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The Effects of Fleet Size Changes on the Risk and Return of Shipping Bonds

An examination of the container-, bulk- and oil-carrier markets

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ABSTRACT

In this thesis, the effects of fleet size changes on the risk and returns of shipping bonds have been examined. First the effects of fleet size changes on freight rates and the EBITDA of shipping lines have been tested. The results showed that fleet size changes are negatively related to both freight rates and EBITDA's of shipping lines. No relationship has been found between the amount of orders made during a year and the EBITDA of shipping lines when these ordered vessels come into operation. Surprisingly, a negative relationship between fleet size changes and default probabilities has been found. This has been explained by the nature of shipping cycles and the emittance of financial buffers as an independent variable. Fleet size changes are incorporated in the returns on shipping bonds, which is in line with the EMH. No relationship between vessel orders during a year and shipping bond returns have been found, which in line with the second finding.

Keywords: shipping bonds, freight rates, default risk, bond returns, container, bulk, oil.

JEL Classification: L92, G12, R40.

EXECUTIVE SUMMARY

The changing environments of the shipping- and financial- industry have increased the popularity of bond issues by shipping lines as a way of financing themselves. A distinct characteristic of the shipping industry is that the price for moving goods, the freight rate, tends to be cyclical. This cyclicality is believed to be caused by the shipping lines themselves. Overcapacity, a time in which part of the fleet is idle and freight rates are at, or below, an operational break-even point, is believed to be caused by the amount of orders placed by the shipping lines during times of high freight rates, since they order more ships than actually needed later on. The mismatch between supply and demand, combined with the average lifespan of a ship lead to large, persistent shocks in freight rates that cause some shipping lines to default on their obligations.

This thesis examines the risks and returns of shipping bonds and makes a distinction between three types of shipping lines: container carriers, bulk carriers and oil carriers. First, the relationship between fleet size changes and freight rates has been tested for every cargo carrying type. The results showed that fleet size changes indeed have a direct, negative effect on freight rates. A relationship that held for every cargo type. To verify if these fleet size changes also led to poorer financial performance, the relationship between fleet size changes and the average EBITDA of publicly listed container carriers has been tested. The results showed that there is indeed a significant, negative relationship between fleet size changes and the average EBITDA of container carriers. The amount of orders for new ships made during a year are not significantly related to the EBITDA with a lag of two years (which is the lead time of building a ship).

A significant relationship between default rates and fleet size changes has also been found, but was surprisingly negative. Reflecting the shipping cycle theory, it can be argued that large upside swings occur directly after times of high freight rates. This means that the fleet size changes may have caused a large downside swing of the freight rate and lowered the average EBITDA of the industry, but did not necessarily put shipping lines at the immediate risk of a default. This is due to the fact that large swings often occur shortly after prosperous times for the shipping lines which allowed them to create reserves. Furthermore, shipping bonds have an average maturity of ± 5 years, which is relatively short. This means that buffers are often high enough to pay the financial obligations during the maturity of the bond. So upside swings in the fleet size do cause a downside swing in freight rates, but are also an indicator that shipping lines had favourable market conditions in the recent past, which makes it unlikely that they default on their financial obligations in the short-term. The relationship is not a causal one, but likely the result of the emittance of financial buffers as an independent variable in the analysis.

Excess returns on shipping bonds have been examined by means of two-steps regressions. First, the excess returns of the bonds were regressed on the risk factors, after which they were regressed on the betas derived in the first step. Fleet size changes during a year and orders made during a year have been separately tested with unexpected interest rate change, change in economic environment and the oil price as independent variables. The results showed that excess bond returns were significantly, negatively related to changes in the fleet size, but not significantly related to the orders made during a year. This is in line with the EMH, since significant, negative relationships between fleet size changes and EBITDA's have been found, which was not the case for orders made during a year and the EBITDA with a lag of two years.

The outcome of this thesis is that positive fleet size changes drive freight rates and earnings down, but short term swings are not likely to put shipping lines in jeopardy of paying their financial obligations. In fact, large upside swings often come after times of prosperity in the shipping market. These allow most shipping lines to buffer up and get them through more difficult times. Investors do react to fleet size changes, but do not react to orders for new vessels only. This is in line with the EMH, since fleet size changes negatively affect the EBITDA of shipping lines, while no such relation has been found for vessel orders.

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CHAPTER 1 Introduction

The shipping industry is exceptional by both its size and its dynamics. Approximately 90% of all trade is conducted by means of a ship and the industry itself earns roughly 500 billion USD a year, solely from its freight tariffs (Albertijn, 2011). The supply side, consisting of the shipping lines, is highly competitive and freight rates are often determined on a daily basis. The supply side is highly elastic due to its great adaptability to demand. When demand is low, shipping lines can adjust supply by lowering vessel speeds, taking longer, less expensive routes (e.g. via a less expensive canal) or simply laying up some of their ships. When demand is high, vessel speeds can be increased and more expensive routes can be taken. When supply is fully utilized, it becomes highly inelastic due to the time span in which new vessels need to be built (approximately 2 years) (Kavussanos, 2014). Due to the derived demand for shipping, demand is closely related to the business cycle and highly volatile. Demand, contrarily to supply, is highly inelastic to price, since it only contributes to a small portion of the total costs of products, there are no close substitutes, and its necessity is often high. For these reasons, earnings of shipping companies are highly volatile, which is reflected in the ways shipping companies are being financed.

Due to the size and capital intensity of the business, the shipping industry is one of the most finance intensive industries in the world, in which approximately 80 billion USD per year is spent on new operational assets (Goulielmos, 2006). Traditionally, banks are the biggest providers of capital (50%), followed by private equity (24%) and capital markets (16%) (KPMG, 2012). The current trend shows, however, that after the financial crisis in 2008, a growing amount of capital is, and will be provided by capital markets by means of bond issues and securitization of shipping assets. This can be attributed to both the supply and demand side of capital. After the financial crisis, banks have become more reluctant to provide capital to shipping lines due to the high volatility of earnings in the shipping industry and stricter regulations from governing institutions. Furthermore, new banking rules in Basel III make loans more expensive for lenders who now need more equity to back up the loans they provide to the market. On the demand side, more capital will be needed to build new vessels that can satisfy an increasing demand and replace an aging fleet (Albertijn, 2011). It can therefore be expected that capital markets will play an increasingly important role in financing shipping companies.

A distinctive phenomenon in the shipping industry is that shipping lines, in times of strong economic growth, tend to over order new vessels which creates excess supply when the new vessels become operational. By over ordering, shipping lines are squeezing their own freight rates which affects their profitability, liquidity and solvability (Stokes, 1997; Zannetos, 1966). Not only is it remarkable that shipping lines have been subject to this fallacy multiple times, but that banks, the biggest providers of capital, seem to be oblivious too (Goulielmos, 2006).

Since capital markets play an increasingly important role in the financing of shipping companies, it is both interesting and relevant to examine how changes in fleet sizes have affected the risks and returns on publicly traded shipping bonds and if capital markets incorporate information regarding future fleet size changes in the pricing of the bonds. Especially since most of these changes are, and will be, financed by the capital markets themselves. Historic fleet size changes are important, because the life-span of a ship is 25 years on average, meaning that a large addition of ships can have a large, enduring effect on freight rates and EBITDA's.

Besides studying how financial markets react to fleet size changes, it is important to study to what extent orders for new ships are related to the future earnings of shipping lines. By doing this, the efficient market hypothesis (EMH) is tested by examining if orders for new ships (which are publicly known) have predictive power regarding future earnings and if financial markets incorporate this information. The research question of this thesis is therefore formulated as:

How are changing fleet sizes affecting the risks and returns of global shipping bonds and are financial markets incorporating information regarding these changes?

Answering this research question will fill the current research gap in which the risk components of shipping bonds are linked to the excess returns on these bonds. The current literature regarding shipping bonds mainly examines the determinants of default probabilities by studying financial ratios of firms with a few industry specific variables to assess default probabilities. Using fleet size changes, rather than the industry specific variables being used in the existing literature, such as current freight rates and current earnings, can be useful, because fleet size changes can have predictive value and might be anticipated on. Excess returns are studied to examine how financial markets incorporate knowledge regarding future fleet sizes in bond prices.

Since ships are often designed to carry a specific cargo type, the research question will be addressed to the three main cargo carriers in the shipping industry: container carriers, oil tankers and bulk carriers. This differs from the current research that has been done, which examined shipping bonds in general without making a distinction between cargo carrying types. Differentiating shipping lines by the cargo they carry is done in this thesis, because it is assumed that each cargo type has idiosyncratic factors that affect their freight rates and are therefore affecting the bond characteristics that are examined in this thesis. These assumptions are underpinned by data analysis in Chapter 3.

Data regarding these carriers: the total fleet size per cargo type, financial statements, returns on bonds and Fama and French bond factors are obtained from Clarksons' Shipping Intelligence Network, Bloomberg and Thomson Reuters' Datastream. Uni- and multi-variate regressions have been conducted to study the relationship between fleet sizes, freight rates, EBITDA's, bond returns, and the Fama and French bond factors. Logistic regressions have been conducted to examine the effect of fleet changes on default probabilities with the inclusion of determinants found in the literature.

This thesis is structured as follows: first a literature study is conducted that elaborates on shipping bonds: the determinants of default probabilities and returns, and the role of fleet sizes regarding these topics. Next, the data and methodologies used to test the hypotheses will be described, after which the results will be presented. The conclusion will summarize these findings and explain what it means in the context of the existing literature.

CHAPTER 2 Literature Review

The main literature regarding the research topic can be divided into two themes: literature regarding fleet sizes and their relationship with freight rates and shipping line earnings, and literature regarding shipping bonds and the determinants of default probabilities and returns.

2.1 Fleet sizes and freight rates

Market conditions in the shipping industry are affected by a wide variety of factors. Most of these factors tend to move together with the business cycle, which is why the shipping industry often shows a similar cyclicality (Goulielmos, 2010). Shipping cycles can differ from regular business cycles, because the supply side can push freight rates in different directions. A changing fleet size can be one of the main causes for such a deviation (Stopford, 2009). The five most important determinants of demand and supply, as recognized by Stopford, are shown in Table 1. It shows the importance of changing fleet sizes in the market for shipping. Dead weight tonnage (DWT) is used as a measurement of capacity and amount of goods shipped.

Table 1. The five main determinants of supply and demand in the shipping market.

Demand	Units	Supply	Units
1. The world economy	Δ%GDP	1. World fleet	DWT
2. Seaborne commodity trades	DWT shipped	2. Fleet productivity	DWT/mile/year
3. Average haul	Days	3. Shipbuilding production	DWT
4. Random shocks	Δ%GDP	4. Scrapping and losses	DWT
5. Transport costs	$/DWT/mile	5. Freight revenue	$/DWT/mile

Source: Maritime Economics, Stopford 2009

The first scholar known to explicitly relate fleet sizes with the movement of freight rates was Fayle (1933). Fayle argued that business cycles and random shocks, like wars or the opening of the Suez Canal, create excess demand (supply) for shipping which leads to high (low) freight rates. These high (low) rates (dis)encourage both existing ship owners and potential entrants to order new vessels which, when becoming operationable, drive freight rates down and demand up again. Note that this is highly similar to the pig-cycle theory and Cobweb model of Coase and Folwer (1937), which explains how people fail to match production lags with fair expectations about future prices.

Excess capacity after a boom in the shipping market often forced a vast amount of shipping lines out of business, which raises the questions why overinvestment occurred more than once and if people could have seen it coming. The phenomenon of overinvestment and the fact that it occurred multiple times has been studied by Fayle, who believed it to be due to relatively low entry barriers, which make it easy for speculators to enter the market during periods of high freight rates (Fayle, 1933).

Cufley (1972) agreed with Fayle that shipping cycles follow a certain pattern mentioned in the previous paragraph, but added booms and crises that could not be predicted in the long-term because they are simply too irregular and heavily dependent on changes in demand (Cufley, 1972). High rates, for example, can be sustained for a long period, even when a lot of new vessels come into operation. This is due to the fact that supply, although rapidly increasing, can still be lagging behind a fast(er) growing demand. Investments only become overinvestments when supply overtakes demand. Investing in new vessels during a boom, with the knowledge that other parties do so too, can be regarded as a form of speculation, since the belief in excess returns is based on the assumption that demand remains larger than supply. This can be an explaination of why overinvestment occurred more than once: people speculated on it.

Another answer, besides speculation, on why overinvestments keep on happening comes from studies in behavioral economics. Hampton (1991) stated that overinvestments in the shipping industry keep on happening because investors are not always rational and are partly driven by fear and greed. These emotions tend to dominate during booms and crises. Seeing how other people fare well during booms triggers greed but also makes people fear that they are missing out, leading to investments that are not based on rationallity (Hampton, 1991).

