ΟΙΚΟΝΟΜΙΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ

ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS

MASTER OF SCIENCE (MSc) in

International Shipping, Finance & Management

Sentiment Augmented Pace of Investment in Dry Bulk Shipping Segment

By

Charitos Emmanouil

Triantafillidou Margarita-Maria

Thesis submitted to the Secretariat of the MSc in International Shipping, Finance and Management of the Athens University of Economics and Business, in partial fulfillment of the Requirements for the Master's Degree in International Shipping Finance and Management.

Athens

30/11/2021

"I hereby declare that this particular thesis has been written by me, in order to obtain the Postgraduate Degree (MSc) in International Shipping, Finance and Management, and has not been submitted to or approved by any other postgraduate or undergraduate program in Greece or abroad. This thesis presents my personal views on the subject. All the sources I have used for the preparation of this particular thesis are mentioned explicitly with references being made either to their authors, or to the URL's (if found on the internet)."

TABLE OF CONTENTS

TABLES

1 ABSTRACT

This paper examines the effect on investment to new-building vessels caused by shipping sentiment, focusing on the Dry-Bulk sector. To quantify the pace of this investment, the ratio of New Contracts to Total Fleet development is used. Specifically, by employing sentiment variables, constructed based on proxies that were used in prior literature, this paper tries to capture the impact of shipowners' sentiment on investing in new-building vessels. In addition, we employ shipping and fundamental related variables, as control variables. The data is organized in panels, thus a panel data analysis is best suitable. Throughout the analysis, three different models are examined, which differ from one another based on which variable of interest is employed in them. In two of these panel data regression models, a random effects regression is favored while on the third one a fixed effect one is favored. Our findings support that New Contracting to the Total Fleet is indeed positively affected by sentiment.

2 INTRODUCTION

Shipping is a hyperglobal industry contributing to hundreds of billions to the world economy every year. In 2020, the total World Seaborne Trade was 11.5 million tonnes, making the percentage of goods being transported by sea 86% of total trade. When we also take into account the distance of transportation for the goods, the total seaborne trade of 2020 was equal to 56,600 billion tonne-miles. For reference purposes, the respective numbers in 2021 were 6,378 billion tonnes and 29,773 billion tonne-miles. (Clarksons Research , 2021)

Due to the different types and quantities of cargo being transported, the main markets in shipping are the Bulk, the Specialized and the Liner market. The bulk market refers to cargo in vast quantities, able to fill a vessel, fully or partially, and can be subcategorized in Liquid and Dry bulk market (Stopford, 2009), the latter being analyzed in this paper.

Dry Bulk shipping refers to the transportation of homogeneous cargo, in bulk, in account for one shipper usually. The main commodities being transported are iron ore, coal and grains along with bauxite, cement, sugar and other minor bulks. The types of the segment's vessels are: Handysize (capacity: 10,000–39,999 dwt), Handymax (40,000–64,999 dwt), Panamax (65,000–99,999 dwt) and Capesize (100,000 dwt and above) (UNCTAD, 2021).

The shipping industry is one of the most capital-intensive ones (Alexandris, et al., 2020) , with newbuilt ocean going vessels being priced from 20 to 200 million dollars, depending on the segment, size and mainly the state of the market. In the Dry Bulk segment, on which this paper is focusing on, historically the prices, on average, vary from $20m for a Handysize to $60m for a Capesize [see (Clarksons Research , 2021)]. More specifically, as vessels' prices are affected by the state of the market, during market peaks, the price of a newly built Capesize vessel may reach $99 million and for a Handysize vessel's one $34 million, whereas during market troughs the same categories of vessels could be acquired with $34 million or $13 million respectively [see (Clarksons Research , 2021)]. Consequently, the choice of investing in a newbuilding vessel requires a substantial amount of capital, making it risky and many times irreversible decision (Drakos & Tsouknidis, 2021). Considering the fact that dry bulk fleet currently comprises of around 12,500 vessels, the overall capital invested in the industry can be considered exorbitant, especially while taking into account the irreversibility of the investment.

Apart from capital intensity, the sector presents some additional distinct characteristics. First of all, the nature of demand can be characterized as derived, as demand for the transportation service is the derived demand for each commodity, thus affected by external factors (Stopford, 2009). Supply, on the other hand is determined based on the total active fleet on each segment and the speed of this fleet. Vessels, as the mean of transportation of the service, are subject to different risks, including price volatility, regulatory changes, and high operating costs.

Shipping is also a highly volatile sector, where spot freight rates along with vessel prices can vary substantially even within months. The more recent example is the one of 2021, when Spot Freight rates for a Capesize vessel tripled from February to May 2021 and then almost doubled from May to October 2021 [see (Clarksons Research , 2021)]. Even though, contradictory examples exist, such as that of Lehman Brothers financial crisis, during which freight rates declined by around $35 thousand for a Panamax vessel within a month (from around $45 thousand in middle September 2009 to a bit less than $10 thousand in middle October 2009) [see (Clarksons Research , 2021)]. A general rule is that volatility is higher in larger vessels, as they are more restricted regarding both the cargo they can transport and also the ports they may enter due to their size (Kavussanos, 1996). Although, to enhance this general rule, one should consider that in shipping the segments and their sub-segments sometimes can overlap. For example, containers are able to carry some commodities that are typically transported through dry bulk vessels, smaller vessels may be chartered to carry bulk commodities to smaller ports, and also investors are able to relocate their funds between all markets. Relevant research from (Tsouknidis, 2016) focusing on dry bulk and tanker markets, reveals that volatility spillovers are actually present in the market, both in segments and in sub-segments. Additionally, the direction is mainly from smaller vessels to larger ones in the dry-bulk and between these markets is from tanker to dry-bulk.

Volatility however can also prove beneficial. Investors may try to take advantage of bull market conditions by staying in the spot market or selling vessels. When they judge that the cycle is coming to its end, they may choose to enter time charter contracts, so to ensure higher than average rates. During bear market conditions, they may choose to acquire vessels due to the reduction in vessels' prices. A relevant example is the surge in vessel acquiring that happened during 2021 in the tanker segment, even if the tanker freight market was in a bear state.

Moreover, seasonality, another characteristic of the business, may enhance volatility in the short-term as main commodities in shipping have a cycle of their own, like grain or oil, whose fluctuations are transferred to freight rates. Although, in shipping exists deterministic seasonality, i.e., specific patterns occurring at specific periods every year (Kavussanos & Alizadeh-M, 2001). The latter stated that in Dry bulk shipping, the freight rates are higher in early spring and autumn months. Additionally, as seasonality differs among different vessel types (due to the different cargo they carry), it may be contained through vessel diversification. However, seasonality, being deterministic, can be exploited in the right manner by choosing the appropriate freight contract based on the market's state and schedule maintenance when the cycle is expected to present a fall.

Cyclicality is another characteristic of the shipping industry. Such a global industry absorbs shocks from various industries, the global economy and the environment, among others. Sometimes they may diminish in the short-term, other times they may cause a structural change. According to (Stopford, 2009) there are three types of cycles: long, short and seasonal. Long cycles may last decades and typically result from structural changes. Short-term cycles may last from 3 to 12 years and are mainly affected by demand and supply, where only supply is manageable in the sector. Lastly, seasonal cycles are known, and occur at a yearly basis. He stated that, except for the seasonal one, cycles in shipping are completely unpredictable and without a pattern.

The market cycle is highly affected by the time-lag between a vessel's order and its delivery. From the moment a vessel is ordered until it is delivered there will be a time-lag of 18-36 months (Kalouptsidi, 2014). New contracts are more common during bull market conditions, where the freight rates are high and the market's sentiment positive. Evidently, the higher the level of uncertainty (which harbors negative sentiment), the lower the investment amount (Drakos & Tsouknidis, 2021).

However, the state of the market might not be the same when the vessel will be delivered.

In order not only to profit, but also to survive during the shipping cycle and its rapid developments, the appropriate choice of vessel regarding its acquisition period, characteristics and age is essential. New-building vessels, discarding their high acquisition cost, offer the advantage of lower operating costs due to their higher efficiency and increased earnings through freight rates. The cost of a newly built vessel is also highly volatile, since it depends on the state of the market and the economy, impacting the overall amount of dollars invested in the new-building market. For example, in 2007 the total value of new contracts was $263,650.20 million, while two years later, in 2009, a year after the financial crisis, only $42,193.97 million were invested (Clarksons Research , 2021).

Last but not least, the shipowners' attitude regarding risk and returns is different than the typical CAP model. Stopford (Stopford, 2009) defines it as "RAP" model, meaning Risky Asset Pricing model, based on which, high volatility investments are preferred by shipowners because they are aware of the cyclicality in the market. The example given by Stopford is of a vessel's sale right after its delivery, which had a construction cost of $23.5 million and was sold for $55 million.

By focusing on rational decisions driven by economic cycles and demand-supply equations, one can explain some of the decisions made in shipping. But since humans are not entirely rational, another component of decision making should be taken into consideration and that is sentiment. From 1936, J M Keynes stated the -ahead of his time fact-, that if firms depended only on quantitative decisions, they shall fail, implying that something beyond pure mathematics drives investment decisions, which he called "innate urge to activity" (Keynes, 1936). Sentiment in regard to stock market returns is examined to a great extent in the literature, and the findings are promising, stating that sentiment is proved to be related to market returns. In shipping, an industry considered to be affected by shipowners' sentiment, its impact came into the spotlight through relevant research in the last 10 years.

