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Predicting Shipping Defaults

An empirical study of the driving forces of default in the shipping industry

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Preface

This master thesis was written as a part of the Master of Science in Economics and Business Administration, major in Finance at Norwegian School of Economics. Throughout the process of completing this thesis, we have gained valuable experience of the shipping industry and modelling probability of default.

We would like to thank our supervisor Karin Thorburn for excellent guidance and insights during the semester. Despite unexpected circumstances with the COVID-19 outbreak, she was always available when we needed assistance.

Abstract

This study empirically investigates the driving forces of default at the time of issue in the shipping industry. By developing a logit model based on a sample of 64 shipping bonds and loans, it is shown that the most important factors in predicting shipping defaults are the financial health of the company and the macroeconomic state of the world. This study contributes to the existing literature by emphasizing the forward-looking features of the model, strengthening the long-range predictive accuracy. For the first time in the shipping literature, VIX is shown to be an important factor when predicting shipping defaults. The study is of interest to banks specializing in shipping, shipping bond investors, and any institution or professional dealing with credit assessment in the shipping industry.

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1. Introduction

We live in a world where no country is self-sufficient and instead relies on someone else to obtain commodities and finished products. From the Brazilian coffee to the Chinese cotton to the Saudi Arabian oil, every country has its specialties. The earth's resources are unevenly distributed across regions. As the world population continues to increase, the need to evenly spread these recourses becomes crucial for us to survive. Around 90% of all the goods transportation is done by sea (Castonguay, 2009), placing the shipping industry at the heart of a working global economy. Further, this means the industry is very sensitive to whether countries and regions interact with each other, making it risky to operate in times of trade wars and political uncertainty.

A recent victim of the industry's unforgiving volatility is the South Korean container carrier, Hanjiin Shipping. The company was in 2016 the world's seventh-largest container shipper, and represented close to 8% of the trans-Pacific trade volume for the US market (The Guardian, 2016). Hanjiin Shipping's default in the third quarter of 2016, caused devastating problems for numerous actors. As the default became public news, ports started to refuse Hanjin ships docking, as they feared the company would be unable to pay the fees (Illner, 2016), leading to up to USD 14 billion worth of cargo being stranded at sea (Paris and Phillips, 2016). Many customers failed to have crucial merchandise delivered, resulting in shelves being empty and profits bled. To solve this urgent problem, Hanjin Shipping had to take desperate loans to help unload the stranded cargo (The Straits Times, 2016). Researchers have identified several reasons for the default of Hanjiin Shipping, including managerial decisions (Pauli and Wolf, 2017) and industry-capacity outpacing demand (Gonzales, 2019), as well as numerous unfortunate macroeconomic events such as a weak Gross Domestic Product (GDP) and a slowdown in the Chinese economy (Saini, 2017). The failure of such an established shipping player supports a notion that no matter size, experience, and reputation, no company is immune to the shifting economic currents in the shipping industry.

Moreover, the shipping industry is characterized by its capital-intensive nature. The cost of building a new ship often exceeds USD 200 million (Fotis, 2016), creating a big ship-financing market. To navigate through this volatile environment, banks and bond investors rely on credit models (and other instruments) when evaluating which companies to finance, making the quality of the credit model a vital part of the investor's performance. In this study, we seek to identify the driving forces of shipping defaults, strengthening the current pool of shipping research by approaching the problem from a new angle. In contrast to prior findings in the shipping literature, we emphasize on the forward-looking features when developing our default-risk model. By performing a logistic regression analysis on a sample of 28 bonds issued by shipping companies and 36 shipping loans, we show that the driving forces of shipping defaults are debt/assets (D/A), working capital/total assets (WC/TA), the world GDP and the Chicago Board Options Exchange Volatility Index (VIX), which measures the 30-day volatility for the S&P500 index. Our study is of interest to banks specializing in shipping, shipping bond investors, and any institution or professional dealing with credit assessment in the shipping industry.

The paper is structured as follows. Section 2 presents prior research on defaults and shipping defaults. Section 3 describes the main hypotheses of the paper, as well as the reasoning behind them. Section 4 describes the sampling process and the dataset. In section 5, we explain the methodology used in the study, followed by the descriptive statistics in section 6. The results from our regressions and statistical tests are presented under empirical results in section 7. Finally, we present our conclusion in section 8.

2. Prior Research

The desire to identify predictive elements of financial distress goes back a long time. In the early 1900s, economic research began to focus on financial ratios to predict default. The first such ratio was the current ratio, which Rosendale (1908) discussed and used to assess the company's corresponding creditworthiness. By the time of Beaver (1966), the research had evolved and centered no longer around a single financial ratio. Through a paired-sample design based on industry and asset size, Beaver tested 30 financial ratios meant to predict the failure of a company. He selected financial data five years before bankruptcy occurred for the defaulted companies. Performing a univariate discriminant analysis, Beaver concluded that the best predicting ratios of company failure were cash flow (CF)/total debt, followed by net income (NI)/TA and D/A. However, Beaver (1966) raised an essential concern about using ratios retrieved from the financial statements. He argued that, if such ratios could indeed be useful in predicting financial distress, the companies would detect such indicators and take appropriate actions, resulting in them being able to avoid failure. He further explained that this would create a sample bias since information regarding the firms that detected the warning signs and took actions is missing.

Two years later, Altman (1968) developed on Beaver (1966) by employing a multivariate discriminate analysis to a sample of 66 publicly held manufacturing corporations. Altman's final model included five financial ratios: WC/TA, retained earnings (RE)/TA, earnings before interest and taxes (EBIT)/TA, market value of equity/book value of total debt, and sales/TA. Besides employing a different methodology, Altman (1968)'s study differed regarding long-range predictive accuracy. He found that bankruptcy can be accurately predicted from financial ratios up to two years before the failure of the company. However, the accuracy rapidly diminished when moving further back in time.

The next step in the research focusing on predicting financial distress was the use of a logit model. Several studies adopted this method, there among Santomero and Vinso (1977), Ohlson (1980), and Estrella et al. (2002). Ohlson (1980) found four underlying factors of the company that affect the probability of default: size, financial structure, performance, and current liquidity. These findings were based on an even shorter time gap (one year) between the date of default and the time that the data for that company were observed.

Gentry et al. (1985) contributed to previous research by emphasizing the importance of cash-based fund flow components. Their study showed that cash-based components such as dividend, investment, and receivables, along with the previously studied financial ratios, could yield superior results in predicting financial failure. An interesting conclusion made by Gentry et al. (1985) is that cash outflows are more useful in explaining financial distress than cash inflows.

As the pool of research on default prediction became larger, studies evolved from being company-general to focus on more specific sectors and segments. Ciampi and Gordini (2008) analyzed 22 financial ratios and tested their ability to predict defaults of small enterprises in Italy. The study aimed to investigate whether previous findings, which were based on samples with mainly large companies, also applied to smaller firms. In their study, they applied a stepwise method to identify the best predicting financial ratios. The first step included an initial selection of variables based on prior research. Next, they applied a univariate analysis, followed by a variance inflation factor test (VIF) to control for the presence of multicollinearity. Further, the variables with VIF > 6 were eliminated, and a principal component analysis was applied as a final step. Their final model consisted of five ratios: debt/equity (D/E), EBIT/net operative assets, bank loans/turnover, return on equity (ROE), and the acid test, defined as (current assets less inventories)/current liabilities. Ciampi and Gordini (2008) concluded that small enterprises should indeed be considered separately from large and medium-sized firms when predicting default.

While the studies focusing on predicting default are many and well documented, the research focusing on default in the shipping industry is scarce. Grammenos et al. (2008) was the first such paper, using a sample of 50 high-yield shipping bonds issued between 1992 and 2004, to predict default. They defined default as the inability of the bond issuer to make timely payments to bondholders. By the end of 2004, 13 of the bonds had defaulted, and 37 had expired or were still trading. In addition to the previously common approach of using mainly financial ratios as explanatory variables, they also tested industry-specific variables to capture the effects specific to events and trends in the shipping sector. By applying logistic regression techniques, they identified five variables useful in predicting default for high yield shipping bonds: the gearing ratio, the amount raised/TA, WC/TA, RE/TA, and a self-constructed industry specific variable capturing the shipping market conditions.

