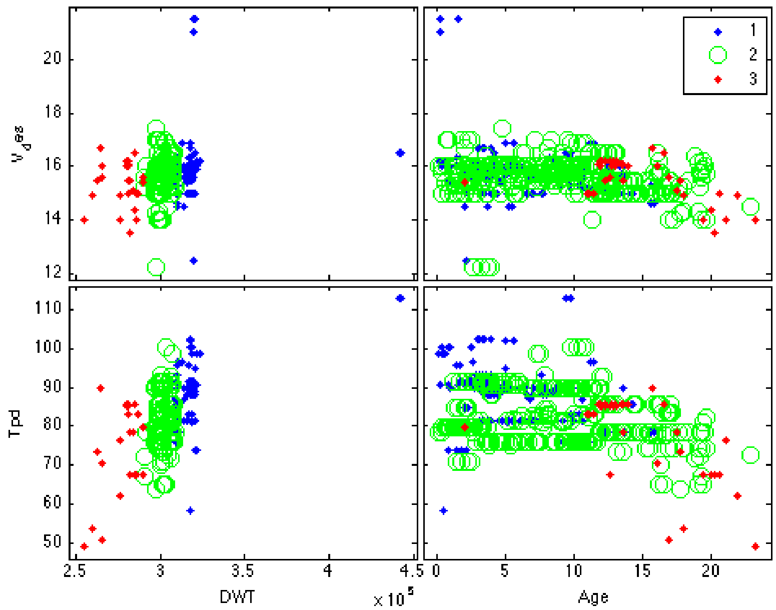

FIGURE 3. Cluster Analysis of Ship Characteristics

Table 9. Imputed ships available to match (Baseline model)

ShipID	Start	Supply	Type	Age	Dwt	Tpd	V_des	Fixc
1	CALI	2.1	1	8	302,159	83	16	30,100
2	ECI	1.1	1	8	302,159	83	16	30,100
3	JAP	7.8	1	8	302,159	83	16	30,100
4	KOR	4	1	8	302,159	83	16	30,100
5	NCH	0.3	1	8	302,159	83	16	30,100
6	PHIL	0.2	1	8	302,159	83	16	30,100
7	SCH	10.9	1	8	302,159	83	16	30,100
8	SPOR	5.1	1	8	302,159	83	16	30,100
9	THAI	1.9	1	8	302,159	83	16	30,100
10	TWN	1.2	1	8	302,159	83	16	30,100
11	WCI	6.4	1	8	302,159	83	16	30,100
12	BRZ	0.8	1	8	302,159	83	16	30,100
13	ECC	0.5	1	8	302,159	83	16	30,100
14	SAF	0.1	1	8	302,159	83	16	30,100
15	UKC	10.3	1	8	302,159	83	16	30,100
16	USG	12.7	1	8	302,159	83	16	30,100
17	AG	57.9	1	8	302,159	83	16	30,100
18	WAF	14.9	1	8	302,159	83	16	30,100

Table 10. Imputed cargo demand

Trader ID	Load	Discharge	Distance	Oil buy price	Demand
1	AG	CALI	11353	100.69	1
2	AG	ECC	12885	100.69	2
3	AG	ECI	2698	100.69	1
4	AG	JAP	6358	100.69	8
5	AG	KOR	6187	100.69	6
6	AG	SCH	5729	100.69	24
7	AG	SPOR	3671	100.69	2
8	AG	THAI	4409	100.69	2
9	AG	TWN	5290	100.69	3
10	AG	UKC	6360	100.69	1
11	AG	USG	13436	100.69	4
12	AG	WCI	1358	100.69	3
13	BRZ	SCH	10766	104.48	1
14	CAR	SPOR	11179	94.82	4
15	CAR	WCI	10694	94.82	2
16	REDS	PHIL	6358	106.86	1
17	UKC	SPOR	9025	112.01	1
18	WAF	ECI	6942.8	104.48	1
19	WAF	SCH	9579	104.48	2
20	WAF	TWN	9118	104.48	1