In this paper, we try to explain the factors that trigger the shipowners' choice to invest in a new-building vessel in the Dry Bulk market. Our models aim to explain this choice based on the market conditions but most importantly, to focus on shipowners' sentiment in regard to this choice. Previous research was performed by (Drakos & Tsouknidis, 2021) who by using as dependent variable New Contract to Fleet Development, depicted whether or not shipowners would invest in different vessel types, along with investment's volume. They revealed that this investment is negatively affected by uncertainty, which also reduces the volume of investments occurred. However, higher reversibility can trim this negative effect caused by uncertainty.

The second-hand market is excluded from our analysis, as it does not affect the number of vessels in the active fleet.

The paper is organized as follows: Section 1: Abstract, Section 2: Introduction, background and overview, Section 3: Literature Review, Section 4: Data and Variables, Section 5: Methodology, Section 5: Correlation Matrix and regression models' presentation, Section 6: Methodology, Section 7: Results, Section 8: Discussion, Section 9: Conclusion.

3 Literature Review

In order to commit to a new-building's acquisition, the primary objective is its expected cash flows. These cash flows depend, to a great extent, on the freight market, and due to the time lag in construction, to the expectations regarding this market. Recently, scholars [specifically (Michail & Melas, 2021)] have investigated how new orders are affected by macroeconomic and shipping related shocks and concluded that an improvement, actual or perceptional, of macro conditions can affect "shipowners' behavior". In practice, freight rates are considered to be unpredictable, although prior literature [e.g., (Kavussanos & Visvikis, 2004)] has discovered a relationship among spot rates and FFAs, while others [(Baker, et al., 2012) and (Zhang, et al., 2014)] examined the possibility to forecast the spot market through TC rates and FFAs. A study performed earlier by (Batchelor, et al., 2007) also found spot market to be cointegrated with forward market and that forecasting can be performed on spot rates but not on FFAs, using Vector Equilibrium Correction Models. While the freight market is correlated with decision for vessel acquisition, the research of (Wu, et al., 2020) supports the relationship between this market and sentiment by constructing a fear index which was found to affect freight rates forecasting and their volatility.

It should be noted, that from 1980 researchers started investigating the robustness of the Efficient Market Hypothesis, as specific actions could not be explained just through the fundamentals. Previous studies on sentiment did concentrate more on the stock market and its effect on business cycles and prices. Other researchers, [e.g., (Brown & Cliff, 2004)] examined if sentiment actually affects the stocks' price formation. Their results showed that the stock market does affect future sentiment, although the reversed could not be proven, i.e., that sentiment affects the stock market's conditions in the future. Additionally, sentiment could not predict the market even in the short-term and thus was deemed an inappropriate strategy for predicting the stock market. (Berger & Turtle, 2012) who emphasized the importance of information, argued that when investor sentiment, measured based on forecasts, increases, the performance of stocks of firms which are not listed, and thus their data is "hidden" decreases, which does not happen with stocks whose data is public. (Baker & Wurgler, 2006), trying to measure it, constructed a sentiment index (employing principal component analysis) through proxies and tested whether these proxies were able to predict stock returns. The results showed that proxies of this index affect the returns of specific types of stocks ("valuation is highly subjective and difficult to arbitrage") in opposite and significant way. The aforementioned, (Baker & Wurgler, 2007) evolved their research trying to find the equilibrium among high-low sentiment and the outcome of its aggregate effects. Also, they examined if forecasting of the returns based on current sentiment is actually possible. The results showed that the returns of stocks that are highly speculative is lower than the ones that are not, like bonds, during high sentiment periods. As the problem of high correlated omitted variables occurred, they used return predictability to overcome this issue. However, (Sibley, et al., 2016)**,** emphasizes considerably this issue, stating that any forecasts derived from this index would be due to the proxies being driven from the cycles themselves. A way to overcome this issue was to estimate sentiment directly through machine learning. (Audrino, et al., 2020) through a regression model containing a 5-year dataset of stock prices and social media posts of public companies in different industries, investigated the impact of investors' sentiment and attention (to news) on variation. They concluded that these variables (sentiment and attention) and especially attention, are able to predict volatility in the long-term.

Sentiment analysis might be focusing on the stock market, but several studies incorporated it into shipping. So far, shipowners were considered to take into account sentiment for a lot of decisions, but no empirical studies were conducted to support this notion. (Papapostolou, et al., 2014) by concentrating on shipping sentiment, constructed proxies regarding participants' beliefs of shipping market and used them as indices to quantify sentiment for the dry bulk market. Also, they stated that sentiment analysis can be used as a forecasting method for future vessel price returns, and as a "market timing tool" for sale and purchase transactions. (Papapostolou, et al., 2016), focusing again on shipping segment, investigated whether shipping investor sentiment can predict stock returns by using the proxies constructed on their previous paper. Their hypothesis was proved correct, concluding that during periods with high shipping sentiment, next period's returns in the stock market are low. The existence of a relationship between sentiment and vessel acquisition is also supported by (Michail & Melas, 2021) who also stated that sentiment does not affect demolitions.

Sentiment, especially regarding such a complex industry, is hard to be measured as the literature is not clear regarding whether sentiment reacts or drives the markets. Through the years the identification of global sentiment may be captured more accurately, as in the research of (Gao, et al., 2019) who used specific words from a database containing Google searches to construct sentiment proxies. Their results were remarkably promising, as "sentiment predicts market returns". We expect in the foreseeable future to obtain more advanced databases, aiding to procure a more accurate snapshot on each period's sentiment that may be used as a variable in such regressions.

4 Data and Variables

We examine a data set of 240 monthly observations for each vessel type of the Dry-bulk sector. Handysize vessels (capacity 10,000 to less than 40,000 dwt) are the smallest vessels of the sector and the most flexible in terms of port accessibility. The main commodities they carry are grain, steel products, cement and other minor bulks.

Due to their small size, they can be employed on several areas. Handymax (40,000–64,999 dwt) are also flexible vessels, employed mainly for ore, cement, phosphate and grain transportation worldwide. Panamax vessels (65,000–99,999 dwt) carry mainly grain and coal but may also carry iron ore. Their typical destinations are China, Japan and West Europe. The largest dry-bulk vessels are Capesize (100,000 dwt and above) and their typical cargo is iron ore, although in some cases they may carry coal and bauxite. The main routes include the transport of iron ore from Brazil or Australia to China, Rotterdam, and Japan. Their large size permits specific trade routes and ports, while their passage through Canals is prohibited (Baltic Exchange, 2021).

The range on the date is the period from January 2001 to December 2020, using the Clarkson's Shipping Intelligence Weekly Network.

The selected time-series are the following:

1. New Contracting: includes the official contracts signed between shipping firms and shipyards regarding the construction of a vessel (Clarksons Research , 2021)
2. Fleet Development: refers to the existing fleet, having added delivered vessels and subtracted demolitions (Clarksons Research , 2021)
3. Spot Market's Earnings: the average earnings for a spot voyage agreement (Clarksons Research , 2021)
4. 1-Year Time-Charter Earnings: Long Run historical Earnings for a time charter trip of 1 year (Clarksons Research , 2021)
5. GDP Major 5 Asia: the value added by the production of goods and services domestically for a specific period in China, Japan, S. Korea (OECD.org, 2021)
6. LIBOR Interest Rate[1]: the average interest rate that banks borrow funds in London market (FRED, 2021)
7. Fleet's Average Age: the average years of the fleet for each examined vessel type (Clarksons Research , 2021)
8. Trade Weighted Steel Production Index (Clarksons Research , 2021)
9. Second-Hand Prices: the average second-hand price of a 5-year-old Vessel (Clarksons Research , 2021)

[1] Should be noted that Libor is to be abandoned by 2022 (J.P.Morgan, 2021)

10. Major Coal Exports: the seaborne coal exports of Australia, US, Canada, Indonesia, Colombia which account for approximately 80% of total seaborne coal exports over the years. (IEA, 2021)
11. Major Iron Ore Exports: the seaborne Iron Ore exports of Australia, South Africa, Brazil, Canada, India which account for more than 85% of total iron ore seaborne exports. (OEC, 2021)
12. Steel Plate Price: the average price of steel plates in the major shipbuilding nations (Clarksons Research , 2021).
13. Demolitions per type of vessel examined (Clarksons Research , 2021).

4.1 Dependent Variable

<u>New Contracts to Fleet Development (NCFD)</u>

Our dependent variable is the ratio of new contracts to fleet development. New Contracts are in essence the orders that take place each month, i.e., the official contracts signed between shipping firms and shipyards regarding the construction of a vessel, while Fleet Development refers to the existing fleet. The ratio depicts which percentage of the existing fleet is being ordered each month.

The data employed where the number of new contracts and the number of vessels in the active fleet per each vessel type. Both variables, and thus the ratio created, are time-variant and sector-variant at the same time.

$$NCFDi,t = \frac{NCi,t}{FDi,t}$$

4.2 Independent variables

Net Contracting is expected to be affected by three categories of variables. Fist, the shipping variables, which explain the conditions of the industry that trigger changes in the supply of vessels. Second, the fundamentals, including macroeconomics and financial related variables, which affect to a great extend this extremely global and capital-intensive industry. Finally, the variable this dissertation will mostly focus on, the sentiment variables. The reason lies to the fact that this cluster is based on information exchange and networks, and also large-scale action shipowners take, cannot be explained by supply and demand.