Kavussanos and Tsouknidis (2016) empirically investigated the probability of shipping loan defaults through a panel data logit model with two-way clustering adjusted standard errors. One of the key takeaways from this study was that their methodological approach allowed them to report standard errors adjusted for loan and time effects more accurately. The study was based on a sample of 128 loans issued to 63 shipping companies between 1997 and 2011. They showed that the most important factors driving the probability of default are not derived from the financial statements. They argued that this information could many times be considered as outdated due to the rapidly changing market conditions in the shipping industry. Consequently, the best predicting factors of default are derived from the current and expected market conditions (Kavussanos and Tsouknidis, 2016).

Mitroussi et al. (2016) used a sample of 30 shipping loans issued by Greek banks to finance the purchase of a ship between 2005 and 2009. Out of the full sample, 18 shipping loans were fully paid and 12 experienced financial problems. In contrast to previous research on default in the shipping industry, this paper focuses exclusively on a more turbulent period in which financing options to shipping companies were limited. After utilizing a binary logit model, they found that both financial and non-financial factors are essential drivers of credit risk, especially in turbulent times. Additionally, their study shows that the ship-builders' experience and employability, and market risk indicators influences the probability of financial distress.

Another important consideration when predicting default in the shipping industry is the definition of default. Lozinskaia et al. (2017) defined default as not only companies that go out of business but also include financially distressed companies that get saved by an acquisition or merger. In their study, they tested several macroeconomic indicators, there among the Brent oil price, in order to analyze the effect of fuel cost on the probability of default. Lozinskaia et al. argued that an increase in fuel cost would lead to shipping companies leasing vessels less often, resulting in a decrease in income. Further, they tested for "the percentage of shares held by the largest owner", which was expected to be negatively correlated with the probability of default. The hypothesis was based on Andreou et al. (2014)'s findings that investors and shareholders will more closely examine maritime companies that increasingly turn to the financial markets for funding. In their final model, Lozinskaia et al. (2017) found statistical significance for one-year lags of Tobin Q, Earnings Before Interest, Taxes, Depreciation and Amortization (EBITDA), GDP, and the natural logarithm of TA.

Several credit rating models and default risk models are being used today by professionals and agencies within the industry. The Credit Transition Model from Moody's Analytics is used to predict default and credit transitions. The model utilizes a forward-looking view on macro-economic variables and focuses on two specific ones: the unemployment rate and the high yield spread over treasuries (Moody's analytics, n.d.). Further, it considers the company-specific rating variables: current rating, last upgraded/downgraded, time of holding current rating, time of holding any rating, and the company's outlook or watch-list status.

The SEBRA model is used by Norges Bank to estimate the probability of bankruptcy of and expected losses on loans to Norwegian listed companies[1]. The original model has been continuously updated since 2001 and relies on key figures from the companies' annual accounts, age, size, and industry (Bernhardsen and Larsen, 2007). As of today, Norges Bank presents two versions of the SEBRA model on its website: the basic model and the extended model. The basic model includes ordinary profits before depreciation and write-downs/total debt, equity/TA, and (liquid assets less short-term debt)/operating revenue. The extended model includes, in addition to all the variables in the basic model: TA, trade accounts payable/TA, unpaid taxes and dues/TA, and the age of the company.

[1] SEBRA is derived from the Norwegian expression for "System for EDP-based Accounts Analysis" (Bernhardsen and Larsen, 2007).

Table 1: Previous Research on Shipping-Defaults

	Grammenos et al. (2008)	Kavussanos and Tsouknidis (2016)	Mitroussi et al. (2016)	Lozinskaia et al. (2017)
Time-period	1992-2004	2005-2009	2005-2009	2001-2016
Sample	50 high yield bonds	128 shipping-loans	30 shipping loans	192 listed shipping companies
Definition of default	Non-payment of interest of principal to bondholder	Missed payment for more than 90-days	Loan not fully repaid at maturity	Bankruptcy, liquidation or reorganization (including semi-defaults)
Defaults	13	7	12	41
Methodology	Binary logit model	Binary logit model	Linear probability model, Binary logit model	Linear probability model, Binary logit model, Ordered logit model
Contribution	Model predicting the probability of default for shipping high yield bonds	Shipping bank loans agreements within the 6C's of credit theory and Panel data logit model with two-way clustered adjusted standard errors	Performance drivers of shipping loans during times of financial turbulence	Identifying a wide range of potential risk factors using an extended dataset and Model calculating how to add the credit risk to the loan rate

As shown in table 1, prior research differs widely regarding the definition default, sample size and time-period. Research on default prediction in the shipping industry tends to emphasize macroeconomic explanatory variables more than the general research on predicting default does. This suggests the shipping industry is more exposed to the state of the global economy than other industries on average. We find this noticeable since the literature on shipping defaults lacks models with forward-looking explanatory macroeconomic variables, such as the Credit Transition Model from Moody's Analytics. We argue that this is an unexplored area of the shipping research. In this study, we aim to apply and translate some of the forward-looking features of the Credit Transition Model to the shipping industry, improving on prior shipping default models by increasing the long-range predictive accuracy.

3. Hypothesis

Based on prior research, we argue that there are three forces driving the probability of default: the company's financial health and profitability, as well as the macroeconomic state of the world.

H1. *In the shipping industry, the financial health of a company reduces the probability of default*.

When considering a company's financial health, we look at two concepts. First, we argue that an important factor is the liquidity, which refers to the company's ability to meet short-term debt obligations. Numerous unexpected events could result in liquidity problems. However, in general, a company experiencing liquidity problems can resolve this relatively quickly as long as it is solvent (Heejung, 2016). Solvency is the other concept we consider, and it refers to the company's long-term ability to handle debt. As the company takes on more leverage, it becomes less solvent, resulting in banks becoming more reluctant to provide funding. Even if the company retains a healthy debt level, inadequate liquidity will result in a decrease of that solvency if additional loans are taken to cover for the liquidity problem. Hence, we argue that the financial health of a company is important to consider when predicting default and that both liquidity and solvency should be evaluated. To test H1, we will investigate the effect of the variables WC/TA and D/A on shipping defaults.

H2. *The probability of default decreases in the change of profitability of a shipping company.*

We will assess the company's profitability by measuring its efficiency in turning capital into revenue as well as turning that revenue into profit. As discussed earlier, the shipping industry is very capital intensive. Hence, the ability to utilize these assets are central in predicting default. However, generating revenue does not necessarily mean the company is profitable. In addition, we include measures capturing its ability to turn revenue into profits. It is essential to not only include one of these profitability variables but both, as they capture different operating stages. One risk of conducting this study based on the date of issue is that the data we consider may have changed prior to default. However, by instead considering the change in our profitability ratios (similar to last upgraded/downgraded in the Credit Transition Model), we might be able to capture a trend that describes a longer-lasting effect. This will increase the long-range predictive accuracy of the model and add to the forward-looking ability. To test H2, we will investigate the effect of the change in Revenue (REV)/TA and the change in the Profit Margin on default rates of shipping firms[2].

H3. *The macroeconomic state of the world has a negative effect on the probability of default.* Lastly, we believe the macroeconomic state of the world affects the probability of default in the shipping industry. Kavussanos and Visvikis (2017) states that the world GDP is the most important driver of the shipping market. However, they argue that it is less the absolute number of the GDP and more the level at which regions interact and trade with each other that matters. Although, we argue that by the time the GDP has dropped, it is likely that the number of defaulted companies has already increased since the former indirectly measures the latter. Hence, we question the predictive value of GDP alone. An economic downturn can be triggered by just about any major negative event, making it impossible to cover all predictable factors in one model. One potential way of predicting the future is to look at VIX. Historical data shows that VIX tends to dramatically increase in the period leading up to financial crises. We argue that the inclusion of VIX, along with GDP, makes a better model than one with solely GDP, as this adds a forward-looking feature. To test H3, we will investigate the World GDP and VIX. Table 2 shows the expected directions of our explanatory variables.

Table 2: Expected directions of the explanatory variables

	Test Variables	Expected Sign
H1 - Financial Health	*Total Debt/Total Assets*	+
	Working Capital/Total Assets	-
H2 - Profitability	*Δ Revenue/Total Assets*	-
	Δ Profit Margin	-
H3 - Macroeconomic State	*World GDP*	-
	VIX	+

[2] The change is defined as the profitability ratio at time t less the profitability ratio at t-1, where t is the year of issue.