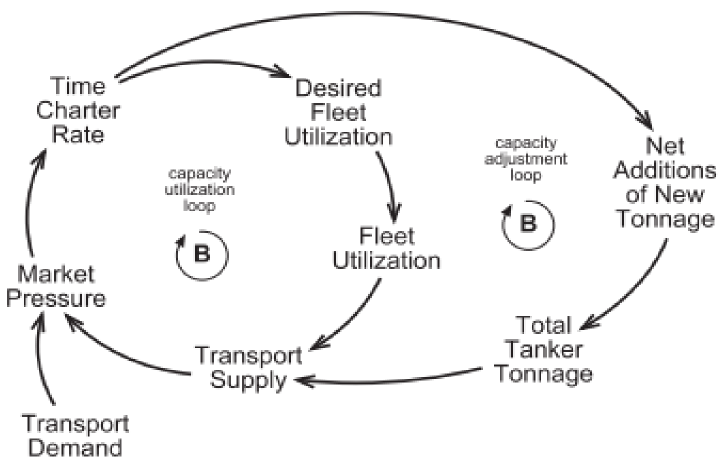
In short, there has been a general agreement that fleet sizes play a significant role in the determination of freight rates, but also that freight rates cannot be predicted due to unpredictable shocks in demand. This view has been challenged by Randers and Göluke (2007) who claim that the time pattern of shipping freight rates is dominated by two feedback loops on the supply side: the fleet size loop and the fleet utilization loop. The first feedback loop, the fleet size loop, describes how shipping lines buy ships in times of prolonged high freight rates and demolish old ships in times of prolonged low freight rates[1]. The utilization loop describes how shipping lines adjust the utilization of their ships as a reaction on changing freight rates. To illustrate these loops, a full loop is described below.

When there are too many ships, freight rates are low and tend to move near the refusal rate: a rate at which the shipping line is indifferent between selling and not selling its services. During this period, many ships are laid up because freight rates only allow the most efficient (usually large) ships to operate profitably. When freight rates increase a little because of increased demand, some laid up ships are taken back in operations and freight rates drop back to the refusal rate of the ships necessary to fulfil demand. For this reason, utilization cycles are not very visible during times of over-capacity: freight rates stay around the refusal rate. Ships continue to operate at the refusal rate of the least efficient ships until, at some point, all ships are taken out of layup (i.e. all vessels are operating).

[1] It should be noted that the price of scrap steel is also a very important determinant in the decisionmaking process to demolish ships, since it is the main component of ships and has substantial residual value.

At this point, demand overtakes supply and shipping lines need to increase speeds and take quicker routes to meet it. This is more costly and compansated for by the higher freight rates. For his reason, utilization adjustments are more visible during times of under-capacity: an increasing demand can not be offset by taking ships back into operations, with freight rates remaining low, but utilization needs to be increased by incurring more costs and hence: higher freight rates. When demand decreases again, the cost efficient routes will be taken, combined with lower vessel speeds which lowers costs and freight rates (closing the utilization loop). When rates stay high for a while, new ships are ordered to meet the excessive demand. It takes a while, however, for ships to be built, which allows the freight rates to keep increasing (as long as demand keeps increasing), since there are often no close substitutes for (sea) shipping. These soaring rates attract more people who also order new ships which leads to an excessive amount of ships when the new ships become operationable. The new ships will be squeezing rates, triggering the demolishment of old ships and start the fleet size loop all over again. A schematic overview of the utilization loop and fleet size loop can be seen in figure 1.

Figure 1. Schematic representations of the fleet size loop and utilitization loop for oil tankers[2]



Source: Forecasting Turning Points in Shipping Freight Rates, Randers & Göluke 2007

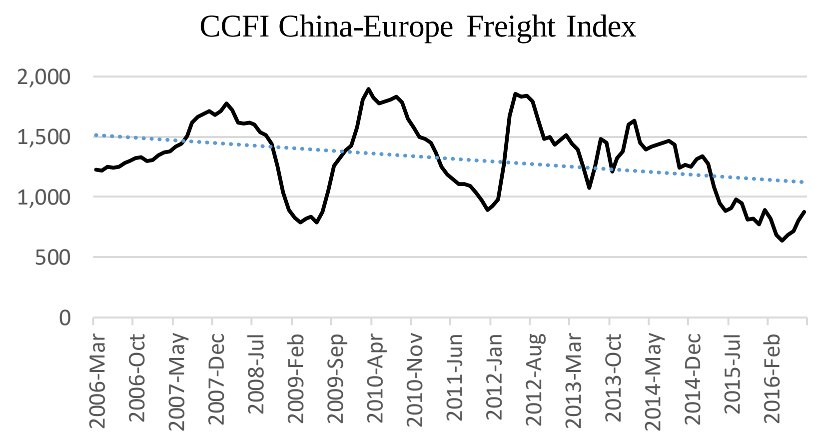
Utilization loops were believed to last approximately 4 years, while fleet size loops were believed to last approximately 20 years. The authors argue that demand does indeed affect freight rates, but that shipping cycles are mostly caused by shipping lines themselves and that demand fluctuations are only noise imposed on these cycles. Noise is used to describe demand shocks and regular fluctuations caused by

[2] This figure shows the different stages in the fleet- and utilization-loop for oil tankers. Supply and demand lead to a certain equilibrium rate in the short-run to which the shipping lines adjust their utilization rate. Prolonged freight rate levels lead to shipping lines adjusted their fleet size.

the business cycle. Demand shocks are referred to as large, unexpected changes in demand due to big events like wars or trade treaties. To support their statement, the authors show that their model with both feedback loops, when used as a forecast model from 1950-2005, manages to roughly predict many of the major turning points in freight tariffs with long term swings of approximately 20 years (+/- 20%) and short term swings of 4 years (+/- 20%). The models failed to predict some large swings when shocks in demand were too disrupting. For example, the oil crisis from 1978-1980 (Randers & Göluke, 2007). The conclusion that Randers and Göluke (2007) derive and the added value of their study is that the authors show that volatility in the shipping market is largely caused by the shipping lines themselves, rather than the business cycles on the demand side of transport.

A generic example of freight rate developments of the last 10 years is shown in Figure 2, which reflects changes in the Clarksons' Shipping Freight Index China-Europe (2006-2016). This index reflects the costs of shipping goods from China to Europe. It is a nice illustration of short-term cycles that seem to appear between May 2007 and April 2013, but also a prolonged decline from March 2013 until now due to declining world trade and major vessel orders in 2011.

Figure 2. Development of the CCFI China-Europe freight index 2006-2016



Source: Clarksons' Shipping Intelligence Network

In their paper, Randers and Göluke describe the major components of their model and the way these interact with each other. Their main technique to study and forecast turning points in freight rates is to impose a utilization loop, modelled as a sinusoid, on a fleet size adjustment loop. A more extensive review of this model can be found in Appendix A.

Goulielmos (2010) re-examined the statements of Randers and Göluke because he believed them to be lacking econometric evidence. He also claimed that cycles are not symmetrical, meaning that the use of sinusoids is not appropriate to study (and forecast) shipping cycles. Goulielmos did agree with Randers and Göluke that downturns in the shipping industry were most likely caused by overinvestments by shipping lines themselves, but disputed that they result in symmetric cycles of equal length. The goal of Goulielmos' study was to econometrically examine and validate the presence and duration of different cycles in the shipping market. He studied the freight market for the period 1741-2007 and conducted a rescaled range analysis to detect repeating patterns in freight rates. He found that the duration of the most frequent freight rate cycles differed between 10 and 20 years, which is significantly longer than the average rate, but also that shipping cycles on average have become shorter over the 266-year time-period. Goulielmos showed high statistical certainty, that cycles have indeed occurred in the shipping business with substantially differing lengths, but also that freight rates are hard, if not impossible to predict on the short-term based on historic values (Goulielmos, 2010). This is important to take into account when studying bond returns. If freight rate changes cannot be predicted, they will also not be included in the pricing of shipping bonds.

The literature above shows that there is a clear linkage between fleet sizes, freight rates, earnings and the financial health of shipping lines. It also shows that freight rates cannot be predicted based on historic values only. Since fleet size changes and overinvestments have been mentioned as probable causes of shipping cycles, or at least as important determinants of fluctuations in freight rates, it is interesting to study if orders of new vessels, which are assumed to be related to changes in fleet sizes, have predictive abilities regarding shipping line earnings and default probabilities as well. If so, the EMH can be tested by examining if financial markets also include this (publicly known) information in the pricing of shipping bonds.

An overview of the existing literature regarding fleet sizes and freight rates can be found in Table 2.

Table 2. Overview literature study fleet sizes and freight rates.

Author, year	Theory	Criticism/remarks
Overstone, 1857	Identified short-term cycles as such and described ten different stages within the cycle.	Stopford (2009) used these stages as a reference to identify four distinct phases in a shipping cycle.
Fayle, 1933	Shipping cycles are driven by business cycles and random shocks. The supply side adapts by changing the fleet size / utilization rate. Cycles keep on happening because entry barriers are low and speculators will continue to enter during prolonged high rates.	Multiple scholars have rejected the idea that shipping cycles are caused by the demand side and argued that cycles are driven by the supply side.
Cufley, 1972	Cufleys' main point is that business cycles cannot be predicted, because of the nature of supply shocks.	Exact levels of freight rates might be hard to predict, but underlying patterns and turning points in cycles can be predicted to a certain degree.
Hampton, 1991	Agrees with Cufley that it is almost impossible to forecast where a shipping cycle is going, but emphasizes the role of the supply side. Investors are driven by emotions and are therefore acting irrationally quite often. This, combined with the supply shocks, makes shipping cycles impossible to predict.	Makes sense in theory, but hard to test empirically.
Randers & Goluke, 2007	Disagree with the previous authors and state that shipping cycles are caused by the supply side. Cycles are caused by fluctuating fleet sizes and utilization rates which cause 20- and 4- year cycles respectively. Fluctuations from these trends are caused by noise from the demand side (e.g. supply shocks).	Their models are based on a sinusoid, while it is highly unlikely that cycles are symmetrical. Furthermore they don't explicitly state the formulas used nor do they show econometric evidence of their claims.
Goulielmos, 2010	Recurring symmetrical cycles are a myth. Their study aims at statistically validating the existence and length of shipping cycles. These have been found and cycles are shown to differ in length over time.	-

The next section describes the existing literature regarding shipping bonds to identify which other factors affect their default probabilities and returns, and need to be taken into account when studying the effects of fleet size changes.

2.2 Shipping bonds

This section is divided in three parts: determinants of default probabilities, determinants of recovery rates and determinants of shipping bond returns.

2.2.1. Determinants of default probabilities

The current literature regarding default probabilities of shipping bonds can be divided into three segments: literature that examines the relationship between default probabilities and financial ratios for firms in general, literature that examines the relationship between default probabilities and cash-flows for firms in general, and literature that examines shipping specific factors regarding default probabilities of shipping bonds.

2.2.1.1 Financial ratios

One of the first scholars to study financial distress related to firm financials was Beaver (1966). Beaver defined financial distress, or "failure" as "the inability of a firm to pay its financial obligations as they mature" (Beaver, 1966). The goal of Beavers' study was to empirically verify if data from financial statements have any predictive ability for "important financial events" including failure. Beaver used 30 financial ratios that were classified in six main categories: cash flow ratios, net-income ratios, debt-to-total-asset ratios, liquid-asset-to-total-asset ratios, liquid-asset-to-current-debt ratios and turnover ratios. These can be found in Table 3. The author used univariate discriminant analyses, meaning that he examined the predictive ability of each ratio separately. A multiple discriminant analysis (MDA) could have also been used, Beaver stated, but his single best ratio showed an equal predictive value as other models with multiple ratios. The univariate analyses of all ratios showed that two ratios had a particularly strong predictive value: working capital over total assets and net income over total assets (which correctly pinpointed 90% and 88% of the total bankruptcies respectively).

Shortly after Beaver, Altman (1968) did use an MDA to study financial ratios and their interactive effects to have a clearer view on individual predictive abilities of ratios on financial distress. Altman chose to use an MDA because it was better able to estimate probabilities for models with binary outcomes, compared to regular regression analysis. In his model, Altman used five ratios that, combined, managed to identify 94% of the firms that eventually went bankrupt. Another useful characteristic of Altman's model was that it has been able to predict bankruptcy up to two years beforehand. After these two years, the model lost most of its predictive ability (Altman, 1968).

Rather than using an MDA, Ohlson (1980) applied a logistic regression (logit) model to examine the predictive value of multiple ratios on the bankruptcy of banks. Ohlson used a logit model, because it is more robust to assumption failure compared to MDA (i.e. assumptions regarding error distributions) and coefficients are easier to interpret. Besides these differences, both methods have proven to have the same predictive ability (Ladd, 1966). In his paper, Ohlson showed that size, leverage, performance and liquidity[3] have a significant relationship with the probability of bankruptcy (Ohlson, 1980).

A more recent article written by Dewaellheyns and Van Hulle (2006) extended the framework by adding group variables to account for differences between stand-alone entities and firms that are part of a

[3] Multiple measures have been used, such as total liabilities over total assets, working capital over total assets, current liabilities over current assets, net income over total assets and funds provided by operations divided by total liabilities.

conglomerate. These group variables took into account whether a firm was part of a conglomerate and to what extent the conglomerates earnings were driven by the particular company. The authors argued that examining the firm as a stand-alone entity is not giving a fair reflection of relationships between financial ratios and default probabilities, because firms that are part of a larger corporation often have higher survival rates. This can be due to access to internal capital markets, but also due to the fact that sustained losses are accepted because of the strategic value of the firm. Other arguments are that total debt can be quite high given the size of the firm, because debt levels can longer be sustained due to the size of the conglomerate. Dewaellheyns and van Hulle found that these group effects play a significant role, and verified that leverage, liquidity, current performance and company size had a significant predictive value on bankruptcy (Dewaelheyns, 2006). An overview of the specific variables can be found in Table 3.

2.2.1.2 Cash-flow ratios

Rather than looking at ratios related to liquidity, debt levels and working capital, some scholars specifically examined how cash-flow ratios could be used as a predictive indicator for financial distress. The idea behind the use of cash-flow ratios, rather than financial ratios, is that cash-flow ratios are more specifically related to the performance of a company, while financial ratios are more indicative for the current financial health of a firm.