4.2.1 Shipping Related Variables

Spot Market Earnings (ES)

The ratio of number of contracts to the number of vessels in the existing fleet, in contrast to the orderbook, depicts at once the decision made, since the factor of the lag of shipbuilding is omitted. Thus, it should also be captured by factors that depict the current state of the market. Following this rationale, we employed spot earnings as an independent variable. The economic rationale behind this decision is self-explanatory, since higher freight is the response to insufficient supply, as when demand for the transportation service offered by vessel increases, the inelasticity of supply in the short-term drives freight rates up as well. We expect the variable to enter the model with high significance and a positive sign. The variable is both time and section variant. The data employed are as follows:

Handysize: 6-month Time Charter Rates 36,000 DWT

Handymax: Average Spot Rates of 45,000 DWT

Panamax: Average Spot Rates of 72,000 DWT

Capesize: 6-month Time Charter Rates (January 2001 to November 2017: 150,000 DWT and from December 2017 to December 2020: 170,000 DWT)

Fleet Average Age (FAA)

The economic life of a vessel greatly depends on the market cycle. In bear market conditions vessels may be scrapped as early as when they are 15 years old. In contrast, in bull market conditions they may even reach an age of 30 years old and depending on the segment they participate in even more. In bulk carriers, historically, the average age of vessels being scrapped is around 25 years old [see (Clarksons Research , 2021)].

A higher average fleet age could reflect reluctance to scrap vessels, due to bull market conditions, providing incentive to keep the vessel since it can be employed. A reduction in the fleet average age could point to a bear market, forcing owners to scrap their vessels, since the cost of maintaining the vessel is not viable. However, the fleet's average age is also impacted by deliveries, which due to the time lag of construction were probably made 18-36 months prior (Kalouptsidi, 2014). Thus, it is not certain whether or not this variable can actually explain our dependent variable. On the other hand, one could argue that we could face endogeneity, due to reversed causality. Even though there exists the time lag of construction, the decision to build is often considered irreversible (Drakos & Tsouknidis, 2021) and has an impact to the fleet's average age.

All things considered, the variable is both time and sector variant and is chosen considering its impact on shipowners view when evaluating the timing to build a new vessel.

4.2.2 Fundamental Variables

<u>GDP Major 5 Asia Index (GDP)</u>

The important of the Major 5 Asia countries (i.e., China, Japan, South Korea, India, Indonesia) is paramount in shipping. China is a leader in the dry bulk sector, accounting for a considerable percentage of the world's iron ore, coal and grain imports (Clarksons Research , 2021) and steel production (World Steel Association, 2021). The country itself has established many of the most important trade patterns. Furthermore, India and Indonesia are rapidly developing economies and their presence in dry bulk trade grows stronger each year. Furthermore, China, South Korea and Japan account for the vast majority of shipbuilding (Clarksons Research , 2021). Based on the above, all of these countries have a strong presence in the dry bulk sector.

As world economic output is the most important factor for seaborne trade volume (Stopford, 2009), the GDP of the Major 5 Asia countries was employed as an independent variable. The economic conditions of these countries greatly affect the industry and should have an impact, both directly and indirectly at the decision to order a vessel or not. Based on the aforementioned, we expect this variable to enter the model with a positive sign and to be significant.

The latest, are considered to be the leaders if seaborne trade, thus as demand in shipping is the derived demand for the commodities being transferred, GDP of the specific area is the appropriate variable to depict the economic conditions and their effect in new contract's timing.

Steel Price Index (SPI)

Steel as a commodity is at the center of dry bulk shipping for multiple reasons. First, to produce steel, iron ore and coal, the two major dry commodities are essential, which also need to be transferred, unless produced domestically. We do not account for the production of green steel, since this trend has only recently begun and is still in very early stages. Coupled with the fact that our data series cover the period from January 2001 to December 2020, it seems illogical to even contemplate on the abovementioned. Second, steel will need to be exported, unless used domestically, further enhancing its importance in dry bulk shipping. Third, steel plates, a major steel product, is highly important when it comes to shipbuilding, since it affects the prices. Around 20% of the cost of construction of a vessel depends on steel plates. Based on the abovementioned, two variables are employed: a steel price index and Clarkson's Trade Weighted Steel Production Index. The steel price index is constructed as the average of the prices of steel plates in the top 3 shipbuilding nations, i.e., Japan, South Korea, and China. The data used were all downloaded from Clarkson's Intelligence. We expect the steel price index to enter the model with a positive sign. While enhanced steel plate prices would lead to higher shipbuilding prices, the effects of a strong iron ore/steel market should affect freight rates to the extent that shipowners are not affected by the fluctuations steel plate prices have on vessel prices.

Trade Weighted Steel Production Index (TWSPI)

Based on the same rationale, we also employed as an independent variable the trade weighted steel production index. Apart from the importance of steel plate, and the need to transport the iron ore used in steel production, there is also the need to transport by sea the steel products. This variable is only time variant, and we expect it to enter the model with a positive sign.

Coal Exports (CE) and Iron Ore Exports (IO)

Coal and iron ore are the two most important commodities in dry bulk shipping, accounting for almost half of it. Even though they are most commonly transported by Capesize vessels and rarely by Panamax vessels, the literature points out that there exist spillover effects which may affect the decision of ordering [see (Michail & Melas, 2021)].

For each commodity, we chose the most important countries in terms of exports;

Coal: Australia, US, Canada, Indonesia, and Colombia

Iron Ore: Australia, South Africa, Brazil, Canada, India

These two variables are only time variant. We expect them to enter the model with a positive sign. After all, a high volume of exports means activity in the trade patterns of the commodity, which is derived by demand. The demand for transportation is very important when it comes to the decision of committing capital to order a new vessel.

The volumes of the five countries were added for each commodity and expressed in million tones.

Considering the volume of dry bulk trade which is 50% of total volume of total carried cargo, iron ore and coal are by far the most traded commodities, accounting for almost half of dry bulk trade. So, two variables that depict trade for this segment were Coal and Iron Ore exports of top 5 exporters globally, which are Australia, US, Canada, Indonesia, Colombia for coal and Australia, South Africa, Brazil, Canada, India for Iron Ore (Clarksons Research , 2021). We expect the exports of these two commodities to positively affect the decision to commit capital to a new building, as when exports are expected to increase, demand will be created, and the specific vessel type will be deployed.

12-month Libor Interest Rates based on the US Dollar (LIBOR)

Shipping is often depicted as a close to perfectly competitive industry. One of its primary characteristics is its capital intensity [see (Stopford, 2009)]. Thus, newbuilding orders or second-hand acquisitions are generally financed through debt. That is to say, by borrowing capital from financial institutions. With this in mind, another variable that enters our model, due to its importance when it comes to debt-financing is LIBOR, as it is a highly important factor in shaping the interest rates of bank loans. Libor (London Interbank Offered Rate) is a benchmark interest rate at which major global banks lend to one another in the international interbank market for short-term loans. However, although the vast majority of the capital needed to finance a project in shipping might be obtained through a loan, a relatively high interest rate is not expected to be the reason for not proceeding with the project, especially when market conditions look promising. We remain uncertain on whether or not LIBOR will be deemed significant in our analysis and thus on the sign with which it may enter the model with.

Data for this variable was downloaded from the Federal Reserve Economic Data (FRED, 2021).

Vessels' Demolitions

Demolitions have the most imminent effect in shipping's supply. When a vessel is being ordered, it will take around 18-36 months for this decision to affect supply. On the other hand, the decision to scrap a vessel has an immediate effect, reducing supply at once. An increase in vessel demolitions indicates a period of oversupply. In order to capture the instances where scrapping is increased, we employ a simple ratio of the number of vessels being scrapped to the sum of the previous 12 months' demolitions. In cases where not even one vessel was scrapped the previous 12 months, the number of demolitions in that month is used instead of the ratio, magnifying the impact of a surge in demolitions after a long period of no scrapping. It has already been shown that in low (negative) sentiment periods, scrapping is dictated by herding. Herding in essence means that you follow the rest of the market instead of your own gut (Melas & Michail , 2021). In their research, they provide evidence that when market sentiment is negative, investors tend to follow market leaders, which they define as intentional herding.

Someone could argue that a surge in scrapping can be the result of increased steel prices. While this holds true, as shown recently during the summer of 2021 when increased steel prices pushed scrap prices up as well, it occurs when the market conditions are negative. This is evident by the fact that while demolitions in the tanker market did increase due to the steel prices' increase, demolitions in the bulkers and containerships' markets did not, since it was way more profitable to keep the vessels employed in such blooming market conditions.

We expect the variable to be significant, as it captures effectively market conditions and to enter the regression model with a negative sign.

Independent Variables - Sentiment

While contemplating on whether to order a new vessel or not, many factors are taken into consideration before reaching a conclusion. At the same time, many people might be willing or requested upon to offer their opinion. Nonetheless, in most cases, the decision ultimately is taken by the owner of the shipping company. And since that decision relies upon an individual, it is subject to sentimental bias. It is evidenced that individuals with positive (negative) sentiment make optimistic (pessimistic) judgments and selections (Bower, 1981) (Bower, 1992).

In shipping specifically, periods with high sentiment are expected to urge shipowners to prefer spot-charter or negotiate price in a time-charter contract. On the other hand, when market sentiment is low, proactive time-charter contracts will be their strategy to survive the period.