4. Data

4.1 Dataset and variable definition

As shown in table 3, we gathered a sample of 64 shipping bonds and loans between 1993 and 2015[3]. The most recent defaulted observation was issued in 2015. Therefore, we used 2015 as the last year of issue to have a similar timeframe for both the defaulted and non-defaulted observations. In two instances, the sample includes both a bond issued, and a loan taken by the same company. Hence, the sample comprises 62 unique shipping companies[4]. Out of the full sample, 47 of the observations are attributed to publicly traded companies and 17 to private companies. Further, 28 observations are bonds and 36 are loans. The total number of defaults is 19, where 14 of these defaults are attributed to bond issues and 5 to loans.

Table 3: Bonds & Loans in the sample

	Bonds	Loans	Total
Defaulted	14	5	19
Non-defaulted	14	31	45
Total	28	36	64

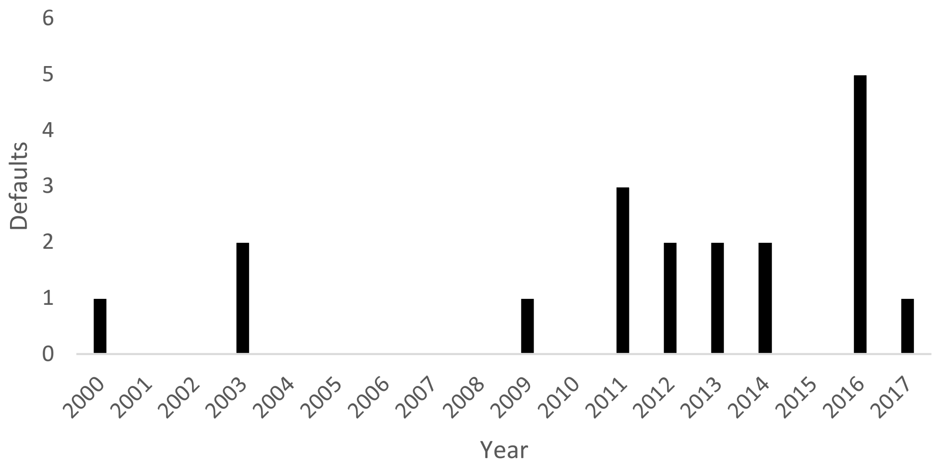
The default of a company is identified through the Bloomberg terminal and is defined according to the Bloomberg Credit Risk Model's definition of default.

"Default is defined as the first of any of the following: failure to pay interest /principal on an interest-bearing bond or loan, or bankruptcy." - (Drsk Bloomberg Default Risk, n.d.)

Figure 1 shows that the earliest default in our sample occurred in 2000, and the most recent in 2017. The largest number of defaults is found in 2016 when five companies defaulted.

[3]We identified the bonds and loans in the Bloomberg terminal by using the search (SRCH) function and then transport & logistic as BICS classification. Thereafter we limited the sample to companies identified as marine shipping. To find observations that defaulted, we used SRCH and then limited the data to defaulted observation by setting "has data" on default date as a requirement.
[4] Hereafter, when describing the sample, we refer to number of observations and not unique companies.

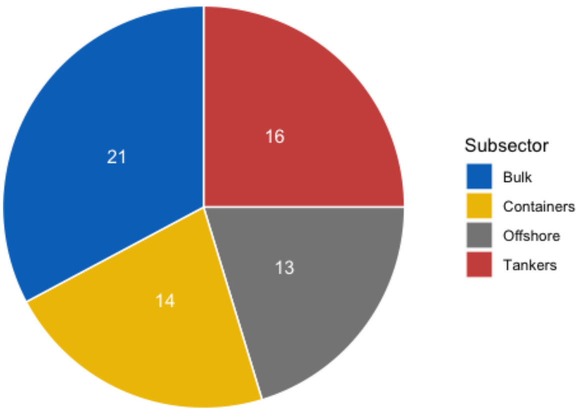
Figure 1: The number of bond and loan defaults in the sample



For the defaulted companies, the average time between the date of issue to the date of default is three years and one quarter. All data for the categories financial health and profitability are retrieved from each company's financial statements in the Bloomberg terminal at the time of issue. The data for GDP and VIX is retrieved from the World Bank and the Chicago Board Options Exchange, respectively. Since we aim to take the investor's perspective, we will only use data that were available at the time of issue.[5]

Figure 2 shows the subsectors of the observations in our sample. Several companies operate in multiple subsectors of the shipping industry. In these cases, we have assigned the company to their largest subsector in terms of revenue.

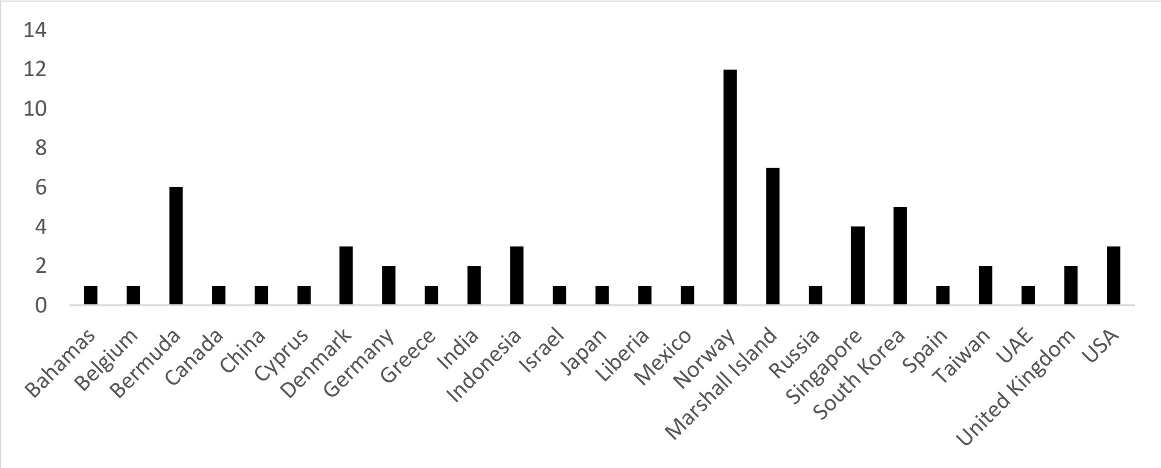
Figure 2: The number of observations in each subsector



[5] As the world GDP is published at the end of each year, we will use GDP_{t-1} where t indicates the year of issue.

Figure 3 shows the country of incorporation of the observations, which is spread out over 25 countries where Norway and Marshall Island are the most frequent countries of incorporation with 12 and 7 observations respectively.

Figure 3: Country of incorporation



This paper was written at a turbulent time during the COVID-19 outbreak. Due to this, we were no longer able to access the Bloomberg terminal after only two months into the paper, resulting in us being locked to the dataset early in the process. This has led to some restrictions on the sampling process which could potentially yield bias results. Our initial idea was to do a paired-sample design matching the risk of the bonds with the risk of the loans. Further, we wanted to obtain a larger sample to divide it into sub-samples, enabling us to verify our findings from one sample on the other. However, none of this was possible under the circumstances. To work around this, we applied extensive testing for robustness by controlling for the suspected differences. Table 4 shows the additional variables included in the robustness test and their definition.

Table 4: Variable Definition

Variable	Variable Definition
TA	Total Assets of the company, USD
Financial health	
Cash Ratio	Cash / Current liabilities
Current Ratio	Current assets / Current liabilities
Profitability	
RE/TA	Reitained Earnings / Total Assets
EBITDA/TA	Earnings before interest, taxes, depreciation and amortization / Total Assets
EBITDA/REV	Earnings before interest, taxes, depreciation and amortization / Revenue
Macroeconomic	
MSCI	MSCI World Index, USD
BDI	Baltic Dry Index, USD
Oil Price	Brent oil price, USD

5. Methodology

Evaluating prior research, we find several methodologies problematic. Beaver (1966) based his hypotheses on the mean differences of each explanatory variable between defaulted and non-defaulted companies. We argue that this way of quantitatively form a hypothesis runs a high risk of finding significant variables specific to the sample but not to the population. Hence, we base our hypotheses solely on the literature and our own reasoning. Further, both Ciampi and Gordini (2008) and Grammenos et al. (2008) applied a stepwise method, where the final multivariate model was based on univariate models. This method could easily generate an overfitting problem, resulting in the final model failing to replicate in future samples (Babyak, 2004). Another potential problem with using such an approach is that the final model often depends on the order in which the variables are dropped or added (Wooldridge, 2013). To avoid such a problem, instead of performing a univariate analysis of all possible variables, we conduct a logit model based on the six selected explanatory variables only. We control for robustness by using the rest of the variables identified through our literature review, as well as winsorizing the variables at a 2.5% level.