The first scholars to find significant relationships between cash-flows and future financial distress were Aziz et al. (1989). They showed that operating cash-flows, taxes, net capital investment and lender cash-flows have significant predictive value for financial distress (Aziz, 1989). The results were contrasting towards previous results from Casey and Bartczak (1985) and Gombola et al. (1987), who claimed that cash-flow-based models do not improve the accuracy of existing models based on accrual accounting. According to Aziz et al., this was due to the fact that previous authors did not incorporate important cash-flow variables such as lender cash-flow and that previous authors used different definitions of cash-flows. Most importantly, they used cash-flows as a stand-alone factor and did not combine it with existing financial ratios (not related to cash-flows). Aziz et al. found that using cash-flows adds value to the accrual-based models currently in existence (Aziz, 1989).

More recently, Shumway (2001) used a hazard model, rather than a static model (used by the previous authors) to study financial ratios and their predictive value. Static models, Shumway claimed, are biased because they don't control for each firm's period at risk. Hazard models are incorporating time-varying variables that have explanatory power that differs over time. This basically means that macroeconomic variables that affect nearly all observations, but differ over time, can be included. Shumway found that incorporating time-varying "risk periods" adds predictive value to the previous models. The specific ratios used by these authors can be found in Table 3.

2.2.1.3 Shipping specific determinants

The first scholars to apply insights from financial- and cash-flow ratio- analysis to the shipping industry (shipping bonds to be specific), were Grammenos et al. (2008). In their paper, the authors used a binary logit model to examine if and which ratios in the existing literature are relevant when predicting default probabilities for shipping bonds. 13 independent financial ratios have been applied, combined with four bond-specific characteristics: total amount raised, total amount raised over total assets, coupon (%), time to maturity and the credit rating (see next section). Furthermore, an industry specific variable, returns on shipping freight indices, has been used to incorporate market conditions at the issuance dates of the bonds.

To construct the most suitable model for predicting default probabilities, the authors used a stepwise method, which means they conducted univariate logistic regressions from which they derived statistically significant explanatory variables. This was followed by adding these variables one by one into a multivariate logistic regression to see which variable added predictive value to the model. The model that Grammenos et al. found to be most accurate in assessing default probabilities of shipping bonds was a model with a constant and 5 ratios: working capital over total assets, retained earnings over total assets, gearing (debt/equity), amount raised over total assets and returns on the shipping index. The authors back-tested their model on a sample of 50 high-yield shipping bonds with fixed coupon rates that were issued from 1992-2004. The authors correctly identified 36 of a total 37 bonds as non-defaulting, meaning that 12 out of 13 defaulted bonds have been correctly recognized as defaulting ones (Grammenos, 2008). These variables will be included in the logistic regression that tests the relationship between fleet size changes and default probabilities.

An overview of all literature discussed above regarding default probabilities and the determinants of defaults probabilities can be found in Table 3.

Table 3. Overview literature study on default probabilities of shipping bonds.

Author(s), year	**Time period**	**Method(s)**	**Dependent variable**	**Independent variables**	**Control variables**
Beaver, 1966	1954-1963	Univariate discriminant analysis	Probability of default	Cash-flow/sales, cash-flow/total assets, cash-flow/net worth, cash-flow/total debt, net income/sales, net income/total assets, net income/net worth, net income/debt, current liabilities/total assets, long-term liabilities/total assets, total liabilities/total assets, current plus long-term plus preferred stock/total assets, cash/total assets, quick assets/total assets, current assets/total assets, working capital/total assets, cash/current liabilities, quick assets/current liabilities, current assets/current liabilities, cash/sales, accounts receivable/sales, inventory/sales, quick assets/sales, current assets/sales, working capital/sales, net worth/sales, total assets/sales, cash/fund expenditures for operations, defensive assets/fund expenditures for operations, defensive assets minus current liabilities/fund expenditures for operations.	-
Altman, 1968	1946-1965	Multiple discriminant analysis	Probability of default	Working capital/total assets, EBIT/total assets, market value equity/total debt, sales/total assets, current ratio, years of negative profits, total debt/total assets and net worth/total debt.	-
Ohlson, 1980	1970-1976	Conditional logistic regressions	Probability of bankruptcy	Total liabilities/total assets, working capital/total assets, current liabilities/current assets, binary variable that takes value 1 if total liabilities exceed total assets, net income/total assets, funds provided by operations/total liabilities, binary variable which take the value 1 if net income was negative for the last two years, change in net income (%).	Total assets/GNP price level.
Casey and Bartczak, 1985	1971-1982	Multiple discriminant analysis and conditional stepwise logistic regressions	Probability of bankruptcy	Cash-flow from operations (CFO), CFO/current liabilities, CFO/total liabilities.	Cash/total assets, current assets, total assets, current assets/current liabilities, sales/current assets, net income/total assets and total liabilities/owners' equity.

Table 3. continued…

Author(s), year	**Time period**	**Method(s)**	**Dependent variable**	**Independent variables**	**Control variables**
Gombola et al., 1987	1970-1982	Multiple discriminant analysis	Corporate failure	CFO/sales, CFO/total assets, CFO/total debt,	Cash/current debt, cash/sales, cash/total assets, cash/total debt, costs of goods sold/inventory, current assets/current debt, current assets/sales, current assets/assets, current debt/total debt, income/sales, income/assets, income/total debt, income plus depreciation/sales, income plus depreciation/total assets, income plus depreciations/total debt, sales/receivables, sales/total assets, assets/total debt, working capital from operations (WCFO)/sales, WCFO/total assets and WCFO/total debt.
Aziz et al., 1989	1973-1982	Multiple discriminant analysis and logistic regressions	Probability of bankruptcy	The Lawson Cash Flow Identity (taxes paid + net capital expenditures and liquidity changes, any surpluses/deficits flow to or from landers or shareholders)	Working capital/total assets, retained earnings/total assets, EBIT/total assets, market value of equity/book value of total debt, sales/total assets, net capital investment and liquidity changes (%),
Shumway, 2001	1962-1992	Logistic regressions	Time spent as "healthy firm"	Working capital/total assets, retained earnings/total assets, EBIT/total assets, market equity/total liabilities, sales/total assets and ln(Age)	Idiosyncratic standard deviation of a firm's stock returns and average excess returns.
Dewaelheyns and van Hulle, 2006	1996-2001	Logistic regressions	Probability of default	Dummy variables: 1 if net commitments to affiliated companies < 1/3 of total assets; 0 otherwise, dummy variable: 1 if an ultimate corporate owner is identified; 0 otherwise.	Ln (total assets), (current assets-inventory)/current liabilities, (reserves + retained earnings)/total assets, operating profits/total assets, total debt/total assets, sales/total assets.
Grammenos et al., 2008	1994-2004	Logistic regressions	Probability of default	Working capital/total assets, current assets/current liabilities, cash/freight revenue, freight revenue/current liabilities, net income/freight revenue, EBITDA/freight revenue, net income/total assets, retained earnings/total assets, freight revenue/total assets, net income/interest expenses, long-term debt/ long-term debt+ shareholders' equity, amount raised/total assets.	Coupon rate, maturity, credit rating, normalized index for time-charter rates for each specific sector in the shipping industry (3-year moving average of the earning index)

2.2.2. Risks and returns on shipping bonds

Studying the determinants of asset returns (or asset pricing models) is one of the main the topics in finance. Two leading articles have been consulted and used to study the effects of fleet size changes on shipping bond returns. These are the papers of Fama & MacBeth (1973) and Fama & French (1993).

Fama and Macbeth (1973) studied the relationship between risk factors and the average (excess) return on common stocks. They did so by conducting a two stage regression that estimates the premium for each risk factor that is included in the model being estimated. A similar regression will be conducted in this thesis. The first part of this method consists of regressing the returns of each specific asset (or portfolio in the authors' case) on the factors which they believed to affect these returns. This results in betas that represent the exposure of the returns to each of these variables. These were referred to as "factor exposures". Next, a cross-sectional regression has been conducted in which the returns of the assets were regressed against these betas for each observation moment. These result in risk premium coefficients for all factors at each point in time. If, for example, 50 stocks have been examined for which monthly data has been obtained for 5 years, then the first part of the Fama Macbeth regression consists of 50 regressions and the second part of 60 (12*5) regressions. The last part of this method is the taking of an average of the risk premia, which is the expected premium for each factor (Fama, 1973).

In 1993, Fama and French extended the research on variables that are able to explain stock- and bond-returns. They conducted time-series regressions in which the returns of particular stocks or bonds were regressed on the returns of a market portfolio and returns on portfolios specifically constructed to mimic a specific characteristic of the observed stock that they wanted to examine (e.g. size and leverage). By comparing the slopes (betas) of the model, they were able to capture the extent to which bonds or stocks were specifically "sensitive", or, in terms of Fama and MacBeth (1973), the size of their factor loadings.

The main finding of Fama and French (1993) related to excess returns on bonds, is that these returns can largely be explained by two factors: unexpected changes in interest rates and changes in economic conditions. The unexpected change in interest rate was expressed as the difference between the monthly long-term government bond return and the one-month treasury bill rate measured at the end of the previous month. The change in economic conditions was expressed as the difference between the return on a market portfolio of long-term corporate bonds and the return on a long-term government bond. The relevance of these findings for this thesis, is that these (and other) factors need to be included in the analysis to get a clear view on the effects of fleet size changes on the returns of shipping bonds. This makes sense when these factors are translated to basic shipping financing. Unexpected changes in interest rates basically reflect the change of attractiveness of a safe investment compared to an investment in shipping. Changes in economic conditions are highly affecting the demand for transport.

Adding fleet size changes to this model is expected to add value because the addition of a variable representing the supply side gives a better reflection of (shipping) market conditions than demand side (economic conditions) only. An elaboration on this topic is given in the next chapter.

2.3 Overview and hypotheses

In the previous sections, literature regarding shipping bonds and the determinants of default probabilities and returns have been discussed. The role of fleet size changes on the earnings and financial health of shipping lines has been highlighted to underpin the relevance of the research question. To give a clear overview of the basic dynamics regarding shipping bonds and the interaction between the drivers of its components, a flow chart has been constructed, based on the findings in the existing literature. This is shown in Figure 3. This will be followed by the hypotheses that will be tested to answer the research question.

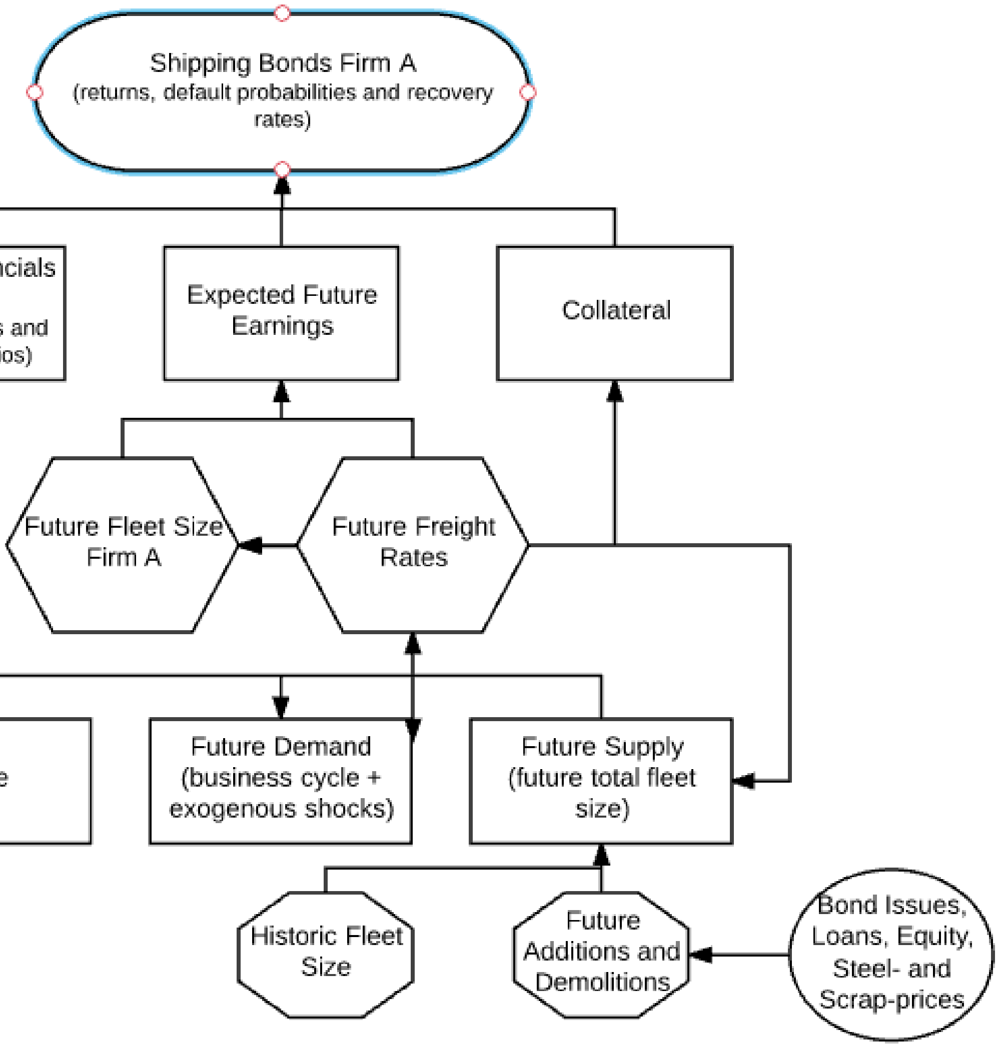
2.3.1. Flow chart shipping bonds

Each arrow in Figure 3 represents the relationship between the dependent and independent variable. The box from which the arrow is leaving is considered the independent variable, the box touching the arrowhead is considered the dependent variable. For example, the upper box (shipping bonds of firm A) has an arrowhead coming from the current financials of firm A, expected future earnings and collateral. This means that shipping bonds of firm A are assumed to be driven by the current financials of firm A, the expected future earnings of firm A and the collateral included in the contract.