Measuring sentiment is subjective since there is no consensus on what the appropriate proxies are (Schmeling, 2009). Moreover, what the appropriate proxies are depends on the sector whose sentiment you are trying to quantify.

The variables chosen to quantify sentiment are inspired from past literature, specifically from the rationale developed by (Papapostolou, et al., 2014). While they constructed an index from five separate proxies, we will only employ two of them. The two proxies employed belong to the category market valuation (Papapostolou, et al., 2014) (Papapostolou, et al., 2016) and are the price-to-earnings (PE) proxy and the second-hand to newbuilding vessel price (SNB) proxy. We find that these two proxies incorporate a great deal of information regarding the state of the market at each point of time.

Periods of high demand are associated with a surge in new vessel orders. This is evident the last months, where the disruptions in the supply chain caused by the Covid-19 pandemic, coupled with a surge in demand for the transportation of finished goods, have led container freight rates to skyrocket, which in turn has led to an extremely high number of orders for new containerships [see (Clarksons Research , 2021)]. Greenwood and Hanson (2013) argue that the overconfidence of shipowners that the high-earnings period will sustain leads to a barrage of new orders (Greenwood & Hanson, 2013). When these vessels join the world fleet, they shatter the balance between supply and demand, leading to a drop in freight rates and earnings. That is to say, shipowners do not take into account herding. While intentional herding takes place in market periods of negative sentiment, when market sentiment is positive, unintentional herding leads to common investment practices among shipping investors (Melas & Michail , 2021).

The first sentiment variable is the <u>second-hand price to newbuilding price ratio (SNB):</u>

$$SNB_{i,t} = \frac{secondhand\ price_{i,t}}{Newbuilding\ Price_{i,t}}$$

where $secondhand\ price_{i,t}$ is the price of 5-year-old second-hand vessels and $Newbuilding\ Price_{i,t}$ is the price of a newly built vessel.

A barrage of new orders leads in both newbuilding and second-hand prices' increase. While typically newbuilding prices are higher than secondhand ones, in bull market conditions investors are willing to pay a premium in order to obtain a vessel which is ready to be operated. There have been instances, where second-hand prices even rose above the newbuilding prices [e.g., from February until May 2010 (Clarksons Research , 2021)]. That reflects the urgency of acquiring a vessel in prevailing market conditions, rather than waiting for a vessel to be constructed. Consequently, a high SNB ratio reflects a period of positive sentiment.

The second sentiment variable is <u>the price-to-earnings ratio (PE):</u>

$$PE_{i,t} = \frac{secondhand\ price_{i,t}}{earnings_{i,t}}$$

where $secondhand\ price_{i,t}$ is the price of 5-year-old second-hand vessels and $earnings_{i,t}$ the annualized earnings (1-year time-charter rates) in sector i for month t. The higher the PE ratio, the more overvalued a vessel is. Thus, it is expected for high PE ratios to be associated with negative sentiment periods. If the ratio is high, vessel values are expected to fall and investors will wait before and if investing (Papapostolou, 2014).

All data for the variables described was downloaded from Clarksons Shipping Intelligence Network (Clarksons Research , 2021), unless referenced otherwise. Wherever we used data that had capital in them, we expressed it in million dollars.

The categorization of variables with their respective expected sign can be found in Table 1.

[Insert Table 1 here]

5 Correlation Matrix and Regression models’ Presentation

The correlation matrix for all independent variables aforementioned can be found in Table 2.

[Insert Table 2 here]

Immediate issues arise when observing the correlations between the SNB and Earnings Spot variables, Coal Exports and Iron Ore Exports, Coal Exports and Steel Production Index, Iron Ore Exports and Steel Production Index. As these pairs have liner correlations that exceed the 60% threshold, they will not be used together in a regression, as to avoid multicollinearity issues. Multicollinearity would lead to biased estimated coefficients and standard errors, which would impact the integrity of the statistical analysis. Apart from this, due to economic intuition, we also refrain from using in the same regression variables which carry similar information. On the same time, correlation matrices for each vessel type separately pinpointed to the presence of multicollinearity between the PE ratio, the SNB ratio and Earnings Spot. Thus, the PE ratio, the SNB ratio, as well as Earnings Spot will not be used in the same panel data regression model. It should also be mentioned that while the Fleet Average Age variable does not present a serial correlation of above 60% in this matrix, when we computed serial correlations for each vessel type, there existed issues between Fleet Average Age and Coal Exports, Iron Ore Exports and Trade Weighted Steel Production Index. This, coupled with our worries for possible reverse causality provided incentive to completely drop the variable from our analysis.

Based on the abovementioned, there are nine different combinations of independent variables, meaning there exist nine different possible panel data regressions to be employed. Be that as it may, our variables of interest are mainly the PE ratio and the SNB ratio. Since Coal exports, Iron Ore Exports and the Trade Weighted Steel Production Index are three control variables, we will choose one of them to remain in the models and exclude the other two. Due to intuition, we choose Coal Exports to remain in the panel data regressions. The reason behind our choice is that the Steel Price Index could carry similar information with both Iron Ore Exports and the Trade Weighted Steel Production Index. One could claim that this issue could also occur when using Coal Exports, since coal is used when producing steel, however it still is a sounder option than the other two.

Following this rationale there are three different panel data regressions which will be used. We choose to employ all of them, since we want to examine the effect of our three variables of interest in the dependent variable, which cannot be used together in a single model, due to multicollinearity issues. The first panel data regression includes the PE ratio and leaves out the SNB ration and the Spot Earnings. The second panel data regression employs the SNB ratio and leaves out the PE ratio and the Spot Earnings, while the third panel data regression model includes only the Spot Earnings from the three variables of interest mentioned above. One does not contain any of the sentiment variables that were presented and is used to make comparisons between the models that employ sentiment in explaining our dependent variable and the one that does not. The three different panel data regressions, will be referred to as Regression A, B and C respectively, based on which variable of interest the include.

Descriptive statistics for the variables which enter the final models can be found at Table 3.

[Insert Table 3 here]

The distribution of observations of our dependent variable, which is the ratio of new contracts to the fleet development, is highly skewed and leptokurtic. This means that the distribution has a sharp peak and presents little symmetry. The fact that the distribution is skewed was anticipated, due to the great difference between the mean and the median. The standard deviation is large relatively to the mean of the distribution, indicating great variability between the observations of the dataset.

Examining the descriptive statistics of NCFD for each vessel type, Handysize, Handymax and Panamax vessels present similar degree of difference between the mean and the median, while relatively to the mean, the standard deviation is large for all three of them. For all three, the distributions are leptokurtic and highly skewed. The same holds for the distribution of observations for the Capesize data, which also present great variance in relation to the mean. For all vessel types, the mean and the median are closer to the minimum values rather than the maximum, indicating that the range of observations is influenced by extreme values due to market conditions which induce positive sentiment increasing sharply the new contracts.

Kurtosis is a common measure of shape. In general, kurtosis characterizes the central peak of the data, with the higher values indicating a higher and sharper peak and lower values indicating a lower, less distinct one. The values provided for the kurtosis of a sample are assessed based on the kurtosis of the normal distribution. The normal distribution has a kurtosis equal to 3. A distribution with kurtosis less than 3 is called platykurtic, a distribution with kurtosis more than 3 is called leptokurtic and a distribution with a kurtosis equal or almost equal to 3 is called mesokurtic.

Skewness measures the symmetry of the data. If the skewness is equal to 0, the sample has perfect symmetry. However, this is highly unlikely for any dataset. To evaluate the skewness of the dataset, the rules Bulmer suggested in 1979 will be used. A distribution will be characterized as highly skewed for a value of skewness, less than -1 or greater than 1. If the value is between -1 and -0.5 or between 0.5 and 1, the distribution will be characterized as moderately skewed. If the value of skewness is between -0.5 and 0.5, the distribution will be characterized as approximately symmetric.

The distribution of observations of the first variable of interest, which is the Price to Earnings ratio is moderately skewed and platykurtic. This means that there exists some degree of symmetry and the distribution's peak is not that distinct. The mean and the median do not differ at a great extent, while the standard deviation of the distribution pinpoints to a degree of variability which is not extreme in relation to the mean.

The above image does not hold when examining each vessel type separately. Each of the four distributions in platykurtic but in contrast to the overall one is also approximately symmetric, meaning that the symmetry of the observations intensifies when examining them alone.

For the second variable of interest, the spot earnings, the distribution of observations is highly skewed and leptokurtic. The peak of the distribution is sharp while there is little to none symmetry. The mean and the median differ importantly, hence the skewness of the distribution. As for the standard deviation, it seems great in relation to the mean. That was to be expected, since spot earnings present extreme fluctuations based on the state of the market, thus a great degree of variability is normal.

The above hold for each vessel type, as well. Leptokurtic distributions of sharp peaks which derive due to the volatility of the spot market, and highly skewed, since the mean and the median are located towards the left tail of the distribution. The high volatility is also represented by the large standard deviation present in all vessel types.

The distribution of observations for the third and last variable of interest, Second-hand to new buildings ratio, is highly skewed and platykurtic. Thus, the peak of the distribution is less distinct than in the case of Spot Earnings, while it does not have a symmetrical shape. The standard deviation does not seem large related to the mean. While vessel prices are greatly influenced by the state of the market, meaning a great degree of variability is expected, they tend to move in the same direction, without this meaning that they cannot differ substantially under certain assumptions.