5.1 Logit Model

According to Wooldridge (2013), a linear probability model explains a binary outcome where the dependent variable y can only be equal to 0 or 1. However, Wooldridge (2013) states that the linear probability model has drawbacks, one being that the fitted probabilities can be less than zero or greater than one. We overcome this limitation by developing a binary response model:

$$P(y=1|x) = G(\beta_0 + \beta_1 x_1 + \cdots \beta_k x_k) = G(\beta_0 + x\beta), \qquad (5.1)$$

where we use a logit model to define G. Wooldridge (2013) mention that in a logit model, G is the cumulative distribution function:

$$G(z) = \frac{\exp(z)}{1 + \exp\,(z)} = \Lambda(z). \qquad (5.2)$$

The logistic function takes on values between zero and one for all real numbers z, which guarantees that the probability function of y is between zero and one (Wooldridge, 2013). The logistic function is shown in figure 4.

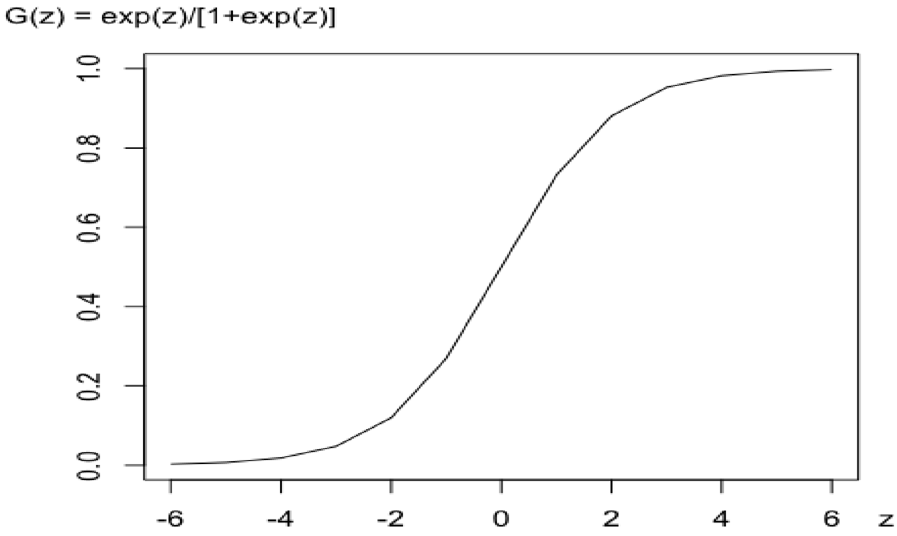


Figure 4: Logistic Function

5.2 Marginal effects

The marginal effect is the effect on the dependent variable from changing one of the independent variables. In a linear probability model, the response probability $y = 1$ is assumed to be a linear function of explanatory variables (Wooldridge, 2013). Hence, the marginal effect is simply the coefficient of the explanatory variable. However, the marginal effect is not as straight forward in the logit model, as the marginal effect is not constant. That is, the effect of an increase in the explanatory variable x_1 from 10% to 20% does not necessarily have the same effect on the dependent variable as an increase in x_1 from 20% to 30%. Wooldridge (2013) claims that the sign of a parameter indicates the direction of the effect on the response probability. However, one can solve an approximation of the marginal effect by applying the average partial effect (APE). The APE is:

$$n^{-1}\sum_{i=1}^{n}[g(\hat{\beta}_0 + x_i\hat{\beta})\hat{\beta}_j]. \tag{5.3}$$

The single scale factor, also known as the derivative $g(\hat{\beta}_0 + x_i\hat{\beta})$, obtained in the APE can be multiplied with the coefficient of the explanatory variable $\hat{\beta}_j$ to show an approximation of the marginal effect. For a logit regression, the single scale factor is:

$$g(\hat{\beta}_0 + x_i\hat{\beta}) = \frac{\exp(\hat{\beta}_0 + x_i\hat{\beta})}{[1 + \exp\,(\hat{\beta}_0 + x_i\hat{\beta})]^2} = \frac{dF}{dx}. \tag{5.4}$$

5.3 Evaluation of Model

To reduce the risk of multicollinearity in our model, we control that the variables are not highly inter-correlated by creating a correlation heatmap. Additionally, we control for the presence of multicollinearity by performing tolerance statistics. The tolerance statistics are performed by regressing each of our explanatory variables on the remaining explanatory variables. Weisburd and Britt (2014) claim that there is no precise number that indicates the presence of multicollinearity. However, a tolerance statistic of less than 0.2 is an indicator that there is a high presence of multicollinearity. Wooldridge (2013) mentions that another common way to measure the presence of multicollinearity is by using the VIF. Nonetheless, same as for tolerance statistics, there is no exact number that indicates a presence of multicollinearity. However, Wooldridge claims a VIF of 10 is a good indication that there is a multicollinearity problem.

Snipes and Taylor (2014) claim that the Akaike Information Criterion (AIC) is a statistical score to compare the outcome of different models. When developing a model, it is essential to consider problems such as under-fitting and over-fitting a model; the AIC score balances these two drawbacks. When comparing two models by their AIC value, the model with the lowest AIC value is selected (Snipes & Taylor, 2014). The AIC value is determined by the following equation:

$$AIC = 2K - 2\log(\mathcal{L}), \tag{5.5}$$

where $\log(\mathcal{L})$ represents the log-likelihood for the estimated model, and K is the number of parameters in the model. Hence, AIC penalizes models with many parameters since as K increases, the AIC value increases.

McFadden pseudo R-squared measures the binary response of a model, and is defined as

$$Pseudo\ R^2_{McFadden} = 1 - \frac{L_{ur}}{L_0}, \tag{5.6}$$

where L_0 is a model's log-likelihood function with only an intercept, and L_{ur} is the estimated or the unrestricted model's log-likelihood function (Wooldridge, 2013).

The Hosmer and Lemeshow (H-L statistic) is a goodness of fit test for logistic regression, where lower chi squared values and higher p-values indicate a good fit (Hosmer & Lemeshow, 2013).

Wooldridge (2013) argues that the likelihood ratio statistic (LR statistic) is the corresponding F-statistics for a logit regression and can be used to test the multiple hypotheses. The LR statistic is computed by

$$LR = 2(L_{ur} - L_r), \tag{5.7}$$

where L_r represents the log-likelihood for the restricted model and L_{ur} the log-likelihood for the unrestricted model.

We will also look at the goodness of fit measure "percent correctly predicted" by the model. Wooldridge (2013) suggests that the total percent correctly predicted can be misleading and that one should compute the percentages for each of the outcomes. We use 0.5 as a threshold. Hence, if the observation has a predicted probability of default greater than 0.5, it is predicted to default. The significance levels used in our thesis is 1%, 5%, and 10%. Although 10% may be considered a weaker significance level, we will consider it significant due to our limited number of observations.