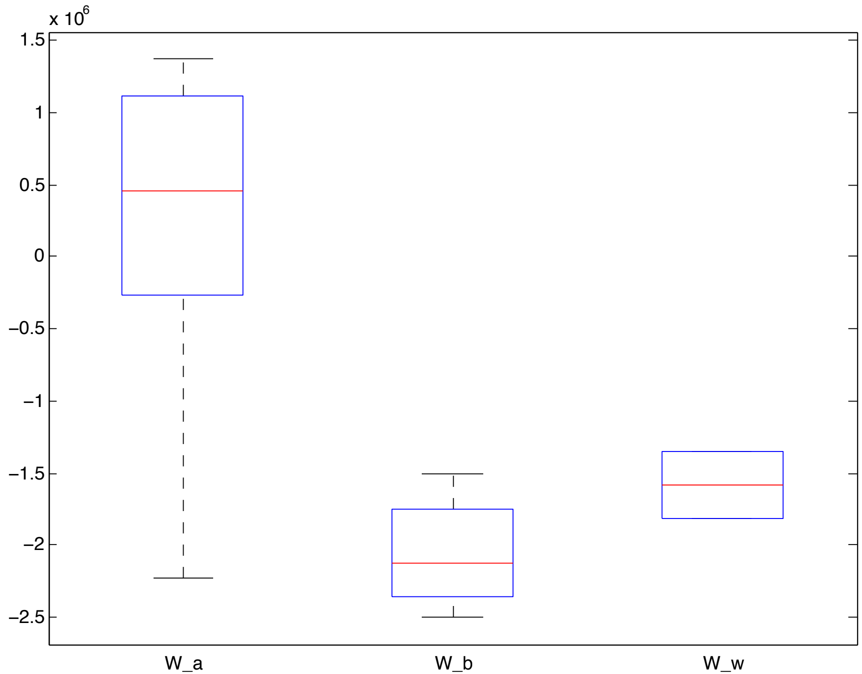

Figure 4. Terminal Option Values (2011): a= Load Area; b= Discharge Area; w= Waiting Area

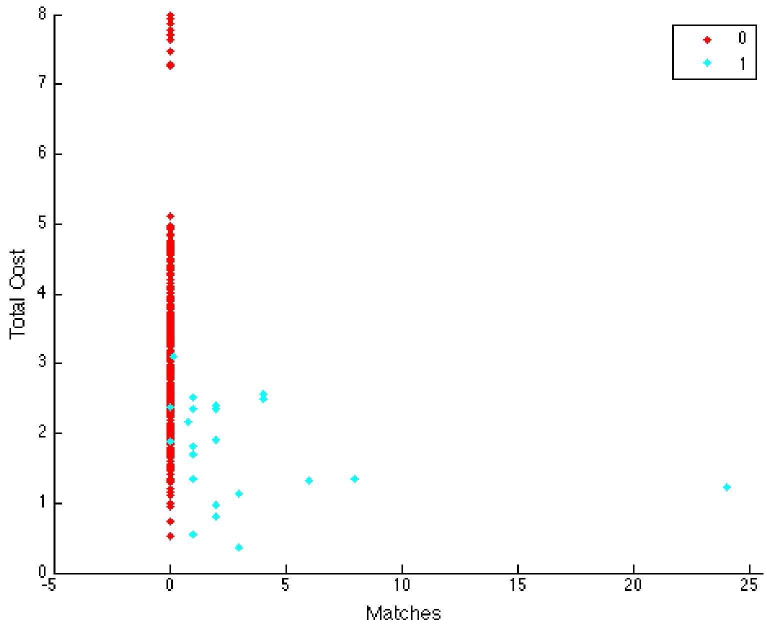

FIGURE 5. Impact of Cost on Optimal Matching (0=No Match; 1=Match)

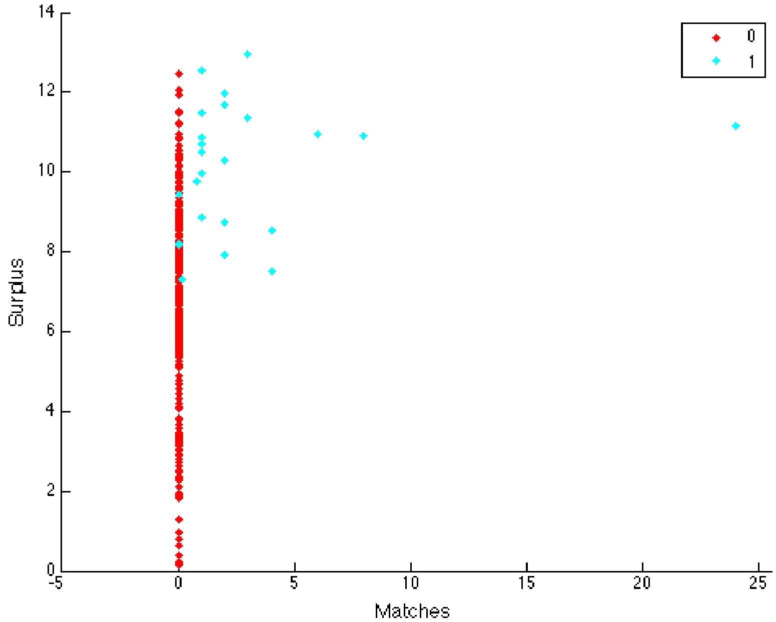

FIGURE 6. Matches and Surplus (Model 1; 0=No Match, 1=Match)

