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The Influence of Trading Performance and Fleet Allocation on Tanker Earnings

An empirical study of differences in quarterly reported average vessel earnings for publicly listed tanker companies in terms of fixing skill and fleet allocation

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Abstract

This study considers the time charter equivalent (TCE) earnings reported by publicly listed crude oil tanker companies and multiple data sources to assess shipowner's degree of skill in timing and positioning of vessel through space and time. It contributes to the literature by developing new variables to analyze the degree of skill in timing and positioning of vessels by using AIS-derived voyage data and data on regional freight rates. Furthermore, it tests whether or not these variables are associated with changes in average vessel earnings between Q1 2014 and Q2 2020. Additionally, it measures the influence of particular shipowners on TCE. The study confirms that there are differences in earnings across different areas, and that exposure to such routes seems to add excess value for shipowners. Furthermore, it attempts to measure whether shipowners are able to add value terms of the time of fixture but finds no evidence to support this.

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1 Introduction

The seaborne crude oil freight market is the market for transporting crude oil from production point to refinery, with a total carrying capacity of approximately 429 million deadweight tons (DWT) (Clarksons Research, 2020a). It is generally regarded as a textbook example of a ‘perfect’ market by economists (Stopford, 2009). On aggregate global level, the crude oil freight market certainly is a good candidate as it is highly decentralized and fragmented (Prochazka et al. 2019a), while shipbrokers deal with asymmetric information and speed up the matching process between buyer and seller which provides transparency (Strandenes, 2000).

Conversely, the perfect market conditions are likely not met in the short run, as the price is determined by the immediate equilibrium between supply and demand of tonnage in regional micro-markets. In these markets charterers (buyers) and owners (sellers) are not price-takers as they have significant impact on the price (Adland et al., 2016). Furthermore, the transportation service provided by a particular shipowner is not regarded as identical, as ships are vetted upon hiring (Prochazka et al. 2019a). The global tanker fleet is spread over a large geographical area, and therefore differences in regional freight rates cannot be instantaneously equalized. Differences may persist for weeks due to the time and costs associated with repositioning of tonnage (Prochazka et al. 2019b).

Over time, shipowners allocate their ships to higher-paying areas which will even out temporary price differences (Adland et al. 2017a). Due to the underlying inertia in the overall world fleet, there exist multiple regional ‘micro-markets’ for matching a single cargo with a suitable ship, i.e., individual fixtures (Adland et al., 2016). Market participants in such micro-markets are limited to those who are commercially available to load (open), and physically able to arrive within the required time-frame (laycan) (Adland et al., 2017a).

Furthermore, the level of freight rates in these micro-markets are affected by the matching process involved with individual fixtures. Charterers seek to buy transportation service at the lowest price possible, while making sure not to hire sub-standard and over-aged vessels (Prochazka et al. 2019a). Additionally, heterogeneity with respect to ships, charterers and owners impact the freight rate in individual fixtures (Adland et al., 2016).

Having established that the short-term crude freight market is not a textbook example of a perfectly competitive market, the next step is to test whether market participants are able to utilize short-term inefficiencies to make excess profits with sophisticated chartering strategies. The market is regarded as spatially efficient as long as no economic gains can be extracted from the market using spatially optimized chartering strategies on the basis of publicly available information (Adland et al. 2017a). Put differently, if the market happens to be spatially inefficient, then players have the opportunity to create excess value by pursuing sophisticated trading strategies.

Some publicly listed crude tanker companies provide a measurement of their quarterly time charter equivalent (TCE) earnings as part of their quarterly reports. The measurement is reported separately for different segments, and it is a useful tool for comparing revenue performance of a vessel trading in the spot market[1]. The companies calculate the end-quarter TCE by taking total revenues less voyage expenses and dividing it with the total number of revenue days. Revenue days is the total number of days within a quarter where a vessel is able to generate revenue (Teekay Tankers, 2020). It is calculated as a day-rate which is similar to that of a time-charter contract, where voyage expenses are covered by the charterer.

The findings in this study should be of value for bulk shipping industry players and researchers, as it provides an ex-post evaluation of how trading strategies may explain differences in TCE earnings. TCE is a key performance metric in the industry for comparison across companies and time (Hayes, 2020) and companies which deploy its fleet in a better than average should therefore create more value than its peers, all else equal.

The remainder of this thesis it structured as follows. Chapter 2 reviews relevant previous literature and addresses this study’s contribution. Chapter 3 introduces the methodology and develops the empirical model and a testable hypothesis. Chapter 4 provides a comprehensive explanation on the data collected from different sources as well as listing the key assumptions. Chapter 5 presents and discusses the findings. Chapter 6 concludes and gives suggestions for further research as well as discussing limitations.

[1] TCE is covered in detail in the methodology section.

2 Literature review

This section provides a review of previous work on freight rate modelling and spatial efficiency. Additionally, it positions this study within the literature as well as addressing its contribution.

The crude oil freight is often regarded as a candidate for a classic ‘perfect’ market by economists (Stopford, 2009). On a large scale, the aggregate demand is derived from the global demand of oil and oil products, sequentially rising the demand for its transportation. The aggregate supply is determined by factors such as the world fleet, fleet productivity, shipbuilding and scrapping, and the freight revenue (Stopford, 2009, pp. 135-138).

Instead of analyzing freight rate development at macro level with aggregate supply and demand and assumptions of standardized vessels and indices, a separate strand of the literature investigates microeconomic freight rate determinants by using data from individual fixtures. The purpose is to assess the effect of contract heterogeneity such as vessel specifications, different geographical regions, as well as owner and charterer impact on freight rate.

On a voyage charter, the shipowner is paid on a $/tonne basis and has to pay all costs associated with the voyage. On a timecharter, the shipowner receives a $/day payment, but voyage expenses are paid by the charterer (Adland et al. 2017b). Most papers focus mainly on freight rate development from voyage charter contracts. There is, however, no clear cut between the time charter (TC) and voyage charter markets. A vessel may operate in both types of contracts during its lifespan. Additionally, vessels on a timecharter may be re-let in the spot market for voyage charters (Adland et al. 2017b).

Even if the markets for voyage charters and time charters are interrelated, they are analyzed separately in the literature. For instance, Tamvakis and Thanopoulou (2000) assess medium and large size dry bulk carriers during four separate years from the late 1980s to early 1990s to test if there is a quality premium. They find no significant impact of age on freight rates. They argue that for dry bulk charterers, the preference for quality is perhaps not as substantial as for liquid bulk charterers, although over a bare minimum. They argue that the preference for quality may be present for charterers of crude oil due to previous accidents which have generated considerable media coverage.

Alizadeh and Talley (2011) use an extended version of the model in Tamvakis and Thanopoulou (2000) for analyzing tanker freight rates between 2006 and 2009 using contract- and vessel-specific regressors. They introduce the Baltic Dirty Tanker Index (BDTI) as a control variable which captures the general state of the market as well as the market volatility. Moreover, they study the time between contracting and actual date of loading and find that it depends on load area and freight rate level among others. Also, they report a non-linear relationship between age and freight rate.

Adland et al. (2016) expand the freight rate model in Alizadeh and Talley (2011) and analyze owner and charterer heterogeneity in VLCC and Capesize fixtures. They find that there are significant owner- and charterer-specific determinants of freight rates measured by their fixed effects, i.e., time-constant and/or unobserved determinants of freight rates. Although the fixed effects are not empirically explained in this study, Adland et al. (2016) suggest factors such as bargaining power and market knowledge as possible determinants of freight rates. These variables are difficult to observe and will therefore be captured by the fixed effects. Moreover, they confirm the non-linear age impact on freight rates and report an age minimum of 15 years for crude oil carriers, while the age impact on Capesize freight rate is insignificant.

In the bulk freight market, transactions happen at low frequencies, and essentially all fixtures are different, depending highly on the contracted vessel's technical specifications, routes and owner/charterer influence. The lack of homogeneity in trades requires indices to be generated by market experts, i.e., shipbrokers. They are required to fill the market's information gap and provide market players with their opinion on the prevailing freight rate index (Adland et al., 2017c). They assess the current market rate on the basis of both public information and private information from ongoing negotiations (Adland et al., 2018b). This process is described as a 'black box' where we can observe the output, but it is unknown what information the decision is based upon (Veenstra & Dalen, 2008).

Having established that there is severe heterogeneity in individual fixtures, Adland et al. (2017c) argue that expert-generated freight indices fail to properly adjust this heterogeneity in the fixture data. This is due to the indices themselves being impacted by contract heterogeneity, and therefore cause an endogeneity issue where the indices will affect the estimated coefficients of vessel- and contract specific factors. Consequently, Adland et al. (2017c) suggest implementing transaction-based indices as a proxy for the general market using time-fixed effects, i.e. dummy variables for each relevant time period. They test both weekly and monthly time dummies on an analysis of freight rate determinants in the offshore shipping market.

As for the timecharter market, Köhn and Thanopoulou (2011) investigate whether there is a quality premium in the Panamax dry bulk TC market using generalized additive models. They find strong empirical evidence of a significant two-tier market with respect to quality. Furthermore, they argue that it is unknown whether these differences are of economical relevance, as higher quality is associated with a larger cost of capital. Adland, Alger, et al. (2017) investigate whether there is a premium for energy efficient vessels in dry bulk market. They find that during normal markets, only 14-27% of fuel savings are reflected in the excess rate. However, the efficiency premium is not present during market booms. Furthermore, they find that the general market dominates in explaining variation in timecharter rates, while vessel age, fuel price, DWT and place of delivery are also significantly impacting day rates (Adland et al. 2017b)

Prochazka et al. (2019a) utilize AIS data to empirically analyze contracting behavior in the spot crude oil freight market by analyzing the distance from loading port at the time of fixture. They find that distance to loading port at fixture time is dependent on the loading area as there exist natural “decision points” which makes different loading areas have different lead times between fixture and loading. Other factors affecting the distance are vessel age and the market cycle, i.e., that during market spikes, charterers secure tonnage earlier, thus leading to a greater distance to load port.