The expected future earnings are assumed to be driven by the amount of ships (future fleet size of firm A) and the amount of money they make (based on future freight rates). Future freight rates are also assumed to affect the collateral on bonds, because it determines the return that can be made on a ship and hence its value. The future fleet size of firm A is also assumed to be driven by future freight rates: shipping lines want to expand when rates are high and contract when rates are low.

Future freight rates are driven by the supply- and demand- side of shipping. Demand is determined by the business cycle and exogenous shocks, while supply is determined by the future amount of ships and their utilization rate. The future amount of ships is equal to the historic amount of ships plus future additions minus future demolitions. Note that this is the basic reasoning behind the suspicion that historic fleet size changes have a predictive ability regarding shipping bond characteristics.

Figure 3. Flow chart shipping bond drivers.



2.3.2. Hypotheses

In this chapter, the context of the research question has been examined and discussed. Given the context, the hypotheses used to answer the research question are formulated as follows:

Research Question:

How are changing fleet sizes affecting the risks and returns of global shipping bonds and are financial markets incorporating information regarding these changes?

Hypothesis 1: Changing fleet sizes have a direct effect on freight rates.

Hypothesis 2: Changing fleet sizes have a direct effect on the EBITDA of shipping lines.

Hypothesis 3: The amount of ships ordered during a year has a direct effect on the EBITDA of shipping lines when these vessels come into operation.

Hypothesis 4: Fleet size changes are directly related to the default probability of a shipping bond.

Hypothesis 5: Fleet size changes have a direct effect on excess shipping bond returns.

Hypothesis 6: The amount of orders for new ships has a direct effect on excess shipping bond returns.

CHAPTER 3 Data and Methodology

In this chapter, the data and methodologies used to test the hypotheses will be described. First, the data and data sources will be described. Then the methodologies will be discussed.

3.1 Data

3.1.1. Fleet sizes and cargo carried

As explained in the introduction, multiple cargo carrying types will be examined: oil tankers[4], container carriers and bulk carriers. Fleet sizes and the annual amount of cargo carried are being used to represent the supply and demand side of the shipping market. The annual amount of cargo carried is chosen as a proxy for demand, because demand is highly inelastic. This means that the quantity of shipped goods is only slightly affected by changing freight rates. Demand is therefore expressed as an absolute value, rather than a function. Together, supply and demand lead to an equilibrium price: the freight rate, which is discussed in the next section.

Annual fleet sizes have been obtained from Clarksons' Shipping Intelligence Network. Data regarding the total fleet size of container vessels has been obtained for 1999-2016. Data regarding the oil tanker fleet have been obtained for 1990-2016 and for 1994-2016 for the bulk carrying fleet. Descriptive statistics regarding these fleet sizes can be found in Table 4. The container fleet has grown the quickest with an average annual growth rate of 9.5%. This has mainly been due to a large increase in exports from developing countries to Europe and North America. The fleet size of oil carriers has grown relatively slow (roughly in pace with the world economy). The bulk carrying fleet has grown substantially (faster than the oil fleet, slower than the container fleet) due to the increased demand for raw materials by the emerging economies.

Table 4. Descriptive statistics fleet sizes.

Cargo type	Timeframe	Avg. size[5]	High	Low	Std. dev	Avg. growth rate	N
Container	1999-2016	1025	1,826	425	478	9.53%	17
Oil	1990-2016	339	508	252	86	2.73%	26
Bulk	1994-2016	389	759	220	170	5.80%	12

Source: Clarksons' Shipping Intelligence Network

Demand for the different cargo types has also been obtained from Clarksons' Shipping Intelligence Network. Demand is expressed as the annual amount of goods shipped (measured by its weight) times the distance it has been moved. It has been obtained for the same timeframes of the matching fleet types,

[4] Oil tankers refer to both crude and refined oil tankers, since most ships can (and are) easily be(ing) converted to carry both.
[5] The size of the container fleet is expressed in 10,000 TEU units, the oil- and bulk-fleet are expressed in million DWT units.

except for bulk carriage, which has been obtained from 1999-2016. An overview of the descriptive statistics can be found in Table 5. Not surprisingly, the average growth of demand has been the largest for container transport, followed by bulk and oil transport. Note that this is similar to the fleet size growths in Table 4. This implies that freight rates, which are discussed in section 3.1.4., are likely to have declined much less than the growth in fleet sizes, due to the growth in demand that partly offsets that effect.

Table 5. Descriptive statistics demand (annual cargo carried).

Cargo Type	Time frame	Avg. demand[6]	High	Low	Std. dev.	Avg. growth (%)	N
Container	1999-2016	5664	8423	2774	1845	6.75	17
Oil	1990-2016	7796	9134	5355	1102	2.04	26
Bulk	1999-2016	19075	25780	12675	4726	4.54	17

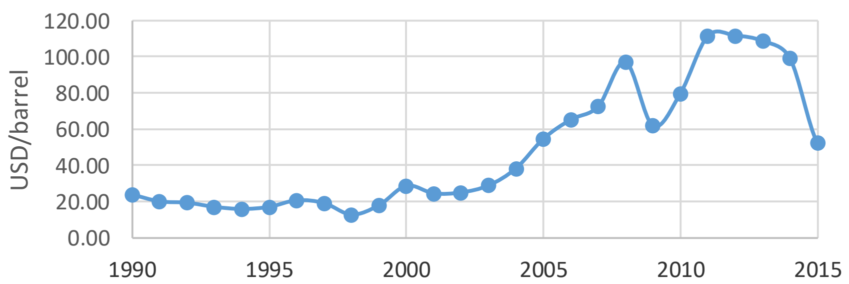
Source: Clarksons' Shipping Intelligence Network

3.1.2. The oil price

The oil price plays a significant role in the determination of freight rates, because it is one of the largest cost accounts for shipping lines. According to a study employed by the United Nations, the elasticity between freight rates and the oil price varies between 0.19 and 0.36 (UNCTAD, 2009). This means that a 10% increase in oil prices results in an increase in freight rates between 1.9 and 3.6%. To get a clear view on the relationship between fleet sizes and freight rates, oil prices need to be taken into account as a control variable.

There are multiple oil prices that differ slightly in costs, depending on the place where the oil is extracted. The most common ones are the Brent, WTI and Dubai/Oman spot rates. Since spreads are very small, the Brent price is being used as a proxy for oil prices in general, since this is the main benchmark in most crude oil contracts. Data have been obtained for 1990-2015 from the US Energy Information Administration (EIA, 2016). The historic price development is shown in Figure 4.

Figure 4. Spot price Brent-oil 1990-2015.



Source: U.S. Energy Information Administration 2016

[6] Demand for all cargo carriage types is expressed in billion tonne-miles.

3.1.3. Freight rates

Freight rates are more difficult to express, since multiple rates exist for different routes. To express freight rates in general terms, the costs of chartering a ship for one year have been used. A time charter means that a shipping line gains control of a specific vessel for a specified period of time (in this case one year). This is, of course, highly dependent on the demand for shipping but more important, independent on the costs for specific routes. For container carriage, the Containership Time Charter Rate Index has been used, which is an index based on assessments of the average charter rates for the six most commonly used vessel sizes for a 1-year time period. This type of index has not been found for oil and bulk carriers, so for these cargo types the average annual charter rate of a 150,000 DWT Suezmax and a 150,000 DWT Bulk carrier have been chosen respectively. These vessels had the most extensive and recent data coverage. Descriptive statistics regarding these variables can be found in Table 6.

Table 6. Descriptive statistics freight rates.

Cargo Type	Time frame	Avg. rate[7]	High	Low	Std. dev.	Avg. growth (decline) %	N
Container	1999-2016	76	152	35	33	(1.3)	17
Oil	1990-2016	26	47	13	11	3.4	26
Bulk	1994-2016	26	90	8	23	(3.6)	20

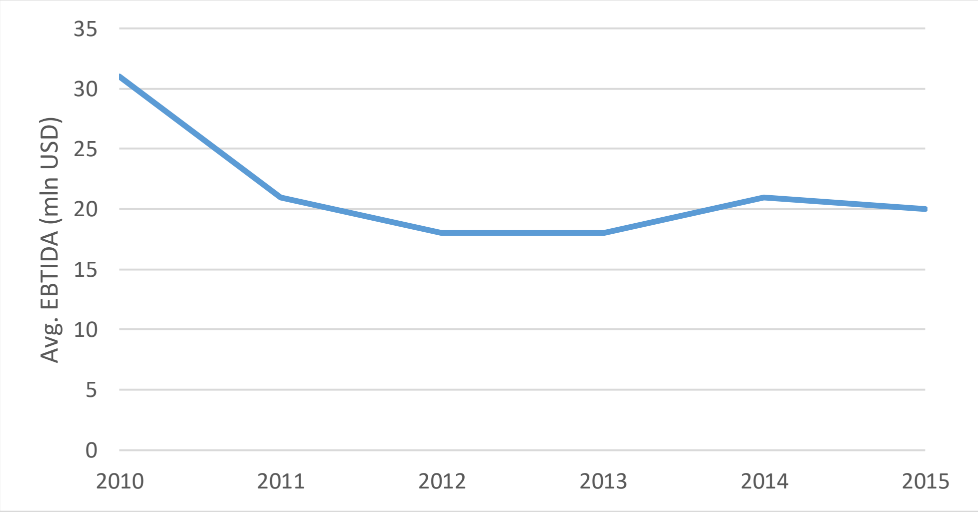
As can be seen in Table 5, there have been major swings in charter prices for all cargo types. At its all-time high, the costs for chartering a container ship for one day have been 434% higher compared to its all-time low. In line with expectations, freight rates have declined over time, due to increasing fleet sizes and scale economies. The decline in freight rates has been much smaller compared to the growth in fleet sizes, due to substantial growth in demand. The costs of chartering oil tankers have, contrarily to bulk and container carriers, not been declining and have even increased over time. This can be explained by the fact that growth of supply was not much higher than demand (roughly 0.9% annually, compared to 2.85% for container carriage and 2.4% for bulk carriage). More importantly, oil tankers, when oil prices are low, are being used as storage units for oil. This results in higher chartering costs, since tankers are a relatively cheap way to store oil. The small discrepancy between supply and demand growth and the double purpose of oil tankers explains why freight rates of oil tankers have increased over time.

3.1.4. Average EBITDA container lines

The average EBITDA of all container lines has been obtained from a report from AlixPartners, a consulting firm. In their report "Finding focus in the shipping industry", the performance of containers lines from 2010-2015 is being reviewed. They provide the average EBITDA of publicly listed container lines from 2010-2015 (AlixPartners, 2016). These are shown in Figure 5.

[7] The rate for container charters is expressed as the Containership Time Charter Rate index. The rates for the oil and bulk vessel charters are expressed in $1,000/day units.

Figure 5. Average EBITDA container lines 2010-2015.

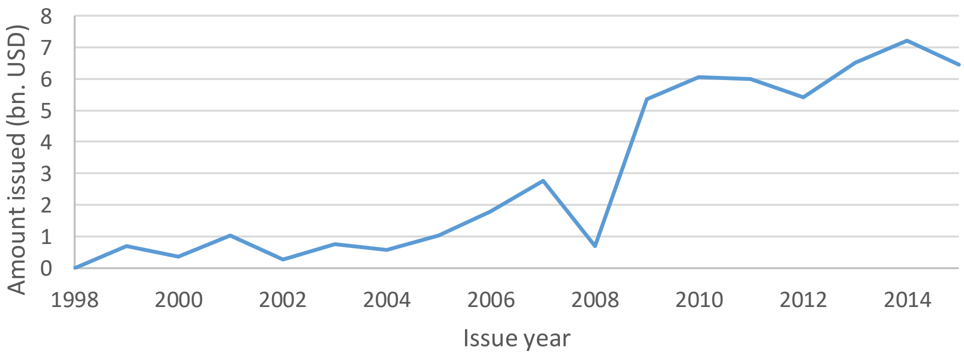


Source: AlixPartners

3.1.5. Shipping bonds

The core of this thesis is the examination of fleet sizes and their effects on shipping bonds. The first shipping bond has been issued in 1992 by Sea Containers Ltd. Since then, the use of shipping bonds has showed an increasing trend which can be seen in Figure 6. Figure 6 shows the total amount of money obtained from shipping bond issues for all cargo carrying types from 1998-2015.

