ΟΙΚΟΝΟΜΙΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ

ΤΜΗΜΑ ΛΟΓΙΣΤΙΚΗΣ & ΧΡΗΜΑΤΟΟΙΚΟΝΟΜΙΚΗΣ

ΠΡΟΓΡΑΜΜΑ ΜΕΤΑΠΤΥΧΙΑΚΩΝ ΣΠΟΥΔΩΝ

AN ASSESSMENT OF CREDIT RISK IN SHIPPING LOANS

ΕΛΕΑΝΑ ΚΩΤΣΑΛΕΝΗ

Εργασία υποβληθείσα στο

Τμήμα Λογιστικής & Χρηματοοικονομικής

του Οικονομικού Πανεπιστημίου Αθηνών

ως μέρος των απαιτήσεων για την απόκτηση

Μεταπτυχιακού Διπλώματος Ειδίκευσης

Αθήνα
Νοέμβριος, 2011

Εγκρίνουμε την εργασία της

ΚΩΤΣΑΛΕΝΗ ΕΛΕΑΝΑΣ

ΕΠΙΒΛΕΠΩΝ ΚΑΘΗΓΗΤΗΣ **ΥΠΟΓΡΑΦΗ**

ΚΑΒΟΥΣΑΝΟΣ ΕΜΜΑΝΟΥΗΛ **…………………**

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ΛΕΛΕΔΑΚΗΣ ΓΕΩΡΓΙΟΣ **...………………**

11/11/2011

ΒΕΒΑΙΩΣΗ ΕΚΠΟΝΗΣΗΣ ΔΙΠΛΩΜΑΤΙΚΗΣ ΕΡΓΑΣΙΑΣ

«Δηλώνω υπεύθυνα ότι η συγκεκριμένη πτυχιακή εργασία για τη λήψη του Μεταπτυχιακού Διπλώματος Ειδίκευσης στη Λογιστική και Χρηματοοικονομική έχει συγγραφεί από εμένα προσωπικά και δεν έχει υποβληθεί ούτε έχει εγκριθεί στο πλαίσιο κάποιου άλλου μεταπτυχιακού ή προπτυχιακού τίτλου σπουδών, στην Ελλάδα ή στο εξωτερικό. Η εργασία αυτή έχοντας εκπονηθεί από εμένα, αντιπροσωπεύει τις προσωπικές μου απόψεις επί του θέματος. Οι πηγές στις οποίες ανέτρεξα για την εκπόνηση της συγκεκριμένης διπλωματικής αναφέρονται στο σύνολό τους, δίνοντας πλήρεις αναφορές στους συγγραφείς, συμπεριλαμβανομένων και των πηγών που ενδεχομένως χρησιμοποιήθηκαν από το διαδίκτυο».

ΕΛΕΑΝΑ ΚΩΤΣΑΛΕΝΗ **ΥΠΟΓΡΑΦΗ**

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ABSTRACT

The aim of this dissertation is to estimate a credit scoring model with high statistical significance and forecasting ability. This model should be able to assess the default risk of a new shipping bank loan with the highest possible accuracy. This study is essential, especially in the 2011 unstable economic environment. The estimation of the model involves estimating weights for each variable that was collected. For that reason, we addressed to the ship finance department of a Greek bank in order to collect historical data of 132 loans that were granted to 63 shipping companies. The sample of the loan data referred to a period beginning from December 2002 and ending September 2011. For each loan, not only quantitative but also qualitative variables were collected. Moreover, because the number of defaults in our sample was small (seven loans defaulted), three definitions of default were considered. The *logistic regression* model was used in order to identify the determinants of credit risk in shipping loans which are relevant when assessing the default risk in an individual shipping bank loan. Generally, the obtained results of the three definitions of default suggest that many factors affect the probability of default, especially, factors that are related to the shipping company and the market where the shipping company operates.

1. INTRODUCTION

The financial system of each country is characterized by the dominant role of the banking sector which plays a fundamental role in economic growth, as it is the basic element in the channeling of funds from lenders to borrowers. The banking system around the world, which differs widely in size and operation across countries, has experienced major transformation in its operating environment during the last two decades displaying the most important changes during the recent years with the unfolding of the international financial crisis.