The literature on spatial efficiency has been assessed with various approaches. Studies using vector autoregressive models show that regional freight rates in general are integrated of order 1 and cointegrated, i.e., their dynamics are themselves non-stationary and integrated of order 1, however there exists a non-trivial linear combination of the processes which is stationary (Engle & Granger, 1987). Furthermore, this is consistent with the efficient market hypothesis, as it implies that regional freight rates revert to a common long-term mean (Berg-Andreassen, 1997; Veenstra & Franses, 1997).

Adland et al. (2017a) investigate whether temporary regional differences are substantial enough to enable optimal switching chartering strategies which are profitable. They use a real option framework to assess the value of geographical switching in the Capesize bulk market, and observe an 'Atlantic premium' i.e., an upwards freight rate bias in transatlantic trades. Adland, Benth, et al. (2018) decompose regional freight rates into a non-stationary global market average and stationary regional deviations. They study freight rates for Supramax bulk carriers within and between the main ocean basins, Atlantic and Pacific. Moreover, they observe that some routes are consistently above or below the global market rate, which is consistent with the findings in Adland et al. (2017a). At first glance, this can be interpreted at evidence against the efficient market hypothesis. However, Adland, Benth, et al. (2018) provide two possible explanations for why of the observed difference between routes is not necessarily inconsistent with market efficiency.

First, differences may be explained by the fronthaul and backhaul freight structure. That is, in order to be able to take advantage of a higher-paying front-haul route, at some point a shipowner must accept a lower-paying backhaul route. Hence, some routes may have consistently higher-than or lower-than average earnings without contradicting the efficient market hypothesis. Second, some routes may have consistently higher earnings due to lower cargo volume which may increase the idle time between contracts. Thus, the higher earnings may be offset by increased risk of unemployment (Adland et al., 2018a).

Compared to the dry bulk, the market for crude oil has a clearer fronthaul-backhaul structure, such that a vessel will typically sail fully laden in one direction and ballast when returning (Prochazka et al. 2019a). It is therefore difficult to postulate that the finding holds true for the crude oil market.

Prochazka et al. (2019b) analyze the value of foresight in the dry bulk market, where they measure the value of perfect foresight compared to a random strategy and perfect foresight for a limited time horizon. In the Capesize market between 2009 and 2016, they find that the strategy with perfect forecast of future regional freight rates has an excess annual result of approximately 24% compared to the random strategy, which is an empirical estimate on the upper bound of the value of perfect foresight. They find that realistic time horizons for forecasting (a few weeks) does not provide reliable outperformance, which may indicate some degree of spatial efficiency in the market. However, they uncover a potential for exploiting regional inefficiencies with certain sophisticated chartering strategies. Prochazka et al. (2019b) observe an asymmetry in the results of the geographical switching function, where the value-loss from an incorrect decision is greater of magnitude than the value-added from the correct decision. A shipowner needs also to assess operational risk, which can indicate that some of the observed inefficiencies may be explained by the risk associated with certain chartering strategies.

Another approach on explaining regional is to assess whether excess returns can be explained as a compensation for excess risk associated with sailing in different regions. The relationship between risk and return is well established in the finance literature within the framework of portfolio theory established by Markowitz (1952). Sharpe (1964) and Lintner (1965) are major contributors to the Capital Asset Pricing Model (CAPM), and introduce the notion that risk should be divided into systematic and idiosyncratic risk. They argue that investors should be compensated only for systematic risk captured by the market portfolio, as the idiosyncratic counterpart can be eliminated by diversification. The CAPM has later been expanded to include more systematic risk factors as empirical research suggests that the original CAPM is insufficient for explaining an asset’s expected return, see e.g. Fama and French (1993) or Fama and French (2015).

On the topic of attitude towards risk in the shipping literature, Adland and Cullinane (2005) analyze risk factors in bulk shipping by assessing the relationship between spot and forward freight agreements. Under the expectation hypothesis, a timecharter is equal to the present value from voyage chartering over the same period (Adland & Cullinane, 2005). However, using theoretical reasoning, they reject the applicability of the expectation hypothesis in bulk shipping freight markets and argue that the risk premium is an increasing function of the spot freight rate, while being negative in most cases. Put differently, the expected present value of voyage chartering is in most cases larger than contracting the same vessel on a period charter. A crucial implication from this is that it allows some routes to have consistently greater earnings over time without necessarily contradicting the efficient market hypothesis. In particular, a route may have higher freight rates as a compensation for greater risk of vessel unemployment (Adland et al. 2017a).

This thesis investigates vessel earnings and trading patterns by analyzing TCE earnings, fleet data and voyage data. The contribution to literature in this study is threefold. First, it develops new variables to analyze the degree of skill in timing and positioning of vessels by using AIS-derived voyage data and use them to explain their effect on vessel earnings. Second, to use the relevant explanatory variables to assess whether some companies out- or underperform in terms of the average vessel earnings. Although only applied to large crude tankers in this study, the techniques can also be applied to other shipping markets. will provide ex-post analysis and measurements of spot fleet employment and on how the voyage decisions impacts earnings.

3 Methodology

3.1 The Gauss-Markov Theorem

When analyzing the ceteris paribus impact of different explanatory variables on TCE, the study relies on Ordinary least square regressions (OLS). The objective is to create a model where the following 5 assumptions are satisfied: The model is 1) linear in parameters, 2) has random sampling and 3) no perfect collinearity. 4) The error term has zero conditional mean, and 5) it exhibits homoscedasticity. Under the assumptions 1 through 4, OLS in unbiased. Furthermore, under assumptions 1 through 5, OLS is the Best Linear Unbiased Estimator (BLUE) by the Gauss-Markov Theorem (Wooldridge, 2018, pp. 79-97).

3.2 Time charter equivalent

For ease of comparison for voyage charters across routes and time, the time charter equivalent (TCE) is the industry standard measure of a vessel's daily performance (Hayes, 2020). TCE is calculated as voyage revenues less voyage costs (including port costs, bunker and canal costs), divided over the number of roundtrip days. Voyage revenue depends on factors such as the current market rate, the size of the cargo and the distance between loading and discharge (Clarksons Research, 2020b). TCE calculation is summarized in the following equations, based upon Clarksons Research (2020b):

$$\boldsymbol{Time\ Charter\ Equivalent}\left(\frac{\$}{\boldsymbol{day}}\right) = \frac{\boldsymbol{Revenue}(\$) - \boldsymbol{VOYEX}(\$)}{\boldsymbol{Duration}}$$

$$\boldsymbol{Revenue} = \boldsymbol{Freight\ rate}\left(\frac{\$}{\boldsymbol{tonne}}\right) * \boldsymbol{Cargo\ size}\ (\boldsymbol{tonnes})$$

$$\boldsymbol{VOYEX}\ (\$) = \boldsymbol{Canal\ costs} + \boldsymbol{Port\ costs} + \boldsymbol{Bunker\ costs}$$

$$\boldsymbol{Duration}\ (\boldsymbol{days}) = \boldsymbol{Ballast\ days} + \boldsymbol{Laden\ days} + \boldsymbol{Port\ days}$$

Equation 1 Time Charter Equivalent formula

Voyage charters are generally fixed using the Worldscale index, which is a schedule for freight rates for a standard ship measured on a USD/tonne basis for a specific route. The

Worldscale flat rates for individual routes are revised annually which makes the freight rate denoted in Worldscale difficult to compare over time (Clarksons Research, 2021).

3.3 Regression variables

This section will establish a testable hypothesis for the empirical analysis. From the TCE formula one can see that total revenue from freight contracts is a key driver for increased average earnings. Previous literature on microeconomic determinants of freight rates generally considers an empirical model where the logarithm of freight rate from individual contract is regressed on vessel and contract-specific characteristics. The objective in this approach is to assess the impact of certain explanatory variables while controlling for factors such as the general market.

In this study, the objective is to assess differences in average vessel earnings reported quarterly by shipowners in terms of fleet allocation and trading characteristics. Thus, it is reasonable to apply a model which is inspired by the regular analysis on fixture data, although somewhat modified. A key issue is that relevant explanatory variables are not necessarily directly observable quantitative measures. Therefore, a considerable emphasis will be put on introducing proxies for trading patterns and fleet specifications which are hypothesized to affect TCE.

The relevant variables in this analysis are summarized in Table 1. The remainder of this section will be used to describe how the key variables are calculated.