Figure 6. Total amount of shipping bond issues (bn.USD) 1998-2015

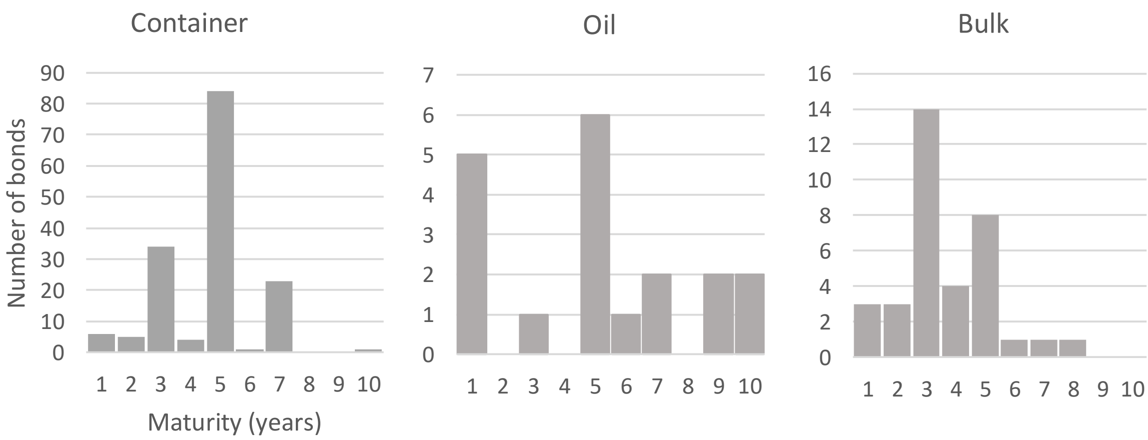


Source: Bloomberg

Shipping bonds that have been issued between 1992-2015 have been obtained from three sources: Bloomberg, Thomson Reuters' Datastream and Clarksons' Shipping Intelligence Network. To gather data from Bloomberg, the following methodology has been applied: first, all listed bonds have been filtered on industry group in the bond search section (the general filter). The industry group Transportation and Logistics contained the bonds issued by all cargo carrying types examined in this thesis. Next, a timeframe has been applied with the requirement that a bond needed to be matured between the 1st of January 1992 and October 1st, 2016. The search filter could not be further specified, so additional filters needed to be created manually. This has been done by using the Bloomberg Industry Classification Standard (BICS). This classification scheme (which is not part of the general filter) contains lists of companies that belong to a certain sub-section of an industry. The Transportation and Logistics industry could be narrowed down to Marine Shipping which contained lists of container shipping companies (Container Shipping), bulk carrying companies (Dry Bulk Shipping) and oil tankers (Oil Tankers). They contained both existing and historic shipping companies. The last filter that has been applied on the firms to belong to a certain sub-industry was the requirement that a company needed to gain at least 50% of its revenue from that cargo specific industry (referred to as primary industry). The companies identified via the BICS system have been used to gather the bonds for each cargo type from the general filter.

Additional bond issues have been obtained from Clarksons' Shipping Intelligence Network. They have been provided by means of a document that contained bond issues from 2006-2016 that were manually collected by the Clarksons team. Bond issues that were not registered in Bloomberg have been looked up in Datastream to verify their existence and obtain additional information (e.g. coupon type). Lastly, all issuing companies have been checked for having the financial data that are required in the analysis (the financial ratios identified in the literature study). Approximately 70% of the issuing companies had these data. The remaining 30% has been removed from the sample. Descriptive statistics regarding the distributions of the maturities of the bonds can be found in Table 7. Other descriptive statistics, like the number of bonds issued by country of residence of the issuer, the number of bonds and defaults per cargo carrying type, the average amount issued and the average maturity of bonds are shown in Table 8.

Table 7. Distribution of bond maturities per cargo type.



Sources: Bloomberg, Thomson Reuters' Datastream, Clarksons' Shipping Intelligence Network

Table 8. Descriptive statistics bond sample

Panel A: Number of bonds for each cargo type				
Cargo type	Number of bonds	Number of defaults	Avg. amount issued (mil.USD)	Avg. maturity (years)
Bulk	35	10	126	3.7
Container	158	18	125	4.6
Oil	19	8	119	5.1
Total	212	36	125	4.5

Sources: Bloomberg, Thomson Reuters' Datastream, Clarksons' Shipping Intelligence Network

Panel B: Number of bonds issued by country of residence of the issuer	
Country of residence of the issuer	Number of bonds
Bahamas	1
Belgium	1
Bermuda	3
China	4
Cyprus	2
Denmark	1
Germany	3
Hong Kong	1
Indonesia	9
Israel	1
Malaysia	3
Marshall Island	7
Singapore	3
South Korea	66
Taiwan	100
Thailand	1
United States	3
Unknown	1
Total	212

Source: Bloomberg

Most issues are done by issuers from Taiwan and South Korea. This is due to the fact that most shipping lines originate from these countries and have their headquarters in these regions. The differences in the amount of bonds that have been issued for each cargo carrying type can be explained by looking at the size of the different markets. In 2015, the revenue of the container line industry was approximately 110 billion USD, while the revenue of the bulk line and oil tanker industries were 20 billion and 14 billion respectively (Bloomberg, 2016). The average amount obtained via a bond issue is approximately the same for all cargo types, while the average maturity of the bonds seems to differ between the cargo types. This could be due to specific risks that might differ between these cargo types. For example, when the idiosyncratic risk for bulk lines is significantly higher compared to container lines, it might be harder or more expensive to obtain money for a longer period. Looking at the amounts of bond issues and their respective default rates, this is a very plausible explanation for the differing maturities.

3.1.6. Financial ratios

To make a fair assessment of the effect of (historic) fleet size changes on shipping bonds, multiple firm-specific conditions need to be taken into account as control variables. These have been identified in the literature study as: working capital over total assets, retained earnings over total assets, gearing (debt/equity), and the amount raised over total asset. These statistics have been obtained from the annual statements of the companies. More specifically, the most recent statement has been used before the issuance of the bond to get the best estimations of the financial accounts at the issuance of the bond. Descriptive statistics regarding these ratios can be found in Table 10 (next page).

In the existing literature, shipping bonds have been examined as a homogenous entity. This thesis differentiates between the different cargo types that exist within the industry. This has been based on the observations regarding the different freight rates that often moved in different directions. To further examine whether differentiating between cargo types is justified (or even essential), t-tests are conducted to see if there are significant differences between the financials of shipping firms of each category. These are shown in Table 9. These values underpin that substantial differences exist between lines that carry a specific type of cargo and justify the differentiation between these types.

Table 9. t-Statistics mean differences shipping lines per cargo type.

Financial ratio	Container-Bulk	Container-Oil	Bulk-Oil
Working capital/total assets	-2.097**	0.440	1.409
Retained earnings/total assets	-2.443***	-1.612*	-0.157
Gearing	0.816	-1.798**	-2.003**
Amount issued/total assets	-1.719**	-2.741***	-1.714*

*: p<0.1, **: p<0.05, ***:p<0.01
Source: Bloomberg

Table 10. Descriptive statistics financial ratios bonds per cargo carrying type.

Variable	All issues		Defaulted issues		Non-defaulted issues	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Container carriers						
Financial ratios						
Working capital/total assets	0.004	0.100	0.02	0.08	-0.001	0.104
Retained earnings/total assets	0.100	0.180	0.089	0.030	0.102	0.196
Gearing	160	97	265	132	146	83
Amount issued/total assets	0.005	0.02	0.00	0.00	0.0058	0.0243
Bulk carriers						
Financial ratios						
Working capital/total assets	0.052	0.127	0.08	0.09	0.04	0.14
Retained earnings/total assets	0.161	0.121	0.23	0.08	0.13	0.13
Gearing	141	130	133	58	144	151
Amount issued/total assets	0.031	0.089	0.00	0.01	0.04	0.10
Oil tankers						
Financial ratios						
Working capital/total assets	-0.015	0.185	0.01	0.07	-0.03	0.24
Retained earnings/total assets	0.168	0.173	0.25	0.16	0.11	0.17
Gearing	213	124	192	97	228	144
Amount issued/total assets	0.090	0.135	0.025	0.045	0.137	0.161

3.1.7. Returns on shipping bonds

Returns on shipping bonds have been collected for container carrying companies. Returns on shipping bonds of bulk- and oil-carrying companies were also obtained, but there were insufficient observations to derive reliable results (30 and 20 bonds respectively). These are therefore left out of this part of the study. Returns are calculated by combining the change in bond price (%) and coupon (% of bond value) of the bond. Excess returns are calculated by subtracting the risk-free interest rate, defined as the interest rate on a one-year US treasury bond from these returns.

The returns on bonds issued by container carriers have been obtained for 2006-2015 by applying the same search method as the one mentioned in section 3.1.5. The total amount of observed bonds is 135. More bonds have been obtained (610) but have been excluded because they were either lacking data regarding the coupon paid or price changes during their maturity. The average annual return on shipping bonds is shown in Figure 7.

Figure 7. Average return on shipping bonds and fleet growth 2006-2016.

Sources: Bloomberg, Clarksons' Shipping Intelligence Network

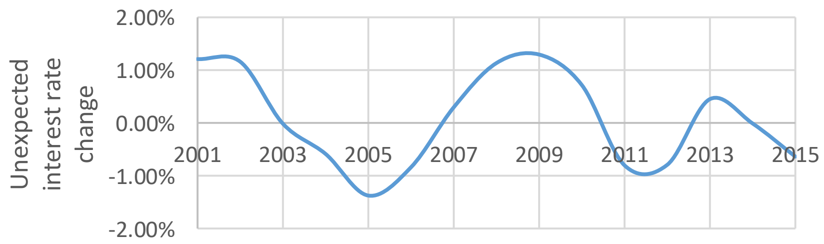
3.1.8. Fama and French bond factors

Fama and French (1993) showed that most variation in bond returns could be explained by two variables: unexpected changes in interest rates and changes in the economic environment.

Unexpected Interest Rate Changes

Unexpected changes in interest rates were expressed as the change in the difference between the monthly return on a long-term government bond and the return on a 1-month Treasury bill. Since fleet size changes and returns are measured on a yearly basis (to leave out seasonal effects), unexpected changes in interest rate, in this thesis, will be expressed as the change in the difference between the annual return on a 10-year (long-term) US government bond and the annual return on a 1-year Treasury bill measured at the end of the previous year. The returns on the 10-year and 1-year government bonds are derived from the U.S. Department of the Treasury (US Treasury, 2016). Data has been gathered for 2001-2015. The unexpected changes in interest rates, as derived by this method, are shown in Figure 8.

Figure 8. Unexpected interest rate changes 2001-2015.



Source: U.S. Department of the Treasury

Change in economic environment

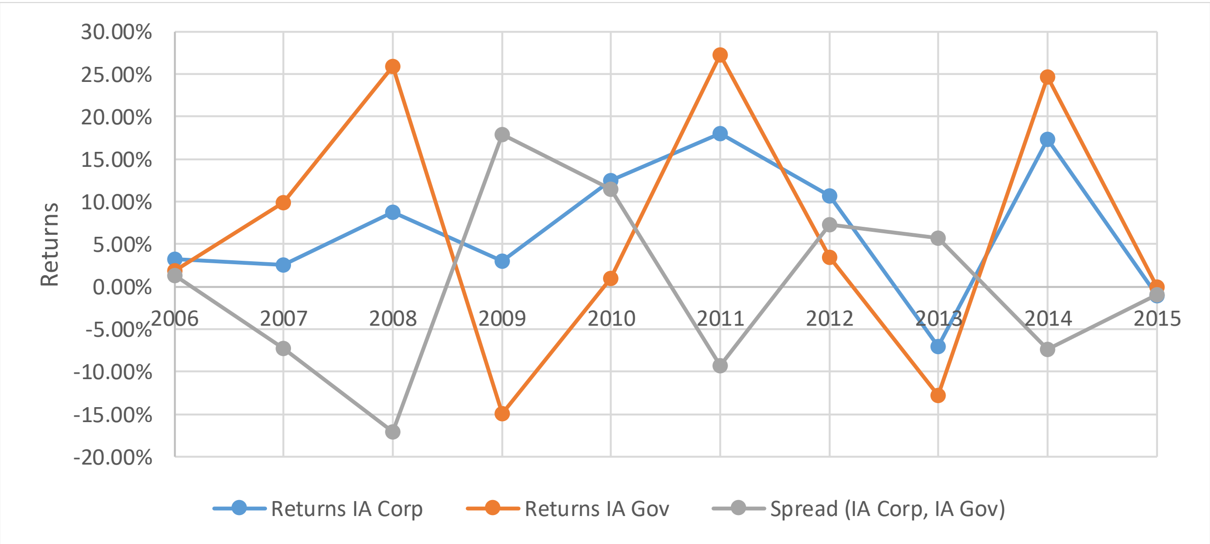
Changes in the economic environment can be expressed as the change in the difference between the return on a market portfolio of long-term corporate bonds and the returns on long-term US government bonds. In this thesis, the Ibbotson Associates U.S. Long-Term Corporate Bond Index (IA Corp) and the Ibbotson Associates U.S. Long-Term Government Bond Index (IA Gov) are being used to represent the return on a market portfolio and the return on long-term government bonds respectively. These are the same indices used by Fama and French (1993).

The IA Corp index is an index that includes most Aaa- and Aa- rated bonds (S&P) with a minimum maturity of 10 years that are traded on an U.S.-based exchange. If the rating of a bond falls below Aa-, the return on that particular bond is included for the period before the downgrade, but removed after the downgrade. The index includes reinvestment of income.

The IA Gov index basically tracks the returns on U.S. treasury bonds with a maturity of 20 years. It is a portfolio consisting of one bond: the most recently issued U.S. treasury bond with a maturity of 20 years. The returns on this index are calculated by taking the change in price and the accrued coupons. Similar to the IA Corp index, this index includes reinvestment of income.