6. Descriptive statistics

Table 5: Descriptive Statistics

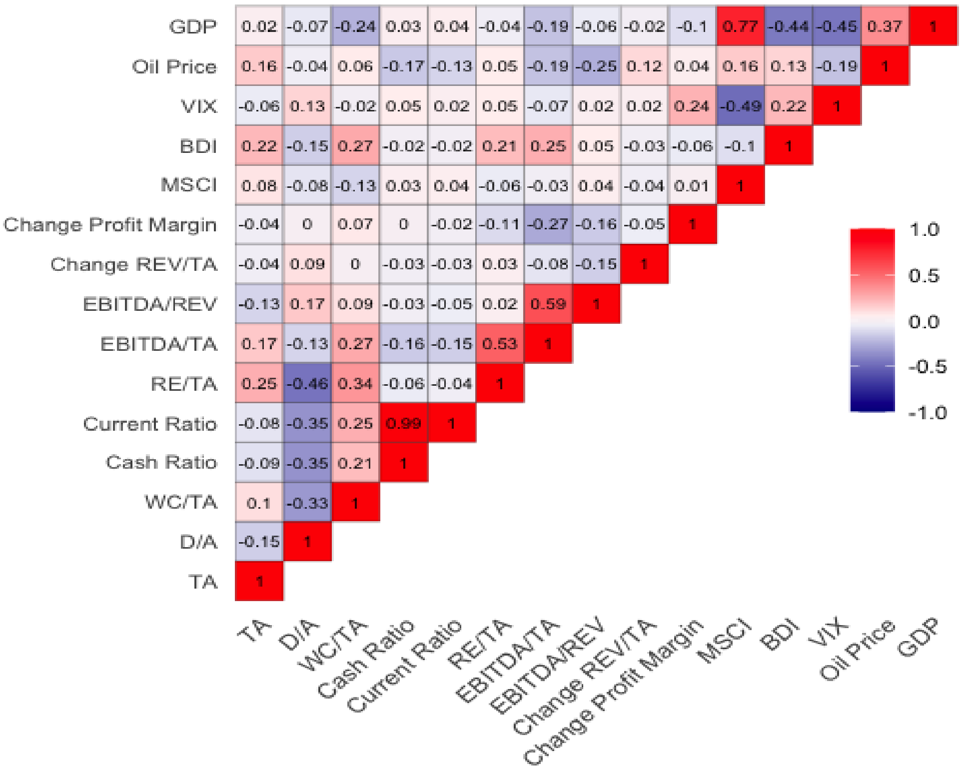
	Defaulted:			*Non-defaulted:*			
Variable	N	Mean	Std	N	Mean	Std	Difference in mean
TA	19	1,685,203	1,920,144	45	5,239,953	13,553,512	−3,554,750*
Financial health							
D/A	19	0.570	0.166	45	0.407	0.204	0.163***
WC/TA	19	0.010	0.239	45	0.077	0.128	−0.067
Cash Ratio	19	1.388	1.728	45	2.393	6.474	−1.005
Current Ratio	19	1.874	1.852	45	3.325	6.526	−1.452
Profitability							
RE/TA	19	0.056	0.142	45	0.168	0.279	−0.112**
EBITDA/TA	19	0.080	0.052	45	0.084	0.054	−0.003
EBITDA/REV	19	0.342	0.265	45	0.296	0.248	0.045
ΔREV/TA	19	0.036	0.106	45	0.154	1.041	−0.118
ΔProfit Margin	19	0.907	4.133	45	−0.062	0.226	0.969
Macroeconomic							
MSCI	19	1,347.841	305.023	45	1,524.065	225.910	−176.224**
BDI	19	2,615.368	2,504.580	45	1,627.333	2,041.016	988.035
VIX	19	19.471	5.900	45	15.515	3.122	3.956**
Oil Price	19	76.841	30.837	45	90.236	27.569	−13.396
GDP_{t-1}	19	57,783,933,363,069	16,062,463,269,896	45	72,475,138,773,668	8,568,409,190,215	−14,691,205,410,598***
Note:	*p<0.1; **p<0.05; ***p<0.01						

Table 5 presents the summary statistics for defaulted and non-defaulted observations. In addition to our six main variables of interest, table 5 also includes 9 variables identified through prior research that are used to test our model for robustness.

Firstly, we notice that TA is significantly higher for the non-defaulted observations than for the defaulted. However, note that there is a high standard deviation for TA of the non-defaulted firms, suggesting that it is driven by extreme values. For the group of variables that represents the firm’s financial health, we observe that the average D/A for defaulted observations is 0.57, versus 0.407 for non-defaulted. However, the standard deviation for the D/A is greater among the non-defaulted than for the defaulted, meaning that the D/A tends to be closer to the average for defaulted issues than for non-defaulted. For the profitability ratios, we notice that RE/TA is significantly higher for the non-defaulted observations than for defaulted. The other profitability ratios do not have a significant difference in mean. The last group shows the macroeconomic variables. We observe that GDP_{t-1} tends to be greater for the non-defaulted observations than the defaulted. However, VIX tends to be greater for the defaulted observations than the non-defaulted. Both differences in GDP_{t-1} and VIX between defaulted and non-defaulted are as expected.

6.1 Correlation and visualization of the data

Figure 5: Correlation Heatmap



The correlation heatmap in figure 5 shows the correlation between all the variables. In the correlation heatmap, the darker the color is, the greater the correlation is. Blue indicates a negative correlation, and red indicates a positive correlation. We can see that the correlation between GDP and VIX is approximately -0.45, while the correlation between D/A and WC/TA is approximately -0.33. Figure 5 also shows that in a few cases, there is a strong correlation, such as between GDP and MSCI, which has a correlation of approximately 0.77.

Figure 6: Visualization, GDP plotted against D/A

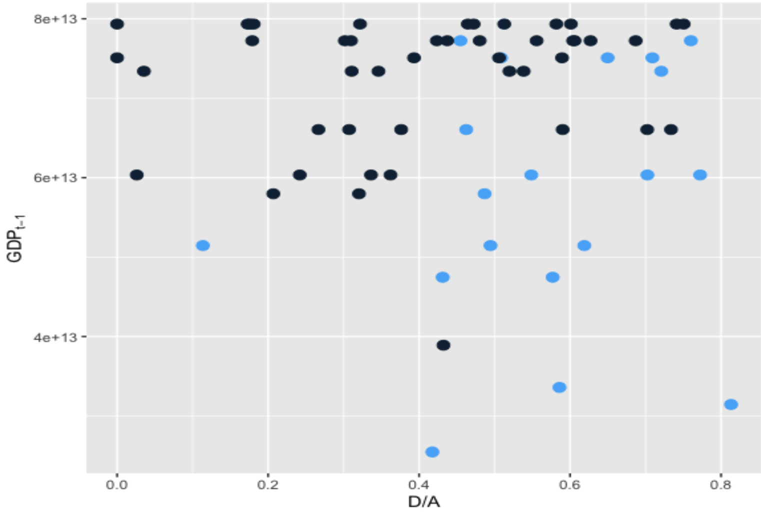


Figure 6 shows a visualization of GDP_{t-1} and D/A for defaulted and non-defaulted observations at the date of issue in our sample. Light blue represents defaulted observations and dark blue non-defaulted. The observations issued during a low GDP tend to default more frequently while the observations issued during a high GDP tend to perform better. The observations that were issued during a high GDP but still defaulted tend to have had a high D/A. The visualizations for the other variables used in the model are shown in appendix A.

7. Empirical Results

Table 6: Logit model for predicting probability of default

	Constant	D/A	WC/TA	ΔREV/TA	ΔProfit Margin	GDP_{t-1}	VIX
Coefficient	3.625	6.757**	−6.458*	-0.101	3.917	−1.590e-13***	0.194*
	(3.545)	(2.795)	(3.789)	(0.634)	(2.404)	(4.921e-14)	(0.112)
Tolerance Statistics		0.8613	0.8101	0.9893	0.9349	0.7264	0.7360
VIF		1.442	1.403	1.067	1.417	1.739	1.071
AIC	52.526						
McFadden R^2	0.5051						
H−L Statistic	8.265 [0.408]						
LR Statistic	39.323***						

*Note: Statistical significance of the estimated coefficients is denoted with *, ** and *** for 10%, 5% and 1% significance levels, (Standard errors) and [P-values].*

Table 6 shows the result from our logit regression for predicting the probability of default. The model includes the solvency and liquidity ratios D/A and WC/TA, the forward-looking profitability ratios change in REV/TA and change in Profit Margin, as well as the macroeconomic variables GDP_{t-1} and VIX. The tolerance statistics and VIF test indicate that there is no presence of multicollinearity. The model has an AIC value of 52.526 and a McFadden R^2 of 0.5051.

The H-L statistic yields a chi squared of 8.265 and p-value of 0.408, which indicates that the model is a good fit for predicting the probability of default for shipping bonds and loans. In the H-L goodness of fit test, we controlled for sensitivity towards a change in grouping with $7 \leq g \leq 15$, where g represents the grouping. We obtain p-values ranging from 0.12 to 0.98, and chi squared ranging from 3.54 to 15.60, none of which indicates a poor fit. Hosmer and Lemeshow (2013) claims that the most common grouping method is based on percentiles. Thus, for the H-L statistic in table 6, we use g = 10, also known as “deciles of risk”. The LR statistic in table 6 rejects the null hypothesis that all estimated coefficients except the constant are equal to zero on a 1 % significance level.

Table 7: Prediction table of the model

	Number correct	% Correct	Number incorrect	% Incorrect
Defaulted	13	68.42 %	6	31.58 %
Non-defaulted	42	93.33 %	3	6.67 %
Total	55	85.94 %	9	14.06 %

Table 7 shows that the percentage of correctly predicted defaults in our model is 68.42%, versus 93.33% for non-defaulted. Hence, the model is more accurate when applied to the non-defaulted observations. One potential reason for this could be that number of non-defaulted observations simply is higher.