Table 1 Description of the variables

Variable	Description	Unit
TCE	Spot TCE from quarterly reports	USD/day
Voyage_Count	Quarterly count of voyages by company	#
Nonindexedroutes	Quarterly number of voyages which are 'indexed'	#
#FS_Avg	# voyages on a route with earnings greater than the calculated weekly average	#
#FS_75th	# voyages on a route with earnings greater than the calculated weekly 75h percentile	#
Laden_days	Total days spent on the laden leg of a voyage fixed in the quarter	Days
Ballast_days	Total days spent on the ballast leg of a voyage fixed in the quarter	Days
Vessel_count	# vessels in fleet (Owned + Chartered in + Under commercial management - Chartered out)	#
Age_avg	Average fleet age	Years
count_Age>=15	Number of vessels in the fleet older than 15 years	#
count_Age=<5	Number of vessels in the younger than 15 years	#
St.dev fleet age	Standard deviation of the fleet's vessel age	Years
Timing_Good	Number of "good timing" voyages	#
Timing_Bad	Number of "bad timing" voyages	#
Major Routes	Quarterly number of 'Major routes'	#
Exotic Routes	Quarterly number voyages on routes which are observed less than 10 times in the voyage data set	#
number_Load	Number of unique discharge areas within a quarter	#
number_Disc	Number of unique loading areas within a quarter	#
LBR	Laden_days/Ballast_days	%
NIR	Nonindexedroutes/Voy_Count	%
Load_div	number_Load/Voy_Count	%
Disc_div	number_disc/Voy_Count	%
Age>=15	(count_Age>=15)/(Vessel_count)	%
Age=<5	(count_Age=<5)/(Vessel_count)	%
FS_>AVG	(#FS_Avg)/(Nonindexedroutes)	%
FS_75th	(#FS_75th)/(Nonindexedroutes)	%
Prop. 'Major' routes	Major Routes/Voyage_Count	%
Prop. 'Exotic' routes	Exotic Routes/Voyage_Count	%
Timing_Good_prop	Timing_Good_prop/Voyage_Count	%
Timing_Bad_prop	Timing_Bad_prop/Voyage_Count	%

3.3.1 General market variable

Previous research establishes that the general market captures a large proportion of the variation in freight rates, see for instance the variance decomposition in Adland et al. (2016, p. 81). To control for the exogenous effect of the general market on freight rates, this study follows the approach in Adland et al. (2017c) where the general market is controlled for using a time-fixed effect, which correspond to quarterly time dummy variables in this case. As discussed in the literature review, Adland et al. (2017c) argue that this approach will enable explanation of the underlying heterogeneity in the transactions, as well as avoiding the circularity issue associated with expert-generated indices.

The end-quarter TCE is the average daily earnings for all voyages in a quarter, and therefore the sum of all individual fixtures, less VOYEX in the quarter. It is expected that the general market plays an even larger role in capturing the TCE conditional variance due to the law of large numbers, as the idiosyncratic variation from individual fixtures likely evens out over time.

3.3.2 Fleet Specifications

Vessel characteristics have been shown to impact individual fixtures, and it is therefore interesting to investigate whether there are characteristics in a company's fleet which impact end-quarter average vessel earnings.

In terms of vessel quality, younger tanker vessels seem to trade at a premium and there seems to exist a non-linear relationship between age and freight rate, where vessels older than 15 years seem to have an increasingly negative association with freight rate (Adland et al., 2016; Alizadeh & Talley, 2011). Using these findings, it seems relevant to analyze the effect of fleet age on vessel earnings. Additionally, as the minimum seems to be at 15 years, it appears interesting to investigate the effect of having a large number of vessels older than 15 years. To test the effect of these characteristics, we introduce a variable which measures the number of vessels older than 15 years as proportion to the overall quarterly fleet vessel count. The fleet data also enables calculation of the quarterly standard deviation in vessel age which may serve as a proxy for how homogenous the fleet is with respect to quality.

To summarize, we add explanatory variables for the average and variance of fleet age, the proportion of vessels with age greater than or equal to 15 years, as well as the standard deviation in fleet age.

3.3.3 Fixing skill proxy

When managing a fleet in the spot market, a rational ship owner seeks to maximize profits by allocating its ships optimally through space and time. As there are regional differences in freight rate, there may be value in fixing a ship in a region which higher paying than the average global freight rate for that particular period. This proxy provides a quantitative measure that captures the potential effect of having a large proportion of voyages load in e.g., West Africa when these rates are high relative to Arabian Gulf rates. It is motivated by the upper bound value of foresight in regional freight rates, investigated in Prochazka et al. (2019b).

Using the voyage data in the sample period, we can observe a ship's geographical position at the time of load and discharge. Additionally, the earnings timeseries provided by Clarkson specify the average earnings for a vessel loading in a certain area in a particular week. These sources of information can be combined to quantify of whether it is possible for a shipowner to persistently outperform within a quarter by repositioning its vessels in a better way than its competitors. Thus, it captures effect of positioning ships in 'fortunate' areas where these rates are relatively high, this is therefore a proxy for geographical skill or luck in managing the fleet.

In principle, we let all indexed routes have a score in terms of its relative earnings, by implementing the following dummy variable $\mathbb{I}_i$ for all voyages on routes where earnings indices are available.

Consider:

$$\mathbb{I}_v \;= \begin{cases} 1, & if\ RE_{rw}\ > TE_w \\ 0, & otherwise \end{cases}$$

$$v = \{voyage\ 1, \dots\ , voyage\ N\}$$

$$r = \{route\ 1, \dots\ , route\ R\}$$

$$w = \{2014\ w1, \dots, 2020\ w26\}$$

where $RE_{r,w}$ is the indexed earnings of route *r* at week *w*, TE_w is the earnings threshold at week w. One can let the earnings threshold, TE_w, represent e.g. the average or the upper quartile of all indices at time *w*, depending on the strictness of the requirement[2].

The variable is further aggregated to a quarterly measure:

$$FS\_TE\_Count_{oq} \;= \sum_{v} \mathbb{I}_v$$

for owner *o* in quarter *q*, which is the number of 'favorable' voyages within a quarter, relative to a threshold TE [3]. This will measure the degree of luck or skill with respect to exploiting temporary regional differences in freight rates, which is plausibly associated with an increase in average vessel earnings, all else equal.

3.3.4 Laden-to-Ballast ratio

The distinct fronthaul-backhaul structure in the crude tanker market may imply that the fixing skill is more appropriate compared to other freight markets, as ships typically sail fully laden in one direction and in ballast when returning to an area where crude oil in produced (Prochazka et al. 2019a). Therefore, the ratio of laden trip duration to ballast trip duration should be close to 1. Using the voyage data, it is possible to measure this laden-to-ballast ratio

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[2] Thresholds proposed in this study are the average and 75th percentile.
[3] Approx. 78% of the voyages in the dataset are "indexed". For Suezmax, a route is indexed when cargo is loaded in an area captured by the Earnings timeseries by Clarkson, while for VLCCs, the entire route (i.e. load area + discharge area) is considered. This is further explained in the Data collection and description chapter.

(LBR) for the companies per quarter. This may serve as a measure of whether the company manages its fleet such that it is on contract a large proportion of the time. When included in the regression model, the hypothesis is that it should be positively impacting average end-quarter vessel earnings. However, higher-paying routes may be offset by increased idle times between voyages (Adland et al., 2018a), and therefore a decreased laden-to ballast ratio may be an indication of strategic ballast in search of higher-paying contracts. Accordingly, it is difficult to predict the sign of the coefficient ex-ante, as the effect may be ambiguous.

It should be noted that the LBR is calculated in days rather than distance between ports, which means that the variable may be affected by differences in vessel speed across companies and time. Generally, ships sail at higher speeds in high-rate markets to increase the supply of tonnage (Stopford, 2009). Fortunately, the exogenous time fixed effects will provide adjustment for the market cycle’s effect on vessel speed which is common for all companies in the sample.

3.3.5 Timing proxy

Fixing a large proportion of the fleet in periods of relatively high rates is plausibly associated with higher average vessel earnings, all else equal. This is the motivation for introducing a timing proxy. In both Suezmax and VLCC segment, we consider the Clarkson c. 2010-built global average TCE earnings which is reported weekly. The intention of this measure is not to capture regional difference, but rather the effect of fixing a large proportion of the fleet during the weeks where rates are relatively high. We have weekly observations which corresponds to approximately 13 observations each quarter simply because there is roughly 13 weeks per quarter. The earnings timeseries have high volatility, and therefore considerable changes from week to week.

A shipowner with perfect forecast of future regional freight rates, may strategically plan ahead or wait with fixing if it expects short-term spikes in the freight rate. If a shipowner manages to fix its ships during sub-period within each quarter where the freight rate is relatively high, then there are reasons to believe it may positively impact the quarterly average vessel earnings.

Consider therefore the following dummy variables:

$$\mathbb{I}_v^G \;=\begin{cases}1, & if\ E_w\ > T_w^G\\ 0, & otherwise\end{cases}$$

$$\mathbb{I}_v^B \;=\begin{cases}1, & if\ E_w < T_w^B\\ 0, & otherwise\end{cases}$$

Which take the value 1 if the voyages are fixed on a good or bad subperiod of the quarter (see superscripts). Put differently, the variables equal 1 if the voyages are fixed within a subperiod (week) where the index earnings E_w are larger than or lower than some arbitrary threshold T_w^G and T_w^B respectively. The threshold could for instance be the upper quartile. The hypothesis is that a large exposure to such routes should be, on average, associated with a ceteris paribus increased TCE. As most quarters have 13 weeks, this study proposes the 3 highest and lowest earning routes for this proxy, which approximately represent the 23rd and 77th percentile respectively. That is, $\mathbb{I}_v^G = 1$ if the voyage is fixed within the highest earning 3 weeks that quarter, while $\mathbb{I}_v^B = 1$ if the voyage is fixed within the lowest earning 3 weeks that quarter.

The dummy variables are aggregated to a quarterly measure using the same approach as the fixing skill proxy variable. That is,

$$Timing\_Good_{o,q} \;=\; \frac{\sum_v \mathbb{I}_v^G}{N},$$

$$Timing\_Bad_{o,q} \;=\; \frac{\sum_v \mathbb{I}_v^B}{N}.$$

The hypothesis is that good timing within a quarter should be associated with a higher TCE, and vice versa for bad timing. This variable relies on the fixture date, which is unknown for most voyages in the dataset. This assumption and its consequences for this variable is discussed in detail in chapter 4.

3.4 Empirical model

$$\ln TCE_{it} = \alpha + \alpha_x FleetSpec_{it} + \alpha_y TradingVariables_{it} + \sum_{i=1}^{N} \gamma_i \mathbb{I}_i + \sum_{t=1}^{T} \delta_t \mathbb{I}_t + a_i + \varepsilon_{it} \ ,$$

Using the log-transformed quarterly reported average vessel earnings as the dependent variable in a regression model with explanatory variables as discussed above, we obtain the empirical model. This can be used to estimate the conditional expected TCE for owner *i* at the end of quarter *t*. The model framework will be applied to the VLCC and Suezmax segment separately. As we have panel data set, we let a_i represent the company specific error term which does not vary over time and let ε_{it} be the idiosyncratic error term which varies across companies and time. The model has a vector of fleet specific variables and a vector of trading variables which represent timing and positioning. These variables and will be further specified in chapter 5. Moreover, the model includes dummy variables for each company to investigate differences between companies, and time dummy variables to control for the exogenous effect of the general market on vessel earnings.

