Master's thesis

NTNU
Norwegian University of Science and Technology

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Determinants of credit events among SME shipping companies in Norway

Master's thesis in International Business and Marketing
Supervisor: Petter Eilif De Lange
Co-supervisor: André Schlingloff

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Determinants of credit events among SME shipping companies in Norway

Abstract

This master thesis explores the highly globalized shipping industry in Norway. While volatile and capital-intensive, the sector is of great importance to the nation in terms of wealth creation and export. This study seeks to answer the following research problem: “Determinants of credit events among shipping SMEs in Norway: Which factors provide information of corporate defaults or increase the probability of corporate defaults?” The study searches for a relationship between the dependent variable non-current liabilities leverage and the independent variables operating leverage, profitability, oil price, size, tangibility, and age by analyzing 178 small and medium-sized Norwegian shipping enterprises.

Previous research has proven leverage to be a major factor in predicting default. While several studies have previously focused their attention on international shipping firms, the Norwegian shipping industry is still largely unexplored. To cover this research gap, we employ multiple different panel regression methods to search for key determinants of default. We find evidence that a positive and statistically significant relationship exists between the dependent variable leverage and the independent variables size, operating leverage, and tangibility. On the contrary, age and profitability are found to be negatively correlated to leverage. Many of our findings are in line with the results of previous international studies on the shipping industry. However, there are also some interesting differences. These differences might be related to underlying factors among the Norwegian shipping firms, such as laws, law enforcement mechanisms, and attitude to debt. The findings of this study suggest that remedies that might reduce the probability of default in the global industry can potentially have a reduced effect when applied to the Norwegian industry and vice versa. This is information that can be useful for practitioners and academics, as well as for future research. Specifically, we encourage other researchers to continue where we left off by connecting our findings about leverage to a proxy variable for default.

Sammendrag

Denne masteroppgaven analyserer den svært internasjonale og volatile shipping industrien ved hjelp av økonometriske modeller og metoder. Oppgaven er avgrenset til små og mellomstore norske selskaper, og forsøker å svare på følgende problemstilling: “Determinanter for kredittbegivenheter blant små og mellomstore shippingselskap i Norge: Hvilke faktorer gir informasjon om konkurs, eller øker sannsynligheten for konkurs?». Problemstillingen blir forsøkt svart på ved å analysere 178 norske shipping selskaper. Mer spesifikt ses det på sammenhengen mellom den avhengige variabelen andel gjeld av totalkapital og de uavhengige variablene alder, oljepris, lønnsomhet, totalkapital, driftskostnader i andel av totalkapital, og anleggsmidler i andel av totalkapital. Studien sammenligner resultatene fra flere regresjonsmodeller for å utforske sammenhengen mellom den avhengige variabelen og de uavhengige variablene. Tidligere forskning har bekreftet at en høy andel gjeld over totalkapital kan være en av hovedårsakene til konkurs, og vi mener derfor at det er behov for å forstå mer om årsakene bak høy bruk av gjeld.

Vi finner gjennom regresjonene en positiv sammenheng mellom andelen gjeld av totalkapital, driftskostnad av totalkapital og anleggsmidler av andel av totalkapital. Samtidig ser vi en negativ sammenheng mellom andelen gjeld av totalkapital, alder og lønnsomhet. Til slutt finner vi at oljepris ikke har noen påvirkning på sammenhengen mellom andel gjeld av totalkapital.

Vi observerer at disse resultatene er på linje med flere internasjonale studier, men enkelte av funnene skiller seg ut. Disse funnene er unike til norsk industri, og vi argumenterer for at årsaken til dette kan skyldes underliggende forhold blant norske selskaper, som forhold til gjeld, eller lover og regelverk rundt kapital.

Preface

This master thesis is part of the International Business and Marketing Master's Programme at the Norwegian University of Science and Technology. It is a joint effort by students majoring in International Business.

We want to thank our supervisors Associate Professor Petter Eilif De Lange and Assistant Professor André Schlingloff, for their helpful insights and guidance throughout the whole process.

Norwegian University of Science and Technology

Ålesund, June 2021

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List of Abbreviations (or Symbols)

AR	Autoregressive model
EBITDA	Earnings before interest, income taxes, depreciation, and amortization
EUR/€	Euro
FD	First difference
GLS	Generalized Least Squares
GMM	Generalized Method of Moments
LEVR_NCLI_	Leverage ratio of non-current liabilities
OIL	Annual oil price change
OLS	Ordinary Least Square
OPLEV	Operating leverage
MA	Moving average
MDA	Multiple discriminant analysis
NACE	Statistical Classification of European Activities in the European Community
NOK	Norwegian crown
PD	Probability of default
ROA	Return on Assets
ROE	Return on Equity
SME	Small and medium-sized enterprise
TANG	Tangibility
USD/$	United States dollar

1 Introduction

The highly leveraged and capital-intensive shipping industry was strongly impacted by the global financial crisis in 2007-2009 and again by the oil price deterioration in later years (Kavussanos and Tsouknidis, 2016). Combined with rapid technological development in the area, it is an industry undergoing considerable changes. The Norwegian merchant fleet has been a great power in international shipping for the past 150 years. Today it is the world's fourth-largest merchant fleet measured in value and a leading driver of technological development in the sector (Norwegian Shipowners' Association, 2021). This has been made possible by knowledge transfer between the Norwegian offshore, shipyard, and shipping industries. These companies are typically found in geographic clusters promoting innovation and cost-efficiency. The clusters form crucial parts of the livelihood for the villages and cities in which they operate (Norwegian Shipowners' Association, 2021). A prominent example of this is the maritime cluster at Sunnmøre.

There are few countries where the maritime sector contributes as much to wealth creation and export as it does in Norway. According to the Norwegian Shipowners' Association (2021), the maritime industry had 82.700 employees in 2020, with value creation of NOK 144 billion. The value creation peaked between 2014 and 2017 before it fell by 25 percent. While there was growth in subsequent years, it has now slowed down due to the pandemic (Norwegian Shipowners' Association, 2021). The costs and impacts of financial distress and bankruptcy on an individual-, firm- and regional level serve as important reasons why avoidance of these events can be of importance. This is especially relevant for the shipping industry in the Norwegian villages that are so dependent on these clusters.

While the topic of bankruptcy among shipping firms has been studied internationally by many researchers, this study covers a research gap by focusing specifically on Norwegian firms. It will identify key determinants of defaults in the Norwegian SME shipping industry, providing stakeholders with helpful insight on which factors should be paid special attention to. This may help avoid or mitigate the negative consequences of financial distress. The following research problem has been developed:

"Determinants of credit events among SME shipping companies in Norway: Which factors provide information of corporate defaults, or increase the probability of corporate defaults?"

The paper is structured as follows: In Chapter 2, we provide a literature review. Here, we discuss a selection of research papers that have looked into the prediction of defaults among shipping companies. In Chapter 3, we present our data sample and variables. The reader will be introduced to the study's research design before we embark on a preliminary analysis. The analysis provides descriptive statistics about the variables and checks if necessary assumptions hold. In Chapter 4, we identify and describe statistical models that fit the dataset. In Chapter 5, we run the models and compare their results. The results are discussed and summarized in Chapters 6 and 7, respectively.

2 Literature review

The shipping industry is highly capital intensive since investment into a single vessel can exceed $100 million depending on type and size (Stopford, 2008). As this amount of money is not easy to raise, bank loans have historically been a popular means of acquiring capital in the industry. Before the financial crisis in 2007-2009, 75% of the external funding of shipping companies took the form of a bank loan (Kavussanos and Tsouknidis, 2016). This rate, however, has decreased since the crisis due to liquidity issues and the lower profitability of shipping companies. Despite this, bank loans are still the primary source of financing in shipping companies (Kavussanos and Tsouknidis, 2016).

The high amount of debt can be problematic for the shipping industry. According to Drobetz et al. (2013), the risk and cyclical nature of the maritime sector mean that avoiding financial distress and maintaining financial flexibility are essential concerns for shipping companies. Their study found that the shipping industry had a substantially higher leverage ratio and thus higher financial risk compared to a large sample of industrial firms. The study criticizes the large amount of excessive leverage in the past and expects leverage to decrease and equity requirements to increase (Drobetz et al., 2013).

The lack of reliable models for estimating the risk of lending to shipping companies has caused severe losses to banks. This motivated several studies internationally, which tried to find the probability of default for shipping companies and the performance drivers of shipping loans (Kavussanos and Tsouknidis, 2016). In the study of Edward I. Altman (1968), the Z-score model was introduced. Altman’s study combined several measures into one predictive model. Multiple discriminant analysis (MDA) was employed using a sample of non-financial US companies to estimate the probability of default. Altman found five significant explanatory variables. These included the ratio of working capital, retained earnings, the ratio of earnings before interest to total assets, and the ratio of the market value of equity to the book value of debt (Altman, 1968). As this was considered the most straightforward approach, it became an influential research paper in the area, creating a basis for further studies on the topic. Later, the work of Ohlson (1980) challenged Altman’s model as he proposed a binary logit method for estimating the probability of default. Altman’s multivariate discriminant analysis assumed multivariate normality and an equal covariance matrix, assumptions that do not always reflect reality. Logistic regression does not have the same assumptions. Therefore, the logistic regression method proved to be superior to the Z-score model, and it became widely used among researchers. Ohlson (1980) found the probability of default to be correlated with firm size, total liabilities divided by total assets, net income divided by net assets, change in net income, funds provided by operations divided by liabilities, as well as a dummy variable for when total liabilities exceed total assets.

Grammenos et al. (2008) attempted to predict the probability of default of high-yield shipping bonds, also with the help of a binary logit model. Their results indicated that higher gearing levels and higher amounts raised relative to total assets were associated with a higher probability of default. Furthermore, a variable capturing shipping market conditions, the working capital over total assets ratio, and the retained earnings over total assets ratio, were negatively related to the probability of default. The findings of Grammenos et al. (2008) are supported in a more recent study by Mitroussi et al. (2016). The latter examined criteria for assessing the security of shipping loans issued by banks. It concluded that a series of financial factors, non-financial factors, market risk factors, shipowners' experience, and employability are helpful criteria for evaluating the performance of shipping loans.

As shown, there have been several studies connected to the probability of default among shipping companies. A number of these studies, and others, have found leverage and gearing ratio to be key indicators when measuring the probability of default. The study of Drobetz et al. (2013) concluded that the shipping industry is characterized by higher leverage ratios and thus increased probability of default compared to other sectors. Studies conducted in other industries by Altman (1968), Ohlson (1980), and Dewaelheyns and Van Hulle (2004) have all proven that a high level of financial leverage is a sign of high financial risk for a company, which again increases the probability of default. Lastly, Kavussanos and Tsouknidis (2016) found in their study that there exists a positive relationship between financial leverage and the probability of default within the shipping industry. In sum, these findings indicate that if one understands more about the causes of high leverage, one might predict and reduce the probability of default. Based on these previous findings, our study will use leverage as the primary dependent variable to identify key determinants that can lead to default. The study will further differ from existing literature by exploring small and medium-sized Norwegian shipping firms. This will provide new knowledge in a field that is currently largely underexplored. Table 1 summarizes some of the previously mentioned studies and presents a comparison of their methodology and findings.