Table 8 presents the APE obtained in our logit model, where the single scale factor dF/dx multiplied by the coefficient shows an approximation of the marginal effect. We note that only D/A and GDP_{t-1} has a significant APE.

Table 8: APE

	dF/dx	Std. Err.
D/A	0.6245*	0.3676
WC/TA	-0.5969	0.4311
ΔREV/TA	-0.0093	0.0587
ΔProfit Margin	0.3620	0.2691
GDP_{t-1}	$-1.47e{-14}^{*}$	$7.64e{-15}$
VIX	0.0179	0.0127
Note:	*p<0.1; **p<0.05; ***p<0.01	

7.1 Financial health of the company

As shown in table 6, our results indicate that the financial health of the company at the date of issue is a driving force of the probability of default in the shipping industry. D/A has a positive and significant coefficient and WC/TA has a negative and significant coefficient, both of which are expected. Hence, we find evidence for our first hypothesis.

Table 8 shows that the APE of D/A is 0.6245, meaning that a 1% increase in D/A increases the probability of default by 0.6245%. However, as mentioned in the methodology section, the single scale factor in table 8 multiplied with the coefficient shows an approximation of the marginal effect of the explanatory variable. Since the marginal effect is not constant, we illustrate the marginal effect of D/A on the probability of default in figure 7. Figure 7 shows that the marginal effect of D/A on probability of default is a sigmoid function. An increase in D/A from 5% to 10%, ceteris paribus, increases the probability of default from 4% to 6%. In comparison, an increase from 40% to 45% increases the probability of default from 32% to 40%. Finally, an increase from 75% to 80% increases probability of default from 83% to 88%, creating an S-shaped function.

Figure 7: Marginal effect of D/A on probability of default

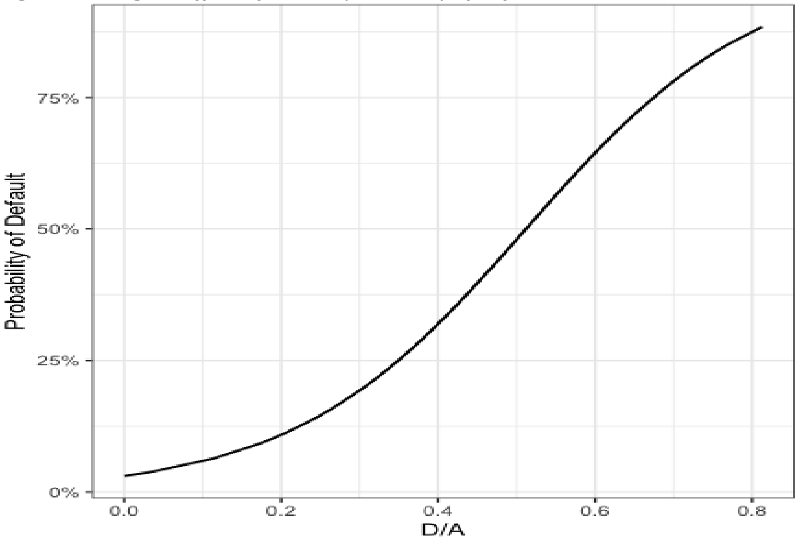
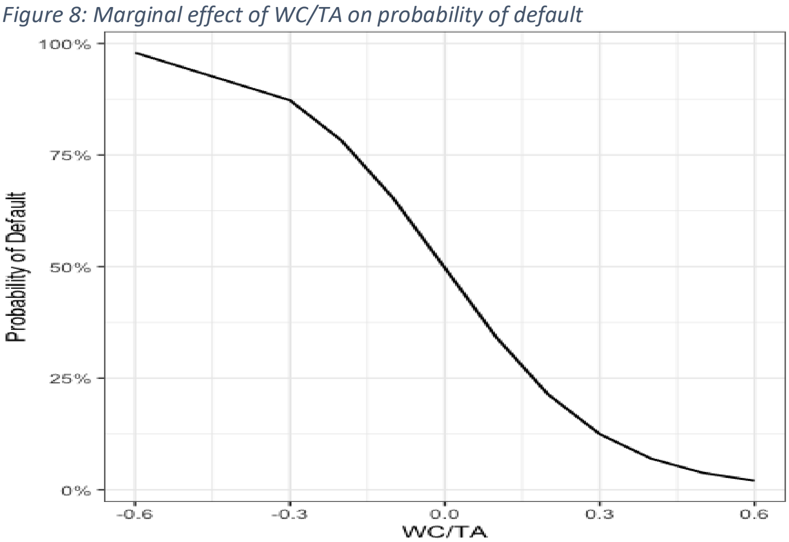


Figure 8 indicates that the marginal effect of WC/TA on probability of default is an inverse sigmoid function[6]. An increase from -60% to -55% in WC/TA, ceteris paribus, decreases the probability of default by 1% unit. In comparison, an increase from 0% to 5% decreases the probability of default by 8% unit. Lastly, an increase from 55% to 60% decreases probability of default by 1% unit.

Figure 8: Marginal effect of WC/TA on probability of default



7.2 Profitability

The results in table 6 do not support our second hypothesis, as the change in neither of the profitability ratios is significant. Hence, the change in profitability at the date of issue does

[6] Figure 8 starts from a negative WC/TA. Harwood (2006) claims that a negative working capital is not uncommon in the shipping sector as a ship owning company often has a small inventory followed by a high amount of account payables.

not seem to be an essential indicator to predict the probability of default in the shipping industry. To investigate this closer, we include a dummy which equals 1 if the observation is a bond. The results of model 2 in table 9 show that the bond dummy is significant on a 5% level, indicating that the probability of default for a bond is greater than for a loan[7]. Model 3 in table 9, uses a bond dummy as an interaction term with the two profitability variables. The results in model 3 show that the change in profit margin has a significance effect on probability of default for bonds. However, it is surprising that the change in profit margin has a positive effect on the probability of default for bonds, as we would expect it to have a negative effect. Further, excluding the profitability ratios from the model, as shown in model 4 in table 9, has a minimal impact on the outcome of the model.

Table 9: Regression result of model 2, 3 & 4

	(2)	(3)	(4)
Constant	2.600	3.914	2.505
	(3.854)	(4.277)	(3.250)
Bond Dummy	2.179**	2.957**	
	(1.076)	(1.382)	
D/A	4.900*	4.540	5.507**
	(2.919)	(3.310)	(2.537)
WC/TA	−8.571**	−11.735**	−5.630
	(4.147)	(4.900)	(3.533)
ΔREV/TA	−0.419	−1.847	
	(0.765)	(5.333)	
ΔProfit Margin	2.513	−1.573	
	(2.524)	(4.291)	
GDP_{t-1}	−1.539e-13***	−1.805e-13***	−1.369e-13***
	(5.036e-14)	(6.000e-14)	(4.169e-14)
VIX	0.230	0.236	0.200*
	(0.141)	(0.173)	(0.106)
Bond:ΔREV/TA		2.768	
		(5.581)	
Bond:ΔProfit Margin		20.747**	
		(9.514)	
N	64	64	64
AIC	49.550	45.569	52.642
McFadden R^2	0.5690	0.6716	0.4522
Note:	*p<0.1; **p<0.05; ***p<0.01		

7.3 The global economy

The results from table 6 support our third hypothesis that macroeconomic variables have a significant effect on the probability of default. The GDP coefficient is negative and significant

[7] This could be due to the restrictions on our sampling process; the bonds in the sample may be of higher risk than the loans.

at a 1% level. Additionally, VIX has a positive coefficient that is significant on a 10% level. As the world GDP reflects the market value of all goods and services produced, it should, in theory, be a good indicator of how well the macroeconomic state is doing. This would then affect the interaction levels between regions, and eventually, the probability of default. However, as discussed above, there is a potential for a reversed causality scenario. GDP captures the effect of a default by no longer registering the value of the product or service produced prior to that default. Therefore, the probability of default may be as much of a driver of GDP as GDP is of the probability of default. This could be a potential violation of the zero conditional mean assumption, which would hinder us from interpreting our results as causal. This should be kept in mind when interpreting our results.

By comparing the model in table 6 with the model in table 10, which is excluding the forward-looking variable VIX, we see that the inclusion of VIX yields a superior model based on the corresponding AIC value. This supports our argument that the GDP fails to explain all the variance attributed to the macroeconomic state.