The TCE data has some data has some properties which calls for some extra considerations when doing causal inference from the data. This can be resolved by a fixed effects estimator (FE), or including dummies for each company, which is shown in the model above, and which will be done in this analysis as FE and dummy variables return the same estimates. In a fixed effects model, unobserved and disregarded time-invariant explanatory variables get differenced out (Wooldridge, 2018). Adland et al. (2016) discuss limitations with the fixed effects approach when applied to fixture data, as FE is devoted not to explain the time-constant effects, but only to the measurement of them. What makes an FE estimator advantageous, is that it allows for arbitrary correlation between unobserved individual specific effects and the error term, and thus often avoids the omitted variable bias in regression models where key explanatory variables which vary over time. The FE estimator does however not provide any explanation of the unobserved or time-invariant explanatory variables, as these get differenced out. (Wooldridge, 2018, pp. 463, 473).

4 Data collection and description

This study relies on compiling data from different sources and creating a dataset which will be used to analyze determinants of TCE. Therefore, special emphasis will be put towards discussing data collection, methodology, assumptions and limitations such that the study may be replicated.

The sample companies in this study are publicly listed companies who operated Suezmax tankers or VLCCs in the international seaborne crude freight market during the period from 1st quarter 2014 to 2nd quarter 2020, and which publish their time charter equivalent earnings for their crude carriers as a part of the quarterly report. Companies included in the sample set are the following: Euronav NV (Euronav), Frontline Ltd. (Frontline), DHT Holdings Inc. (DHT), Teekay Tankers Ltd. (Teekay) and Nordic American Tankers Ltd. (NAT). The companies may operate other segments such as Aframax tankers or product tankers, but only Suezmax and VLCC's are considered in this study. Euronav and Frontline operate and publish TCE figures for both segments, Teekay and NAT operate and publish TCE for the Suezmax segment, and DHT publish TCE only for its VLCC vessels.

4.1 Time Charter Equivalent data

Table 7 and Table 8 summarize the TCE spot earnings for the selected companies in the Suezmax and VLCC segment. These numbers are gathered from the companies' quarterly reports and rely on their own computation of the TCE. The companies report the TCE from the spot market separately from the daily earnings from vessels on time charter, and some also report the combined earnings from TC and spot contracts. This study is however limited to only analyzing the spot market TCE.

4.2 Fleet data

The purpose of collecting and using fleet data is twofold. First, it is plausible that fleet specifications such as age, size and quality impact bulk shipping performance. Second, the use of voyage data is conditional on identifying vessels operated by the companies in the analysis, where all vessels are identified using their IMO number.

The fleet data is obtained from the companies' annual reports, where the fleet is listed as of December 31 for all years in the sample period. The fleet lists contain information on vessel name, build year, DWT, whether it is owned or chartered in among others.

Operated fleet include vessels owned, chartered in on bareboat or time charter contracts, as well as ships under commercial management. As the purpose of this study is to analyze trading performance using spot TCE, one should optimally only consider spot trading vessels as these are the vessels which contribute to the reported average vessel earnings. Due to the limited data on TC versus Spot, this study implicitly assumes that all vessels are traded in the spot market. This does not perfectly reflect the true spot trading fleet, but fortunately the vast majority of vessels in the fleet data is employed in the spot market.

Fleet changes are generally commented in detail in the reports, e.g., at which date the ships entered or left the fleet. This analysis lets the cross-section of the fleet at year-end represent the fleet operated the following year such that the fleet data is subject to annual updates. For instance, this limitation implies that newbuilt ships with planned delivery after year-end, will not be regarded as part of the fleet that year. Although not capturing all details due to simplifications, it is reasonable to assume that it reflects the actual operated fleet during the sample period.

The IMO ship identification number is used to identify vessels, as it is permanent during a ship's lifespan, regardless of owner and name changes (IMO, n.d.). A vessel may change owner between the companies in the sample. This approach of tracking vessels allows for changes in owner between companies in the sample, for instance if a ship transfers owner in year t, e.g., from Euronav to Frontline, the ship will be regarded as operated by Frontline at year $t + 1$. However, in the data set we find no transactions between the companies – only with third parties.

IMO numbers are classified by looking up vessel names from the voyage dataset and the World Fleet Register as of November 2019 (Clarksons Research, 2019). One should acknowledge that there may be some inaccuracies when looking up vessel name in the Voyage data or the World Fleet Register. Vessels which were not found in in the Voyage data or WFR, and in cases where IMO numbers differed, IMO numbers were looked up manually using either the companies' websites or online vessel databases[4].

The final sample contains 268 unique vessels by IMO number, which is summarized in Table 10 Fleet data by company. The time dimension of fleet is adjusted for using dummy variables for years 2014 to 2020 which equal 1 for all years a ship is operated by companies in the sample.

4.3 Voyage data

The raw AIS-derived dataset provided by Signal Ocean (2020) contains approximately 960 000 rows with information on voyages recorded from all vessel classes between January 2014 and October 2020.

After filtering for the vessel classes Suezmax and VLCC, tha sample consists of 33731 Suezmax and 26447 VLCC voyages from January 2014 to October 2020. The data contains detailed information, for instance with respect to port and area of load and discharge, as well as its respective date and time. Furthermore, this analysis considers only the ships operated by the sample companies, which represent 6169 Suezmax and 3595 VLCC voyages. However, most vessels are not part of the companies' operated fleet during the entire sample period[5]. After considering the time dimension of the fleet data, the final sample consists of 6650 voyages, 4263 and 2387 for Suezmax and VLCC respectively.

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[4] Online vessel databases used were www.balticshipping.com and www.myshiptracking.com. All vessels were finally cross-checked with WFR in order to confirm that build year and DWT are consistent with that from the fleet lists.

[5] Ships are on average in the sample during approximately 15 out of the total 26 quarters analyzed.

In the voyage dataset there are 28 unique loading or discharge areas. These areas are bundled into 18 larger areas described in Table 11, which helps with explaining more routes using indices.

4.3.1 Key assumptions with the voyage dataset

This study uses fixture date in order to map a voyage to the end-quarter TCE. The voyage dataset contains information on the fixture date only for 1082 voyages, meaning the fixture date has to be assumed for most voyages. Using the average time to laycan from the 1082 voyages where this information is available, the fixture date is assumed to be the date of loading port arrival minus average time to laycan for each loading area. Hence, this approach assumes also that a ship arrives at loading port at the start of the laycan period. Prochazka et al. (2019a) find that the geographical location at time of fixture is affected by the area, market conditions, vessel age among others. Therefore, the assumed fixture date in this approach will likely not be ideal, as it only adjusts for the loading area.

In the voyage data set, all voyages fixed within a quarter according to the fixture date assumption, are assumed to occur within the same time period. Thus, voyages which have already started at the end of quarter will be recognized in its entirety within the same quarter.

4.4 Earnings time series

Regarding information on route specific earnings in the sample period, data is collected for c. 2010 built VLCC and Suezmax tanker earnings from Clarkson's Research Services Ltd. website, Shipping Intelligence Network (SIN). The goal is to link them with the voyage dataset and obtain measurement of the actual earnings of the voyages sailed by the companies' vessels in the sample period. Routes are defined as the laden leg of the voyage between load area and discharge area. For instance, a ship which sails laden from Ras Tanura in the Arabian Gulf to Huizhou in the Far East, takes on the route AG-Far east.

When evaluating the earnings of a voyage using these timeseries, one should acknowledge the set of assumptions they are estimated upon. The timeseries provide an estimate of the daily ship earnings for the current spot freight rate level as well as regional port and bunker costs (Clarksons Research, 2020b, p. 5). These data will therefore provide information on the average c. 2010 built ship, which may not be directly representative for the actual voyages observed in the voyage dataset. In absence of data on each vessels' earnings, this should serve as a best guess estimate on actual earnings and should work for comparing the route. The metric for comparing routes will be discussed in the methodology section.

The earnings timeseries contain 14 route specific earnings time series for the Suezmax segment, 10 of which are complete for the sample period. These 14 routes account for 3181 out of 6650 total voyages. The fact that under 50% of Suezmax voyages are contained in the list of freight indices implies that some assumptions should be made with regards to the fixing skill proxy. Using a simple arbitrage argument, it is reasonable to assume that freight rate differences within a loading area should be smaller than temporary differences between loading areas, due to less cost and time of repositioning tonnage. If we assume that voyages out of a loading area have the same earnings index, we obtain a larger number of indexed voyages for the Suezmax segment. Although not ideal it should still manage to capture the effect of having ships commercially available to load in a region with temporary high rates, regardless of the discharge port it is headed towards.

The VLCC market is more homogeneous with respect to traded routes, as is confirmed by the voyage data, where the top 15 routes capture 91.5% of VLCC voyages, as opposed to 56.3% for Suezmax (see Table 14 and Table 15)

Regarding the weekly VLCC earnings timeseries from Q1 2014 through Q2 2020, this study considers the majority of the earnings indices provided by Clarkson. Clarkson provides some data on triangulated routes, e.g., Singapore-AG-USG-Singapore, could also have been included. However, in this study the earnings timeseries are utilized to provide an earnings index for a particular combination of loading and discharge area such that one can assess whether or not the route was "favorable". The final sample contains 17 timeseries representing 13 unique routes summarized in Table 16 and Table 17. These 13 routes capture 76,4 % of total voyages in the data set. In the case of duplicate timeseries for a route, i.e., more than one index for a route in a particular week, the route performance is assumed to be the average of the indices for that route.