Table 1. Studies connected to shipping companies' probability of default

	Grammenos et al. (2008)	Mitroussi et al. (2016)	Kavussanos and Tsouknidis (2016)	Lozinskaia et al. (2017)	Drobetz et al. (2013)	**Current study**
Sample	50 high yield bonds issued by shipping companies	30 loans issued by Greek banks to finance ships	128 loans issued to 63 shipping companies	192 internationally listed shipping companies	115 exchange-listed shipping companies	178 medium-sized Norwegian shipping companies
Dependent variable	Non-payment of interest or principal to bondholders by the shipping company	Loan not repaid at maturity	Delay in payment of interest on the loan or principal for more than 90 days	Bankruptcy, liquidation, reorganization	Book leverage and market leverage	Leverage of non-current liabilities
Time period	1992–2004	2005–2009	1997–2011	2001–2016	1992-2010	2007-2016
Method	Binary logit model	Linear probability model, Binary logit model	Binary logit model	Linear probability model, Binary logit model, Ordered logit model	Dynamic panel model	Autoregressive model, first difference model, dynamic model, GMM model, and binary logit model
Independent variables	Issue-specific variables, financial specific variables, industry-specific variables	Loan nature specific variables, vessel nature, and borrower's finances, reliability, and exposure to market risk	Financial specific variables, Firm characteristics'-specific variables, Loan-specific variables, Industry-specific and macro variables	ROA, EBITDA, company size, current ratio, financial leverage, Tobin's Q, percentage of shares held by the largest shareholder, company age, GDP, IRONSTEEL, vessel rent	Tangibility, market-to-book, size, operating leverage, dividend payer, asset risk, rating probability	Operating leverage, tangibility, profitability, company size, company age, oil price change
Main findings	Higher gearing and amount raised over total assets -higher PD. Shipping market conditions, working capital/total assets, retained earnings/total assets – negatively related to PD.	Less experienced and higher leveraged shipowners - more defaulted shipping loans The defaulted loans are large amount, with small spreads, short tenors, and lower asset value	Industry-specific variables, the risk appetite of the ship owners, and the pricing variables are essential factors in explaining PD.	Tobin's Q is positively associated with PD. GDP, company size, and total assets are negatively associated with PD.	Higher leverage – higher PD. Tangibility is positively related to leverage Asset risk and operating leverage are inversely related to leverage	Lower profitability-higher leverage Bigger firm-higher leverage Higher tangibility-higher leverage Younger company-higher leverage Higher operating leverage- higher leverage

3 Data

3.1 Data sample

The data sample consists of data collected from Bureau van Dijk's Amadeus database. Bureau van Dijk provides comparable financial and business information on Europe's 565 000 largest publicly and privately held companies through the Amadeus database. We segmented the database using the NACE 502 sea and coastal transport filter (non-passenger). Only Norwegian medium-sized firms with more than one year of observed financial data were extracted. This means companies with operating revenue below 10 million euros, total assets below 20 million euros, and less than 150 employees. Our study intentionally excludes shipyards, passenger water transport, and inland freight water transport. Holding companies with no employees are also excluded from the sample. These requirements yield 671 valid firms. The data set is narrowed down to 216 firms and 1750 observations when excluding pure management and holding firms. Furthermore, over-indebted firms with leverage ratios above one and firms under receivership or special administration have been removed. This reduces the number of firms down to 178. Financial data for these firms is collected in a period from 2008 to 2017. This means that, for each firm, there can be up to ten observations per variable. However, not all 178 firms have data from all ten years. Some firms might have been founded in the data collection period. Others might have gone out of business. In total, there are 1230 observations for the 178 firms.

3.2 Definition of variables

Financial distress can come in the form of business failure, insolvency, default, and bankruptcy. According to Altman and Hotchkiss (2006), business failure is regarded as a failure to accomplish a rate of return that is higher than the cost of capital. Furthermore, a firm defaults when it fails to meet its financial obligations. If attempts to refinance or restructure the firm are unsuccessful, a firm can be formally declared bankrupt by a court (Altman and Hotchkiss, 2006). Our study uses the leverage of non-current liabilities as the dependent variable (levr_ncli_) to capture the risk of default. This is both due to the shipping industry's capital-intensive nature, and its close relation to defaults. The academic discourse on whether or not short-term debt should also be included in such analyses is ambiguous. Addae et al. (2013)

found a significant negative relationship between long-term debt and profitability, and a significant positive relationship between short-term debt and profitability. To avoid inconsistency, this study, therefore, focuses only on long-term debt. As most SMEs' debt and equity will not be publicly traded, the measures are based on book values.

The independent variables in this study are grouped in two categories: first, firm-level variables (tangibility, profitability, firm size, operating leverage, and company age), and second, an external, macroeconomic variable (oil price). A firm's asset tangibility (TANG) is defined as fixed assets divided by its total assets, its profitability (PROF) as the ratio of its operating income to its total assets, its size (SIZE) as the logarithm of its total assets, and its operating leverage (OPLEV) as the ratio of its operating expenses to its total assets. A firm's age (AGE) is the period from its foundation to the date of observation, measured in years and based upon 365 days per year. As mentioned in the literature review, these independent variables have been frequent in previous studies connected to the probability of default. Table 2 contains an overview of all the variables.

Table 2. Overview of variables

	Name in analysis	Formula	Description
Dependent Variable	LEVR_NCLI_	$\frac{NCLI}{Total\ assets}$	Ratio of non-current liabilities to total assets (payables due beyond 12 months)
Independent variables	OPLEV	$\frac{Operating\ expenses}{Total\ assets}$	Ratio of operating expenses to total assets
	PROF	$\frac{EBIT}{Total\ assets}$	Ratio of operating income to total assets
	TANG	$\frac{Fixed\ assts}{Total\ assets}$	The ratio of fixed assets to total assets
	SIZE		Logarithm of total assets
	AGE		Years since foundation to observation
	OIL		Annual percentage change in oil price

3.3 Preliminary analysis

The preliminary analysis is used to inspect the data to verify appropriateness and fit for further analysis. The dataset will be examined for missing data and outliers before it is checked to see if it meets the assumptions needed for OLS regression. The objective of the preliminary analysis is to provide a description of the critical features of the data and summarize the content into an easily understood format. Ultimately the preliminary analysis will prepare the data for detailed statistical analysis (Blischke et al., 2011).

3.3.1 Data characteristics

All the data collected is on a ratio level, meaning it is categorized, ordered, has equal intervals, and a true zero (Blischke et al., 2011). The collected observations can be described as a short, dated, unbalanced and regular data panel. The data collected is unbalanced because the number of annual observations, *t*, is not equal for all firms, *n*. Furthermore, the data is short because the total number of cross-sections, *N=178 firms*, is greater than the number of periods, *T=10 years*. Finally, it is a regular panel because it follows a structure where each firm is observed annually. Due to its unique characteristics, panel data can be considered a combination of cross-sectional and time-series data, and it has several advantages over its simpler counterparts (Aljandali and Tatahi, 2018). The panel data gives more informative statistics, more variability, less collinearity among variables, more degrees of freedom, and more efficiency. Panel data can also detect and measure effects that cannot be observed in pure cross-sectional or time-series data (Aljandali and Tatahi, 2018). In the following sections of this chapter, the dataset will be checked for missing data and outliers before it is analyzed to ensure that it meets the assumptions of the primary analysis.

3.3.2 Missing data

The main concern regarding missing data is that it can negatively impact the reliability of the regression analysis (Hair et al., 2014). Generally, missing data below 10 percent for an individual variable can be ignored, except in cases where the missing data has specific, nonrandom occurrences (Hair et al., 2014). As can be seen in the descriptive statistics in Table 3, each of our variables has 1230 observations. The data spreadsheet has also been manually inspected to ensure that there are no *NA* or blank cells. It can, therefore, safely be concluded that the dataset is free of missing data.

3.3.3 Outliers

According to Hair et al. (2014), outliers are observations with a unique combination of characteristics identifiable as distinctly different from the other observations. These can be variables with extraordinary high or low values compared to the rest of the observations. Such values can greatly impact any empirical analysis. In some cases, they can result from data collection errors, and in other situations, they can give important information about a subject (Hair et al., 2014). This creates a difficult decision-making process where outliers need to be considered individually to determine their usefulness. For example, excluding extreme values can cause results to become wrongfully statistically significant, while keeping outliers increases variability in the dataset, resulting in decreased statistical power (Hair et al., 2014). The first step in this section is to identify the outliers before they are categorized and finally dealt with.

Identifying outliers

Outliers can be identified from univariate, bivariate, or multivariate perspectives based on the number of variables considered (Hair et al., 2014). To identify outliers in the best possible way, a combination of univariate and bivariate techniques will be used to look for consistent patterns across different perspectives. The *univariate detection* method examines the distribution of observations for every variable in the analysis individually to find any values that fall at the outer ranges (high or low) of the distribution (Hair et al., 2014). The challenge with univariate detection is setting an appropriate threshold for the designation of an outlier because many values will naturally be near the outer ranges of the distribution. In Figure 1 below, histograms have been developed for each variable. The *leverage*, *tangibility*, and *age* variables have observations evenly distributed across the histograms and show little evidence of having outliers. The histogram for *operating leverage* has a tall peak near zero and shows some larger values (33.5, 25, 15.18) to the right that stand out from the rest. Similarly, *profitability* has two extreme negative scores of -33.5 and -25. This is also true for *size*, which has two low observations (6.9 and 7.6). Note that no histogram has been developed for the *oil* variable. This is because the variable only takes ten different values, i.e., the oil price change for each of the ten observed years. This is illustrated in Figure 2 under bivariate detection.

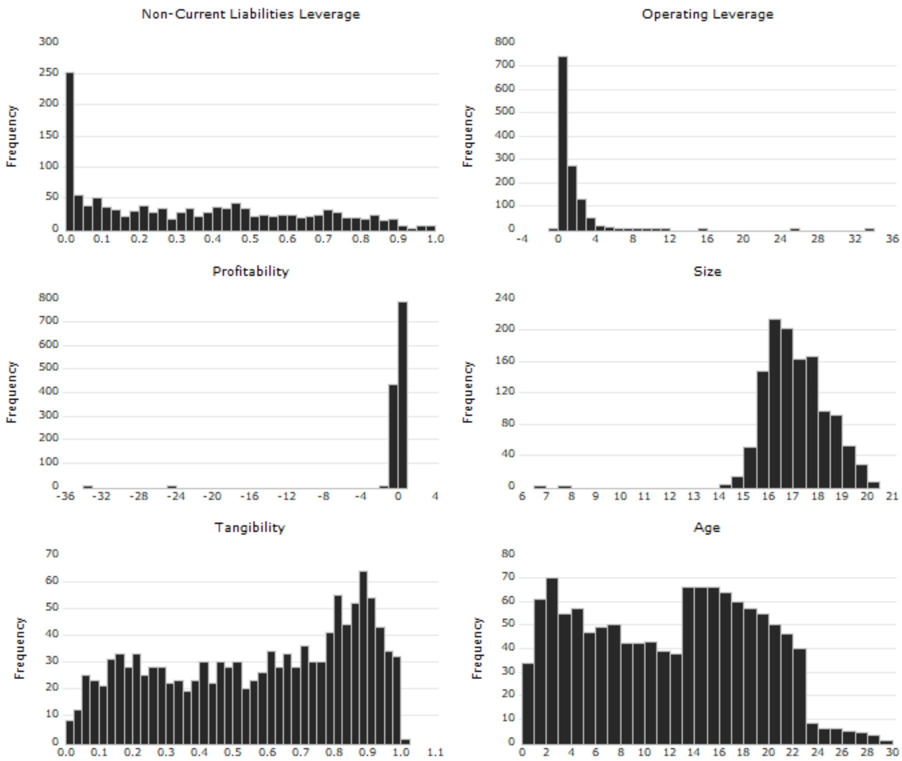

Figure 1. Histogram for each variable

In the bivariate detection method, pairs of variables can be assessed jointly through scatterplots (Hair et al., 2014). Cases that fall markedly outside the range of the other observations will be seen as isolated points. To help identify them, Hair et al. (2014) suggests adding an ellipse that represents a bivariate normal distributions' confidence interval at a 95% level over the scatterplot. A challenge with the bivariate detection method is the potentially large number of scatterplots needed if a researcher attempts to map all potential pairs of variables. Because of this, the scatterplots in Figure 2 are limited to showing all the independent variables compared to the dependent variable (leverage_ncli_). Age, tangibility, and oil price have distributions where all observations are located inside or near the 95% confidence interval ellipse. Like in the univariate detection, some outliers are identified for operating leverage, size, and profitability.

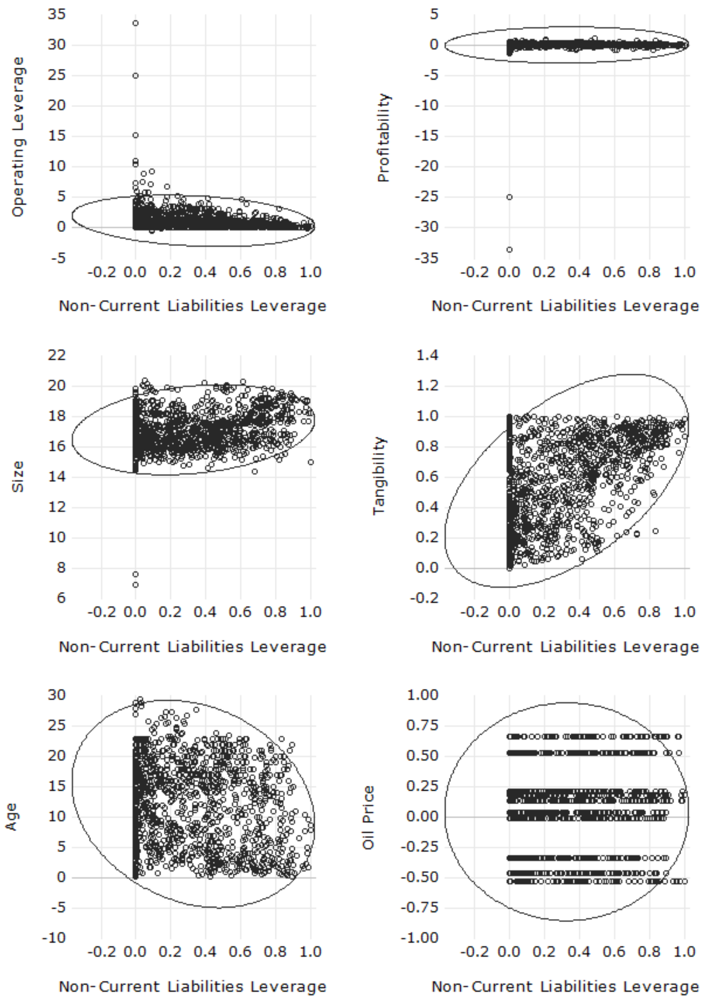

Figure 2. Scatterplots with 95% confidence interval ellipses

Categorizing outliers

The histograms and scatterplots above show that there are some outliers in the dataset. These need to be categorized as procedural errors (data entry mistakes), extraordinary events (e.g., financial crisis), extraordinary observations for which there is no clear explanation, or observations that fall within the ordinary range of values but are unique in their combination of values across the variables (Hair et al., 2014). The most obvious case of outliers in this data set is related to profitability and operating leverage. After inspection of the spreadsheet, it is found that these outliers stem from extraordinary observations of Lloyds Invest AS in 2011 and 2012. More precisely, they result from the firm having assets of one and two thousand Norwegian kroner. This caused profitability of -3550% and -2500% and 25.0 and 33.5 in operating leverage. The univariate and bivariate analyses also show some other potential outliers in operating leverage. For example, Troms Offshore Management has values of 15 and 11 for 2012 and 2013, respectively. Upon closer investigation, we find that this results from 11.6

million and 17.1 million NOK in total assets combined with operating expenses of 176 million and 189 million NOK.