Both the returns on the IA Corp index and returns on the IA Gov index are derived from the Morningstar yearbook of 2015/2016 (Morningstar, 2016). Data has been obtained for 2006-2015. The returns on both indices and their spread (defined as the change in economic conditions) is shown in Figure 8.

Figure 8. Returns on the IA Corp and IA Gov indices 2006-2015.



Source: Morningstar Indexes Yearbook.

3.2 Methodology

3.2.1. Multiple linear regression analysis

Multiple linear regressions will be used to test hypotheses 1, 2, 3, 5 and 6. It is a technique used to assess the relationship between one response- and multiple explanatory-variables. In this thesis, ordinary least squares regressions will be conducted. This means that an intercept, and parameters for each explanatory variable will be estimated for which the sum of squared errors is minimized. In other words: an equation is estimated for which the squared differences between the estimated value of the response variable and the actual value of the response value is minimized. The general form of the equation that is estimated is shown in Equation 1.

Equation 1. Multiple linear regression (OLS).

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_a x_{ia} + \varepsilon_i$$

Where:
i= 1, 2, …, n
n= number of observations
y_i= dependent variable at time i
x_{ia}= independent variable a at time i.
ε_i= error term caused by unobserved factors

Multiple linear regressions are only appropriate as an instrument when four conditions are met. Four conditions need to be met for a regression to be unbiased. Unbiasedness means that the expected value of an estimator is equal to the true value of that parameter. First, the relationships between the dependent and independent variables should be linear in parameters, since a linear relationship is estimated. The second condition is that the independent variables are exogenous and uncorrelated with the error term. In other words: the mean of the error terms for a specific value of the explanatory variable is zero, or $E(\varepsilon_i|x_i) = 0$. Two other conditions that need to be met for a regression to be unbiased are that the sample is random selection of the population and that there is no perfect collinearity. Collinearity between the independent variables can be checked by means of a correlation table which shows the correlations between each of the independent variables. If all conditions are met, the regression provides linear unbiased estimators.

Additional assumptions are required for the regression to deliver the best unbiased estimators and valid t- and F-test statistics. For an estimator to be the best unbiased estimator, the variance of the error term needs to be the same regardless of the values of the independent variables, or $Var(u|x_1,x_2)=Var(u)=\sigma^2$. This assumption implies that the importance of the error term is the same for all individual observations and that the magnitude of uncertainty in the outcome of the dependent variable is the same for all values of the independent variables. If this assumption holds (together with the previous four), the estimators resulting from the regressions are the best, unbiased estimators of the relationships between the dependent and independent variables. This assumption can be tested by means of a Breusch-Pagan test of homoscedasticity.

The last assumption related to OLS is the normality of the data, meaning that the error *u* of the sample is independent of the explanatory variables x_1, x_2,…,x_n and follows the distribution u~Normal(0, σ^2). If *u* does not follow a normal distribution, t- and F-tests do not lead to valid t- and F-statistics in the case of small sample sizes (which is the case in this thesis).

The ability of a model to predict the value of the dependent variable (also known as "the goodness of fit) is reflected by the amount of variance that can be explained by the estimated model. This is referred to as the R^2 of the model. It is calculated by deducting the sum of squared residuals over the total sum of squares from 1. The sum of squared residuals is the sum of the squared values of the differences between the estimated values and the actual values of the response variable. The total sum of squares is equal to the sum of the squared values of the differences between the actual value and the average value of the response variable).

The OLS regressions conducted in this thesis are shown in Table 11. Table 11 gives an overview of the dependent-, independent- and control-variables of each regression conducted in this thesis, combined with expectations regarding the relationship between each of them (being either positive, negative or non-existent).

Table 11. Overview OLS regressions.

Hypothesis	Timeframe	Dependent variable	Independent variable(s)	Control variables	Expectations
Hypothesis 1: Changing fleet sizes have a direct effect on freight rates	1999-2015 (Container, Bulk), 1990-2015 (Oil)	Freight rate	Fleet size	Demand, oil price	Fleet size (-), Demand (+), Oil price (+)
Hypothesis 2: Changing fleet sizes have a direct effect on the EBITDA of shipping lines	2010-2015	Average EBITDA publicly listed container lines	Fleet size	Oil price	Fleet size (-), Oil price (-)
Hypothesis 3: The amount of ships ordered during a year has a direct effect on the EBITDA of shipping lines two years later	2010-2015	Average EBITDA publicly listed container lines	Orders made two years earlier	Oil price	Orders made two years earlier (-), Oil price (-)
Hypothesis 5: Fleet size changes have a direct effect on excess shipping bond returns	2006-2015	Excess return on shipping bonds	Annual fleet size changes	Unexpected interest rate change, change in economic environment, oil price	Annual fleet size change (-), unexpected change in interest rate (-), change in economic environment (+), oil price (-)
Hypothesis 6: Orders for new ships have a direct effect on excess shipping bond returns	2006-2015	Annual returns on shipping bonds	Annual fleet size changes	Unexpected interest rate change, change in economic environment, oil price	Annual fleet size change (-), unexpected change in interest rate (-), change in economic environment (+), oil price (-)

Table 12. Overview logistic regressions

Hypothesis	Timeframe	Dependent variable	Independent variable(s)	Control variables	Expectations
Hypothesis 4: Fleet size changes during the maturity of a bond affect the default probability of a bond	1999-2015 (Container), 1994-2015 (Bulk), 2000-2015 (Oil)	Defaulted (yes/no)	Fleet size changes	Demand, working capital/total assets, retained earnings/total assets, gearing, amount issued/total assets, maturity	Fleet size change (+), Demand (-), working capital/total assets(-), retained earnings/total assets(-), gearing(+), amount issued/total assets(+/-).

3.2.2. Logistic regressions

The third and fourth hypothesis are related to the relationships between multiple variables and the default probabilities of shipping bonds. Contrarily to the other hypotheses, these hypotheses have dependent variables that can only take two forms: defaulted and not-defaulted. A linear regression is therefore inappropriate as an instrument, because the parameters that are being estimated imply a marginal effect of change of a continuous dependent variable, which our dependent variable is not. For example: an estimated parameter β_1=0.1 for x_1 implies that an increase of x_1 by one is estimated to lead to a default increase of 0.1 This makes, of course, no sense since a bond is either in default or not. Furthermore, linear regressions would lead to predicted probabilities outside the [0,1] interval.

As discussed in the literature study, a logit model is a good instrument to study dependent variables with a binary outcome. In logit models, a non-linear S-shaped curve is estimated. The slope of this curve gives the change in probability of the dependent variable being 1, given a unit change in x. It is important that, due to the non-linearity, slopes are not constant which was the case in the linear models. Hypotheses regarding individual relationships between the dependent and independent variables are tested by means of a Wald test (also known as asymptotic t-test).

The general form of a logistic regression is shown in Equation 2. This expression reflects the probability that the dependent variable takes the value 1.

Equation 2. General form logistic regression (dependent variable =1)

$$p = \frac{1}{1 + e^{-(\beta_1 + \beta_2 x)}} = \frac{\exp(\beta_1 + \beta_2 x)}{1 + \exp(\beta_1 + \beta_2 x)}$$

The goodness of fit for logistic regressions is also slightly different compared to linear regressions and is measured expressed as McFadden's R^2. McFadden's R^2 is calculated by dividing the natural logarithm of the maximum likelihood value of the used model by the natural logarithm of the maximum likelihood value of a model with only an intercept and no covariates and deduct this number from 1.

The logistic regressions conducted in this thesis are shown in Table 12. Table 12 gives an overview of the dependent-, independent-, and control-variables used in the logistic regressions, together with expectations regarding these relationships.

3.2.3. Fama Macbeth regressions

Fama Macbeth regressions consist of two steps: first, a time-series regression needs to be conducted with the returns and risk factors of specific assets, second a cross-section regression of the estimated betas needs to be done. It is a method in which the premium for different risk factors affecting assets are being estimated. The usefulness of this technique is that it utilizes the covariance of the risk factors between all assets included in the sample to estimate the premium for each risk factor. In other words: it minimizes the variance within a portfolio and captures the variances across the portfolios. Simply taking the average of each risk factor could also work (and lead to the same result), but that requires an infinite sample size where the average return on each factor will be equal to the true return on each factor. Using the Fama Macbeth regression gives better estimates because of the sample size limitation. The downside of the Fama Macbeth regression is that the standard errors are only corrected for cross-sectional correlation and not for time-series autocorrelation. This is, however, not expected to be that much of a problem, since bonds have a relatively small maturity, decreasing the risk of autocorrelation (Fama 1988).

The first part of this method consist of a time-series regression in which the returns of an asset (bonds in this thesis) are regressed against the factors considered risk drivers. The estimated betas for each risk factor are defined as the factor exposures, or the extent to which the returns are driven by each factor. This can be written down as:

Equation 3. Fama Macbeth time-series regression

$$
\begin{aligned}
R_{1,t} &= \alpha_1 + \beta_{1,F_1}F_{1,t} + \beta_{1,F_2}F_{2,t} + \cdots + \beta_{1,F_m}F_{m,t} + \varepsilon_{1,t} \\
R_{2,t} &= \alpha_2 + \beta_{2,F_1}F_{1,t} + \beta_{2,F_2}F_{2,t} + \cdots + \beta_{2,F_m}F_{m,t} + \varepsilon_{2,t} \\
&\;\;. \\
&\;\;. \\
R_{n,t} &= \alpha_n + \beta_{n,F_1}F_{1,t} + \beta_{n,F_2}F_{2,t} + \cdots + \beta_{n,F_m}F_{m,t} + \varepsilon_{n,t}
\end{aligned}
$$

Where:

$R_{n,t}$= the annual return on asset n in year t

F= the value of risk factor F

n= total amount of assets included in the sample

m= total amount of factors examined in the analysis

The betas derived from Equation 3 now need to be used for the second part of this method. In this cross-sectional regression, the returns are regressed on the betas derived in the time-series regression. This can also be expressed as Equation 4.

The results of these cross-section regressions are m+1 equations with length T (since a cross-section of all time-series is being taken). The eventual risk premium that is being assessed (γ_m) is derived by taking the average of each γ over all T periods. These are the risk premia for each unit of risk factor as they are included in the regressions.

Equation 4. Fama Macbeth cross-section regression

$$
\begin{aligned}
R_{i,1} &= \gamma_{1,0} + \gamma_{1,1}\hat{\beta}_{i,F_1} + \gamma_{1,2}\hat{\beta}_{i,F_2} + \cdots + \gamma_{1,m}\hat{\beta}_{i,F_m} + \varepsilon_{i,1} \\
R_{i,2} &= \gamma_{2,0} + \gamma_{2,1}\hat{\beta}_{i,F_1} + \gamma_{2,2}\hat{\beta}_{i,F_2} + \cdots + \gamma_{2,m}\hat{\beta}_{i,F_m} + \varepsilon_{i,2} \\
&. \\
&. \\
R_{i,T} &= \gamma_{T,0} + \gamma_{n,1}\hat{\beta}_{i,F_1} + \gamma_{n,2}\hat{\beta}_{i,F_2} + \cdots + \gamma_{n,m}\hat{\beta}_{i,F_m} + \varepsilon_{i,T}
\end{aligned}
$$

Where:

R_i= the return on asset i

$\hat{\beta}_i$= the estimated factor exposure for asset i

m= total amount of risk factors

n= amount of assets in the sample

T= total amount of periods

The risk factors examined in this thesis are, as stated in the data section; changes in the economic environment, unexpected interest rate changes, fleet size changes and oil price changes. Testing whether the factor premia are different from zero can be done by calculating the t-statistic for each factor premium (Equation 7).

Equition 5. Formula t-statistic factor premia

$$\frac{\gamma_m}{\sigma_{\gamma m}/\sqrt{T}}$$

CHAPTER 4 Results

4.1. Fleet sizes and freight rates

Hypothesis 1: Changing fleet sizes have a direct effect on freight rates.

The first hypothesis tests the rationale underlying the research question. Freight rates are being regressed on fleet sizes, with demand and oil prices as control variables. First, correlation matrices are constructed to check whether the independent variables are interrelated, which might lead to multicollinearity. These are shown in Table 13.

Table 13. Correlation matrices independent variables

Container

	Fleet size	Demand	Oil price
Fleet size	-	0.97	0.80
Demand	0.97	-	0.85
Oil price	0.80	0.85	-

Bulk

	Fleet size	Demand	Oil price
Fleet size	-	0.89	0.81
Demand	0.89	-	0.81
Oil price	0.81	0.81	-

Oil

	Fleet size	Demand	Oil price
Fleet size	-	0.77	0.88
Demand	0.77	-	0.76
Oil price	0.88	0.76	-

These matrices show very high correlations between the independent variables. Especially between fleet sizes and demand. This is not surprising, since both show a clear trend in the same direction. The high collinearity between these variables is likely to result in an estimated model which suffers from multicollinearity. This is confirmed by running these regressions and looking at the variance inflation factors of the models. Variance inflation factors (VIF) indicate how much of the variance explained by the estimated model (the outcome of the regression) is actually explained because of the collinearity between multiple independent variables. The model related to containers shows VIF-values higher than 20, the other models show VIF-values around 4. The rule of thumb is that multicollinearity is too high when the VIF value is higher than 10 (Kutner, 2004). For this reason, demand is left out as independent variable in the estimated model for container freight rates, but included in the model estimating bulk- and oil-rates. The results of the (adjusted) regressions are shown in Table 14.

Table 14. Results regressions hypothesis 1.