4.5 Final data set

After merging all data sources, we obtain the final data set which will be used for empirical analysis. The previously discussed proxy variables are aggregated to a quarterly measure, which gives a row for all companies in the two segments between Q1 2014 and Q1 2020 The following tables provide summary statistics of the final data.

Table 2 Summary statistics by company

Summary of Suezmax segment by company

	TCE	Age>=15	Age_avg	Laden_days	Ballast_days	FS_AVG_Count	Major_load
Euronav							
mean	27972	0,220	10,836	874,873	862,269	12,038	23,000
sd	13678	0,057	1,344	131,799	160,145	6,390	7,239
Frontline							
mean	26246	0,227	8,347	593,076	670,313	7,462	21,808
sd	11886	0,194	3,164	176,665	137,571	4,081	4,354
NAT							
mean	24413	0,494	13,422	804,476	993,642	10,769	24,654
sd	11313	0,062	1,102	142,283	195,859	4,642	9,612
Teekay							
mean	26028	0,068	10,278	813,343	912,634	11,692	24,308
sd	11194	0,070	0,809	338,952	390,899	6,342	10,252
Total							
mean	26165	0,252	10,721	771,442	859,714	10,490	23,442
sd	11949	0,189	2,577	236,729	267,411	5,679	8,157
Observations	104						

Summary of VLCC segment by company

	TCE	Age>=15	Age_avg	Laden_days	Ballast_days	FS_AVG_Count	Major_load
DHT							
mean	40720	0,118	8,776	883,291	805,316	2,636	23,818
sd	21425	0,077	0,644	255,794	274,752	1,787	3,737
Euronav							
mean	38545	0,061	7,864	1271,759	1102,614	8,077	28,731
sd	18331	0,035	0,579	488,406	414,908	4,118	8,996
Frontline							
mean	36542	0,336	11,228	846,661	900,884	3,731	23,308
sd	19798	0,114	1,908	178,946	244,492	2,822	6,085
Total							
mean	38488	0,174	9,317	1006,910	943,350	4,932	25,365
sd	19601	0,146	1,903	387,576	341,410	3,883	7,119
Observations	74						

Panel a: Suezmax

Variable	Obs	Mean	Std. Dev.	Min	Max
lTCE	104	10.074	.445	9.259	11.015
SD Age	104	4.587	1.323	2.675	7.062
count Age10	104	11.885	6.415	0	23
count Age15	104	5.558	4.665	0	18
count Age5	104	3.962	3.424	0	19
trips pr vessel	104	1.907	.351	1.233	3.312
Vessel count	104	20.942	6.024	10	30
Propavg	104	.337	.139	0	.727
Prop25th	104	.188	.101	0	.458
Prop75th	104	.105	.086	0	.511
Timing Good	104	8.721	3.343	2	17
Timing Bad	104	9.462	3.552	3	19
Load div	104	.234	.067	.129	.444
Disc div	104	.254	.083	.14	.562
LBR	104	.91	.165	.599	1.438
Total areas	104	.488	.138	.295	1
NIR	104	.217	.123	0	.615

Panel b: VLCC

Variable	Obs	Mean	Std. Dev.	Min	Max
lTCE	74	10.427	.525	9.367	11.431
SD Age	74	4.624	.571	3.634	5.924
count Age10	74	10.865	4.298	5	23
count Age15	74	3.919	3.17	0	11
count Age5	74	7.486	5.126	0	19
trips pr vessel	74	1.278	.229	.857	1.933
Vessel count	74	24.757	8.432	14	45
Propavg	74	.196	.124	0	.487
Prop25th	74	.343	.198	0	.818
Prop75th	74	.13	.117	0	.435
Timing Good	74	6.932	2.864	1	15
Timing Bad	74	7.027	3.145	0	15
Load div	74	.194	.06	.103	.417
Disc div	74	.173	.059	.037	.333
LBR	74	1.093	.235	.539	1.823
Total areas	74	.367	.097	.214	.75
NIR	74	.223	.099	0	.486

5 Results

This section discusses the empirical results. First, the proposed new variables will be applied to test whether or not they are associated with changes in TCE. Second, it will discuss how the companies performed in the sample period in terms of their TCE and related explanatory variables. The regression models are estimated on the Suezmax and VLCC sample separately, shown in Table 3 and Table 4, but models 1 through 5 are identically specified for both Suezmax and VLCC.

In model 1, the log TCE is regressed on dummy variables for each time period, which corresponds to the average TCE per quarter. There is substantial variation in the dayrates across the sampling period, and from the first (model 1) regression, we see that and 96.1% and 96,8% of the variation is captured by the time fixed effect (R^2) for the Suezmax and VLCC segment respectively. This is in line with what was expected, and it confirms that the average earnings from vessels operating in the spot market is highly affected by the prevailing market conditions.

The collected data in this study contains information on a set of companies which are tracked over time, i.e., panel data. The sample is therefore not to be regarded as drawn randomly between individuals, and it is likely that an individual specific term is contained in the error term (a_i from the methodology section), causing Pooled OLS to be biased by a violation of the zero conditional mean assumption. Using fixed effects both at the time level and company level reduces the potential for endogenous variables and is arguably preferable when reporting determinants of average vessel earnings. Therefore, Model 2 includes dummy variables for the companies, i.e., both company and time fixed effects. This model analyzes whether there are systematic differences between companies after controlling for the exogenous effect of the general market.

Model 3 adds explanatory variables related to fleet specifications. In particular, the fraction of vessels in the fleet which are older than and 15 years, the average vessel age and the standard deviation in vessel age, SD_AGE. We observe in model 3 that none of the fleet specific variables (AGE_15 and AGE_Avg and SD_AGE) have a significant impact on TCE for Suezmax, they are however significant if not included in the same model. This is due to a multicollinearity problem which is confirmed by the Variance Inflation Factor (VIF) where

AGE_15 and Age_avg have a VIF > 10, and SD_Age has a VIF > 5 [6]. As a rule of thumb, multicollinearity may be an issue when VIF > 10 (Wooldridge, 2018). Consequently, including these variables in the same model will lead to inflated standard errors due to the correlation between the explanatory variables (see for instance Wooldridge (2018, pp. 463, 473)). For this reason, we keep only the AGE_15 variables, in the next models.

It should be clarified that multicollinearity does not affect the point estimates in the regression, but only the standard errors. The model in this study is especially sensitive to multicollinearity due to the limited sample size. In general, one should include all observable explanatory variables which are correlated with the included independent variables and impact the dependent variable, as long as the relationship between explanatory variables is not perfectly linear (perfect collinearity). If not, the model will suffer from an omitted variable bias (Wooldridge, 2018).

It is possible to assess whether the company dummy variables should be included when explaining differences in TCE by employing a Hausman test on model 4 and a similar model without the company dummies. The Hausman test considers two models, one model which is consistent (but inefficient) under both H_o and H_a, and one which is efficient under H_o but inconsistent under H_a (Hausman, 1978). The Hausman test returns a p-value of 0.0331 for the Suezmax sample which suggests that one should reject the null hypothesis that the differences in the models are not systematic. Thus, the two-way fixed effects model is to be preferred, since the one-way fixed effects model is inconsistent. As for the VLCC sample, The Hausman test returns a p-value of 0.5576, i.e. we fail to reject H_o and infer that differences between the models are not systematic.

Regression model 4 tests the new variables to measure fleet allocation and trading performance provided by this study. Given the model specification, the fixing skill proxy (FS_AVG) is statistically significant for both the Suezmax and VLCC sample. Thus, the model suggests that a 10 percentage points increase in exposure to routes with greater than average earnings is, on average, associated with approximately 2.4% and 4.5% increased TCE

[6] VIF(AGE15) = 35.61, VIF(AGE_avg) = 15.97, VIF(SD_Age) = 7.73.

for the Suezmax and VLCC segments respectively[7]. The interpretation from all multiple regression outputs are ceteris paribus, i.e. assuming all other variables are held constant.

Regarding the age variables, the results in model 4 suggest that a 10 percentage points increase the proportion of vessels older than 15 years is, on average, associated with approximately 2.3% decrease in TCE for Suezmax fleets, while there is no significant relationship for VLCCs [8]. This analysis does not provide explanation of why this is the case, but it is reasonable to assume that it may be due to increased voyage costs, which decreases the TCE according to the formula introduced in the methodology section.

The results suggest that LBR has no significant impact on TCE in model 4 and 5. Thus, we find no evidence to suggest that companies with a higher aggregate quarterly LBR tend to have a higher TCE, ceteris paribus. This is noteworthy as it contradicts the a priori hypothesis. This may suggest that it is difficult for shipowners to achieve higher earnings on the basis of triangulation or other methods for increasing the LBR in the crude oil freight market. Put differently, if we were to analyze earnings on a vessel-by-vessel basis, we may have observed a significant relationship between LBR and TCE. On a quarterly level, however, we do not observe such a relationship between the variables. The quarterly LBR is perhaps less applicable to the crude oil freight market, as it has a clear geographical trading pattern which stipulates the majority of traded routes (Prochazka et al. 2019a).

Furthermore, the explanatory variables Number_Load and Number_Disc serve as proxies for the effect of being exposed to a large number of different routes and areas, i.e. a diverse versus a specialized trading strategy. The results suggest no significant relationship between the variables and TCE.

In terms of the Prop. 'Exotic' routes variable, we see no significant relationship between companies which allocate some of their voyages to routes which are rarely traded, and quarterly TCE, all else equal. Regarding the Prop. 'Major' routes variable, model 5 suggests that a 10 percentage points increase in the proportion of routes being one of the 'major routes' is associated with approximately 10.8% increased TCE (see Table 14 and Table 15). This may imply that there is a benefit to primarily considering the major routes for the VLCC segment.