Table 10: Logit Model excluding VIX

	Constant	D/A	WC/TA	ΔREV/TA	ΔProfit Margin	GDP_{t-1}
Coefficient	7.184^{**}	6.169^{**}	-6.203^{*}	-0.141	3.372	$-1.592\text{e-}13^{***}$
	(3.247)	(2.543)	(3.550)	(0.679)	(2.279)	(4.939e-14)
Tolerance Statistics		0.8644	0.8241	0.9895	0.9859	0.9154
VIF		1.294	1.294	1.047	1.412	1.662
AIC	53.833					
McFadden R^2	0.4626					
H−L Statistic	11.222 [0.189]					
LR Statistic	36.016^{***}					

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

7.4 Robustness

In this section, we test the robustness of our model to ensure that the variables and the model hold. In table 11 we test for robustness by controlling for several variables identified through prior research. The results shown in table 11 indicates that D/A, WC/TA, GDP_{t-1}, and VIX remains significant when performing the robustness check.

Table 11: Robustness regression

Constant	-1.527
	(8.794)
D/A	22.466^{**}
	(10.546)
WC/TA	-19.353^{*}
	(11.553)
GDP_{t-1}	$-1.127e\text{-}12^{**}$
	(5.030e-13)
VIX	1.246^{**}
	(0.604)
ΔREV/TA	-1.174
	(1.203)
ΔProfit Margin	6.027
	(4.485)
TA	$-1.474e\text{-}06^{**}$
	(6.965e-07)
Cash Ratio	-0.150
	(1.366)
Current Ratio	0.406
	(1.219)
RE/TA	5.759
	(4.258)
EBITDA/TA	-26.298
	(28.026)
EBITDA/REV	-2.220
	(6.108)
MSCI	0.032^{**}
	(0.016)
BDI	-0.002^{*}
	(0.001)
Oil Price	0.097^{*}
	(0.054)
N	64
AIC.	53.641
McFadden R^2	0.7220
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

To investigate whether the results in the model are sensitive to extreme values, we control for robustness by winsorizing each of the variables in the model at a 2.5% level. Table 12 shows that the result from the logit model remains consistent when the data is winsorized.

Table 12: Winsorized logit model

	Constant	D/A	WC/TA	ΔREV/TA	ΔProfit Margin	GDP_{t-1}	VIX
Coefficient	3.833	6.867^{**}	-6.361^{*}	-0.103	3.965	$-1.632e\text{-}13^{***}$	0.196^{*}
	(3.571)	(2.826)	(3.776)	(0.637)	(2.415)	(4.932e-14)	(0.112)
AIC	52.713						
McFadden R^2	0.5027						
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$						

8. Conclusion

In this thesis, we have empirically investigated the driving forces of default at the time of issue in the shipping industry. From a sample of 64 shipping bonds and loans, we developed a logit model that shows that the most important factors to consider when predicting default are the financial health of the company and the macroeconomic state of the world. Hence, we find evidence for our first and third hypothesis. For the first time in the shipping literature, we show that VIX used together with GDP yields a model superior to one with only GDP, as this adds a forward-looking feature to the model. However, we do not find support for our second hypothesis that change in profitability has a significant effect on the probability of default. This paper agrees with the literature that financial ratios and macroeconomic indicators are important drivers of shipping defaults at the time of issue. Our findings regarding the importance of considering future market conditions are in line with that of Kavussanos and Tsouknidis (2016). Our study is of interest to banks specializing in shipping, shipping bond investors, and any institution or professional dealing with credit assessment in the shipping industry.

In contrast to our study focusing on the global shipping market, a few studies have been conducted on specific shipping markets such as the Greek market. We encourage future research to focus exclusively on the Norwegian shipping market to investigate whether the driving forces of default for Norwegian shipping companies aligns with our findings. Lastly, we suggest that future research investigate whether the driving forces of default differs between the sub sectors.

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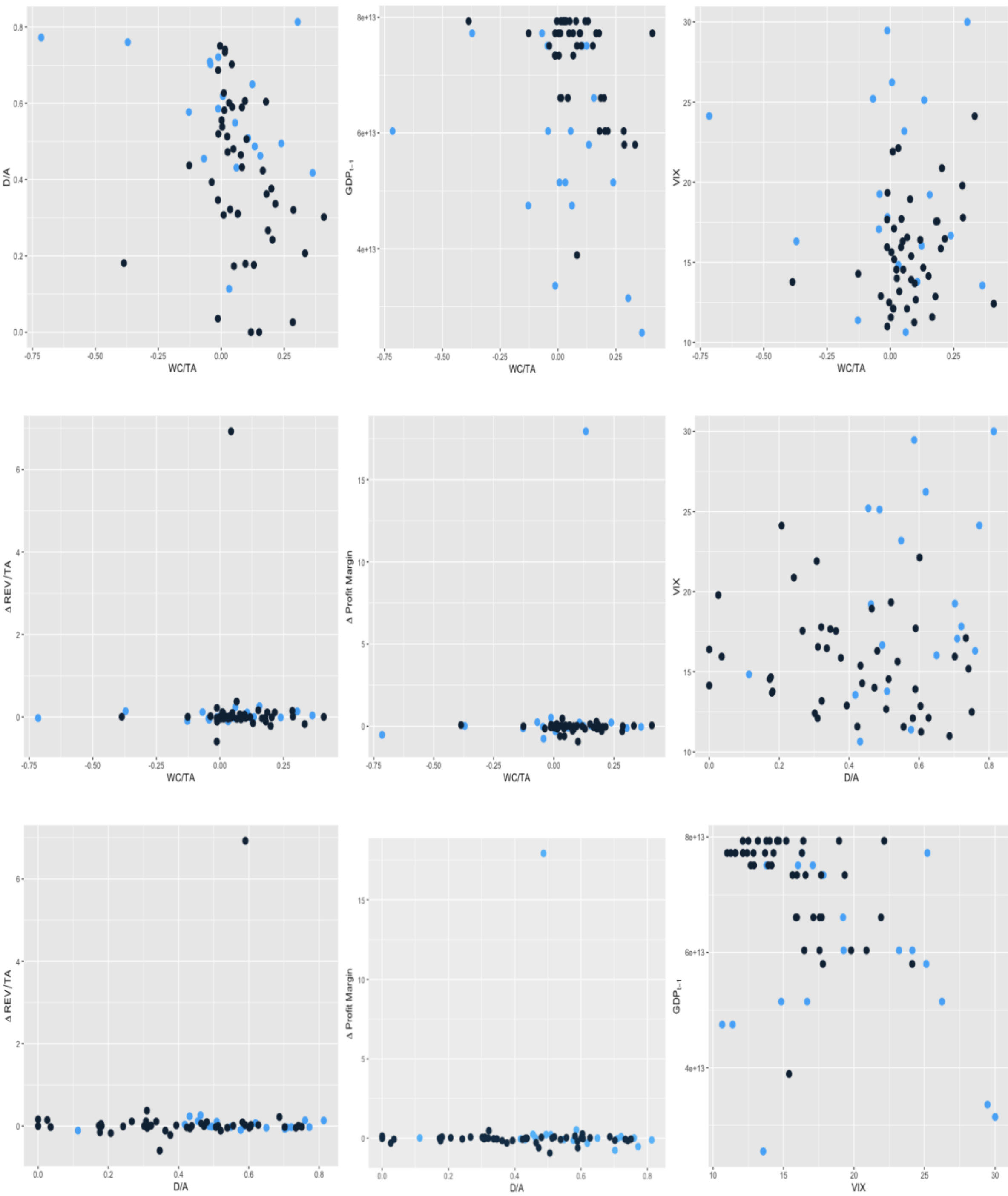
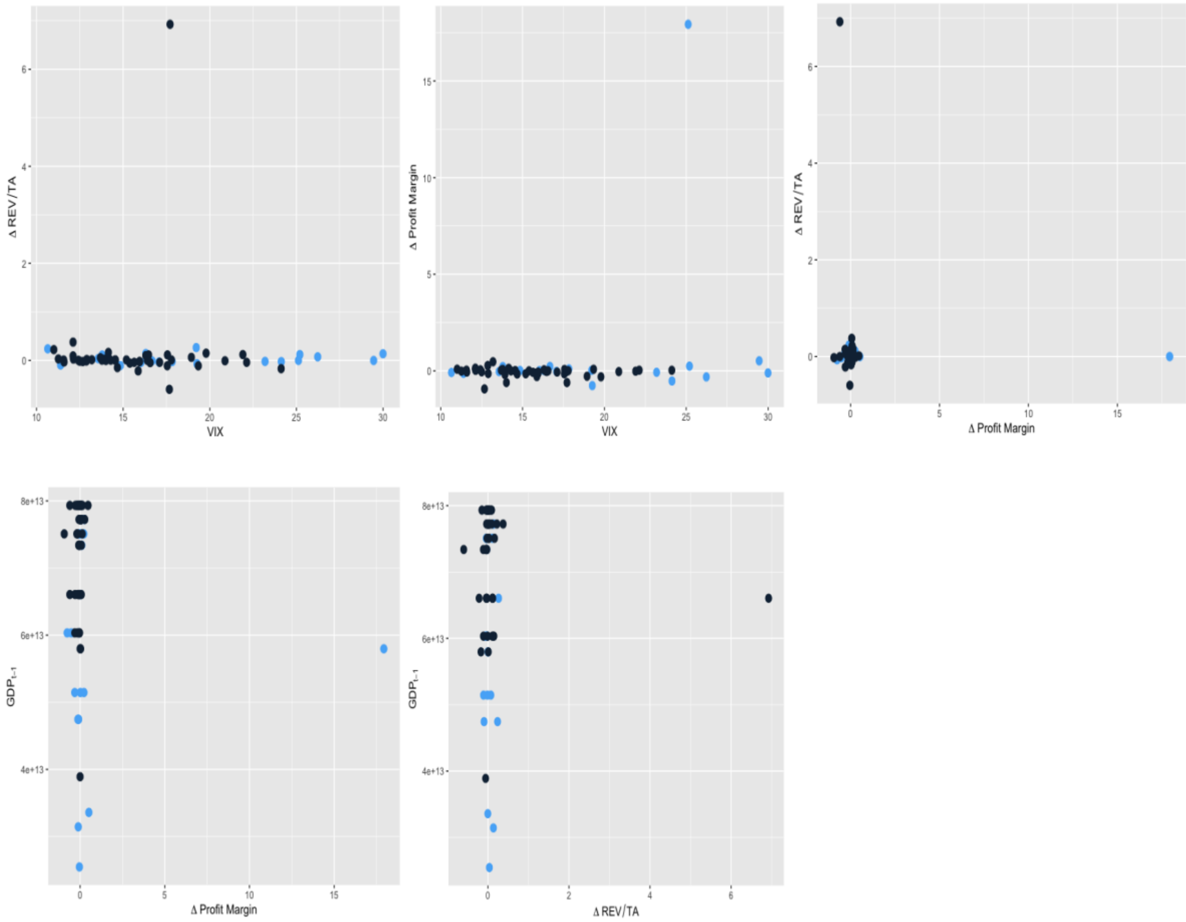
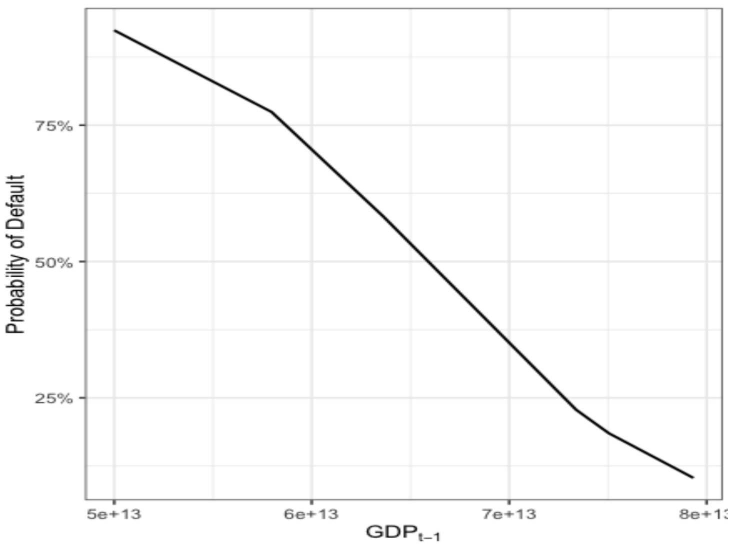
Appendix