When examining each vessel type separately, Handymax, Panamax and Capesize vessels all have distributions which are platykurtic and highly skewed. The mean and the median do not differ greatly and are located towards the left tail of each distribution, while the standard deviation is not great in relation to the mean for none of the distributions. Handysize vessels differ, since their distribution is approximately symmetrical. The mean and the median are located towards the center of the distribution, while the distribution's peak is less distinct, although slightly more towards its left tail. This is natural, since a smaller degree of variability in smaller vessels is expected.

Moving on the control variables, the distribution of the Gross Domestic Product of the Major 5 Asian countries (China, Japan, South Korea, India, Indonesia) is platykurtic and highly skewed. The mean and the median differ slightly and the standard deviation if small in relation to the mean. That was to be expected, since changes in the countries GDPs are not extreme between small time periods, thus having small variability is perfectly normal. The mean and the median are actually really close to the maximum value of the observations. This could be explained due to the presence of extreme values, which enlarge the range of the observations yet since they represent a minority in the observations cannot affect to a great degree the mean and even more the median.

The above notion holds for the distribution of data for the control variable of Libor. The mean and the median differ substantially and are located towards the smaller observations of the distribution. This pinpoints to extreme values in the topside of observations. The standard deviation is moderately large in relation to the mean, while the distribution itself is platykurtic and moderately skewed.

The distribution of observations for the control variable of Coal Exports from major exporters of the fossil fuel is platykurtic and approximately symmetric. The mean and the median do not differ substantially and are located towards the center of the range of observations. The standard deviation presents a moderate to little degree of variability. All in all, this distribution presents similarities to the normal one, although its peak is less distinct than the one presented in a normal distribution.

As for the control variable of Steel Prices in the top 3 Shipbuilding Countries (SPI), which are Japan, South Korea and China, the distribution if platykurtic and approximately symmetric. The mean and the median are located towards the center of the distribution, and they do not differ substantially. This indicates that there do not exist many extreme values. The degree of variability is moderate to little, deriving from the relationship between the mean of the distribution and its standard deviation.

VIF diagnostic

To further ensure the integrity of the analysis, we run robustness diagnostic tests for the absence of multicollinearity for each of the three panel data regression models. We compute the Variance Inflation Factors (VIF).

6 METHODOLOGY

Given the nature of our dataset, panel data regression models will be used for the analysis. Panel data analysis offer advantages over the models that either only comprise cross-sectional observations or pure timeseries. Since panel data contain both, such a model allows for more information and variability.

When performing a panel data analysis, one of the issues that arises is which model to choose. The first choice that needs to be made is between a pooled OLS model, a fixed effect model and a random effects model.

A pooled OLS model is chosen when there is indication or belief that there are no unique characteristics among the different cross sections and no different effects between different periods (Park, 2011). In our case that would mean that the four different vessel categories do not differ and that the time periods (months) do not present any differences as well. Unlikely as this might be, we should test for this possibility.

Should also be noted that fixed effect and random effects models are considered more suitable than a pooled OLS model in cases that the sample of individuals does not differ among the periods (Wooldridge, 2010). Thus, we expect that the specification tests conducted to choose the appropriate model will favor a fixed effect or random effects over a pooled OLS one.

A fixed effect model (also known as Least Square Dummy Variable model – LSDV) assumes that there are unique features between individuals (in our case vessels) which do not change during time. Fixed effect models employ the means of the variables and subtract them from the panel analysis equation. This means that fixed effect models do not allow for time invariant variables. Time invariant variables will have the same value with their mean at each point in time, leading to their eradication from the regression equation. Effectively, this means that a fixed effect model will eradicate the unobserved heterogeneity term of the regression equation.

A random effects model assumes that the unobserved heterogeneity term a_i is not correlated with the independent variables and that they are random. This effectively means that $E[a_i|X_{it}] = 0$. In turn this will mean that the covariance between a_i and X_{it} is equal to zero. And this should hold for every independent variable. So, random effects are most suitable when there is belief that we have already controlled for a large part of the dependent variable's variance. Otherwise, the a_i term will be correlated with our independent variables, or at least some of them, meaning that our estimators will be biased and inconsistent. Consistency of estimators means that as n increases, meaning as the time span of the observations grows larger, the estimators procured by the analysis will approach their true values. A random effects' model will produce inconsistent estimates when individual specific random effect is correlated with regressors (Greene, 2008).

Random effects models allow for variables that are time invariable, such as the a_i term. On the same time, it has been proven that in case a random effects model is appropriate, its standard errors in estimating coefficients will be smaller than the ones a fixed effect model will procure. Effectively, this leads to coefficients that are more efficient, under the hypothesis that the covariance of the term a_i with each independent variable is equal to zero.

In order to choose one of the above models a series of test is employed. First, we will conduct a Hausman Specification Test (Hausman, 1978), which indicates if a fixed effect or random effects model is more appropriate. It checks whether or not there is a correlation between the unique errors and the regressors in the model. The null hypothesis is that there isn't, in which case the random effects model is favored. If the null is rejected, a fixed effect model is preferred, since only its estimators retain their consistency under the assumption that $Cov(a_i|X_{it}) = 0$.

If the Hausman test favors the random effects model, we will conduct a Lagrange Multiplier (LM) test statistic (Breusch & Pagan, 1980). The LM test is a test for heteroscedasticity. In the null hypothesis, the variance of the standard errors is assumed to be equal to zero, implying the presence of homoscedasticity. If the null is rejected, the random effects model is more appropriate than the pooled OLS one, since even if the pooled OLS model's estimators remain unbiased under heteroscedasticity, they are no longer efficient (i.e., no longer precise).

In the case that the Hausman test favors the fixed effect model, an F-test is employed in to decide which of the fixed effect and pooled OLS model is more appropriate. In essence we will be testing whether or not the dummies indicating the different vessels are statistically significant or not. If the null hypothesis of non-significance is rejected, the fixed effect model is favored over the pooled OLS one.

When performing a panel data analysis, another issue that may arise is the presence of endogeneity. This issue could arise as a result of an omitted variable, a measurement error or reverse causality.

An omitted variable will cause the error term to be correlated with the independent variable. This is a problem since it refutes the assumption that the error term of the regression has zero covariance with the independent variables. In turn, this would lead to biased estimators.

A measurement error could occur in the data of the independent variables, which could cause their standard errors to be large, thus the information lost will be included in the error term of the regression. This once more would lead to the error term being correlated with the independent variables, producing biased estimators, since the assumption that the error term's covariance with the independent variables is zero would be violated.

Reversed causality can occur when the dependent variable is the one that affects an independent and not the other way around. This would violate the underlying assumption that the independent variables of a regression are the ones that affect the dependent variable. There can also exist a case of simultaneity, meaning that the independent variable and the dependent variable both affect each other. The case of Fleet's Average Age could very well be a case of simultaneity or reversed causality.

Before using specification tests in order to ascertain which model is more suitable for the analysis, it is essential to run some diagnostic tests on the data. Those tests regard the normality, stationarity and multicollinearity of the dataset.

In order to check for the normality of the dataset, we run the regression for each panel set and extract the residuals. The normality tests employed, which are based on the Jarque-Bera test ascertain whether the distribution of residuals is normal or not (Jarque & Bera, 1980). The null hypothesis of the Jarque-Bera test is normality and the critical value is obtained by the Chi-square table. Another test that may be employed is a skewness-kurtosis joint test, where the null hypothesis is again normality and the critical value is once again obtained through the chi-square distribution. However, there has been evidence that the absence of normality does not impact the integrity of statistical results, since t-test values remain robust (Tsagris, et al., 2020). The absence of normality is evident due to results of the above tests in all three of our panels.

Checking for stationarity is done through the LLC unit root test in panel data (Levin, et al., 2002). The null hypothesis is that the series contains a unit root. If the data contain unit roots, it means that there is a systematic pattern which is unpredictable and may impact the integrity of the analysis. In our case, the independent variable, as well as all our variables of interest are stationary.

Multicollinearity test is conducted by computing the VIF (variance inflation factor) statistic. If all VIF statistics are below 10, the analysis may proceed without issues. We will report a VIF table, containing the mean VIF of each panel, jointly with the regression results. In our case, none of the VIF values pose an issue, since they are all well below 10 (and actually below 3), ensuring the absence of multicollinearity in the analysis.

The analytical results of the specifications tests performed in order to assess which kind of model is appropriate for each of the different regressions we performed are available at Table 4. Based on the results, the appropriate model for the set of variables which includes the PE ratio is a random effects' one. The same holds for the one that includes the Spot Earnings variable. On the other hand, the set of variables which includes the SNB ratio favors a fixed effect model.

Another important issue that needs to be taken into consideration is homoskedasticity and serial correlation. These two tests come after the choice of the appropriate model. For heteroskedasticity we employ a modified Wald test for groupwise heteroskedasticity in fixed effect regression model (Greene, 2000). The null hypothesis of the test is that $\sigma_i^2 = \sigma^2$ for every i. In our case, the null hypothesis is refuted, indicating the presence of heteroskedasticity in the fixed effect model.

For the random effects models, the tests run for the presence of homoscedasticity and serial correlation indicate that the models suffer from both these issues. Thus, we will run the models clustering for vessels, since it has been proven that this method produces robust standard errors to heteroscedasticity and serial correlation (Petersen, 2009).