Retain or delete?

If the identified outlier portrays a representative element or segment of the population, it should be retained to ensure generalizability to the entire population (Hair et al., 2014). As outliers are deleted, the researcher runs the risk of improving the multivariate analysis but limiting its generalizability (Hair et al., 2014). After careful consideration, it is decided that the benefit of adjusting Lloyd's Invest AS' values outweigh the negative consequences. The observations of Lloyd's Invest AS for 2011 and 2012 are, therefore, deleted. Because there are still 1228 observations in the dataset, this adjustment is not expected to impact the generalizability or quality of the study negatively. Finally, the remaining high values in operating leverage will be kept in the dataset. This decision is made on the basis that operating leverage's distribution has a tail to the right. These values can thus be considered observations that fall within the ordinary range of values. Histograms and scatterplots without outliers are shown in Figure 3 and Figure 4 below. The histograms show more evenly distributed values after the adjustments. There are no more apparent outliers in the scatterplots, but it is noted that operating leverage has some high values. While it was decided to retain them in the dataset, the effect of these values will be monitored throughout the analysis.

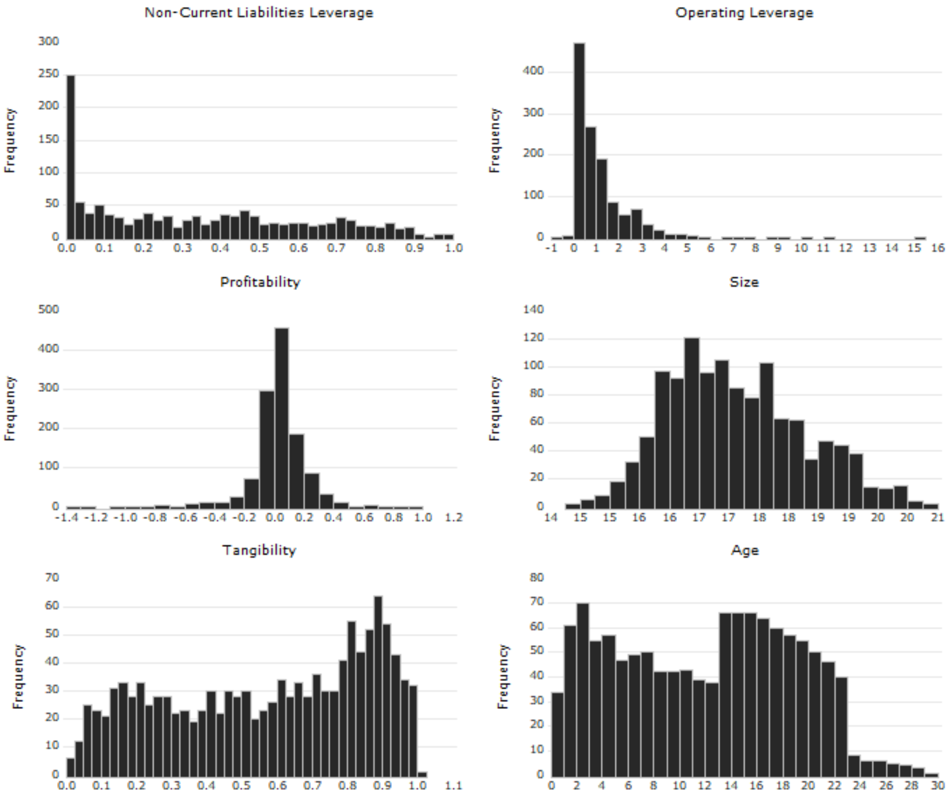

Figure 3. Histogram for each variable (without outliers)

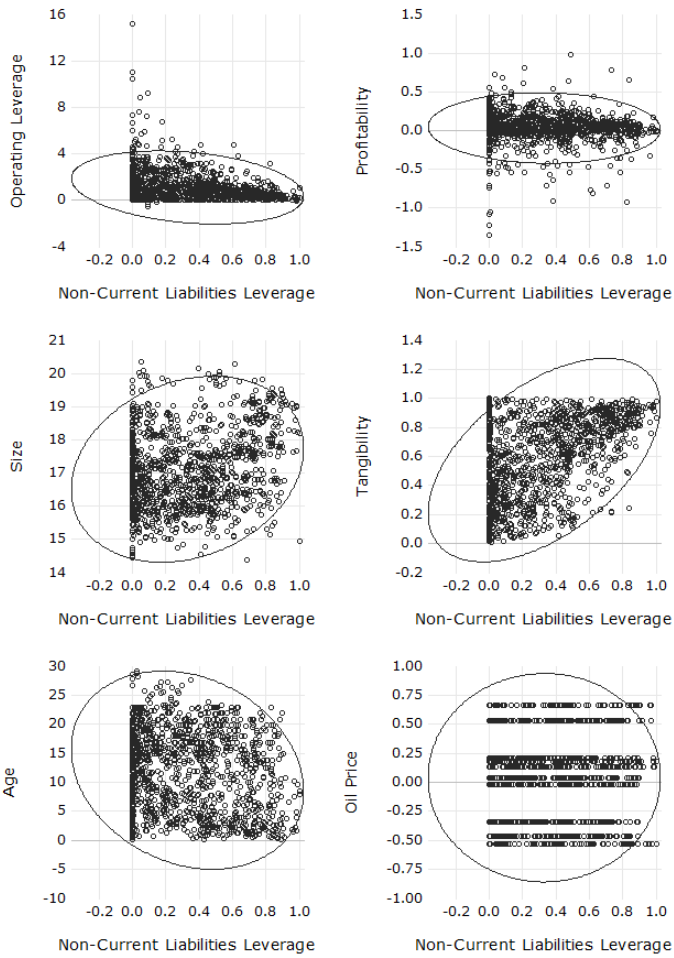

Figure 4. Scatterplots with 95% confidence interval ellipses without outliers

3.3.4 Summary statistics

We have run a descriptive statistics analysis to summarize the main characteristics of the data sample. The results are shown in Table 3 and Table 4. After removing the outliers, the observation count was reduced from 1230 to 1228 across all the variables. The dataset consists of seven variables: *age*, *size*, *profitability*, *tangibility*, *leverage*, *operating leverage*, and *oil*. The average age of the companies in this dataset is 12.1 years, with the oldest being 29 years. Next, the *size* variable is a natural logarithm of the firms' total assets. This variable will be used in further analysis, but the *total assets* variable was developed to make it easier to interpret size in the descriptive statistics. The median total assets of firms in the dataset are 22.8 million NOK. The firms have median profitability of 2.9% and a median tangibility of 61.5%. Leverage and operating leverage have medians of 28% and 72.3%, respectively. Finally, the *Oil* variable, which displays annual percentage change in Brent crude oil price, has varied between negative 53,4% and positive 66,1% throughout the observed years.

Table 3. Descriptive statistics including all observations

	Age	Size	Total Assets	Profitability	Tangibility	Leverage (NCLI)	Operating Leverage	Oil Price Change
Mean	12.0688	17.0970	54400.86	-0.0145	0.5737	0.3284	1.1495	0.0393
Median	12.8260	16.9409	22770.0	0.0289	0.6145	0.2796	0.7232	0.0347
Maximum	29.2356	20.3400	681594.5	0.9841	1.0000	0.9998	33.5000	0.6613
Minimum	0.0603	6.9078	1.0000	-33.5000	0.0000	0.0000	-0.5423	-0.5340
Std. Dev.	6.9670	1.2100	81451.40	1.2070	0.2868	0.2840	1.7211	0.3659
Skewness	0.0072	-0.5139	3.3265	-24.5988	-0.2991	0.4502	8.8920	-0.0083
Kurtosis	1.8670	9.2552	16.8999	631.7647	1.7674	1.9590	138.8385	2.0141
Observations	1230	1230	1230	1230	1230	1230	1230	1230

Table 3 shows the descriptive statistics with every observation originally from the dataset. The dataset includes 178 Norwegian shipping SMEs from the period 2008-2017.

Table 4. Descriptive statistics without outliers

	Age	Size	Total Assets	Profitability	Tangibility	Leverage (NCLI)	Operating Leverage	Oil Price Change
Mean	12.0846	17.1131	54489.46	0.0331	0.5746	0.3289	1.1037	0.0392
Median	12.8562	16.9507	222993.50	0.0293	0.6152	0.2804	0.7223	0.0347
Maximum	29.2356	20.3399	681594.5	0.9841	1.0000	0.9998	15.1815	0.6613
Minimum	0.0603	14.3757	1751.00	-1.3525	0.0079	0.0000	-0.5423	-0.5340
Std. Dev.	6.9614	1.1438	81488.12	0.1858	0.2861	0.2839	1.2838	0.3662
Skewness	0.0049	0.3914	3.3247	-1.3491	-0.2985	0.4482	3.2915	-0.0077
Kurtosis	1.8705	2.5775	16.8823	12.8359	1.7652	1.9581	23.5839	2.0110
Observations	1228	1228	1228	1228	1228	1228	1228	1228

Table 4 shows the descriptive statistics when the dataset is adjusted for outliers. The dataset includes 178 Norwegian shipping SMEs from the period 2008-2017.

3.3.5 The shape of the distributions

Normality refers to the shape of the data distribution for an individual metric variable and is the benchmark for statistical methods (Hair et al., 2014). Having a normal distribution is not a requirement for running regressions in panel data. However, it provides a valuable insight into the distribution of key financial measures among the Norwegian shipping firms. The skewness and kurtosis of the individual variables describe how the shape of the distribution differs compared to a normal distribution (Hair et al., 2014). The kurtosis of a normal distribution is 3. If the kurtosis exceeds 3 the distribution is peaked (leptokurtic) relative to the normal, and if the kurtosis is less than 3 the distribution is flat (platykurtic) relative to the normal. The skewness measures the asymmetry of the distribution of the series around its mean (Hair et al., 2014). The skewness of a symmetric distribution, such as the normal distribution, is zero. Positive skewness means that the distribution has a long right tail and negative skewness implies that the distribution has a long left tail. The findings are summarized in Table 5 below. When seen in combination with the histograms in Figure 3, size and age are the closest to normal distributions. Age, leverage_ncli_, size, and tangibility are all flatter than a normal distribution while operating leverage and profitability are peaked. Furthermore, leverage, size, and tangibility have small shifts to the right, while size, operating leverage, and size shift to the left.

Table 5. The shape of the distributions

Variable	Description of distribution
Age	1.87 kurtosis platykurtic (flatter), 0.005 skewness (normal distribution)
Leverage	1.96 kurtosis platykurtic (flatter), 0.448 skewness (slight right shift)
Oil	2.01 kurtosis platykurtic (flatter), -0.008 skewness (normal distribution)
Operating Leverage	23.59 kurtosis leptokurtic (peaked), 3.292 skewness (shift to the left)
Profitability	12.84 kurtosis leptokurtic (peaked), -1.349 skewness (shift to the right)
Size	2.58 kurtosis platykurtic (flatter), 0.391 skewness (slight shift to the left)
Tangibility	1.77 kurtosis platykurtic (flatter), -0.299 skewness (slight shift to the left)

Table 5 summarizes the kurtosis and skewness of the 178 Norwegian shipping SMEs.

3.4 Assumptions of OLS

This study aims to identify determinants of default through various regression models, and the classic linear regression model will be used as a starting point. As seen in Equation 1 below, it is a simple model where the dependent variable y_t, is estimated using the intercept $\propto$, the regression coefficient β, an independent variable x_t, and the error term u_t. This model can produce consistent, unbiased, and efficient results when certain assumptions hold (Brooks, 2014).