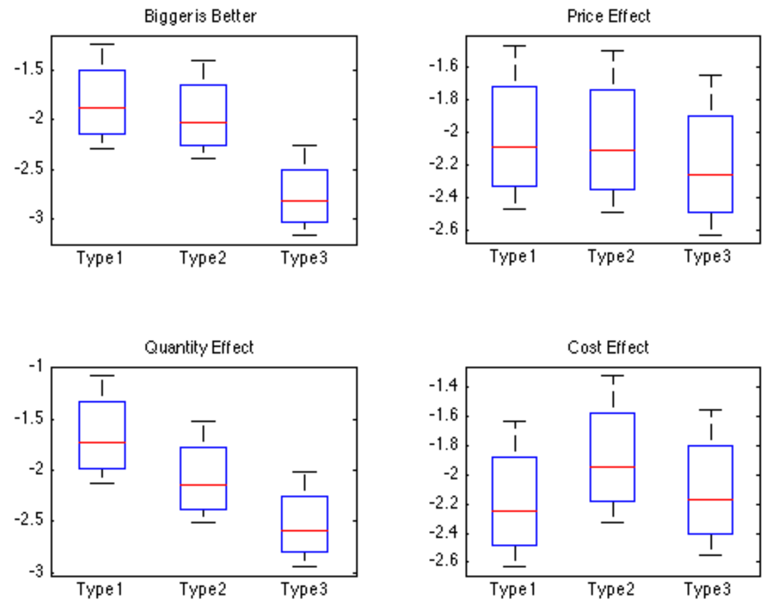

FIGURE 7. Decomposition Analysis of Ship Option Values (*Bigger is Better*)

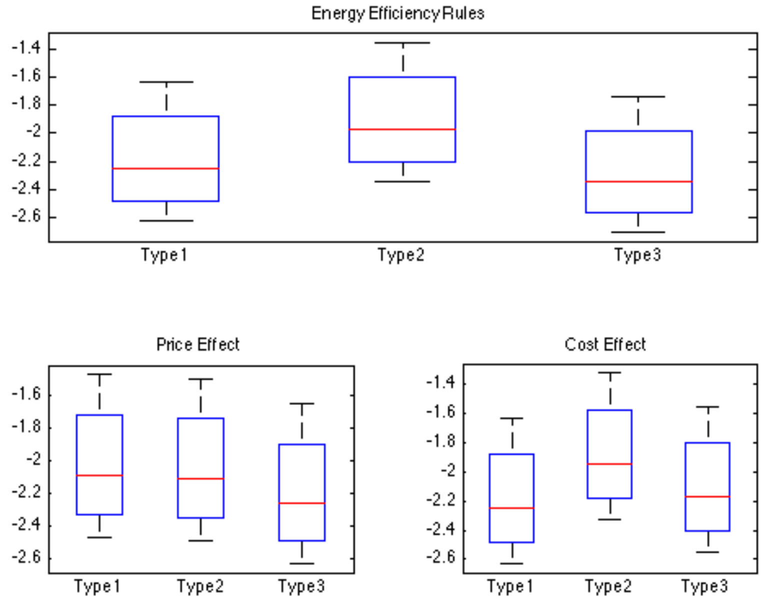

FIGURE 8. Decomposition Analysis of Ship Option Values (*Energy Efficiency Rules*)

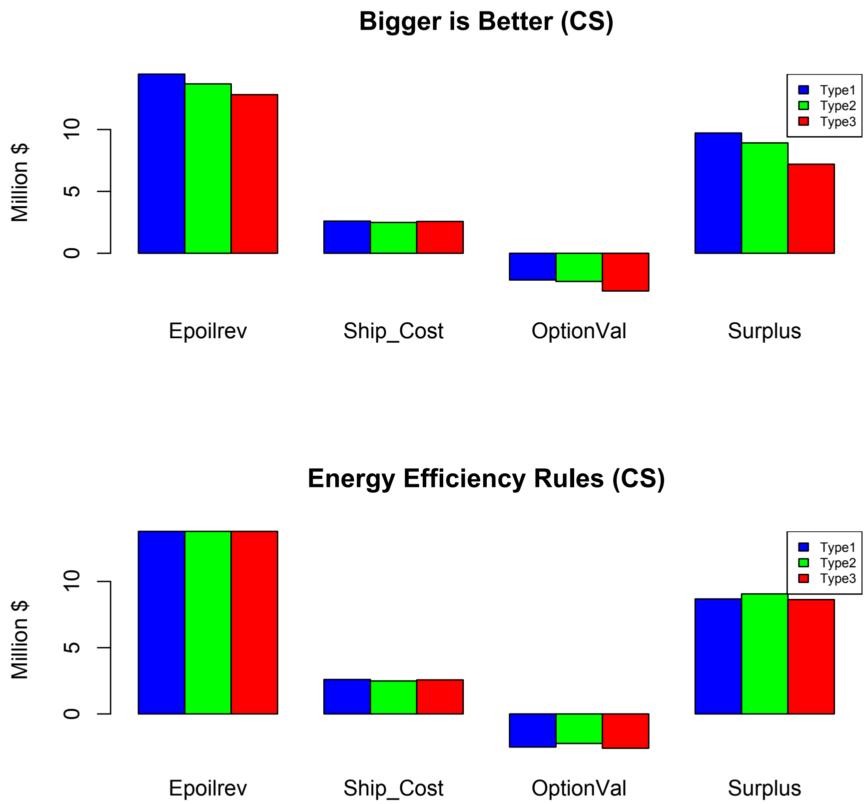

FIGURE 9. Decomposition Analysis of Match Surplus (Constant Speed)