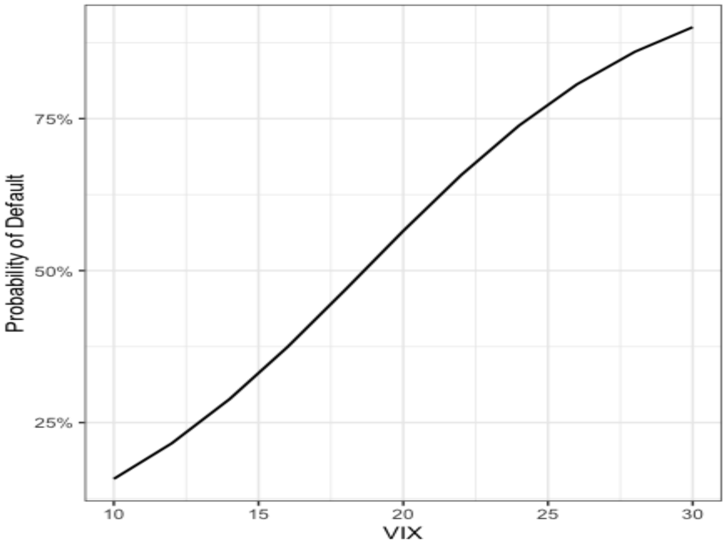
Appendix A – Visualization

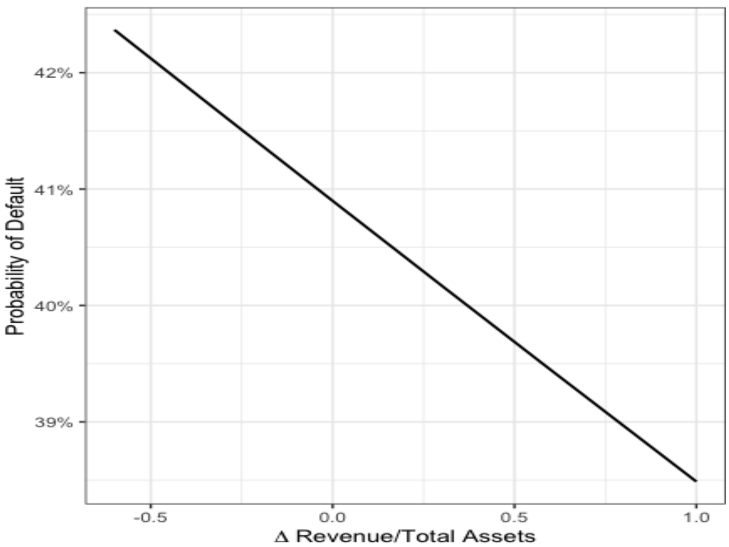


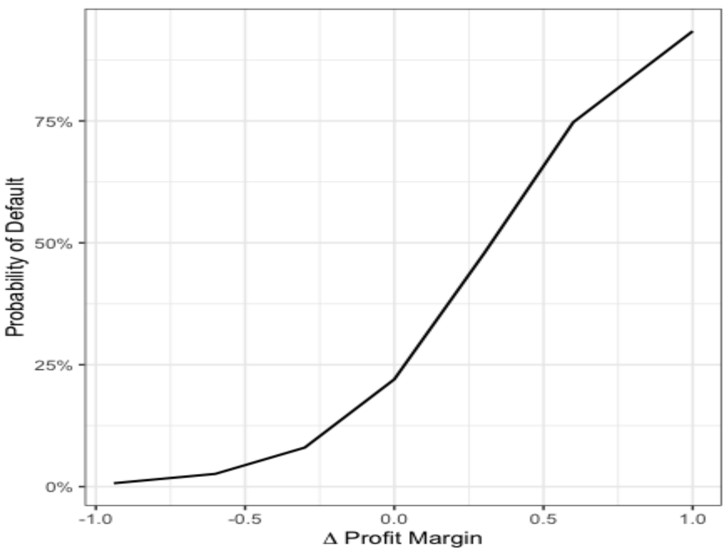


Appendix B – Marginal effects




Probability of Default
75%
50%
25%
10
15
20
25
30
VIX


Probability of Default
42%
41%
40%
39%
-0.5
0.0
0.5
1.0
Δ Revenue/Total Assets


Probability of Default
75%
50%
25%
0%
-1.0
-0.5
0.0
0.5
1.0
Δ Profit Margin