The classic linear regression model

$$y_t = \alpha + \beta x_t + u_t \tag{1}$$

The four assumptions shown in Table 6 are based on suggestions by Brooks (2014). Assumption one requires the error term, u_t, to have zero mean and no systematic pattern. Assumption two is constant and finite variance across errors, often called homoscedasticity. If the variances are non-constant, they are heteroscedastic. Assumption three is that there is no autocorrelation, or covariance over time between error terms. Finally, assumption four requires non-stochastic variables that are uncorrelated with the error terms. The importance of having non-stochastic variables is reduced if assumption one holds (Brooks, 2014). Additionally, because all the variables in this study have fixed and predetermined values, the assumption of non-stochasticity already holds. If all assumptions hold, the OLS regression fulfills the properties needed to be a best linear unbiased estimator (BLUE) (Brooks, 2014). Then, the $\propto$ and β determined by the regression model are close to their real-world values. This means that respecting the assumptions of a regression model is of great importance. Therefore, the remainder of this chapter is dedicated to testing if these assumptions are met in our dataset. However, before testing the actual assumptions, the implicit assumption of no multicollinearity needs to be discussed.

Table 6. Assumptions of OLS

1)	$E(u_t) = 0$	The errors have zero mean
2)	$var(u_t) = \sigma^2 < \infty$	The variance of the errors is constant and finite over all values of x_t
3)	$cov(u_i, u_j) = 0$	The errors are linearly independent of one another
4)	$cov(u_t, x_t) = 0$	There is no relationship between the error and the corresponding x variate

3.4.1 Multicollinearity

Collinearity refers to the association between two independent variables. Multicollinearity is the correlation between three or more independent variables (Hair et al., 2014). Assessing multicollinearity is essential because it reduces any single independent variable's predictive power. As multicollinearity increases, the unique variance explained by each independent variable decreases, and therefore the model's predictivity becomes weaker (Hair et al., 2014). To have a robust model with good predictivity, the model should contain independent variables with low multicollinearity between each other but high correlation with the dependent variable (Hair et al., 2014).

To assess multicollinearity, we run a Pearson correlation analysis. The Pearson correlation coefficient (r) can only take a value between –1 and 1, indicating the direction and volume of the correlation (Pallant, 2016). A negative coefficient means that as one variable increases, the other decreases. In the case of a positive coefficient, as one variable increases, the other variable also increases. The size of the absolute value shows the strength of the relationship, where coefficients 1 and –1 indicate perfect correlation. If the value of Pearson correlation is 0, there is no relationship between the two variables (Pallant, 2016). There are multiple different ways to interpret the output of the Pearson correlation test. However, this research will apply the thresholds proposed by Cohen (1988), suggesting that values between r=0.1 and r=0.2 indicate a small correlation, values between r= 0.3 and 0.4 indicate medium correlation and values between r=0.5 and r=1.0 suggest a large correlation. The output is shown in Table 7 below. The results suggest no high correlation values between the independent variables, but there is one between the dependent variable, leverage, and the independent variable, tangibility. Moreover, only two values suggest a medium correlation: between *operating leverage* and *size* with the value of -0.3373 and between *operating leverage* and *tangibility* with the value of -0.3987. Based on these findings, we conclude that the variables in this study are not affected by a high amount of multicollinearity.

Table 7**.** Output for covariance analysis

Variable	Age	Leverage (NCLI)	Oil Price Change	Operating Leverage	Profitability	Size	Tangibility
Age	1.0000						
Leverage (NCLI)	-0.2137	1.0000					
Oil Price Change	0.0264	0.0030	1.0000				
Operating Leverage	-0.0475	-0.2466	-0.0185	1.0000			
Profitability	-0.0382	-0.0380	-0.0049	-0.0788	1.0000		
Size	0.0432	0.2218	0.0218	**-0.3373**	-0.1148	1.0000	
Tangibility	-0.1515	**0.5271**	0.0148	**-0.3987**	-0.0559	0.1986	1.0000

Table 7 displays the output for the covariance analysis between the different independent variables and the dependent variable. Medium and large correlation values are set in bold. The dataset includes 178 Norwegian shipping SMEs from the period 2008-2017.

3.4.2 Homoscedasticity

Homoscedasticity means equal variance of the error term, u_t, across all values of the independent variables (Porter and Gujarati, 2008). Without homoscedasticity, the error terms are unequal, and the different values will have different pulls in the regression. This is called heteroscedasticity. Heteroscedasticity is sometimes expected in panel datasets due to natural differences between cross-sections (Porter and Gujarati, 2008). For example, firm A might be twice the size of firm B, or it might be much more profitable. Under such circumstances, it intuitively makes sense that one might see an inequal variance of the error term between firms.

Table 8 shows the results of a Breusch-Pagan and simplified White test for heteroscedasticity. Both tests are significant on a 1% level. We reject the null hypotheses and accept the alternative hypotheses that there is strong evidence of heteroscedasticity (Brooks, 2014). This means that OLS assumption three is violated. While a regression model will still yield consistent and unbiased results, heteroscedasticity should be dealt with to prevent a negative impact on the coefficient standard errors (Brooks, 2014). Brooks (2014) suggests doing this by either transforming the variables or using robust standard error estimates. Transforming the variables in this dataset is undesirable because the variables sometimes contain zeros and negative values. This makes them unfit for transformation through, for example, logarithms. We, therefore, choose to use robust standard error estimates in all regression models. Specifically, we will employ the White Period coefficient covariance method in EViews, as Brooks (2014) suggested.

Table 8. Testing for heteroscedasticity

	F-statistic	P-value	Conclusion
Simplified White test	59.88	0.000	Evidence of heteroscedasticity
Breusch-Pagan	27.82	0.000	Evidence of heteroscedasticity

Table 8 shows the result of Breusch-Pagan and a simplified White test for Heteroscedasticity. The dataset includes 178 Norwegian shipping SMEs from the period 2008-2017.

3.4.3 Stationarity and autocorrelation

Before conducting the autocorrelation and stationarity test, it is useful to understand how the different regression models function. This will be helpful knowledge for the selection of stationarity and autocorrelation test parameters, as well as for the primary analysis. Autoregressive (AR) models attempt to forecast a series based solely on the past values in the series – called lags (Brooks, 2014). A model that depends only on one lag in the past is called an AR model of order one (AR1). In this model, every observation in the AR1 model looks back at the Y of the year before. This means that, even though there is only a one-year lag, the first year has a minor impact on today's value (long memory model) (Brooks, 2014). For example, in our dataset, an AR model could be sensitive to the one-time shock caused by the financial crisis. This could reduce the predictive ability of the regression model. However, the effects of those old shocks go away with stationarity, and this is why stationarity is so crucial for autoregressive models. Moving average (MA) models, on the other hand, attempt to forecast a series based on the past errors in a series (Brooks, 2014). An MA(1) model depends only on one lag error of the past, plus some innovation error. The error from yesterday affects the current value of Y. Because the model is only affected by the previous year's error, it is a short memory model. The MA model is unique because of its constant mean and variances (Brooks, 2014).

Due to the sensitivity of AR models, stationarity is a necessary assumption in regression analysis. A data series is stationary when there is a constant mean, variance, and autocovariance for each given lag (Brooks, 2014). Without stationarity, the dataset could contain what is called a unit root (Brooks, 2014). This means that there is no correlation between any *y* value, making the pattern unpredictable. Without any trend over time in *y* values, the regression analysis attempts to predict a random walk process due to the different error terms (Brooks, 2014). Because residuals are estimates of the error terms, a unit root test will be run on them to check for stationarity. With leverage as the dependent variable, and age, oil, operating leverage, profitability, size, tangibility as independent variables, the residuals are shown as a graph below in Figure 5. Visual inspection of the graph shows no apparent trends, and there seem to be roughly constant means and variances across all observations.

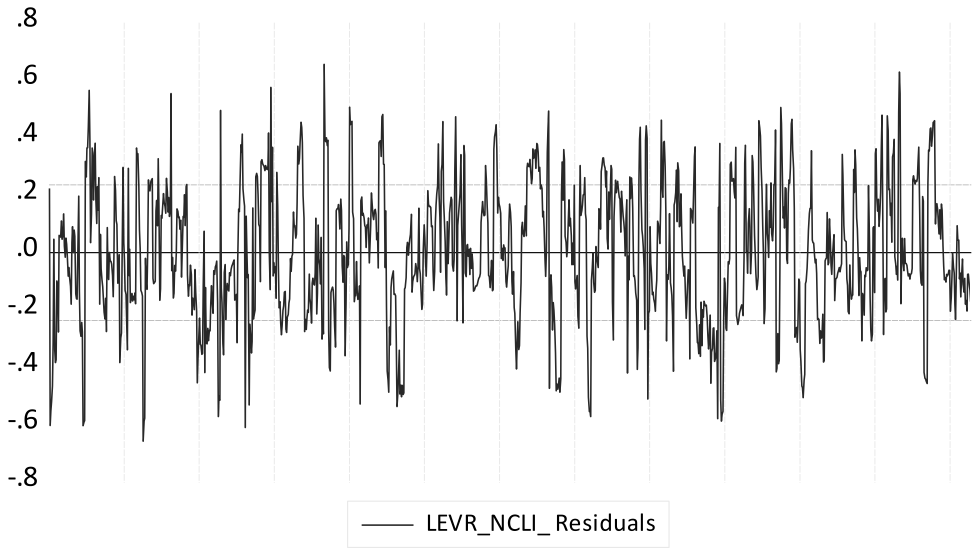

Figure 5. Line graph of residuals

Stationarity can be formally tested by running unit root tests for each variable in the dataset (Brooks, 2014). We employ the Schwarz criterion for lag differences and Bartlett Kernel and Newey-West method for bandwidth. The Im, Pesaran (2015), and Shin (IPS), Fisher ADF, and Fisher PP tests assume that the autoregressive processes vary freely across cross-sections (firms). All tests are run at level, first for intercept and trend, and then for intercept only. The null hypothesis in the intercept and trend test is that the variable is a random walk with a drift around a deterministic trend (Porter and Gujarati, 2008). The null hypothesis in the intercept test is that the variable is a random walk with a drift. This means that for there to be stationarity, the residuals should have a p-value below 0.05. In Table 9 below, we can see that the null hypothesis is rejected at 1% level for all variables except age. We accept the alternative hypothesis that there is no unit root and that we have stationarity and trend stationarity in all other variables. Age is a particular case as it follows a continuous structure where it increases by one for each time a firm is observed. While it is possible to remove the unit root by de-meaning or transforming it into a categorical variable, we decide to keep it in its natural form to maximize its explanatory purpose. However, it will be given attention in the analysis to ensure it does not negatively impact the regression models. Thus, OLS assumption one holds.

Table 9. P-values From Unit Root Tests

	ADF test		PP test		IPS test	
Variables	Intercept	Intercept and trend	Intercept	Intercept and trend	Intercept	Intercept and trend
Levr_ncli	.000	.007	.000	.000	.000	.000
Age	1.00	.000	1.00	.000	1.00	.000
Oil	.000	.000	.000	.000	.000	.000
Oplev	.000	.000	.000	.000	.000	.000
Prof	.000	.000	.000	.000	.000	.000
Size	.000	.000	.000	.000	.000	.000
Tang	.000	.000	.000	.000	.000	.000

Table 9 shows the ADF, PP and IPS unit root tests for all eight variables. The dataset includes 178 Norwegian shipping SMEs from the period 2008-2017.

Autocorrelation is related to stationarity and exists when sequential observations (for example, 2010, 2011, and 2012) have neighboring error terms that correlate (Stratz, 2019). If we consider the simple regression model in Equation 2 below, it consists of the dependent variable y_t, the independent variable x_t, the vector β, and the error term u_t. When studied in greater detail, the error term consists of two components. ρu_{t-1} is the portion of the error term that is carried over from the previous observation, while $\in_t$ is a new uncorrelated innovation. If $\rho = 0$, no portion of the previous observation's error term is carried over, and there is no autocorrelation (Startz, 2019).

A simple autocorrelation model

$$y_t = \beta x_t + u_t \text{ , where } u_t = \rho u_{t-1} + \epsilon_t, 0 \leq |\rho| < 1 \tag{2}$$

Autocorrelation can impact standard errors and t-statistics, as well as lead to bias in estimated regressions. These need to be mapped and dealt with to improve the quality of our forecasting (Startz, 2019). EViews does not offer testing for autocorrelation in panel data but instead includes the Durbin-Watson statistic in the regression output. The null hypothesis in the Durbin-Watson test is that there is no first-order autocorrelation. We run a simple regression with leverage as the dependent variable and age, oil, operating leverage, profitability, size, and tangibility as independent variables. From this regression, a Durbin-Watson of 0.3516 is found. This is far below the recommended value of 2., meaning that we must reject the null hypothesis and assume there is autocorrelation (Startz, 2019). OLS assumption three is, therefore, violated. Generally, the Durbin-Watson statistic is efficient in revealing autocorrelation. However, it will not be reliable under certain circumstances, for example, in a dynamic model (Brooks, 2014). For that reason, a Breusch-Godfrey test is conducted for easier comparison between models throughout the paper. After running a regression, we obtain the residuals and regress them on one or more of its lagged values. When the null hypothesis holds, the errors of the present value are not correlated with the error of the lagged value (Brooks, 2014). The result of the Breusch-Godfrey test is shown in Table 10. We reject the null hypothesis at 1% level and understand that the dataset has autocorrelation.