In order to account for serial correlation in the fixed effect model, we employ the Wooldridge test for autocorrelation in panel data. The null hypothesis assumes that there is no first-order autocorrelation (Wooldridge, 2002). Based on the F test's results autocorrelation is present in the fixed effect regression model. Once again, we employ the solution proposed by Petersen in 2009, which is to run the regressions with robust standard errors.

7 RESULTS

The regressions' results are presented together in Table 4. Regression A refers to the set of variables which include the first variable of interest, the sentiment variable; PE ratio. Regression B refers to the set of variables which include the second variable of interest, the sentiment variable; SNB ratio. Also, Regression C refers to the set of variables which include the third variable of interest Spot Earnings.

[Insert Table 4 here]

The estimated coefficients and their respective t-statistics are reported in Table 4. In order to assess the explanatory power of the three different variables of interest, three different panel models were employed. In each of them, there were five common variables: the Scrap Ratio, the GDP of the major five Asian countries, Libor, coal exports of the most significant coal exporters worldwide and a steel price index. The three variables of interest are the Price to Earnings ratio, the Secondhand to Newbuilding ratio and the Spot Earnings. The first two are considered variables that capture sentiment and have been used before, specifically as proxies for the construction of a sentiment index (Papapostolou, et al., 2014).

Variables which had a linear correlation that exceeded 60% were not simultaneously employed in the same regression. More than that, we refrained from using variables carrying the same information. As the mean VIF values reported for each set of variables in Table 4, multicollinearity is not present. This if further supported by the fact that all VIF values were below 3, where in the literature different thresholds are presented (e.g., 4,5,10).

Two of the models employed a random effects analysis based on the Hausman specifications tests employed in order to choose between fixed effect and random effects and the Breusch-Pagan LM test which determined that the random effects models were more appropriate in comparison to a pooled OLS one. Then, F-tests were employed in order to assess the significance of entity dummies (i.e., vessel types; Handysize, Handymax, Panamax and Capesize) and the significance of monthly dummies.

One of the three models favored a fixed effect regression analysis, since the Hausman test provided significant results. An F-test was employed to choose between a fixed effect model and a pooled OLS regression, with the results favoring the fixed effect model. Since fixed effect models do not allow the presence of time invariant variables, entity dummy variables were not included in the regression. Instead, a fixed effect model accounts by itself for different clusters, in our case for the four different ones. Another F-test deemed the presence of monthly dummy variables significant in the fixed effect model as well.

In all models, in order to obtain unbiased standard errors, the regressions were performed based on Petersen (2009) suggestions. The presence of both heteroscedasticity and autocorrelation dictated this course of action, which has been shown to procure robust to these issues standard errors, ensuring the integrity of the statistical analysis (Petersen, 2009).

In all three panel data regressions, the variables of interest are found to be significant. In Regression A, the PE ratio is significant at a 5% level and has the a priori negative sign. As expected, higher PE ratios, which indicate that a vessel is overvalued are associated with negative sentiment periods. Most control variables in the first model are found to be significant. Specifically, all the following: the Scrap Ratio, the GDP of the Major 5 Asian countries, Coal Exports of Major Coal Exporters as well as the Steel Price Index are all found significant at the 1% level. This also holds for the constant term of the model. The model is capable of explaining 35.84% of the data's overall variability.

In Regression B, the variable of interest, which is the Secondhand-to-Newbuilding ratio, is significant at the 1% level. As expected, the sign is positive, since a secondhand prices' surge indicates the urgency of acquiring a vessel ready to operatable. Thus, in periods where the SNB ratio is high, the sentiment in the market is positive, leading to further investment in new vessels. This is very interesting, since in the summer of 2021, while the prices of secondhand bulk carriers did increase significantly, due to a strong spot market led by the surge in the iron ore's price, the number of new contracts remained small, relatively to the number of sales in the second-hand market (Clarksons Research , 2021). However, based on the regression's results, positive sentiment periods do lead in higher investment.

As for the control variables in the second model, only the Steel Price Index is found significant, specifically at the 1% level. Also, the model is capable of explaining 44.79% of the overall variability.

In Regression C, the variable of interest, Spot Earnings, is found significant at the 1% level, with the expected positive sign. Spot earnings always offer the best reflection of the state of the market, after all. In periods where spot earnings are high, more contracts are being made, as a surge in spot earnings indicates that the current supply is not adequate to satisfy the current demand for shipping transportation. As for the control variables both the Scrap Ratio and The GDP of the Major 5 Asian Countries are found significant at the 1% level. As for the constant term, it is found significant at the 5% level. The model is capable of explaining 49.15% of the overall variability.

The fact that coal exports are only found significant in one of the three regressions is quite interesting, since coal is one of the major commodities in dry bulk shipping and is also connected with steel since it is used for its production.

The Steel Price Index which is the average of the steel prices in the top three shipbuilding nations is found significant in two regressions. This index is connected with the dry bulk industry in three different ways. First, steel is a commodity broadly used in manufacturing and is also transported by vessels. Second, for its production, both iron ore and coal are required, meaning that a surge in steel demand and its price will also affect the price of iron ore primarily and coal to some extent. Third, a major biproduct of steel, steel plates are required for the construction of a vessel, usually accounting for 20% of its overall cost.

LIBOR is not found significant in any of the three regressions. While LIBOR does play a role in shaping interests of loans, including the ones used in debt financing of vessels, shipping companies do not seem to take into account LIBOR when deciding to construct a vessel or not. In retrospect, it would seem irrational to base such an important decision on the ever and rapidly changing shipping landscape on interest rates.

8 DISCUSSION

We performed a panel data analysis, employing three different models for three different variables of interest. Two of the models were random effect ones while the other one was a fixed effect one.

In order to capture how sentiment affects the decision of ordering a vessel in relation to the overall fleet development, we included two sentiment proxies: Price to Earnings and Secondhand to New-building ratios. Both variables were found to be highly statistically significant, the first in 5% and the second at 1% level respectively, meaning that sentiment does indeed affect decision making of further expanding the current fleet.

Our results are in align with those of (Drakos & Tsouknidis, 2021), who used as dependent variable the ratio of New Contracts to Fleet Development as well, with uncertainty and reversibility as variables of interest. Their findings support that uncertainty reduces the likelihood of investment triggering, meaning that negative sentiment affects NCFD accordingly.

Similar results were proposed also by the study of (Michail & Melas, 2020) who by employing the five proxies proposed by (Papapostolou, et al., 2014) to quantify shipping sentiment, constructed a model of Demand and Supply including sentiment. To measure Demand, i.e., what shippers want to transport, they used quantity of transported goods, the BDI (to capture the price of the contract), US Consumption and Industrial production for EU, China and US, while to measure Supply, they used the number of vessels and the BDI. When they included sentiment on both Demand and Supply in their model, BDI was found related to the fleet. They concluded that sentiment strongly affects supply, as the laid-up vessels are reduced, and also new orders are taking place. Also, high sentiment is a sign for lower vessel price return, and vice versa.

Additionally, these findings are in align with (Michail & Melas, 2021) who investigated the relationship between newbuilding’s orders and shocks. Based on their results new orders comove with stock market in the same direction, as 4.3% positive change in stock market resulted to 5% increase in orderbook. Thus, the notion that improvements in macro factors or shocks affect decision making when it comes to ordering new vessels is supported. Should also be noted that the results of our analysis support this notion, since variables such as the Gross Domestic Product of Major 5 Asian Countries and Steel Price Index were deemed significant.

Furthermore, it has also been proposed (Baker & Wurgler, 2006), that sentiment is related to stock market returns, the combination of the findings supports that new orders are influenced by sentiment, captured in the stock market. A shock in the FR of around 8% increase have no impact on new orders for at least the first 7 months, but a 5% increase afterwards. Based on our findings, Spot Market Earnings were found to be significant in explaining our dependent variable, New Contracting to Fleet Development.

Adding to the abovementioned, other researchers have supported the notion that the freight market is correlated with the decision of acquiring a new vessel or not (Wu, et al., 2020). Our findings further support this notion, since spot earnings are found highly significant in our third regression model. The fear index they constructed in order to quantify sentiment was found significant in affecting freight rates, thus implying that due to the correlation between freight rates and the decision of vessel acquisition, sentiment affects the latter as well. This rationale is consistent with our findings.

9 CONCLUSION

This paper contributes to the literature by examining whether or not sentiment affects the decision of ordering a new vessel in comparison to the fleet development in four different vessel types within the same segment. It expands on prior literature which has found that sentiment plays an important role within shipping, its results showing that sentiment’s role is not contained within freight rates and stocks but also affects an investor who contemplates on whether or not to order a new vessel.

We employed a wide range of data within the dry bulk sector, from January 2001 to December 2020, and focused on three different variables of interest, two of them being sentiment proxies proposed by Papastolou et. al in the past. Both sentiment variables, i.e., the Price to Earnings ratio and the Second-hand to Newbuilding ratio, were found important, further expanding on prior literature that sentiment affects shipping, and specifically that it affects the decision to build a vessel. The variable of

Spot Earnings was also found significant, as expected, reflecting the important role of the spot market in the decisions that shape the future supply of the dry bulk market.

Since the Scrap Ratio was also found significant in two of the three models, we also provide evidence regarding the significance of vessels' scrapping, by using a constructed index based on scrapping during the prior 12-months period. Thus, scrapping is a parameter taken into consideration when the decision of ordering is being made.