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[7] Exact value: exp(10%*0.241)-1 ≈ 2.44%. and exp(10%*0.453)-1 ≈ - 4.63%.

[8] Exact value: exp(10%*(-0.227))-1 ≈ - 2.03%.

For the Suezmax segment, we observe no such significant relationship. The coefficient for the proposed timing variable is not statistically significant, which suggests that there is significant luck or skill in “timing” the market within a particular quarter. This variable is, however, subject to some limitations which affect the estimate.

Table 5 and Table 6 show that some routes are overrepresented in being better than average within a particular period. Therefore, the variable may fail to distinguish between fixing skill and graphical positioning as it might reflect persistent differences between routes rather than exploitation of temporary freight rate differences. Nevertheless, it is an interesting observation as it confirms that there are regional differences, and that exposure to these particular areas is associated with an increased TCE on average.

A possible way of disentangling “space” and “time” for the Fixing skill variable is to add loading areas as control variables, which is done in regression model 5. This may decrease the potential bias from a persistent effect of particular loading areas on TCE[9]. In model 5, the fixing skill variable is still associated with a positive ceteris paribus effect on TCE in both segments, although it is only significant at a 10% level of significance for the Suezmax segment. This is in line with the a priori hypotheses and is interesting as it confirms that there is an upwards potential of strategically positioning the fleet in areas which pay better than average and is closely related to the studies on geographical optimization in previous literature.

Regarding company out- or underperformance, we consider first the results in model 2 where only company and time dummy variables are included. These models show a significant difference in TCE across companies, for instance a 13.8% lower TCE for NAT than the others, on average.

Table 2 shows that, on average, almost half of NAT’s vessels are older than 15 years. As previously discussed, this seems to be negatively associated with TCE. After controlling for the other variables in models 3-5, the results suggest that NAT no longer has significantly lower TCE. A take-away from this is that even if NAT has a lower average TCE overall, it

[9] Loading areas used as control variables are those considered as “major”. That is: AG, WAF, Med, USG&Caribs, BlackSea, UK&Cont, see Table 12 Loading areas by segment and total in the appendix.

seems to be explained by its fleet characteristics. Put differently, the “underperformance” of NAT is eliminated when controlling for other fleet characteristics.

Moreover, model 4 shows that Teekay has a persistently ceteris paribus lower average vessel earnings of approximately 6,6% compared to others in the Suezmax segment. However, after controlling for categorical variables related to loading areas, the negative Teekay coefficient is no longer significant, as shown in model 5.

As for the VLCC segment, the differences between companies shown in model 2 are eliminated when controlling for the relevant variables, as models 3-5 show no significant difference between companies. Adland et al. (2016) find substantial influence of owners and charterers for VLCC fixtures. In this case, we observe that there is some owner influence on TCE in model 2, as there are differences between companies, but the differences seem to be explained by the explanatory variables.

It is difficult to evaluate whether the observed significant association between variables represents the causal relationship between them, or if they for instance are correlated with some other variables which is the true causing factor. The Laden-to-Ballast ratio (LBR) variable is perhaps a mediate variable, i.e., rather than being the causal TCE determinant, it may explain the relationship between average vessel earnings and multiple variables. LBR may be explained by exposure to different routes and geographical areas. For instance, a fleet which sails mainly on a fronthaul-backhaul structure should, on average, have a LBR of 1. In this study, we observe the aggregate LBR over for all voyages fixed in a quarter. The idea is that a shipowner who manages to have some degree of triangulation in his voyages should be better off, which will be reflected in a higher LBR. This is discussed in further detail in Section A.6 in the appendix.

Table 3 Suezmax regressions

Suezmax TCE regressions

	(1) lTCE	(2) lTCE	(3) lTCE	(4) lTCE	(5) lTCE
Euronav		0	0	0	0
		(.)	(.)	(.)	(.)
Frontline		-0.0500**	-0.0105	0.0195	0.0991*
		(0.036)	(0.816)	(0.644)	(0.093)
NAT		-0.138***	-0.0425	-0.0350	0.0203
		(0.000)	(0.365)	(0.345)	(0.695)
Teekay		-0.0556**	-0.117***	-0.0658**	-0.0583
		(0.020)	(0.001)	(0.041)	(0.183)
Age>=15			-0.331	-0.228***	-0.302***
			(0.203)	(0.010)	(0.006)
Age=<5			-0.174		
			(0.195)		
Age_avg			-0.00491		
			(0.703)		
St.dev fleet age			0.00286		
			(0.869)		
FS_>AVG				0.241***	0.194*
				(0.006)	(0.083)
LBR				0.0578	0.0253
				(0.418)	(0.736)
NIR				0.162	0.587*
				(0.113)	(0.095)
Number_Load				-0.174	-0.256
				(0.503)	(0.356)
Number_Disc				0.173	0.144
				(0.389)	(0.536)
Voyage_Count				-0.000902	-0.0104
				(0.679)	(0.145)
Vessel_Count				0.00210	0.00515
				(0.627)	(0.289)
Prop. 'Major' routes				-0.0936	-0.105
				(0.373)	(0.379)
Prop. 'Exotic' routes				-0.272	-0.372
				(0.328)	(0.220)
Timing_Good_prop				0.0133	0.0100
				(0.876)	(0.908)
Constant	10.21***	10.27***	10.43***	10.13***	10.11***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time FE	YES	YES	YES	YES	YES
Load Area FE	NO	NO	NO	NO	YES
Observations	104	104	104	104	104
R^2	0.961	0.974	0.978	0.981	0.983
Adjusted R^2	0.948	0.964	0.968	0.969	0.970

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 VLCC regressions

VLCC TCE regressions

	(1) lTCE	(2) lTCE	(3) lTCE	(4) lTCE	(5) lTCE
DHT		0	0	0	0
		(.)	(.)	(.)	(.)
Euronav		0.0323	0.0532	-0.0715	-0.0714
		(0.311)	(0.292)	(0.303)	(0.340)
Frontline		-0.0617^{*}	0.00466	-0.00929	-0.00733
		(0.056)	(0.937)	(0.877)	(0.910)
Age>=15			-0.766	-0.181	-0.213
			(0.144)	(0.436)	(0.417)
Age=<5			-0.631^{*}		
			(0.064)		
Age_avg			0.00150		
			(0.975)		
St.dev fleet age			0.0649		
			(0.208)		
FS_>AVG				0.453^{**}	0.546^{**}
				(0.019)	(0.044)
LBR				0.0239	0.0338
				(0.801)	(0.746)
NIR				0.252	0.232
				(0.221)	(0.495)
Number_Load				0.733	0.810
				(0.115)	(0.177)
Number_Disc				0.406	0.617
				(0.323)	(0.148)
Voyage_Count				0.00169	0.000415
				(0.702)	(0.973)
Vessel_Count				0.000522	0.00440
				(0.934)	(0.527)
Prop. 'Major' routes				0.621	1.083^{**}
				(0.132)	(0.050)
Prop. 'Exotic' routes				-0.0496	-0.307
				(0.932)	(0.627)
Timing_Good_ prop				0.0603	-0.0400
				(0.742)	(0.842)
Constant	10.42^{***}	10.44^{***}	10.40^{***}	9.431^{***}	8.962^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time FE	YES	YES	YES	YES	YES
Load Area FE	NO	NO	NO	NO	YES
Observations	74	74	74	74	74
R^2	0.968	0.974	0.979	0.985	0.987
Adjusted R^2	0.952	0.959	0.963	0.968	0.968

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 Fixing skill proxy areas, Suezmax

Suezmax	#	#	%	%
FS_AVG	0	1	0	1
AG	717	125	85,2%	14,8%
WAF	967	110	89,8%	10,2%
Med	50	363	12,1%	87,9%
USG/Caribs	338	279	54,8%	45,2%
Black Sea	25	165	13,2%	86,8%
UK & Cont	127	82	60,8%	39,2%
∑	2224	1125		

Table 6 Fixing skill proxy areas, VLCC

VLCC	#	#	%	%
FS_AVG	0	1	0	1
AG	1149	78	93,6%	6,4%
WAF	265	36	88,0%	12,0%
Med	2	16	11,1%	88,9%
USG/Caribs	1	173	0,6%	99,4%
Black Sea	0	0	NA	NA
UK & Cont	22	76	22,4%	77,6%
∑	1439	380		

6 Concluding remarks

This study is a first attempt in developing new variables for analyzing skill in timing and positioning of vessels in order to analyze the drivers of differences in average vessel earnings. Also, it provides an analysis of whether differences between companies are significant after controlling for the different fleet and trading specific variables.

Similar to previous literature on freight rate determinants from fixtures, a large proportion of the variation in the TCE rates is also explained by the general market. In addition, there are some differences between companies, but the differences are eliminated when controlling for the explanatory variables in model 5.

Furthermore, the results provide some evidence which suggests that market participants are able to utilize short-term inefficiencies in the FS_AVG variable. This confirms that there are temporary differences, and that exposure to such routes with higher-than-average relative earnings seems to add excess value for shipowners. Thus, an increased exposure to favorable routes is associated with an increase in average vessel earnings, all else equal. This is important as it provides empirical evidence that fleet allocation through space and time actually impacts the quarterly reported average vessel earnings. However, there is a substantial overrepresentation of certain routes which admittedly makes it difficult to assess whether this significant effect is due to persistent freight rate differences across areas, or a shipowner’s fixing skill/luck.

Regarding the timing variable, Timing_Good, we observe no evidence which suggests that companies are able to increase TCE by fixing a voyage within a relatively beneficial subperiod of the quarter. This variable may, however, be too generally specified, as it considers short term differences in the global index instead of regional differences, but one could argue that this result is in line with a market which is spatially efficient on aggregate quarterly level.