Table 10. Breusch-Godfrey test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESID(-1)	0.8190	0.0175	46.8187	0.0000

Table 10 shows the output of a Breusch-Godfrey autocorrelation test. A p-value of 0.000 means we reject the null hypothesis at 1% level. The results are based on the 178 Norwegian shipping SMEs.

In summary, the dataset violates some assumptions needed for the OLS to be the best linear unbiased estimator. Having autocorrelation violates assumption three, and it is negative because it puts restrictions on which models can be used. However, an upside to autocorrelation is that we can use it to our advantage by lagging the dependent variable, which essentially gives us another explanatory variable (Brooks, 2014). Furthermore, the analysis uncovered that the data is heteroscedastic, which violates assumption two. All regression models will have to use a coefficient covariance method that produces robust standard error estimates to account for this.

We will now discuss a series of models and see which ones give good results while also reducing autocorrelation.

4 Methodology

In this chapter, we give a brief account of the statistical methods that will be used in the analysis. First, we present fixed- and random effect estimators as two different approaches to handling the intercept terms of regression models. Then, we will run a Hausman test to determine which of the techniques is more appropriate for our dataset. Finally, we discuss the five different panel regression models.

4.1 Choosing a panel estimator

We are interested in studying the effects of independent variables on the dependent variable to identify possible indicators of default. However, it is not always possible or desirable to find variables that account for all possible impacts on a dependent variable. This introduces the omitted variables problem (Wooldridge, 2001b). Consider the simple population regression function in Equation 3 below. This function represents the true relationship between variables and simplifies the actual data generation process (Brooks, 2014). The dependent variable y, in our case non-current liabilities leverage, depends on some observable explanatory variables, as well as some unobservable random variable denoted c. Because we are only interested in studying the partial effects of the observable independent variables, we want to control for the unobserved variable by using a fixed effects or random effects estimator.

The omitted variables problem

$$E(y|x,c) = \beta_0 + x_1\beta_1 + \cdots + x_n\beta_n + c \tag{3}$$

To help select the most suitable estimator, we can continue the example in a simplified manner in Equation 4 by studying a specific y_{nt} and dividing c into two separate parts. The first part is a time constant variable, μ_i. This is an unobserved effect that accounts for constant firm characteristics such as the sector of operation and organizational structure (Wooldridge, 2001b). The second part, v_{it}, accounts for other disturbances that vary across time and cross-section (Brooks, 2014). Notice that μ_i only varies from cross-section to cross-section. This means it is an individual effect. The idiosyncratic disturbance v_{it}, on the other hand, varies across both cross-section and time (Wooldridge, 2001b).

A panel data model with individual effect and idiosyncratic disturbance

$$y_{it} = \alpha_i + \beta x_{it} + u_{it}\ , where\ u_{it} = \mu_i + v_{it} \tag{4}$$

According to Brooks (2014) a random-effects model is more appropriate when the entities in the sample are randomly selected from a population, while a fixed-effects model is a better fit when the sample constitutes the entire population. Based on this presumption, fixed effects models could be a better choice for our dataset since it includes nearly all the Norwegian shipping SMEs, not only a random sample of them. The unobserved effect is, therefore, not expected to be random. More technically, the random effects estimator requires u_{it} to be entirely uncorrelated with all independent variables (Brooks, 2014). If there is a correlation, the fixed effects estimator is preferable.

The Hausman test (1978) is a popular tool to test for exogeneity. The hypotheses of this test are shown in Equation 5. If the null hypothesis of no covariance is rejected, we must treat the variables as endogenous. This means that we accept the alternative hypothesis and assume there is a correlation between y_{nt} and u_{nt}, and the fixed effects estimator should be used (Brooks, 2014). The result, which can be found in Table 11, is significant at 1% level. We reject the null hypothesis and note that a fixed effects estimator will compute more consistent results in our data set. A fixed-effects estimator will therefore be applied to the chosen regression models that are discussed below.

The hypothesis of the Hausman test

$$H_0 = Cov(u_{it}, x_{it}) = 0\ and\ H_1 = Cov(u_{it}, x_{it}) \neq 0 \tag{5}$$

Table 11. Results of the Hausman test

Test summary		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob
Cross-section random		36.155291	6	0.0000
Cross-section random effects variables:				
Variable	Fixed	Random	Var (Diff.)	Prob.
Age	-0.014787	-0.011163	0.000001	0.0002
Oil Price Change	-0.004579	-0.004555	0.000001	0.9751
Operating Leverage	0.014272	0.006784	0.000009	0.0139
Profitability	-0.044524	-0.030037	0.000051	0.0426
Size	0.113762	0.082086	0.000048	0.0000
Tangibility	0.314875	0.351618	0.000197	0.0089

Table 11 shows the result of the Hausman test for exogeneity. The results are based on the 178 Norwegian shipping SMEs included from the period 2008-2017. A p-value of 0.000 means we reject the null hypothesis at 1% level. This indicates endogeneity.

As shown in Equation 6, the fixed effects estimator subtracts the time-mean value of each firm from the values of each variable, as well as from the unobserved effect (Brooks, 2014). This within transformation creates a regression model, shown in Equation 7, with only demeaned variables. In this model, it does not matter if a firm has very high or low values on its variables over time, because it only studies the variation around the mean values. One of the benefits of doing this is that it removes the unobserved individual effects ($\bar{\mu}_i$) that are constant for each firm over time (Brooks, 2014). This could include factors such as city, the segment of operation, organizational structure, or other time-constant firm-specific characteristics. The fixed effects estimator essentially removes the effects of cross-firm indifferences, making it easier to study the observed independent variables separately. However, some omitted variable bias can remain if any of the explanatory variables correlate with the idiosyncratic disturbance (v_{it}) (Wooldridge, 2010).

The fixed effects estimator

$$y_{it} - \bar{y}_i = \beta(x_{it} - \bar{x}_i) + u_{it} - \bar{u}_i \tag{6}$$

The demeaned regression model

$$\ddot{y}_{it} = \beta\ddot{x}_{it} + \ddot{u}_{it} \tag{7}$$

4.2 GLS weight and coefficient covariance method

As we discovered in the preliminary analysis, the dataset has autocorrelation and heteroscedasticity. According to Woolridge (2001b), fixed cross-section effects, no GLS weight, and white period coefficient covariance method with no d.f. correction is an effective way to compute standard errors that are robust to autocorrelation. In EViews, the White period coefficient covariance method allows for one-way cross-section clustering and assumes that the cross-sections' errors are heteroskedastic and serially correlated. It is also important to note that EViews automatically adjusts for missing values in the data. When different effects, GLS weights, and coefficient covariance methods are used, the software might drop both periods and observations that do not correspond with the specific settings used. This will be reflected in the number of observations reported in the regression output.

4.3 The AR model

A popular method to deal with autocorrelation is the autoregressive model. This model assumes that the autocorrelation’s structure is of a particular form, usually a first-order autoregressive process (Brooks, 2014). The model is specified in Equation 8.

Autoregressive model

$$y_t = \beta_1 + \beta_2 x_{2t} + \cdots + \beta_{nt} x_{nt} + u_t, where\ u_t = pu_{t-1} + v_t \tag{8}$$

A constant is not needed for the specification of errors, since $E(u_t) = 0$. Furthermore, since the model holds at time t, it would also hold for t-1, meaning that Equation (8) above is lagged one period. After the equation is rewritten with t-1 and multiplied with ρ, this new equation is subtracted from the original. After factorizing, the final specification of the autoregressive model is shown in the following Equation 9.

The final specification of the autoregressive model

$$y_t^* = \beta_1^* + \beta_2 x_{2t}^* + \ldots + \beta_n x_{nt}^* + v_t \tag{9}$$

The final specification of the autoregressive model contains an error term, v_t, that is free from autocorrelation. This means that an OLS can be applied directly to it, effectively applying GLS regression (Brooks, 2014). To run the first first-order autoregressive model in EViews, leverage will be the dependent variable, and AR(1) will be included among the independent variables on the right side of the equation.

4.4 Dynamic model

A more modern approach to autocorrelation is viewing it as an opportunity rather than a problem. Sargan et al. (1978) suggest that autocorrelation in the errors exists due to a dynamic structure in the regression that has not been modeled and thus is not captured in the fitted values. Compared to a static model where the change of one or more of the independent variables at time t causes an instant change in the dependent variable, the current value of y in a dynamic model depends on the previous value of y, or a chosen number of other lagged variables (Brooks, 2014). A one-year lag of the dependent variable (leverage) is included among the independent variables to transform our static model into a dynamic model. This is seen in Equation 10. In addition to the model including a one-year lag of leverage, we run a separate dynamic model with a two-year lag of leverage. The inclusion of leverage can capture important dynamic structures in the dependent variable. Lastly, according to Margaritis and Psillaki (2010), the effect of leverage on firm performance and vise versa is usually not immediate. To test if this is true in our data sample, we run a final dynamic model where we include a one-year lag of all the independent variables.

The dynamic model

$$y_t = \beta_1 + \beta_2 x_{2t} + \cdots + \beta_{nt} x_{nt} + p y_{t-1} + u_t \qquad (10)$$

4.5 First difference model

Another version of a dynamic model is one where variables of first differences instead of levels are constructed. The first difference of a variable can be found by subtracting the previous year's value from the current value. This means that the model will study only the annual change in each variable, which can help reduce autocorrelation in the residuals (Brooks, 2014; Wooldridge, 2001b). The first difference model is very similar to a fixed-effects model. If $T = 2$, their coefficients will be the same. However, because $T > 2$ in this dataset, the coefficients and significance are expected to differ. An example of a first difference model is shown for the dependent variable in Equation 11. Similarly, the first difference can be calculated for all the independent variables, as shown in Equation 12. In practice, we then have a lagged version of each series in the model. This solution, however, means that we lose the first time-period observation for each firm in the dataset (Wooldridge, 2001b). The total observation count is, therefore, expected to be lower than for the other models. Additionally, the first difference model introduces a moving average structure of order one (Brooks, 2014). The regression is now calculated using both the current and the lagged error term. The benefit of the first difference model is also a possible downside. By studying the change on an annual basis, the model is one of short-term memory. Long-term trends, previous shocks, or other vital information can be lost in the regression. It will therefore be compared to the other models to ensure reliability.

The first difference of a variable

$$\Delta y_t = y_t - y_{t-1} \tag{11}$$

The first difference model

$$\Delta y_t = \beta_1 + \beta_2 \Delta x_{2t} + \beta_3 \Delta x_{3t} + \cdots + \beta_n \Delta x_{nt} + \Delta u_t \tag{12}$$

4.6 Generalized method of moments model

A more advanced approach to autocorrelation uses Generalized method of moments (GMM) (Wooldridge, 2001a). This method was introduced by Hansen (1982). When combined with the Arellano-Bond estimator, it can take on a dynamic panel structure where lags of the dependent variable are included among the other regressors. However, what makes GMM unique compared to the other models is how it attempts to estimate moment conditions on the population level through analysis on a limited sample (Woolridge, 2001a). The complexity of GMM means that it is not feasible to explain in detail here. A simplified explanation of what makes the GMM stand out from the other models in our study follows.

A moment condition can be a defined as specific characteristic or effect present in the population (Woolridge, 2001a). If multiple moment conditions contain similar parameters, most models will struggle because this means more moment conditions, or equations to be solved, than parameters, or degrees of freedom. When GMM allows more moment conditions than parameters, it essentially makes it possible to solve equations that cannot be solved in other models (Woolridge, 2001a). These moment conditions are estimated by combining the model variables with instruments. An instrument is a proxy variable that is highly correlated with the explanatory variable while remaining uncorrelated with the error terms (Gujarati and Porter, 2009). Thus, finding good instruments can often be a key issue when using GMM, unless the topic of interest has several known and measurable exogeneous variables. Another issue is that researchers add instruments in an ad hoc manner, meaning that what one researcher may add, the other one may not. For example, a researcher may be tempted to add more and more moment conditions until the desired result is achieved (Wooldridge, 2001a). In our study, the instruments chosen are based on the Arellano-Bond estimator. This estimator uses lags of the dependent variable and lagged first differences of the independent variables as instruments (Baltagi, 2005).