Furthermore, our analysis points to the insignificance of Libor when it comes to the number of new contracts to the fleet development. Investors are not concerned with interest rates when deciding to order a vessel.

Coal Exports are only deemed significant in one model, the one whose variable of interest is the PE ratio. Exports reflect the demand for a specific commodity and increased demand for the transportation of goods by sea is associated with periods of higher freight rates, which in turn are associated with increased ordering.

The Steel Price Index reflects the price of steel in the major shipbuilding countries. Steel as a commodity is highly important, since a major biproduct of steel, steel plates, plays an important role in newbuilding prices, because it constitutes 20% of the actual cost of the vessel. Thus, investors do take into consideration the price of steel when deciding whether to order or not in relation to the current fleet.

One of the limitations of our analysis is the fact that in order to examine our variables of interest we had to employ three different models. This also affects our inferences on the control variables used in the analysis, with all of them found significant in either one or two of the three different panel data regression models.

Further extensions are indeed possible. The construction of a sentiment index using the two proxies employed in this analysis through a principal component analysis can prove beneficial, since it might affect the correlation between the proxies and the spot earnings, allowing for a model which incorporates all the variables of interest which we used and found significant. Such a conclusive model would allow to draw definitive inferences on the importance of our control variables, since there wouldn't exist contradictory results, such as "partial" significance, something all our control variables exhibited.

Moreover, coal and iron ore are indeed the major commodities in the dry bulk sector and this fact led the choice of the variables we employed. However, perhaps the choice of a weighted index which comprises many different commodities of the dry bulk could prove fruitful, since it would cover commodities that the smaller vessels carry.

10 References

Alexandris, G., Antypas, N., Gulnur, A. & Viviskis, I., 2020. Corporate financial leverage and M&As choices: Evidence from the shipping industry. *Transportation Research Part E: Logistics and Transportation Review,* Volume 133.

Audrino, F., Sigrist, F. & Ballinari, D., 2020. The impact of sentiment and attention measures on stock market volatility. *International Journal of Forecasting,* 36(2), pp. 334-357.

Baker, M. & Wurgler, J., 2006. Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance,* 61(4), pp. 1645-1680.

Baker, M. & Wurgler, J., 2007. Investor Sentiment in the Stock Market. *Journal of Economic Perspectives,* 21(2), pp. 129-152.

Baker, M., Wurgler, J. & Yuan , Y., 2012. Global, Local and Contagious Investor Sentiment. *Journal of Financial Economics,* 104(2), pp. 272-287.

Baltic Exchange, 2021. *Baltic Exchange.* [Online]
Available at: https://www.balticexchange.com/en/data-services/routes.html
[Accessed 11 2021].

Batchelor, R., Alizadeh, A. & Viviskis, I., 2007. Forecasting spot and forward prices in the freight market. *International Journal of Forecasting,* 23(1), pp. 101-114.

Berger, D. & Turtle, H., 2012. Cross-sectional performance and investor sentiment in a multiple risk factor model. *Journal of Banking & Finance,* 36(4), pp. 1107-1121.

Bower, F. W. a. G., 1992. Mood effects on subjective probability assessment. *Organizational Behavior and Human Decision Process,* Volume 52, pp. 276-291.

Bower, G., 1981. Mood and memory. *American Psychologist,* Volume 36, pp. 129-148.

Breusch, T. S. & Pagan, A. R., 1980. The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. *The Review of Economic Studies,* pp. 239-253.

Brown, G. W. & Cliff, M. T., 2004. Investor Sentiment and the Near-Term Stock Market. *Journal of Empirical Finance,* 11(1), pp. 1-27.

Clarksons Research , 2021. *Clarksons Research.* [Online]
Available at: https://www.clarksons.net/portal
[Accessed 07 2021].

Drakos , K. & Tsouknidis, D., 2021. *Investment under Uncertainty and Irreversibility: Evidence from the Shipping Markets,* s.l.: s.n.

FRED, 2021. *Federal Reserve Economic Data (FRED).* [Online]
Available at: https://fred.stlouisfed.org/series/USD12MD156N
[Accessed 9 2021].

Gao, Z., Ren , H. & Zhang, B., 2019. Googling Investor Sentiment around the World. *Journal of Financial and Quantitative Analysis,* 55(2).

Greene, W. H., 2000. *Econometric Analysis.* 4th ed. s.l.:s.n.

Greene, W. H., 2008. *Econometric Analysis.* 6th ed. s.l.:Pearson Prentice Hall.

Greenwood, R. & Hanson, G. S., 2013. Waves in ship prices and investment. *unpublished working paper, Harvard Business School.*

Hausman, J. A., 1978. Specification Tests in Econometrics. *Econometrica*, pp. 1251-71.

IEA, 2021. *International Energy Agency.* [Online]
Available at: https://www.iea.org/data-and-statistics/charts/total-coal-exports-by-major-exporters-1978-2020
[Accessed 09 2021].

J.P.Morgan, 2021. *J.P.Morgan.* [Online]
Available at: https://www.jpmorgan.com/solutions/cib/markets/leaving-libor
[Accessed 11 2021].

Jarque, C. M. & Bera, A. K., 1980. Efficient Tests for Normality, Homoscedasticity and Serial Independence of Regression Residuals. *Economics Letters*, October, pp. 255-259.

Kalouptsidi, M., 2014. Time to Build and Fluctuations in Bulk Shipping. *Time to Build and Fluctuations in Bulk Shipping,* 104(2), pp. 564-608.

Kavussanos, M. G., 1996. Comparisons of volatility in the dry cargo ship sector. *Journal of Transpor,t Economics & Policy,* 30(1), pp. 67-82.

Kavussanos, M. G. & Alizadeh-M, A. H., 2001. Seasonality patterns in dry bulk shipping spot and time charter freight rates. *Transportation Research Part E: Logistics and Transportation Review,* 37(6), pp. 443-467.

Kavussanos, M. G. & Visvikis, I. D., 2004. Market Interactions in Returns and Volatilities Between Spot and Forward Shipping Freight Markets. *Journal of Banking & Finance,* 28(8), pp. 2015-2049.

Keynes, J. M., 1936. Theory of Employment. In: s.l.:s.n.

Levin, A., Lin, C.-F. & Chu, C.-S. J., 2002. Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics,* pp. 1-24.

Melas, K. D. & Michail , N. A., 2021. *Buy Together but recycle alone: Sentiment driven herding behavior in the ocean-going shipping industry,* s.l.: s.n.

Michail, N. A. & Melas, K. D., 2020. Sentiment Augmented Supply- Demand Equations. *Economies,* Volume 9.

Michail, N. & Melas, K. D., 2021. *Newbuilding orders and freight rate shocks: Evidence from the containership market.* [Online]
Available at: http://dx.doi.org/10.2139/ssrn.3858521
[Accessed September 2021].

OEC, 2021. *Observatory of Economic Complexity (OEC).* [Online]
Available at: https://oec.world/en/profile/hs92/iron-ore
[Accessed 09 2021].

OECD.org, 2021. *OECD Data.* [Online]
Available at: https://data.oecd.org/gdp/gross-domestic-product-gdp.htm
[Accessed 9 2021].

Papapostolou, N. C., Nomikos, N., Pouliasis, P. K. & Kyriakou, I., 2014. Investor Sentiment for Real Assets: The Case of Dry-Bulk Shipping Market. *Review of Finance*, 18(4), pp. 1507-1539.

Papapostolou, N. C., Pouliasis, P. K., Nomikos, N. K. & Kyriakou, I., 2016. Shipping investor sentiment and international stock return. *Transportation Research Part E Logistics and Transportation Review*, pp. 81-94.

Park, H. M., 2011. *Practical Guides to Panel Data Modeling: A Step by Step Analysis Using Stata.* Niigata: International University of Japan.

Petersen, M. A., 2009. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *The Review of Financial Studies*, 22(1), pp. 435-480.

Schmeling, M., 2009. Investor sentiment and stock returns: some international evidence. *Journal of Empirical Finance* , Volume 16, pp. 394-408.

Sibley, S. E., Wang, Y., Xing, Y. & Zhang, X., 2016. The Information Content of the Sentiment Index. *Journal of Banking & Finance*, 62(C), pp. 164-179.

Stopford, M., 2009. *Maritime Economics.* 3rd ed. s.l.:Routledge.

Tsagris, M., Alenazi, A., Verrou, K.-M. & Pandis, N., 2020. Hypothesis testing for two population means: parametric or non-parametric test?. *Journal of Statistical Computation and Simulation*, pp. 252-270.

Tsouknidis, D. A., 2016. Dynamic volatility spillovers across shipping freight markets. *Transportation Research Part E: Logistics and Transportation Review*, Volume 91, pp. 90-111.

UNCTAD, 2021. *Review of Maritime Transport 2021*, s.l.: s.n.

Wooldridge, J. M., 2002. *Econometric Analysis of Cross Section and Panel Data.* Cambridge: MIT Press.

Wooldridge, J. M., 2010. *Econometric Analysis of Cross Section and Panel Data.* 2nd ed. s.l.:The MIT Press.

World Steel Association, 2021. *WSA.* [Online]
Available at: https://www.worldsteel.org
[Accessed 10 2021].

Wu, C.-Y., Chou, H.-C. & Liu, C.-L., 2020. Fear Index and Freight Rates in Dry-Bulk Shipping Markets. *Applied Economics*, pp. 1235-1248.