7 Limitations and further research

This study has certain limitations which should be acknowledged as they probably affect the credibility of the findings. First, it is worth noting that the TCE in this study is the quarterly average earnings per day per vessel, which means that we comparing quarterly averages calculated from a list of vessel earnings which itself has a probability distribution. To assess whether TCE is actually different between companies, it is required to measure of the variance in vessel earnings. This is not specified in the quarterly reports, and since the companies do not offer the earnings of each vessel, we are not able to calculate it either. Small differences in the quarterly reported daily TCE have great impact on earnings whey they are aggregated over the entire quarter. The OLS model framework may underestimate the 'real-world' effect of certain explanatory variables and differences between companies.

The fixing skill proxy is clearly biased towards particular routes and loading areas which may impair the attempt to separate "space" and "time" (see Table 5;Table 6;Table 19). Although introducing load area categorical variables may provide some adjustment, the proxy still will be biased towards particular routes.

There is inaccuracy in the analysis due to the assumption behind the lead-time between fixture and laycan. A better measurement of the fixture proxy could therefore increase the accuracy. Both the fixing skill and timing proxies rely on a relatively accurate estimate of fixture date. Especially the timing proxy where the goal is to give a score for voyages which are fixed in weeks within a quarter where rates are relatively high.

Furthermore, the laden and ballast days calculations rely on a correct specification in the Voyage data. For instance, laden days is assumed to be the days between load port departure and discharge port arrival, while ballast days is assumed to be the days between starting port departure (previous voyage's discharge port) and load port arrival. Optimally, one should consider the distance between ports, as the duration in days is dependent on a ship's sailing speed.

Finally, as discussed in Adland and Cullinane (2005), it is difficult to assess earnings without taking the risk premium into account. Such unobserved characteristics may impact freight earnings and explain substantial and persistent freight rate differences between companies and routes, and whether or not this leads to optimal trading strategy should depend on not only the expected earnings, but also the risks associated with the decision.

Regarding suggestions for further research, this study is limited to those companies which report their quarterly vessel earnings. Unfortunately, this turns out to be a fairly limited number of companies. Inclusion of a larger number of companies over a greater set of segments and time could for instance increase the accuracy of the analysis. It would also be relevant to investigate more sophisticated trading and fleet allocation proxies for a more comprehensive analysis of average vessel earnings.

When matching routes with an earnings index, this study considered only loading areas for the Suezmax segment. That is, all voyages loading in WAF is represented by the same index. This was assumed such that one could assign the largest possible number of voyages with an associated earnings index. A more sophisticated categorization of voyages could help with increasing the number of 'indexed routes' in the analysis, for instance by categorizing voyages as either east-bound and west-bound out of the major load areas, such as WAF and AG. However, these topics are left for future research.

8 Appendix

A.1 TCE data
Source: The companies' quarterly reports from Q1-2014 to Q2-2020

Table 7 Suezmax TCE

Suezmax				
Company	**NAT**	**Euronav**	**Frontline**	**Teekay**
Mean	24 412,5	27 972,0	26 246,2	26 028,2
25th Percentile	14 550,0	17 193,0	16 200,0	16 263,0
50th Percentile	22 150,0	22 868,5	24 150,0	22 988,0
75th Percentile	35 250,0	40 435,0	33 800,0	36 508,8
Standard Deviat	11 312,8	13 677,9	11 886,5	11 193,8
Minimum	10 500,0	12 883,0	12 400,0	12 543,0
Maximum	48 400,0	60 750,0	57 800,0	49 067,0
# observations	26	26	26	26

Table 8 VLCC TCE

VLCC			
Company	**DHT**	**Euronav**	**Frontline**
Mean	40 720,0	38 544,8	36 542,3
25th	20 275,0	24 300,3	22 150,0
50th	35 300,0	33 969,0	30 300,0
75th	59 775,0	53 168,5	52 550,0
Standard Deviation	21 424,6	18 330,7	19 798,1
Minimum	11 900,0	16 751,0	11 700,0
Maximum	92 100,0	81 500,0	75 800,0
N	22	26	26

A.2 Time to laycan assumption

Table 9 Laycan calculations

Load area	Time_to_laycan	Time to Layca	Fixture (#)
AG	14,21833046	14,22	399
Australia/NZ	NA	14,87	0
Far East	12,00058513	12,00	9
WAF	19,22515239	19,23	312
Med	11,31110498	11,31	51
EC SAM	24,12218277	24,12	120
ECC	8,688443287	8,69	4
Red Sea	14,04146329	14,04	7
USG/Caribs	17,74000767	17,74	92
Black Sea	16,0240621	16,02	29
UK & Cont	10,51060378	10,51	36
WC SAM	9,246304012	9,25	3
EC CAM	17,74675275	17,75	16
WC CAM	18,37594618	18,38	4
USAC	NA	14,87	0
USWC	NA	14,87	0
S/E AF	NA	14,87	0
India/Pakistan	NA	14,87	0

A.3 Fleet data, Source: The companies' annual reports from 2013-2019

Table 10 Fleet data by company

Vessel count			
Company	**Suezmax**	**VLCC**	∑
Frontline	38	41	79
NAT	33	0	33
Euronav	36	54	90
DHT	2	32	34
Teekay	32	0	32
∑	141	127	268

A.4 Voyage data

Source: Voyage dataset by Signal Ocean (2020). Tables are created by the author.

Table 11 Area categories

Signal Areas	**Area abbreviation**	**Assumed Areas**
Arabian Gulf	AG	Arabian Gulf
Arctic Ocean & Barents Sea	UK & Cont	UK and Continent
Australia / New Zealand	Australia/NZ	Australia/New Zealand
Baltic	UK & Cont	UK and Continent
Black Sea / Sea Of Marmara	Black Sea	Black Sea
Caribs	USG/Caribs	US Gulf and Caribs
China / Taiwan	Far East	Far East
East Coast Canada	ECC	East Coast Canada
East Coast Central America	EC CAM	East Coast Central America
East Coast Mexico	EC CAM	East Coast Central America
East Coast South America	EC SAM	East Coast South America
India / Pakistan	India/Pakistan	India / Pakistan
Korea / Japan	Far East	Far East
Mediterranean	Med	Mediterranean
North Sea	UK & Cont	UK and Continent
Red Sea	Red Sea	Red Sea
Russian Pacific	Far East	Far East
South East Africa	S/E AF	South East Africa
South East Asia	Far East	Far East
UK Continent	UK & Cont	UK and Continent
US Atlantic Coast	USAC	US Atlantic Coast
US Gulf & Mainland	USG/Caribs	US Gulf and Caribs
West Africa	WAF	West Africa
West Coast Central America	WC CAM	West Coast Central America
West Coast Mexico	WC CAM	West Coast Central America
West Coast North America	USWC	US West Coast
West Coast South America	WC SAM	West Coast South america
Pacific Islands	Far East	Far East

Table 12 Loading areas by segment and total

	VLCC		Suezmax		Total	
Load area	#	%	#	%	#	%
AG	1390	58,2%	842	19,8%	2232	33,6%
WAF	331	13,9%	1077	25,3%	1408	21,2%
USG/Caribs	217	9,1%	617	14,5%	834	12,5%
Med	30	1,3%	413	9,7%	443	6,7%
EC SAM	146	6,1%	224	5,3%	370	5,6%
UK & Cont	103	4,3%	209	4,9%	312	4,7%
Far East	89	3,7%	201	4,7%	290	4,4%
Black Sea	0	0,0%	190	4,5%	190	2,9%
USWC	5	0,2%	134	3,1%	139	2,1%
EC CAM	21	0,9%	114	2,7%	135	2,0%
Red Sea	10	0,4%	114	2,7%	124	1,9%
WC CAM	39	1,6%	57	1,3%	96	1,4%
WC SAM	5	0,2%	39	0,9%	44	0,7%
ECC	0	0,0%	23	0,5%	23	0,3%
USAC	0	0,0%	4	0,1%	4	0,1%
India/Pakistan	1	0,0%	3	0,1%	4	0,1%
S/E AF	0	0,0%	2	0,0%	2	0,0%
∑	2387	100%	4263	100%	6650	100,0%

Table 13 Discharge areas by segment and total

	VLCC		Suezmax		Total	
Discharge are	#	%	#	%	#	%
Far East	1720	72,10%	1088	25,50%	2808	42,20%
UK & Cont	132	5,50%	610	14,30%	742	11,20%
Med	27	1,10%	563	13,20%	590	8,90%
India/Pakistar	166	7,00%	369	8,70%	535	8,00%
USG/Caribs	99	4,10%	390	9,10%	489	7,40%
USWC	73	3,10%	253	5,90%	326	4,90%
ECC	13	0,50%	279	6,50%	292	4,40%
S/E AF	67	2,80%	117	2,70%	184	2,80%
USAC	0	0,00%	154	3,60%	154	2,30%
WAF	5	0,20%	81	1,90%	86	1,30%
WC SAM	1	0,00%	80	1,90%	81	1,20%
EC SAM	15	0,60%	57	1,30%	72	1,10%
Red Sea	57	2,40%	15	0,40%	72	1,10%
AG	5	0,20%	54	1,30%	59	0,90%
Black Sea	0	0,00%	58	1,40%	58	0,90%
Australia/NZ	0	0,00%	50	1,20%	50	0,80%
EC CAM	1	0,00%	44	1,00%	45	0,70%
WC CAM	6	0,30%	1	0,00%	7	0,10%
∑	2387	100%	4263	100%	6650	100%