4.7 Binary probit model

Binary probit regression helps study if a particular event has taken place. This is because it predicts the relationship between the regressors and a binary dependent variable (Gujarati and Porter, 2009). A binary variable only takes values 0 and 1. Because leverage_ncli_ is a continuous variable, it must be transformed to a dummy variable to make it suitable for binary logit regression. Specifically, the dummy variable will have value 1 when non-current leverage increases by 10% or more in one year and value 0 if non-current leverage increases by less than 10%. This will make it possible to study which factors cause firms to raise funds through long-term debt. A simple binary logit model is shown in Equation 13. The left part of the equation shows the probability of the dummy taking a value of 1, divided by the probability of the dummy taking a value of 0. In other words, it shows the odds of a 10% increase in leverage. A log function is then applied to the odds to make it more appropriate for statistical calculations (Gujarati and Porter, 2009). This allows us to estimate the probability of an increase in leverage based on the independent variables. As suggested by Brooks (2014), we will use Huber/White to ensure heteroscedasticity robust standard error estimates.

A simple binary probit model

$$\ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + u_t \tag{13}$$

5 Results

In this chapter, we will first present the details about how each model was run. This involves getting an overview of which effects and independent variables have been included. Based on some key measures, we select which models will be used for further analysis. These models will be compared, and special attention is given to the coefficients, signs of the coefficients, and the p-values of each variable. These are also the models that the discussions in Chapter 7 will be based on.

5.1 The AR model results

The first thing we need to do is to find out if the autocorrelation is of first-order or higher order (Startz, 2019). We will do this by comparing an autoregressive model with AR(1) included to a model where both AR(1) and AR(2) are included. It is important to note that with the autoregressive model in EViews, both the R^2 and the Durbin-Watson statistic output together with the regression result will be based on the model's innovations rather than the errors (Startz, 2019). This means that the AR(1) term is now included in the R^2 and that the Durbin-Watson statistic turns into a test for remaining autocorrelation after the first-order autocorrelation has been corrected for (Startz, 2019). Thus, the Durbin-Watson is an effective measure to determine whether the autoregressive model managed to remove autocorrelation.

5.1.1 Comparing the AR(1) and AR(2) model

To determine which of the two models is more appropriate, we run a regression and extract the values of the AR components. While AR(1) only corrects for first-order autocorrelation, AR(2) corrects for first-order and second-order autocorrelation. The results of the models are shown in Table 12 below. We can see that the coefficient for the first-order autocorrelation AR(1) term, 0.86, is much larger than zero. This is a strong sign confirming previous results that there is autocorrelation of the first order present in the dataset (Startz, 2019). When AR(2) is included in addition to AR(1), the coefficient of AR(2) is smaller (0.055) and statistically insignificant at 10% level. This means there is no evidence of second-order autocorrelation. Additionally, the increase in the Durbin-Watson statistic between the models is negligible at only 0.033, and the included observations are greatly reduced from 1050 with AR(1) to 879 with AR(2) included. These are strong indications that AR(2) should not be included in the autoregressive model and that AR(1) is sufficient for removing the autocorrelation.

Table 12. AR(1) and AR(2) results

	AR(1) model	AR(2) model
AR(1)	0.8614***	0.8368***
	(0.0185)	(0.0342)
AR(2)		0.0553
		(0.0321)
Observations	1050	879
Adj. R^2	0.7950	0.8180
Durbin-Watson	1.9041	1.9313
Breusch-Godfrey	0.5150	0.9864

Table 12 shows the results of two autoregressive models. The AR(1) model only includes AR(1), and the AR(2) model includes both the AR(1) and AR(2) terms. The terms' coefficients are presented, as well as their standard errors in parentheses. The p-value of Breusch Godfrey is also presented (*** means autocorrelation)
*Significant at 10% level
**Significant at 5% level
***Significant at 1% level

While the inclusion of AR(1) is already shown to be sufficient for this model, this can be proven further by looking at the correlogram of the AR parameters. These are called the autocorrelation functions (ACF) (Startz, 2019). The theoretical line (solid) is compared to the empirical line (top of the spikes) to determine whether the specification of the AR(1) model is sufficient (Startz, 2019). The results are shown below in Figure 6 and Figure 7Figure 7 and indicate that the theoretical and empirical line is closer with only AR(1) included. Based on these results, it is decided that the autoregressive model with AR(1) is better suited than the model with both AR(1) and AR(2) included.

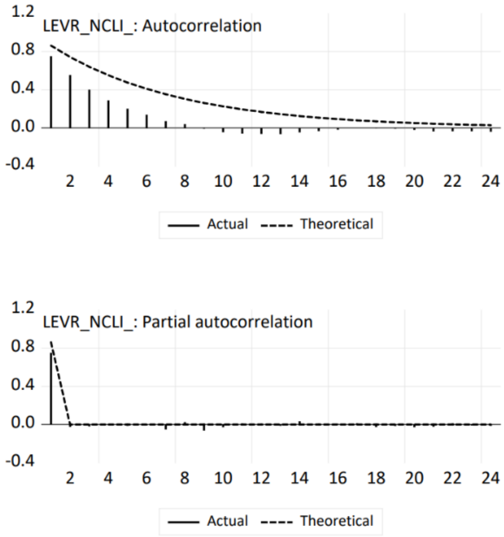

Figure 6. Theoretical and empirical correlogram AR(1)

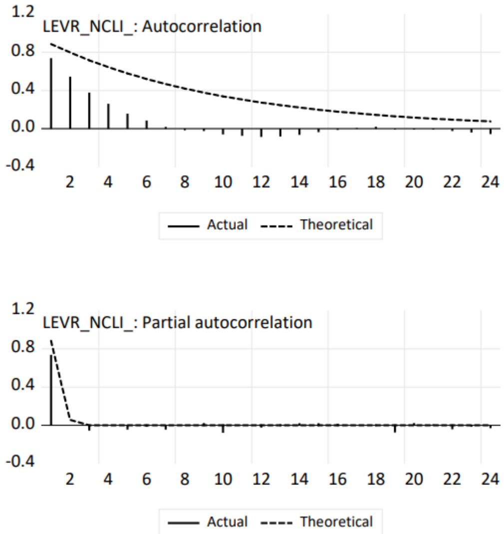

Figure 7. Theoretical and empirical correlogram AR(1) and AR(2)

We have applied fixed cross-section effects and white-period coefficient covariance method with no d.f correction to the AR(1) model. The results are shown in Table 13 below. Column 1 contains the regression output without firm fixed effects, and column 2 contains the results with firm-fixed effects. The first thing to notice is the increase in Durbin Watson from 1.90 to 1.95 when fixed effects are applied, as well as the increase in R^2 from 0.79 to 0.84. The R^2 is not necessarily an objective measure, but it can be a helpful tool when comparing two models with each other (Brooks, 2014). Even though the R^2 increases, the coefficient value of AR(1) decreases from 0.86 to 0.46. Finally, the Breusch-Godfrey test results at the bottom of the table confirm that autocorrelation of order one is no longer an issue in the model, as we retain the alternative hypothesis at 1% level. Based on these findings, it is concluded that the AR(1) model with fixed effects applied is more appropriate for further analysis.

Table 13. Autoregressive model results

	[1]	[2]
C	-2.1704***	-1.7705***
	(0.3709)	(0.4579)
AGE	-0.0027	-0.0132***
	(0.0046)	(0.0039)
OIL	-0.0009	-0.1167
	(0.0092)	(0.0112)
OPLEV	0.0119**	0.0127*
	(0.0058)	(0.0068)
PROF	-0.0720**	-0.0620*
	(0.0211)	(0.0364)
SIZE	0.1330***	0.1225***
	(0.0219)	(0.0255)
TANG	0.2689***	0.2627***
	(0.0417)	(0.0528)
AR(1)	0.8614***	0.4556***
	(0.0185)	(0.0473)
Firm fixed effects	No	Yes
White period	Yes	Yes
Observations	1050	1050
Adj.R^2	0.7937	0.8430
Durbin-Watson	1.9041	1.9549
Breusch-Godfrey	0.5150	0.4538

Table 13 shows the results of the first-order autoregressive model with and without firm fixed effects. The variables and their coefficients are presented, with the clustered, robust standard errors at a firm-level are given in parentheses. [1] shows the autoregressive model without firm fixed effects applied. [2] shows the results of the autoregressive model with fixed effects applied. The p-value of Breusch Godfrey is also presented (*** means autocorrelation)
*Statistically significant at 10% level.
**Statistically significant at 5% level.
***Statistically significant at 1%level.

5.2 Dynamic model results

The results of the dynamic models are shown in Table 14 below. A series of different models were run to study whether the variables would be more apparent when we allowed some time to pass before observing leverage. Columns one and two contain the results of a regression where leverage is lagged once, with and without fixed effects, respectively. Similarly, columns three and four use two-year lags of leverage with and without fixed effects. Column five is different from the rest. Here, all the independent variables are lagged once. This is in line with Margaritis and Psillaki (2010), who suggest that leverage is more likely to be impacted by the previous year's financial measures than the current year. However, the model inspired by Margaritis and Psillaki (2019) is excluded from further analysis for two reasons. First, it only finds one significant variable. Second, the low Breusch-Godfrey value indicates that it still has some autocorrelation. The best results are achieved when firm fixed effects are applied, shown in columns one and three. The dynamic model in column three, which includes leverage lagged twice, has a marginally higher adjusted R-squared than the model where it is only lagged once in column 1. However, since the LEVR_NCLI_(-2) variable is not statistically significant, and because of the reduction of observations from 1050 to 879, the model with fixed effects and leverage lagged once will be used for further analysis. The Breusch-Godfrey test confirms that there is no remaining autocorrelation for the dynamic model.

Table 14. Output for the dynamic model

	[1]	[2]	[3]	[4]	[5]
C	-1.4224*** (0.3713)	-0.1060 (0.0904)	-1.3458*** (0.3905)	-0.1228 (0.0919)	-0.0147 (0.3410)
AGE	-0.0083*** (0.0021)	-0.0007 (0.0008)	-0.0061* (0.0022)	3.1706 (0.0008)	-0.0073*** (0.0021)
OIL	-0.0153 (0.0118)	0.0033 (0.0120)	-0.0177 (0.0125)	-0.0075 (0.0131)	0.0090 (0.0099)
OPLEV	0.0108 (0.0071)	-0.0042 (0.0026)	0.0112 (0.0077)	-0.0047 (0.0031)	-0.0008 (0.0064)
PROF	-0.0775** (0.0343)	-0.1007*** (0.0311)	-0.0866** (0.0411)	-0.1017*** (0.0350)	-0.0186 (0.0286)
SIZE	0.0919*** (0.0212)	0.0068 (0.0053)	0.0863*** (0.0223)	0.0070 (0.0055)	-0.0154 (0.1983)
TANG	0.2347*** (0.0511)	0.1130*** (0.0239)	0.2161*** (0.0526)	0.0911*** (0.0228)	0.0357 (0.0395)
LEVR_NCLI_(-1)	0.4009*** (0.0413)	0.7871*** (0.0253)	0.3948*** (0.0477)	0.0771*** (0.0372)	0.4182*** (0.0459)
LEVR_NCLI_(-2)			-0.0013 (0.0350)	0.0572* (0.0302)	
Firm fixed effects	Yes	No	Yes	No	Yes
White period	Yes	Yes	Yes	Yes	Yes
observations	1050	1050	879	879	1050
Adj. R^2	0.8395	0.7652	0.8492	0.7833	0.8095
Breusch-Godfrey	0.8575	0.5493	0.2074	0.5057	0.1014

Table 14 shows the output of the result for the dynamic model with different specifications. [1] denotes the results with using a one-year lag of levr_ncli with using effects, meanwhile [2] is the one-year lag of levr_ncli without using effect. [3] is the two-year lag of levr_ncli with using effects and [4] is the two-year lag of levr_ncli without effects. [5] shows the results of the dynamic model with every variable lagged one year. The terms' coefficients are presented, as well as their standard errors in parentheses. The p-value of Breusch Godfrey is also presented (*** means autocorrelation). The data stream includes the data of 178 companies from the period 2008-2017.

* Statistical significance at 10% level.

** Statistical significance at 5% level.

*** Statistical significance at 1% level

5.3 First difference model

The results from the first difference model are shown in Table 15 below. The first differences of the different variables are denoted by D(AGE), D(OIL), D(OPLEV), D(PROF), D(SIZE), and D(TANG). When fixed effects are applied (shown in column 2), the adjusted R-squared decreases marginally from 0.19 to 0.18, and the Durbin-Watson increases from 2.02 to 2.40. However, the results from the Breusch-Godfrey test indicate that there is still autocorrelation left in the model, even after applying fixed effects and white period. Because of this, the results from the first difference model will be ignored.