		Coefficient	T-statistic	Probability		
Container	Constant	107.000	8.433	0.000***	R^2-value	0.346
	Fleet size	-0.006	-2.522	0.022**	Breusch Pagan (prob.)	0.814
	Oil price	0.425	1.277	0.219	Jarque-Bera (prob.)	0.160
Bulk	Constant	-89889	-2.344	0.036**		
	Fleet size	-272.411	-5.161	0.000***	R^2-value	0.680
	Demand	27.140	3.711	0.003***	Breusch Pagan (prob.)	0.016**
	Oil price	130.725	0.621	0.545	Jarque-Bera (prob.)	0.514
Oil	Constant	-28905.700	-1.972	0.061*		
	Fleet size	-93.572	-2.427	0.024**	R^2-value	0.575
	Demand	11.010	5.025	0.000***	Breusch Pagan (prob.)	0.127
	Oil price	18.902	0.200	0.843	Jarque-Bera (prob.)	0.597

*: 10% significance level, **: 5% significance level, ***: 1% significance level

The results in Table 13 show that the fleet size for every cargo type is significantly, negatively related to its respective freight rate, which is in line with expectations. The relationship between fleet sizes and freight rates is significant at the 5% level for container- and oil- cargo, and significant at the 1% level for bulk cargo.

The estimated coefficient of fleet size related to the container model shows that an increase of the container fleet by 1,000 TEU[8] would lead to a decrease in the containership time charter index of 0.006. To put this in perspective, the release of the largest ship that is currently operational, the MSC Sveva which has a capacity of 19,224 TEU. Given the estimated coefficient of 0.006, the release of this ship would lead to a decrease in the time charter index of 0.115 (0.006*19.224). So freight rates would go up by 0.115% compared to the base year (1992). Oil prices are positively related to freight rates, but this relationship is not statistically significant. The R^2-value shows that the model is able to explain a 34.6% of the variation, making it a very decent model. The probability of the Breusch-Pagan test shows that there is no statistical evidence of heteroscedasticity. The probability of the Jarque-Bera test shows that there is no statistical evidence that the errors are not normally distributed. The regression therefore gives the best linear unbiased estimators with t- and F-statistics that follow t- and F- distributions.

The estimated coefficient of fleet size related to bulk freight rates shows that an increase of the container fleet by one million DWT would lead to a decrease in the one-year time charter rate for a bulk carrier of 272 USD/day. Demand is positively related to freight rates. An increase in demand by one billion tonne-

[8] Remember, one TEU is the equivalent for one 20-foot container.

miles would lead to an increase in the one-year time charter rate for a bulk carrier of 27 USD a day. This relationship is significant at the 1% level. Oil prices are positively related to freight rates, but this relationship is not statistically significant. The R^2-value shows that the model is able to explain 68% of the variation, making it a very decent model. The probability of the Breusch-Pagan test shows that there is statistical evidence that the model suffers from heteroscedasticity. This means that the error term differs for differing values of the independent variables. Although the estimated parameters are still unbiased, they are not the best anymore and the wrong inference is made. The t- and F-statistics are no longer valid. For this reason, the same regression has been conducted, but this time with robust standard errors. The values of the parameters changed but the signs remained the same. It can therefore still be said that freight rates are negatively related to fleet sizes and positively related to demand in the bulk carrying industry.

The estimated coefficient of fleet size related to oil freight rates shows that an increase of the oil carrying fleet by one million DWT will lead to a decrease in the one-year time charter rate for Suezmax ship of 93,57 USD/day. This is approximately 3 times lower compared to a similar fleet increase in the bulk carrying industry. This is most likely to be due to the value of the transported goods. Demand is positively related to freight rates. An increase in demand by one billion tonne-miles would lead to an increase in the one-year time charter rate for a Suezmax ship of 11,01 USD/day. Oil prices are positively related to freight rates, but this relationship is not statistically significant. The R^2-value shows that the model is able to explain 58% of the variation, making it a very decent model. The probability of the Breusch-Pagan test shows that there is no statistical evidence that the model suffers from heteroscedasticity. The probability of the Jarque-Bera test shows that there is no statistical evidence that the errors are not normally distributed. The regression therefore gives the best linear unbiased estimators with t- and F-statistics that follow t- and F-distributions.

In short: these simple models verified the underlying rationale of this thesis. Fleet sizes play a significant role in the determination of freight rates, which is why it is interesting to see if they also affect the earnings of shipping lines and their default probabilities.

4.2. Fleet sizes and the EBITDA of container lines

Hypothesis 2: Changing fleet sizes have a direct effect on the EBITDA of shipping lines.

The second hypothesis tests if changing fleet sizes are also related to the earnings of shipping lines. The average EBITDA of publicly listed container lines has been regressed on fleet sizes and oil price. The results are shown in Table 15.

Table 15. Results regression hypothesis 2.

	Coefficient	t-Statistic	Probability		
Constant	69.911	5.246	0.0135**	R^2- value	0.816
Fleet size	-0.002	-3.369	0.0435**	Breusch Pagan (prob.)	0.779
Oil price	-0.139	-2.539	0.0848*	Jarque-Bera (prob.)	0.667

*: 10% significance level, **: 5% significance level, ***: 1% significance level

The results in Table 15 show that fleet sizes are negatively related to the average EBITDA of publicly listed container lines. A relationship that is significant at the 5% level. The estimated coefficient shows that a fleet size increase of 1,000 TEU leads to a decrease of the average EBITDA of 2,000 USD. The oil price is also significantly, negatively related to the average EBITDA of publicly listed container lines. An increase of the oil price by 1% is estimated to lead to a decrease in the average EBITDA of 139.000 USD. This relationship is significant at the 5% level. The probability values of the Breusch Pagan and Jarque-Bera tests show that the model does not suffer from heteroscedasticity and that there is no statistical evidence that the errors are not normally distributed.

These results imply that fleet size changes aren't only affecting the freight rates, but also have a negative impact on the earnings of shipping lines. They also imply that if the EMH holds, shipping bond returns should be negatively related to fleet size changes. The next hypothesis tests whether orders of new vessels have predictive abilities regarding future EBITDA's of container lines.

4.3. Vessel orders and future EBITDA's

Hypothesis 3: the amount of ships ordered during a year has a direct effect on the EBITDA of shipping lines two years later.

The third hypothesis relates to the predictability of future earnings of shipping lines when knowing the fleet size additions in the coming years. Instead of using actual fleet sizes as independent variable, the average EBITDA is being regressed on the amount of vessels ordered two years earlier. The results are shown in Table 16.

Table 16. Results regression hypothesis 3.

	Coefficient	t-Statistic	Prob.		
Constant	-1.181	-0.038	0.972	R^2-value	0.338
Orders	0.187	0.996	0.393	Breusch-Pagan (prob.)	0.257
Oil price	-0.017	-0.157	0.885	Jarque-Bera (prob.)	0.788

The results in Table 16 show that there is no statistical evidence that the orders for new vessels made during a year are related to the earnings of shipping lines two years later. This can be due to the fact that the orders made during a year are poor predictors for actual fleet sizes, since scrapings are not taken into account. Furthermore, EBITDA is to a large extent dependent on demand, which is highly unpredictable two years in advance. This also means that the expected outcome of hypothesis 6, where the relationship between the amount of orders made during a year and the excess returns on shipping bonds is tested, is that there is no significant relationship, assuming the EMH holds.

Before the relationships between fleet size changes and orders for new vessels are regressed on shipping bond returns, they are regressed on the default probabilities to test if poorer financial performance also leads to higher chances of defaults.

4.4. Fleet sizes and default probabilities

Hypothesis 4: Fleet size changes are directly related to the default probability of a shipping bond.

The fourth hypothesis tests the relationship between fleet sizes and default probabilities of shipping bonds. The financial ratios in the existing literature found to be relevant have been combined with fleet size- and demand- changes during the maturity of the bond and have been used in a logistic regression to assess the relationship between these variables and the probability of default of a shipping bond. The results of the logistic regressions are found in Table 17.

Table 17. Results logistic regressions hypothesis 4.

		Coefficient	**z-Statistic**	**Probability**	
Container (N=160)	Change in fleet size during maturity	-77.11	-2.481	0.013	McFadden's R^2 0.8367
	Retained earnings / total assets	-14.80	-1.791	0.073	
	Amount raised (mil) / total assets	-0.249	-1.799	0.072	
	Working capital / total assets	-10.69	-0.753	0.451	
	Maturity (years)	7.880	2.738	0.006	
	Gearing	-0.007	-0.886	0.376	

		Coefficient	z-Statistic	Probability	
Bulk (N=35)	Change in fleet size during maturity	7.378	0.951	0.342	McFadden's R^2 0.4167
	Change in demand during maturity	-31.51	-2.134	0.033	
	Retained earnings / total assets	0.034	0.008	0.994	
	Amount raised / total assets	-64.14	-0.989	0.323	
	Working capital / total assets	1.386	0.200	0.842	
	Maturity (years)	1.366	1.462	0.144	
	Gearing	-0.005	-0.937	0.349	

		Coefficient	z-Statistic	Probability	
Oil (N=19)	Change in fleet size during maturity	50.63	1.035	0.301	McFadden's R^2 0.4211
	Change in demand during maturity	-54.46	-0.783	0.434	
	Retained earnings / total assets	-3.895	-0.201	0.841	
	Amount raised / total assets	-35.92	-1.222	0.222	
	Working capital / total assets	-11.78	-1.041	0.298	
	Maturity (years)	-1.974	-0.875	0.381	
	Gearing	0.009	1.042	0.297	

Container

The container-related results in Table 17 are interpreted as follows. The change in fleet size is negatively related to the default probability of a shipping bond. A relationship which is significant at the 5% level. The negative relationship is against expectations, since fleet sizes are negatively related to freight rates and EBITDA's. A negative relationship therefore does not make sense in the first place. However, when taking a closer look at the shipping cycles discussed in Chapter 2 and the descriptive statistics of the obtained data, the following could be argued.

When shipping lines order new ships, it takes approximately 2 years before they are released and ready to be used. Given an increasing demand, freight rates keep increasing, because supply is not capable of matching it in the short term (i.e. 2 to 3 years). The increasing rates seem to make the investments in new ships even more attractive, leading to more investments and a large amount of ships coming into operations a few years later. This leads to a downward swing in freight rates and financial distress for some of the shipping lines as long as new vessels come into operation and demand is not growing fast enough to meet it. The reason why fleet size changes during the maturity of a bond and the default probability of a bond might be negatively related, is that firms don't directly default after a decrease in freight rates. Like regular firms, most (if not all) shipping lines have a buffer which they can exploit during times of low freight rates. It is only when freight rates stay low for a severe period of time that buffers will not be enough and a firm will default on its obligations. It is during that same period of low freight rates that no new investments are being made and no new ships will come into operation. This is underpinned by the estimated coefficient for retained earnings over total assets, which reflects a negative relationship between default probabilities and retained earnings. For these reasons, during a period of low changes in fleet sizes, a relatively high amount of shipping lines will default. The shipping lines don't default because the fleet size growth is small, the shipping lines default because market conditions are bad which is reflected by the small growth of the fleet. So even though the outcome might seem counterintuitive, it is actually in line with the shipping cycle theory. This makes it interesting to see how financial markets incorporate these changes, which is examined in the next sections.

The financial ratios identified in the literature study are related as follows. Retained earnings over total assets are negatively related to the default probability of a bond. This relationship is significant at the 10% level. This is in line with expectations and means that companies with a relatively higher buffer are less likely to default compared to companies with a relatively smaller buffer, ceteris paribus. The amount raised over total assets is negatively related to the default probability. This relationship is significant at the 10% level. The rationale behind this outcome can be that companies that are more likely to default are less capable of raising public debt, meaning that more credible companies are able to obtain relatively more capital. Working capital over total assets and gearing are both negatively related to the default probability of a shipping bond. Both relationships are, however, insignificant. The maturity of a bond is positively related to the default probability of a bond. This relationship is significant at the 1% level. This is in line with expectations, since lenders are longer exposed to the risk of a default.

Bulk / Oil

The bulk-related results in Table 17 are interpreted as follows. The change in fleet size is positively related to the default probability of a shipping bond. This relationship is, however, insignificant. Change in demand during the maturity of a bond is negatively related to the default probability of a shipping bond. This relationship is significant at the 5% level and in line with expectations, since higher demand reflects better market conditions and hence less chance on a default. The retained earnings over total assets, the total amount raised over total assets, the working capital over total assets and maturity of the bond are all negatively related to the default probability of a shipping bond and gearing is positively related to the default probability of a shipping bond. These relationships are, however, insignificant. The insignificance, which did not appear in the container related regression is most likely due to an insufficient amount of observations (N_{bulk}=35, whereas $N_{container}$=160). This also holds for the oil-related results, in which none of the variables has been found to be significantly related to the default probability of default (N_{oil}=19).

4.5. Fleet size changes and bond returns

Now that relationships between fleet size changes, EBTIDA's and default probabilities have been distinguished, it is interesting to see if, and how they affect the returns on shipping bonds. The fifth hypothesis tests whether fleet size changes that occurred in a given year affected the bond returns during that same year. The sixth hypothesis tests whether orders themselves (rather than actual changes) are related to the returns on shipping bonds. In other words: are investors complying to the EMH? Both hypotheses are tested by means of Fama Macbeth regressions.