Zhang, J., Zeng, Q. & Zhao, X., 2014. Forecasting Spot Freight Rates Based on FFA and TC Contract. *Applied Economics*, 46(29), pp. 3639-3648.

Table 1 Categorization of Variables and their respective expected sign in the regression equation

Variable	Description	Expected Sign
Dependent Variable	NCFD: New Contracts/Fleet Development: the ratio of new contracts, i.e. the number of deals between shipowners and shipyards for a vessel's construction, over the fleet development, i.e the number of vessels in the global fleet, for each vessel type	
Variables of interest	PE: Price per Earnings, i.e. the price of a 5-year-old vessel, of each segment, over the segment's average earnings on a time-charter voyage. It will be used to capture investor sentiment	-
	SNB: Secondhand to Newbuilding, i.e. a 5-year-old vessels's price over the construction price of a newbuilt vessel, for each vessel type. It will be used to capture investor sentiment	+
	ES: Spot Market's Earnings, i.e. the average $/day earned by a Voyage Charter for each vessel type	+
Control Variables	Libor: the 12-Month LIBOR based on $, i.e. the average interest rate at which banks borrow considerable size of funds from other banks in the London Market	
	GDP: the value added through the production of goods and services domestically ,in the Major 5 Asian countries, for a specific period	+
	FAA: Fleets Average age, which is used to interpret the supply of each vessel type	
	SR: Number of Demolitions/sum of the previous 12	-

	months	
	TWSPI: Trade Weighted Steel Production Index, since steel plays a vital role in many industries and since in order to produce steel both iron ore and coal are needed which are the major commodities in dry bulk shipping	+
	SPI: Steel Price Index since steel affects shipping both as a commodity and as a main component for a vessel's construction	+
	IO: Iron Ore Exports of Australia, South Africa, Brazil, Canada, India, representing more than 80% on total seaborne Iron Ore Exports	+
	CE:Coal Exports of Australia, US, Canada, Indonesia, Colombia, which represent more than 80% of total seaborne Coal Exports	+

Notes: This table presents all the variables employed in the analysis, a short description of them and their expected values in the regression models. Variables of interest only enter each model once, while the control variables and also naturally the dependent variable enter all three different models (p. 22).

Table 2 Correlation Matrix for the Independent Variables Sample Period 2001:01 – 2020:12

	PE	SNB	GDP	Libor	CE	IO	SPI	TWSPI	FAA	ES	SR
PE	1										
SNB	-44.87%	1									
GDP	-14.53%	43.10%	1								
Libor	-37.19%	39.42%	30.80%	1							
CE	38.19%	-25.45%	23.64%	-44.34%	1						
IO	29.16%	-41.58%	-15.04%	-46.63%	**80.24%**	1					
SPI	2.17%	30.03%	9.68%	2.17%	14.25%	7.98%	1				
TWSPI	31.24%	-39.94%	-21.19%	-47.32%	**77.58%**	**96.16%**	9.94%	1			
FAA	-31.04%	30.84%	4.96%	36.48%	-49.29%	-51.90%	-54.35%	-50.47%	1		
ES	-51.07%	**74.50%**	31.54%	37.01%	-22.72%	-27.22%	33.08%	-28.29%	9.23%	1	
SR	11.19%	-10.54%	-8.01%	3.90%	-4.07%	-6.59%	8.85%	-5.29%	5.36%	-7.17%	1

Notes: The above table presents the liner correlation matrix between the independent variables of the analysis. PE refers to the Price to Earnings ratio, SNB to the Secondhand to Newbuilding ratio, GDP to the Gross Domestic Product of the Major 5 Asian Countries, Libor to the London Interbank Borrowing rate, Coal to the coal exports of the major 5 coal exporters, Iron ore to the iron ore exports of the major 5 iron ore exporters, SPI to the steel price index (steel prices in the top three shipbuilding nations), TWSPI to the Trade Weighted Steel Production Index, FFA to the Fleet's Average Age, Earnings to the Spot Earnings and Scrap to the Scrap Ratio we constructed based on the 12-month prior period (p.22).

Table 3 Descriptive Statistics for the variables which entered the final models, Sample Period 2001:01 – 2020:12

	Mean	Median	SD	Kurtosis	Skewness	Min	Max	N
NCFD	0.00788	0.00418	0.010663	10.94	2.94	0	0.078740	960
PE	0.00176	0.00171	0.000478	1.35	0.73	0.0007	0.003874	960
ES	0.02072	0.01255	0.023244	17.48	3.66	0.0026	0.180500	960
SNB	0.84793	0.79262	0.221526	1.92	1.28	0.4500	1.703704	960
GDP	99.90027	100.07855	1.171372	15.71	-3.19	92.0141	101.81	960

Libor	2.12608	1.69274	1.485165	-0.22	0.95	0.3359	5.661211	960
CE	62.99828	64.88017	18.631353	-1.47	-0.10	30.6930	92.869414	960
SPI	583.7079	609.5941	166.399	0.51	0.16	282.185	1079.329	960
SR	0.12022	0.06061	0.375756	335.18	15.62	0	9	960

Notes: The above table presents the descriptive statistics for the independent variables of the analysis. PE refers to the Price to Earnings ratio, ES to the Spot Earnings SNB to the Secondhand to Newbuilding ratio, GDP to the Gross Domestic Product of the Major 5 Asian Countries, Libor to the London Interbank Borrowing rate, CE to the coal exports of the major 5 coal exporters, SPI to the steel price index (steel prices in the top three shipbuilding nations), and SR to the Scrap Ratio we constructed based on the 12-month prior period. Min and max are the minimum and maximum values of the sample data, respectively. Skewness and kurtosis are the estimated centralized third and fourth moments. SD refers to the Standard Deviation and N is the number of observations for each variable (p.23).

Table 4 Panel Data Regressions Models of New Contracting to the Fleet's Development (NCFD) for dry-bulk vessels: Sample 2001:01-2020:12

		Regression A	Regression B	Regression C
	Constant	-0.208761$^{(***)}$	-0.025913	-0.112548$^{(***)}$
		(-5.02)	(-1.03)	(-4.63)
Variables of Interest	PE	-5.469089$^{(**)}$		
		(-5.08)		
	SNB		0.032295$^{(***)}$	
			(6.31)	
	ES			0.270742$^{(***)}$
				(21.98)
Control	SR	-0.001748$^{(***)}$	0.001031	-0.000397$^{(***)}$

Variables		(-2.98)	(1.87)	(-10.67)
	GDP	0.002284(***)	0.000086	0.001147(***)
		(5.16)	(0.33)	(4.37)
	Libor	-0.000511	0.000826	0.0003598
		(0.83)	(1.33)	(0.63)
	CE	-0.000092(***)	0.00007	-0.000017
		(-3.78)	(2.24)	(-0.56)
	SPI	-0.000016(***)	-0.000009(***)	0.000002
		(14.21)	(-8.62)	(0.92)
	Observations	960	960	960
	Groups	4	4	4
	Observations per Group	240	240	240
	R-squared overall	35.48%	44.79%	49.15%
Specification Tests	Hausman	**1.98**	**9.31**	**0.85**
	[p-value]	*[0.3723]*	*[0.0095]*	*[0.6547]*
	BP LM test (re vs pooled OLS)	**299.06**	**-**	**25.72**
	[p-value]	*[<0.001]*	-	*[<0.001]*
	F - Test (vessel dummies)	**57.77**	**12.33**	**19.94**
	[p-value]	*[<0.001]*	*[<0.001]*	*[<0.001]*
	F - Test (time dummies)	**70.74**	**8.24**	**88.84**
	[p-value]	*[<0.001]*	*[<0.001]*	*[<0.001]*
	Fixed Effects	No	Yes	No
	Random	Yes	No	Yes

Effects			
Vessel Fixed Effects	Yes	No	Yes
Monthly Fixed Effects	Yes	Yes	Yes
Mean VIF	**1.71**	**1.88**	**1.78**

Notes: This table depicts the results of the panel data regression models A, B, C which differ from one another based on the variable of interest. The coefficients of vessel and year dummies are suppressed to preserve space. In order to choose between fixed effect and random effects in each of the models, the Hausman (1978) test is utilized. In regression models A and C, random effects are favored over fixed effects. In order to choose between random effects and pooled OLS the Breusch-Pagan LM test (1980) is utilized. Separate F-tests for the significance of vessel and monthly fixed effects are utilized as well, leading to random effects model with both vessel and monthly dummies. So, to account for the presence of both serial correlation and heteroskedasticity, we cluster based on Peterson (2009). In regression model B, fixed effect is favored over random effects by the Hausman test (1978). In order to choose between fixed effect and pooled OLS, an F-test for the significance of vessel fixed effects is utilized, its results found significant. An F-test for the inclusion of monthly fixed effects is utilized as well, leading to a final regression model of fixed effects with monthly dummies. In order to account for the presence of serial correlation and heteroskedasticity, we cluster based on Peterson (2009). T-statistics and p-values are reported in (.) and [.], respectively. Statistical significance of the estimated coefficients is denoted with *, ** and *** for 10%, 5% and 1% significance levels, respectively. We also present the R-squared overall values and the number of observations, groups and observations per group. Mean values of the Variance Inflation Factors (VIF) are presented as a diagnostic for multicollinearity in all three regression models. As a rule of thumb, VIF values below 10 indicate the absence of multicollinearity. A description for each variable can be found in Table 1 (p.31).