Table 15. Results using the first difference model

	[1]	[2]
C	0.0272	0.0524
	(0.0932)	(0.1027)
D(AGE)	-0.0432	-0.0674
	(0.0926)	(0.1017)
D(OIL)	-0.0018	-0.0067
	(0.0090)	(0.0091)
D(OPLEV)	0.0110**	0.0101*
	(0.0056)	(0.0055)
D(PROF)	-0.0695**	-0.0671**
	(0.0299)	(0.0318)
D(SIZE)	0.1405***	0.1338***
	(0.0234)	(0.0224)
D(TANG)	0.2680***	0.2731***
	(0.0426)	(0.0419)
Firm fixed effects	No	Yes
White period	Yes	Yes
Observations	1050	1050
Adj. R^2	0.1949	0.1834
Durbin-Watson	2.0257	2.3985
Breusch-Godfrey	0.0028***	0.0000***

Table 15 shows the output of the result for the first difference model with different specifications. [1] denotes the results without using effects, meanwhile [2] with using effect. The terms' coefficients are presented, as well as their standard errors in parentheses. The p-value of Breusch Godfrey is also presented (*** means autocorrelation). The data stream includes the data of 178 companies from the period 2008-2017.
* Statistical significance at 10% level.
** Statistical significance at 5% level.
*** Statistical significance at 1% level

5.4 GMM results

The results from the GMM model are shown below in Table 16. Column one shows a GMM model where leverage is lagged once, while column two shows one where it is lagged twice. While both models have multiple significant variables, the results from the Breusch-Godfrey test indicate that there is still autocorrelation left in the GMM model. We, therefore, choose to reject the results provided by the GMM model.

Table 16. GMM results

	[1]	[2]
AGE	-0.0082*** (0.0022)	-0.0012 (0.0027)
OIL	-0.0105 (0.0087)	-0.0176 (0.0106)
OPLEV	0.0179*** (0.0066)	0.0105 (0.0084)
PROF	-0.0690*** (0.0191)	-0.0966*** (0.0266)
SIZE	0.1369*** (0.0187)	0.0806*** (0.0215)
TANG	0.3406*** (0.0445)	0.3139*** (0.0476)
LEVR_NCLI_(-1)	0.4840*** (0.0483)	0.4059*** (0.0723)
LEVR_NCLI_(-2)		0.2096*** (0.0669)
Cross-section	Difference	Difference
White period	Yes	Yes
Observations	879	722
J-statistic	31.24	27.26
Breusch-Godfrey	0.0000***	0.0000***

Table 16 shows the output of the result for the GMM model with different specifications. [1] denotes the results with levr_ncli_ lagged once. [2] denotes the results with levr_ncli_ lagged twice. The terms' coefficients are presented, as well as their standard errors in parentheses. The p-value of Breusch Godfrey is also presented (*** means autocorrelation). The data stream includes the data of 178 companies from the period 2008-2017.
* Statistical significance at 10% level.
** Statistical significance at 5% level.
*** Statistical significance at 1% level

5.5 Binary probit results

The results of the probit model are displayed in Table 17. The purpose of this model is to give us a point of reference when we study impacts on leverage. Because the dependent variable here is a dummy for 10% increase in leverage, the results may differ from what we find in the other models. The results show significant relationships between leverage and all the independent variables. However, it is noteworthy that some of the coefficients have opposite signs of what was found in the other models. This will be discussed more in the next chapter. Note that the coefficients can not be interpreted directly in probit regression like in our other regression models (Brooks, 2014). We leave it up to the reader to calculate marginal effects for each variable, as that goes beyond the objective of the current analysis.

The Hosmer-Lemeshow test measures the goodness of fit for our probit model (Brooks, 2014). A poor fit is indicated by a significance value less than 0.05 (Pallant, 2016). As seen below, the Hosmer-Lemeshow test has a chi-square value of 5.9174 with a significance level of 0.6565, which indicates high goodness of fit in this model. The significance value of the Andrews test also has a high value of 0.4731, which strengthens the previous evidence for a good model fit. This means that the observed and expected proportions of leverage do not differ significantly (Brooks, 2014).

Table 17. Output for the binary probit test

	[1]
AGE	0.0237***
	(0.0062)
OIL	0.3771***
	(0.1172)
OPLEV	0.0713**
	(0.0349)
PROF	-1.0261***
	(0.2346)
SIZE	-0.0965***
	(0.0094)
TANG	0.5577***
	(0.1685)
Observations	1228
Obs with Dep=0	1013
Obs with Dep=1	215
Hosmer-Lemeshow test	5.9174 (0.6565)
Andrews statistic	9.6345 (0.4731)
Breusch-Godfrey	0.5984

Table 17 shows the output of the result for the binary probit model. Coefficient covariance was computed using the Huber-White method. The data stream includes the data of 178 companies from the period 2008-2017. The table also contains the Hosmer Lemeshow test and the Andrews statistic for the probit model, where the Chi-Square values of the tests are presented with the significance value in parenthesis.
* Statistical significance at 10% level.
** Statistical significance at 5% level.
*** Statistical significance at 1% level

5.6 Comparison

The regression outputs from our best models are summarized and compared in Table 18. Columns one, two, and three show the AR(1), dynamic, and binary models, respectively. The results will be interpreted to understand which variables have a positive or negative relationship with leverage. This is done by analyzing each variable's coefficients and the corresponding p-values. The coefficient explains the relationship between the dependent and independent variable and whether it is positive or negative (Stratz, 2019). The p-value is a critical value regarding the variables' significance (Startz, 2019). We set our threshold for significance at 10% level, 5% level, and 1% level, which are standard thresholds in scientific research (Startz, 2019). This means that if the p-value is above 0.1, the model fails to find a significant relationship. When the p-value is between 0.1 and 0.05, it is weakly significant. If it is between 0.05 and 0.01, it is significant, and when it is below 0.01, it is strongly significant (Startz, 2019).

According to the results, leverage was found to negatively affect age in both the autoregressive and the dynamic models. This result is, according to the autoregressive model, significant with a coefficient of -0.013. A negative coefficient of -0.013 means that when a firm gets one year older, it is expected to decrease leverage by 1.3%. In the dynamic model, age is strongly significant, with a coefficient of -0.008. However, the binary model shows that age is strongly significant and positively related to leverage. An explanation for this contradiction could be that the binary model focuses on the increase in leverage, not on whether the leverage level is low or high. This means that if an older company increases its leverage by 10%, it does not necessarily mean that it has high leverage, only that it increased.

Next, while we did not find a significant relationship between leverage and oil in the AR(1) and dynamic models, the binary model found a significantly positive relationship. This could indicate that there is a connection between debt and short-term oil price fluctuations. Other potential causes for this will be discussed in detail in the next chapter. The binary model found another positive relationship between operating leverage and leverage. This finding is supported by a significant coefficient of 0.013 in the autoregressive model.

Profitability is found to have a negative relationship with leverage in all our models. In the autoregressive model, the relationship is weakly significant with a coefficient of -0.06. The dynamic model suggests the relationship is significant with a coefficient of -0.08. Finally, the binary probit model claims the negative relationship is strongly significant. Size also has a significant relationship with leverage in all the models. However, there are conflicts in whether this is a positive or negative relationship. While both the autoregressive model and the dynamic model suggest size has a positive relationship with leverage, with coefficients of 0.12 and 0.09, the binary probit finds a negative relationship. The reason for this is likely similar to the reason for the conflict connected to the age variable. Because the dependent binary variable only studies change, it is difficult to use it to say something about determinants of high leverage levels. However, it does indicate that a change in size is closely related to a change in leverage.

Finally, tangibility is found to have a strongly significant relationship with leverage in all the models. This is the variable with the most impactful relationship out of all the included independent variables. According to the autoregressive model, the coefficient is 0.26, and according to the dynamic model, the coefficient is 0.23.

Table 18. Comparison of selected models

	[1]	[2]	[3]
C	-1.7705***	-1.4224***	
	(0.4173)	(0.3713)	
AGE	-0.0132**	-0.0083***	0.0421***
	(0.0036)	(0.0021)	(0.0114)
OIL	-0.0117	-0.0153	0.6691***
	(0.0102)	(0.0118)	(0.2157)
OPLEV	0.0128**	0.0108	0.1196**
	(0.0128)	(0.0071)	(0.0500)
PROF	-0.0620*	-0.0775**	-1.7469***
	(0.0332)	(0.0343)	(0.3908)
SIZE	0.1225***	0.0919***	-0.1654***
	(0.0232)	(0.0212)	(0.0178)
TANG	0.2627***	0.2347***	0.9889***
	(0.0481)	(0.0511)	(0.3112)
AR(1)	0.4556***		
	(0.0431)		
LEVR_NCLI_(-1)		0.4009***	
		(0.0413)	
Firm fixed effects	Yes	Yes	No
White period	Yes	Yes	No
Observations	1050	1050	1228
Adj. R^2	0.8430	0.8395	
Durbin-Watson	1.9549	1.8960	
Breusch-Godfrey	0.4538	0.8575	0.5984

Table 18 shows a comparison between the autoregressive model [1], the dynamic model [2] and the binary probit model [3]. The data stream includes the data of 178 companies from the period 2008-2017. The terms' coefficients are presented, as well as their standard errors in parentheses. The p-value of Breusch Godfrey is also presented (*** means autocorrelation).
* Statistical significance at 10% level.
** Statistical significance at 5% level.
*** Statistical significance at 1% level

6 Discussion

In this chapter, we will compare and discuss the findings of our analysis with the findings of international studies. This is useful because it allows us to study the generalizability of the studies mentioned in Chapter 2. While it seems that parts of their findings are also applicable to the Norwegian shipping industry, it becomes apparent that the Norwegian firms might have slightly different attitudes to long-term debt.

6.1 Placing our results in the international context

In the study of Grammenos et al. (2008), shipowner’s experience proved to have a negative relationship with the probability of default. Suppose we assume that the company's age is proportional to the shipowner’s (company’s) experience. In that case, the result of the current study is in line with this previous study’s conclusion, namely that the younger the firm, the higher the leverage and, therefore, the probability of default. However, this contrasts with Kavussanos and Tsouknidis (2016) and Lozinskaia et al. (2017), who did not find a significant relationship between age and the probability of default. This could indicate that age is a more important determinant for Norwegian companies than for their international counterparts. However, a more likely cause can be that the small and medium-sized shipping firms in this study have a lower average age of 12. This is much lower than the 19 and 32 years in the studies by Kavussanos and Tsouknidis (2016), and Lozinskaia et al. (2017), respectively.

While profitability was found to have a negative relationship with leverage in our analysis, the results of Kavussanos and Tsouknidis (2016) were vaguer. They did not find a relationship between the ratio of earnings before interests, taxes, depreciation, and amortizations, and the probability of default, but they did find a negative relationship between the probability of default and the ratio of cash reserves divided by total assets. This supports the fundamental definition of bankruptcy in the sense that firms only default when they are unable to pay their obligations. Hence, increased cash reserves mean that firms will have a reduced probability of default. A similar relationship can be expected with increased profitability since it implies that firms will have better liquidity than in the reverse scenario. This logic is supported by Drobetz et al. (2013), Lozinskaia et al. (2017), Altman (1968), Ohlson (1980), and Grammenos et al. (2008), who all found a decreased probability of default given a rise in profitability. This means that the findings of our study are in line with those of the international studies.

The results regarding tangibility are comparable to the study by Drobetz et al. (2013). According to their study, the most significant contributor of increased leverage is, in fact, increased tangibility. Similarly, tangibility is the most dominant independent variable in our study. According to every one of our models, it is statistically significant at the 1% level, and its coefficients are higher than those of the other independent variables. It was mentioned at the very beginning of this paper that the shipping industry is highly capital intensive due to investments in vessels. Furthermore, bank loans were declared to be the most important source of capital in the industry. With these considerations in mind, it makes sense that increased tangibility, i.e., increased amounts of fixed assets such as vessels, lead to increased leverage. During the multicollinearity test under the preliminary analysis, it was found that tangibility has a medium to high correlation with leverage. The issue of collinearity could, therefore, explain why none of the other studies used both leverage and tangibility among their explanatory variables even though it seems to represent an essential determinant for the probability of default.

Oil price is a variable that seems to have often been excluded from studies on leverage and default. Among the studies mentioned in the literature review, only Lozinskaia et al. (2017) and Drobetz et al. (2013) include it in their analysis. Lozinskaia et al. (2017) attempted to measure the effect of fuel cost indirectly through levels of vessel rent. Assuming that higher oil prices lead to lower demand of vessels, they did not find a significant impact on the probability of default. Contrary to our results, Drobetz et al. (2013) found oil price negatively correlated with leverage. They argued that this could stem from the fact that higher oil prices indicate an economic upswing. Their oil price variable, like ours, was based on annual price change. To identify possible causes of this difference in the result, we turn to the characteristics of the datasets. Our study includes only Norwegian firms observed from 2008 and 2017, while Drobetz et al. (2013) included firms of thirty-one nationalities observed from 1992 to 2010. Two potential explanations are apparent. First, it is possible that Norwegian shipping companies are less impacted by changes in oil price than their international counterparts. Second, differences in time periods might have been a decisive factor. While prices rose steadily from 19 USD per barrel of Brent Crude in 1990 to 80 USD per barrel in 2010, they were much more volatile from 2008 to 2017 (U.S. Energy Information Administration, 2021). Thus, oil price deterioration and volatility might have made the annual price change variable less suitable for explaining leverage.