The outcome of the first regression is shown in Table 18. It shows that a change in fleet size is negatively related to the return on a shipping bond. This relationship is significant at the 5% level. Although it makes intuitive sense, it contradicts the outcome of hypothesis four, which showed that fleet size changes are negatively related with default probabilities. This can be explained by the fact that fleet size changes reflect recent market conditions, which are likely to have increased the buffers built up by shipping lines. Since these buffers are left out of the regression, the estimated sign of the relationship between fleet size changes and default probability is negative. It does not reflect a causal relationship, but merely an opposing trend that can be observed when only these variables are taken into account. This is also known as omitted variable bias. It is therefore not believed that this outcome undermines the EMH.

Whether vessel orders are included in the bond pricing can be checked by using vessel orders during a year as independent variable. Conducting the regression(s) this way leads to the results shown in Table 19. In line with expectations, no significant relationship between the amount of orders placed during a year and the returns on shipping bonds has been found. It is in line with expectations, since no significant relationship between orders made during a year and $EBITA_{t+2}$ has been found.

Table 18. Results Fama Macbeth regression (hypothesis 5)

	Risk premium	**Std. dev.**	**t-Stat**	**Prob.**
Constant	0.062	0.062	2.845	0.012
Change in fleet size	-0.031	0.035	-2.549	0.019
Change in economic environment	0.029	0.152	0.535	0.305
Unexpected change in interest rate	0.006	0.009	1.895	0.050
Oil price	4.256	15.707	0.766	0.234

Table 19. Results Fama Macbeth regression (hypothesis 6)

	Risk premium	**Std. dev.**	**t-Stat**	**Prob.**
Constant	0.04286	0.039	2.440	0.036
Orders for new vessels	-0.00726	0.029	-0.551	0.305
Change in economic environment	0.027796	0.182	0.341	0.375
Unexpected change in interest rate	0.007944	0.007	2.660	0.028
Oil price	-5.79677	23.735	-0.546	0.307

The control variables: change in economic environment, unexpected change in interest rate and the oil price are interpreted as follows: when change in fleet size is used as independent variable, unexpected changes in the interest rate are positively related to the returns on shipping bonds. A relationship that is significant at the 5% level. This is counterintuitive, since yields have a negative relationship with the interest rate with which they are discounted. It could be due to the fact that the observed period is relatively small and had multiple unexpected upside (downside) interest rate changes that happened to coincide with higher (lower) returns on the shipping bonds. Since the observed timeframe is only nine years, it is a plausible cause of the deviation from the existing knowledge regarding (unexpected) interest rate changes. Changes in the economic environment is also positively related to the returns on shipping bond, although this relationship is not significant at the 10% level. Oil prices are also significantly related to returns, but also insignificantly.

When the change in fleet size is replaced by the amount of orders placed during that year, the unexpected change in interest rate stays positively related at a 5% significance level. The other variables are still insignificant, although the oil price is now negatively related to the returns on shipping bonds.

CHAPTER 5 Conclusion

In this thesis, the effects of fleet size changes on the risk and returns of shipping bonds have been examined. First, a distinction between multiple shipping lines has been made. Three different shipping line types have been distinguished: the container lines, bulk lines and oil lines. Differentiating between these types is useful, because the freight rates of these lines often move in opposing direction, meaning that they are affected by different factors. Furthermore, as has been shown in Table 9, they are also different in the way they are financially structured, meaning that one carrier type can be more sensitive to an external shock compared to another carrier type.

Second, the effect of fleet size changes on freight rates and average EBITDA's has been tested by conducting a multiple linear regression analysis with freight rate data from 1999-2016. Demand (measured as volume times the distance it has been moved) and the oil price have been used as control variables. The results showed a significant, negative relationship between the freight rates and fleet sizes for all respective cargo types. It also showed a significant, negative relationship between fleet sizes and the average EBITDA of publicly listed shipping lines. It strengthened the idea that expansion of capacity comes at the cost of lower freight rates which jeopardizes future incomes. The next part examined if fleet size changes were also related to the default rates among the shipping lines.

Testing the relationship between fleet size changes and default rates has been done by conducting logistic regressions for each cargo type with retained earnings over total assets, amount raised over total assets, working capital over total assets, maturity time and gearing as independent variables. The results showed that changing fleet sizes during the maturity of a bond were significantly, negatively related to the default probability of container carrying shipping lines and not significantly related the other shipping line types. This result was against expectations at first, since positive fleet size changes were found to be negatively related to freight rates and EBITDA's, which should lead to higher probabilities of default. However, when taking a closer look, it is in line with the existing shipping cycle theory. Ships are often build during or shortly after times of prosperity. When they come into operations, freights often go down quickly, but this doesn't lead to an immediate default of the shipping line. In fact, given that ships are ordered during times of good market conditions and lead times are approximately two years, it is very unlikely that the shipping lines will default shortly after the release of the ship, since they have built up some reserves during the recent good times and won't default after a freight rate decrease directly. The rationale behind the negative relationship is not that bigger fleets make shipping lines less likely to default. Fleet size changes occur due to changing market conditions. Big fleet size changes reflect a prosperous short-term past and that is the reason why default rates are negatively related to the fleet size changes themselves. Leaving shipping line buffers out of the equation is likely to have led to omitted variable bias, since there is no reason to believe in a causal relationship. It is therefore also unlikely that this outcome contradicts the EMH.

The last part of this thesis examined how the returns on shipping bonds are affected by fleet size changes by conducting a two-step regression (Fama Macbeth regression) in which the bonds were regressed on the risk factors first, after which the returns were regressed on the betas that were derived from the first step. Two different time-series have been used as independent variable: fleet size changes during a given year and the capacity ordered to be built during a given year. Unexpected change in interest rate, change in economic environment and the oil price have been used as independent variables.

The results showed that bond returns are significantly, negatively related to the fleet size changes in a given year but are not significantly related to the capacity that is ordered to be built. This is in line with expectations, since similar relationships have been found between fleet size changes and the average EBITDA of shipping lines. The lower EBITDA makes shipping lines more likely to default, which is why investors require a higher return / lower bond prices, which result in a drop in the current returns on these bonds.

The outcome of this thesis is that positive fleet size changes drive freight rates and EBITDA's down, but short term swings are not likely to put shipping lines in jeopardy of paying their financial obligations. In fact, large upside swings often come after times of prosperity in the shipping market. These allow most shipping lines to buffer up and get them through more difficult times. Investors do react to fleet size changes, since they effect the earnings and financial stability of shipping lines, but do not react to orders for new vessels only, since fleet scrapings are highly volatile and fleet size changes themselves are hard, if not impossible to predict up front.

DISCUSSION AND FURTHER RESEARCH

The main topic of this thesis has been the examination of fleet size changes and their effects on the risks and returns of shipping bonds. One of the main findings was that fleet sizes are negatively related to the EBITDA of shipping lines, which makes intuitive sense. Another finding was that default probabilities are negatively related to fleet size changes, which does not make intuitive sense. The outcome has been explained by the fact that large fleet size changes reflect recent prosperous times in which shipping lines fared well and were able to build up some reserves. These reserves have not been taken into account, which is why the model is likely to show omitted variable bias. Further research could include variables that reflect the amount of reserves that shipping lines have, to get a clearer view on the actual relationship between fleet size changes and default probabilities.

Another finding was that orders for new vessels were not significantly related to the EBITDA's of shipping lines when these vessels come into operation. Not finding a significant relationship between these variables could be due to an incomplete model. Future fleet size changes are not only determined by fleet size additions, but also but subtractions, which are determined by the price of scrap steel and the average age of the fleet. Adding these variables lead to different results in which orders for new vessels are indeed related to the EBITDA of shipping lines when these vessels come into operation.

A broader extension could be the examination of the relationship between fleet size changes and the recovery rates of defaulted shipping bonds. Given the law of supply and demand, positive fleet size changes should lead to a decrease in the value of the existing ships, which are often part of the collateral of a bond. This would imply that fleet size changes aren't only increasing the risk of a default, but also decrease the recovery value when the bond actually defaults.

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APPENDIX A The Shipping Cycle Model of Randers and Göluke (2007)

The model used to predict shipping cycles is shown in Figure 25. The main input of the model is the demand for oil transport, modelled as a sinoid which is shown in Figure 26 (down left). The demand that is given as input is adjusted for time varying factors like the trend of demand growth of recent years. Some components of the supply side are adjusted for time varying factors as well (e.g. scrapping rates).

When demand is given as an input in the model shown below, it starts interacting with the other components that Randers and Göluke included in their model. These predetermined relationships convert the demand in (spot) freight rates, which trigger the fleet utilization- and fleet size- adjustment mechanisms. These determine the total supply which, given a certain demand, lead to a certain market pressure and an altered freight rate. This is seen as a continues process that, according to Randers and Göluke, is highly predictable due to the cyclicality of demand. As discussed in Chapter 2, this is also the main critique on their model. It accounts for the most important factors in the freight rate determination, but is based on the assumption of extremely cyclical demand, which is far from realistic.

Figure 25. The extended model to predict shipping cycles by Randers and Göluke (2007)

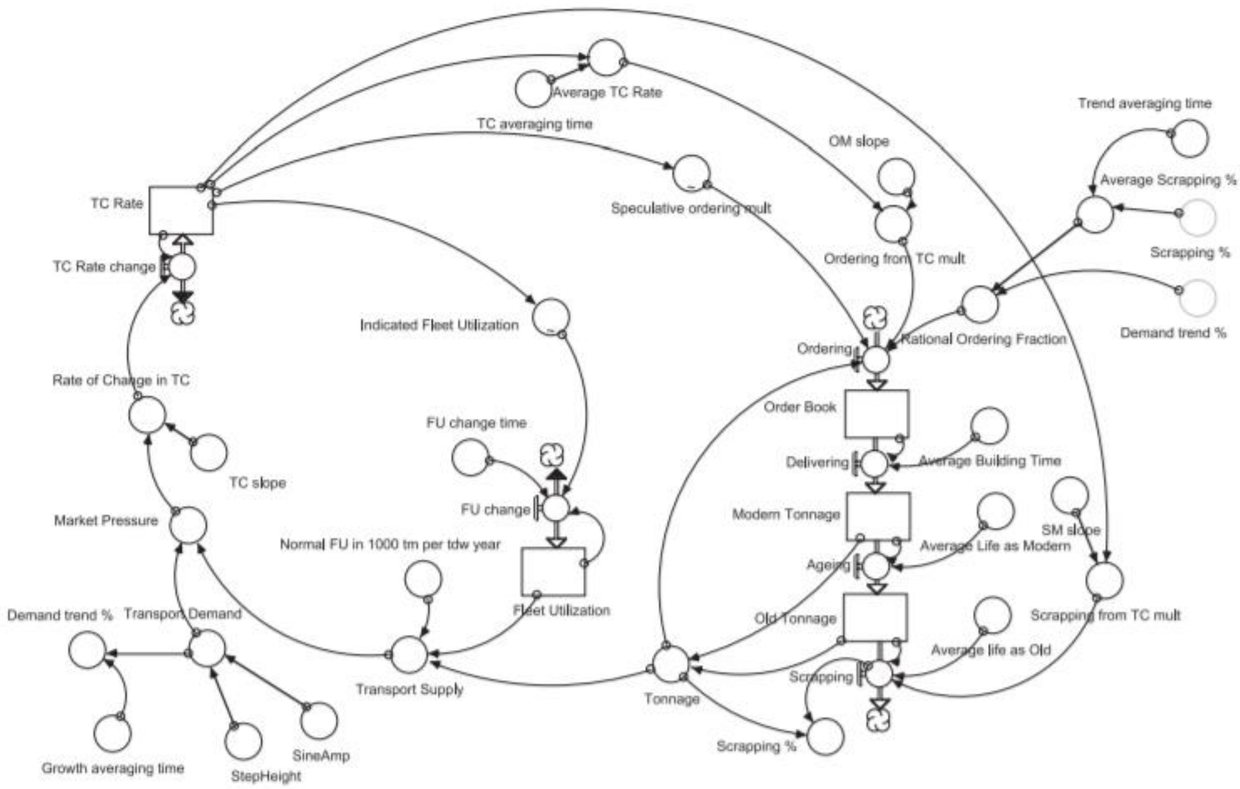
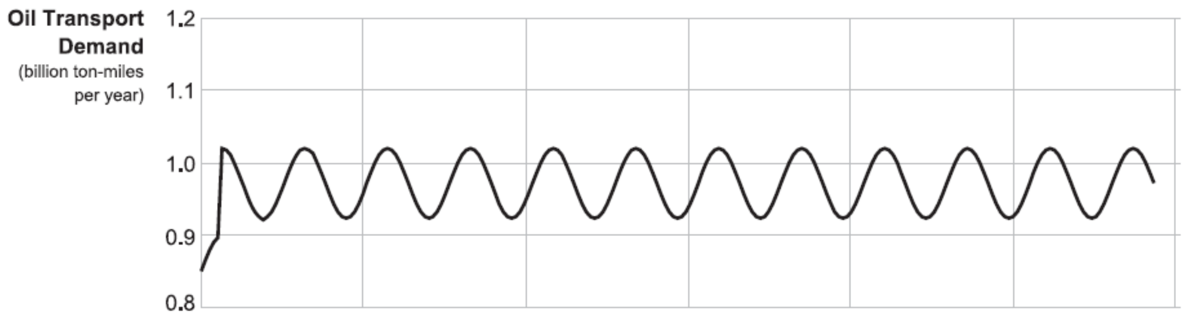


Figure 26. Oil transport demand modelled as a sinoid by Randers and Göluke (2007)



The authors have not published the exact interactions that the components of their model have with each other, since they use it for a commercial purpose.