Table of the major Suezmax routes

Table 14 Suezmax route summary

Route	# Suezmax	% Suezmax
WAF-UK & Cont	314	7,37%
AG-India/Pakistan	272	6,38%
AG-Far East	223	5,23%
USG/Caribs-USG/Caribs	209	4,90%
WAF-Med	206	4,83%
Far East-Far East	188	4,41%
USG/Caribs-ECC	145	3,40%
Med-Far East	130	3,05%
AG-Med	124	2,91%
USG/Caribs-Far East	113	2,65%
USWC-USWC	104	2,44%
WAF-Far East	98	2,30%
Red Sea-Far East	93	2,18%
Med-Med	92	2,16%
WAF-S/E AF	90	2,11%
Other	1862	43,68%

Table of the major VLCC routes

Table 15 VLCC route summary

Route	# VLCC	% VLCC
AG-Far East	940	39,38%
WAF-Far East	237	9,93%
USG/Caribs-Far East	174	7,29%
EC SAM-Far East	136	5,70%
UK & Cont-Far East	98	4,11%
AG-UK & Cont	93	3,90%
AG-USG/Caribs	90	3,77%
Far East-Far East	78	3,27%
AG-S/E AF	57	2,39%
WAF-India/Pakistan	56	2,35%
AG-Red Sea	55	2,30%
AG-USWC	54	2,26%
AG-India/Pakistan	49	2,05%
USG/Caribs-India/Pakistan	38	1,59%
WC CAM-Far East	29	1,21%
Other	203	8,50%

A.5 Earnings timeseries summary

Source: Clarkson SIN

Table 16 Suezmax earnings timeseries summary

Suezmax Earnings Timeseries

Route (Ports)	Route (area)	Mean	25th	median	75th	stdev	N
Sidi Kerir-Fos	Med-Med	31017	14573	25107	43658	21695	339
Bonny Off-Philadelphia	WAF-USAC	24911	10601	20184	34352	18161	339
Bonny Off-Lavera	WAF-Med	26032	11045	21622	36508	19327	339
Ras Tanura-Huizhou	AG-Far East	27178	13624	21736	36553	19956	339
Sture-Wilhelmshaven	UK & Cont-UK & Cont	50254	21605	48930	73441	32888	264
Novorossiysk-Augusta	Black Sea-Med	35420	16616	28821	47918	25077	339
Ras Tanura-Jamnagar (Sikka)	AG-India/Pakistan	24821	9903	18281	34661	22023	339
Basra-Lavera	AG-Med	22703	7141	16314	35210	19966	339
Marsa El Hariga-Ningbo	Med-Far East	37241	23354	31068	50821	19375	339
Bonny Off-Rotterdam	WAF-UK & Cont	27501	12475	23055	37412	18901	312
Corpus Christi-Rotterdam	USG/Caribs-UK & Cont	34755	12920	28193	50242	26379	95
Corpus Christi-Singapore	USG/Caribs-Far East	50438	28397	47095	67122	26963	95
Sture-LOOP	UK & Cont-USG/Caribs	17981	6520	13795	26415	14838	339
Covenas-LOOP	USG/Caribs-USG/Caribs	30008	12310	21886	41498	24075	339

Table 17 VLCC earnings timeseries summary

VLCC Earnings Timeseries

Clarkson reference	Route (Ports)	Route (area)	Mean	25th	median	75th	stdev	N
530976	Ras Tanura-Rotterdam	AG-UK & Cont	31372	6105	20837	44399	39706	298
530980	Ras Tanura-Ulsan	AG-Far East	37849	13634	28763	50687	35884	339
530984	Ras Tanura-Chiba	AG-Far East	40833	15877	30339	54532	37457	339
530988	Ras Tanura-LOOP	AG-USG/Caribs	38300	10087	26996	52432	45208	315
530992	Bonny-LOOP	WAF-USG/Caribs	48086	25049	40826	63055	34270	339
530996	Bonny-Ningbo	WAF-Far East	38437	16316	30614	49873	32266	339
531000	Bonny-Kaohsiung	WAF-Far East	41801	19718	33674	53325	32003	339
531004	Ras Tanura-Ain Sukhna	AG-Red Sea	48140	21492	38397	61387	38932	339
531008	Sidi Kerir-Rotterdam	Med-UK & Cont	55974	27811	47039	73234	43479	339
531012	Ras Tanura-Singapore	AG-Far East	41925	16747	30909	54718	39654	339
531016	Ras Tanura-Jamnagar	AG-India/Pakistan	47454	14922	35210	66856	44954	338
531020	Mongstad-LOOP	UK & Cont-USG/Caribs	49735	41563	52124	58520	9097	8
531024	Bonny-Jamnagar	WAF-India/Pakistan	46232	21303	37899	60666	35739	339
531028	Rotterdam-Singapore	UK & Cont-Far East	53075	25580	44737	67635	39807	339
531032	Bonaire-Singapore	USG/Caribs-Far East	76334	44544	67516	97345	47014	339
535037	Bonny-Rotterdam	WAF-UK & Cont	51571	26039	42929	67973	37967	278
542438	Ras Tanura-Ningbo	AG-Far East	53579	18072	39277	60224	55695	100

A.6 LBR and FS_AVG regressions

The following regressions provide some explanations of the two trading performance variables. The two main trading variables in this study are the LBR and Fixing skill. Table 18 and Table 19 show regressions with LBR and FS_AVG as dependent variable in order to assess potential drivers of these variables. In Model 1 and 3 in both tables, the dependent variables are regressed on company dummies as well as time dummies to control for exogenous market conditions, and in the Suezmax segment there seems to be substantial differences in LBR across companies. In the VLCC segment, Frontline seems to have a significantly lower LBR than DHT and Euronav. It should again be noted that the LBR is calculated in days rather than distance between ports, which means that the variable may be affected by differences in vessel speed across companies and time. Regarding the FS_AVG variable, we see that some loading ad discharge areas are associated with increased or decreased FS_AVG. This shows similar results as in Table 5 and Table 6.

Table 18 Second step regression. LBR as dependent variable

	Suezmax	Suezmax	VLCC	VLCC
	(1)	(2)	(3)	(4)
Dependent Var	LBR	LBR	LBR	LBR
FS_AVG	0.175	-0.185	0.348	0.0958
	(0.212)	(0.292)	(0.299)	(0.858)
Age>=15	-0.236*	-0.498***	-0.535	-0.593
	(0.066)	(0.006)	(0.167)	(0.242)
Euronav	0	0	-0.0448	0.0435
	(.)	(.)	(0.612)	(0.719)
Frontline	-0.133***	-0.0465	-0.0532	-0.0244
	(0.001)	(0.516)	(0.590)	(0.829)
NAT	-0.144***	-0.0297		
	(0.006)	(0.781)		
Teekay	-0.158***	-0.167***		
	(0.000)	(0.009)		
DHT			0	0
			(.)	(.)
load_AG		-0.00472		-0.0282**
		(0.467)		(0.047)
load_WAF		-0.00807*		-0.0207
		(0.074)		(0.209)
load_Med		0.0191**		0.0158
		(0.048)		(0.717)
load_USG/Caribs		0.00965		-0.0296
		(0.122)		(0.229)
load_Black Sea		0.0133		0
		(0.302)		(.)
load_UK & Cont		0.0245*		0.0172
		(0.062)		(0.651)
disch_Far East		-0.000679		0.0210
		(0.883)		(0.113)
disch_UK & Cont		0.00235		0.00183
		(0.742)		(0.951)
disch_Med		-0.0100		-0.0317
		(0.328)		(0.545)
disch_India/Pakistan		0.00407		0.0122
		(0.655)		(0.567)
disch_USG/Caribs		-0.0121		0.0531**
		(0.114)		(0.029)
Constant	1.105***	1.258***	1.351***	1.369***
	(0.000)	(0.000)	(0.000)	(0.000)
Time FE	YES	YES	YES	YES
Observations	104	104	74	74
R^2	0.537	0.649	0.646	0.754
Adjusted R^2	0.347	0.416	0.412	0.471

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19 Second step regression. FS_AVG as dependent variable

	Suezmax	Suezmax	VLCC	VLCC
	(1)	(2)	(3)	(4)
Dependent Var	FS_AVG	FS_AVG	FS_AVG	FS_AVG
LBR	0.122	-0.0967	0.0704	0.00990
	(0.212)	(0.292)	(0.299)	(0.858)
Age>=15	-0.125	-0.304^{**}	0.207	0.0815
	(0.245)	(0.021)	(0.235)	(0.619)
Euronav	0	0	0.199^{***}	0.126^{***}
	(.)	(.)	(0.000)	(0.000)
Frontline	-0.0879^{**}	-0.0243	0.00829	-0.00215
	(0.012)	(0.639)	(0.852)	(0.953)
NAT	0.0140	0.0536		
	(0.753)	(0.486)		
Teekay	-0.0437	-0.0383		
	(0.258)	(0.420)		
DHT			0	0
			(.)	(.)
load_AG		-0.00351		0.00877^{*}
		(0.453)		(0.055)
load_WAF		-0.0101^{***}		-0.00128
		(0.001)		(0.811)
load_Med		0.0187^{***}		0.0217
		(0.007)		(0.116)
load_USG/Caribs		0.00785^{*}		0.0241^{***}
		(0.081)		(0.001)
load_Black Sea		0.0105		0
		(0.260)		(.)
load_UK & Cont		0.00986		0.0444^{***}
		(0.304)		(0.000)
disch_Far East		-0.000456		-0.0108^{***}
		(0.891)		(0.009)
disch_UK & Cont		-0.00156		-0.0252^{***}
		(0.763)		(0.006)
disch_Med		0.00392		-0.00266
		(0.597)		(0.875)
disch_India/Pakistan		0.00720		0.00666
		(0.271)		(0.330)
disch_USG/Caribs		-0.00379		-0.0109
		(0.498)		(0.173)
Constant	0.347^{**}	0.528^{***}	-0.145	0.00514
	(0.010)	(0.000)	(0.192)	(0.956)
Observations	104	104	74	74
R^2	0.544	0.740	0.743	0.909
Adjusted R^2	0.357	0.567	0.574	0.804

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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