Another difference between our study and the one by Drobetz et al. (2013) is that they found operating leverage to be inversely correlated with leverage. They argue that their findings align with trade-off theory, suggesting that firms take on a more risk-averse approach to debt as operating leverage increases. On this basis, it was unexpected to find a positive relationship between operating leverage and leverage among the Norwegian companies. This is especially interesting considering that the median operating leverage in the study by Drobetz et al. (2013) is 0.39, much lower than the median of 0.72 among the Norwegian shipping firms. Continuing the logic from the trade-off theory, we would then expect Norwegian firms to be risk-averse and adopt a more conservative capital structure. Another distinct difference between the two datasets is that while the median age was only six years in Drobetz et al.'s study, it was close to thirteen years in the current study. This could indicate some underlying factors among the more mature Norwegian firms that affect their attitude to long-term debt.

Lastly, our results show that there is a positive relationship between size and leverage. These results are in line with those presented by Ohlson (1980) and Drobetz et al. (2013). Drobetz et al. (2013) implied through the trade-off perspective that there is an inverse relationship between size and expected bankruptcy costs. This is because larger firms have a smaller probability of default as they tend to be more diversified. However, a small Norwegian shipping firm might not be as well diversified as some of the larger international firms in other studies. Another possible explanation for the positive relationship can be found in the characteristics of the Norwegian shipping industry. As mentioned in Chapter 2, the industry's capital-intensive nature means that long-term debt is a major source of capital. This means that the relationship between size and leverage might be caused by the fact that firms tend to take on long-term debt to invest in more vessels.

The different variables can also be seen in combination to uncover other potential explanations of their relationships. Our study found a connection in that the younger Norwegian firms have increased leverage. This could be because younger companies depend on leverage to finance the fixed assets required to operate as shipping companies. As the companies age, it might become easier to raise capital through other means. This can also be seen in combination with the finding that more profitable firms have decreased leverage. It is a known fact that younger firms tend to be less profitable. As they mature and their profitability increases, they might also gain access to alternative means of financing. For example, increased profitability can make firms more attractive for investors and increases the likelihood of having retained earnings in the company. This could reduce a firm's demand for long-term debt. However, a positive relationship was also found between tangibility and leverage, and size and leverage. So, while a more mature and profitable shipping firm might have lower leverage, the findings indicate that they still seem to rely on some amount of long-term debt for increasing their fixed assets.

A more surprising finding was that the Norwegian companies had a much higher ratio of operating costs to total assets than the international firms. Despite this, there was still a positive relationship between operating leverage and leverage. This indicates that there might be underlying factors among the Norwegian companies that affect their attitudes toward the use of debt. Some other studies have shown indicators of this as well. Levine et al. (2001) studied financial structure across a large number of countries. They found that the Norwegian financial system was bank-based rather than market-based, and suggested that these differences might be caused by laws and law enforcement mechanisms. A bank-based financial system is, according to Levine et al. (2001), one where the bank system is more developed than the financial market systems.

Similarly, La Porta et al. (1997) suggested that differences in shareholder rights, law enforcement quality and bankruptcy laws strongly impact capital structure decisions. Comparing their results for Norway and, for example, the United States, Norway seems to have stronger creditor rights and weaker shareholder rights. These studies could serve as examples of why Norwegian shipping companies might be more prone to raise capital through long-term debt. While most of the findings of this analysis are in line with the findings of the international studies, it is apparent that their results are not directly transferrable to the small and medium Norwegian shipping enterprises.

6.2 Limitations

Although this study provides information and knowledge to an existing research gap, there are some limitations to the study. The most important limitation is whether or not leverage is a good predictor for default. We justify leverage as the dependent variable in Chapter 2 through multiple previous studies that have proven leverage as one of the most essential factors in predicting defaults. This gives reason to believe that leverage is sufficient as an explanatory dependent variable. However, it is important to note that high leverage does not guarantee a high probability of default in all cases. Furthermore, only one external variable is included in the dataset. This means that other macroeconomic factors that might influence the dependent variable are excluded as variables. They are instead accounted for through fixed effects in the regression models. Finally, the data may be impacted by two exogenous shocks in the sector: the financial crisis in 2007-2009 and the oil price shock in 2014.

6.3 Validity

6.3.1 Internal validity

Internal validity measures the effectiveness of the research, or in other words, the extent to which our results represent the population we are studying (Gertler et al., 2016). We conducted a thorough preliminary analysis to verify the quality of the dataset. Here we found evidence of heteroscedasticity and autocorrelation. To get reliable results, we proceeded with advanced regression models which can solve these problems, in combination with using clustered standard errors that are robust to heteroscedasticity. The remaining autocorrelation was tested with both the Durbin-Watson and Breusch-Godfrey tests. Some remaining autocorrelation was found in the dynamic model and the GMM model, which lead to their results being deemed invalid. However, the rest of the tests do not suffer from autocorrelation, and, therefore, their results can be considered internally valid.

6.3.2 External validity

According to Gertler et al., (2016) external validity means whether or not the evaluation sample accurately represents the population of interest. The working data of this study consists of all the Norwegian shipping SMEs that engage in sea- and coastal freight water transport (NACE code 502) with operating revenue below 10 million euro, total assets below 20 million euro, less than 150 employees, and more than one observed year of financial data. This makes the data and the results representative of Norwegian shipping SMEs and accurately represents the population of interest. Thus, making our research externally valid.

6.4 Further research

This analysis draws attention to a research gap that has been left largely unexplored previously. The importance of the industry in Norway means it is likely to be a topic of interest for academics and researchers in the future, where this quantitative study can serve as a foundation for more research. Our findings suggest that although there are significant similarities between the Norwegian and the global shipping industry, not all the characteristics of the global shipping industry seem to be directly applicable to the Norwegian industry. Consequently, remedies that might reduce the probability of default for the global industry can potentially have a reduced effect when applied to the Norwegian industry and vice versa.

As mentioned in the limitations, this study did not have data on defaulted firms. We encourage other researchers to continue where we left off. Future research can use a proxy variable for default to find more direct connections between financial determinants and the probability of default. Our study also uncovered that Norwegian shipping firms seem to have different attitudes to long-term debt than their international counterparts. Therefore, it would be interesting to see a study focusing on determinants of long and short-term debt among Norwegian shipping companies.

7 Conclusion

The Norwegian shipping industry is an important contributor to wealth creation and export in the country. Moreover, the industry is organized as clusters that form important parts of the livelihood in the villages where they operate. Here, the costs and impacts of default serve as important reasons why avoidance of these events can be of importance. Therefore, the purpose of this study was to find key determinants of defaults by answering the following research question:

"Determinants of credit events among SME shipping companies in Norway: Which factors provide information of corporate defaults, or increase the probability of corporate defaults?"

Multiple previous studies have found leverage and gearing ratio to be key indicators when measuring the probability of default. Their findings indicate that if one understands more about the causes of high leverage, one might be able to predict and reduce the probability of default. Our study uses leverage as the main dependent variable to identify key determinants that increase the probability of default. Through our preliminary analysis, we found that the dataset suffers from autocorrelation and heteroscedasticity. An autoregressive model, a dynamic model, and a binary logit model were used in combination with clustered standard errors to account for this.

We found evidence that a positive and statistically significant relationship exists between the dependent variable leverage, and the independent variables size, operating leverage, and tangibility. Contrary, age and profitability were found to have significant negative relationships with leverage. Most of our conclusions are in line with what has been shown in international studies previously. However, there are some deviations. This means that the results of the international studies are not directly transferrable to small and medium Norwegian shipping enterprises. We argue that the differences might stem from underlying factors in the Norwegian financial system. Considering this, the study provides stakeholders with new and unique insight into determinants that can help predict default among small and medium Norwegian shipping enterprises. Our results can be useful for practitioners and academics, as well as for future research. Specifically, we encourage other researchers to continue where we left off by connecting our findings about leverage to a proxy variable for default.

References

Addae, A. A., Nyarko-Baasi, M., & Hughes, D. (2013). The effects of capital structure on profitability of listed firms in Ghana. *European Journal of Business and Management, 5*(31), 215-229.

Aljandali, A., Tatahi, M. (2018). *Economic and Financial Modelling with EViews : A Guide for Students and Professionals Statistics and Econometrics for Finance,* (1st ed.). Springer International Publishing. ://doi.org/10.1007/978-3-319-92985-9

Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance, 23*(4), 589-609. https://doi.org/10.2307/2978933

Altman, E. I., Hotchkiss, E. (2006). *Corporate Financial Distress and Bankruptcy: Predict and Avoid Bankruptcy, Analyze and Invest in Distressed Debt* (3rd ed.). Wiley.

Baltagi, B.H. (2005). Econometric Analysis of Panel Data (3rd ed.). John Wiley & Sons, Ltd.

Blischke, Wallace R, Rezaul Karim, M, & Prabhakar Murthy, D. N. (2011). Preliminary Data Analysis. In Warranty Data Collection and Analysis (pp. 159–189). Springer London. https://doi.org/10.1007/978-0-85729-647-4_8

Brooks, C. (2014). *Introductory Econometrics for Finance* (3rd ed.). Cambridge University Press.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Laurence Erlbaum Associates.

Dewaelheyns, N. & Hulle, C. (2004). The Impact of Business Groups on Bankruptcy Prediction Modeling. *Review of Business and Economics, XLIX*, 623-645.

Drobetz, W., Gounopoulos, D., Merikas, A., & Schröder, H. (2013). Capital structure decisions of globally-listed shipping companies. *Transportation Research Part E: Logistics and Transportation Review*, *52*, 49-76. https://doi.org/10.1016/j.tre.2012.11.008

Gertler, P. J., Martinez, S., Premand, P., Rawlings, L. B., & Vermeersch, C. M. (2016). *Impact evaluation in practice*. The World Bank.

Grammenos, C. T., Nomikos, N. K., & Papapostolou, N. C. (2008). Estimating the probability of default for shipping high yield bond issues. *Transportation Research Part E: Logistics and Transportation Review, 44*(6), 1123-1138. https://doi.org/10.1016/j.tre.2007.10.005

Gujarati, D. N., & Porter, D. C. (2009). *Essentials of Econometrics* (5th ed.). McGraw-Hill Education.

Hair, J. F., Jr., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate Data Analysis* (7th ed.). Pearson Education Limited.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the Econometric Society*, 1029-1054. https://doi.org/10.2307/1912775

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the econometric society*, 1251-1271. https://doi.org/10.2307/1913827

Kavussanos, M. G., & Tsouknidis, D. A. (2016). Default risk drivers in shipping bank loans. *Transportation Research Part E: Logistics and Transportation Review, 94*, 71-94. https://doi.org/10.1016/j.tre.2016.07.008

La Porta, R., Lopez-De-Silanes, F., Shleifer, A., & Vishny, R. W. (1997). Legal Determinants of External Finance. *The Journal of Finance (New York),* 52(3), 1131–1150. https://doi.org/10.1111/j.1540-6261.1997.tb02727.x

Lozinskaia, A., Merika, A., Merikas, A., & Penikas, H. (2017). Determinants of the Probability of Default: The Case of the Internationally Listed Shipping Corporations. *Maritime Policy & Management*. https://doi.org/10.1080/03088839.2017.1345018

Margaritis, D., & Psillaki, Maria. (2010). Capital structure, equity ownership and firm performance. *Journal of Banking & Finance*, 34(3), 621–632. https://doi.org/10.1016/j.jbankfin.2009.08.023

Mitroussi, K., Abouarghoub, W., Haider, J. J., Pettit, S. J., & Tigka, N. (2016). Performance drivers of shipping loans: An empirical investigation. *International Journal of Production Economics, 171*, 438-452. https://doi.org/10.1016/j.ijpe.2015.09.041

Norwegian Shipowners' Association. (2021). *Maritime Outlook*. Retrieved from Oslo: https://rederi.no/rapporter/

Ohlson, J. (1980). Forecasting financial failure: a re-examination. *Journal of Accounting Research*, 109-131. https://doi.org/10.2307/2490395

Pallant, J. (2016). *SPSS survival manual : a step by step guide to data analysis using IBM SPSS* (6th ed.). McGraw Hill Education.

Pesaran, M. H. (2015). *Time Series and Panel Data Econometrics*. Oxford University Press. https://doi.org/10.1007/s00362-016-0816-1

Porter, D. C., & Gujarati, D. N. (2008). *Basic Econometrics (5th ed.)*. McGraw-Hill Education.

Startz, R. (2019). *EViews Illustrated*. IHS Global Inc.

Stopford, M. (2008). *Maritime Economics (3rd ed.)* Taylor & Francis.

U.S. Energy Information Administration. (2021). *Europe Brent Spot Price FOB*. https://mdanderson.libanswers.com/faq/26219

Wooldridge, J. M. (2001a). Applications of Generalized Method of Moments Estimation. *Journal of Economic Perspectives, 15*(4), 87-100. https://doi.org/10.1257/jep.15.4.87

Wooldridge, J. M. (2001b). *Econometric Analysis of Cross Section and Panel Data* (1st ed.). The MIT Press.

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

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