Nowadays, the banking sector faces the dilemma on whether to provide a loan to a company (borrower), at the risk of a potential default. Companies around the world face severe liquidity and profitability problems and consequently the need to accurately identify and measure the credit risk and the probability of financial distress becomes even more intense than it was in the past. As creditworthiness of a company, affects several aspects of the entire economic system, creditors (i.e. Financial Institutions) have to be very careful when it comes to credit decision. This is the reason why the evaluation of a borrower's credit risk becomes such a crucial issue.

Credit risk is the risk stemming from the uncertainty in a counterparty's inability to meet its obligations. It may be the most important risk that finance intermediaries have to manage and inadequate credit risk management is the biggest source of serious banking problems according to the Basle Committee.

Banks and other financial intermediaries have an ultimate goal to maximize their profit, which require an accurate pricing of the risks contained in their assets portfolios. A more clear understanding of credit risk determinants may help to predict if and when will a firm default on its credit liabilities. On the one hand, firm-specific characteristics should clearly be determinant on their decision to default on bank loans. On the other hand, macroeconomic developments may also have an important role in explaining the evolution of credit risk over time.

In assessing credit risk for a single counterparty, an institution must consider three issues:

- Default probability: What is the likelihood that the counterparty will default on its obligation either over the life of the obligation or over some specified time span, such as a year? Calculated for a one-year horizon, this may be called the expected default frequency.

- Credit exposure: In the event of a default, how large will the outstanding obligation be when the default occurs?
- Recovery rate: In the event of a default, what fraction of the exposure may be recovered through bankruptcy proceedings or some other form of settlement?

In order to assess the credit risk of a company it would be extremely useful for a financial institution to develop a model, based on several historical data, of deciding whether to finance a company or not and also, to try (as far as it is possible) to “predict” the default of a company.

Considering the above, the main purpose of this project is to empirically examine the determinants of corporate credit default, which is a major issue for financial stability, by taking simultaneously into account firm’s specific data as well as macroeconomic information.

This analysis is based mainly on those characteristics in the frame of shipping loans. The main reason why the shipping sector was chosen in order to implement this analysis is mainly attributed to the fact that there is no previous bibliography about credit risk in shipping loans and because shipping is an area of continuously growing economic significance.

1.1 Shipping Industry

Bank shipping finance began to grow in importance in the 1960’s. The use of debt was limited to small amounts and conservative leverage because of the high risk of the shipping industry which was reflected on fluctuating earnings and asset values.

Ship financing has always evolved in consonance with the commercial market’s trends. Bankers and shipowners have had to deal with many changes in the commercial environment over the last 50 years. There has been a “Golden Age” in the 1960’s where the rapidly growing industrial economies of the USA, Europe and Japan led to a significant development in both the demand for ships and the size and types of vessels. In the 1970’s there has been a “bubble” because more banks entered the shipping industry by providing easily loans. This helped shipowners to order more and more new ships and broke the link between Supply and Demand. The overcapacity was followed by an oil crisis and a deep recession in the 1980’s, which changed completely the way the world banking community addresses shipping risk issues. Through the 90's, banks having tremendous experience from the previous years, financed shipping companies in more conservative way by making detailed control of the shipowner, the fleet and the financial assets of the shipping company.

Shipping industry is competitive, thus rigorous analysis of the risks attached to shipping finance is necessary. Each bank has its own methodology so as to ensure that the shipowner can service its loan, meet the ship's operating expenses and leave a small surplus for growth and/or emergencies. Naturally, the ship's operating expenses have to be paid first because a vessel that breaks down through lack of maintenance, or that is seized for non-payment of bills, is a non-income producing asset and this will lead to problems in repaying the debt. The degree of intuition or variables applied to the analysis is considered very important in the risk analysis.

Indicative variables:

i. Growth or decline in world seaborne trade (will affect freight rates).
ii. Size of world fleet (will determine overtonnaging and influence freight rates).
iii. Number of vessels that are laid-up or scrapped or ordered (will determine overtonnaging and influence freight rates).
iv. Interest rate fluctuations (increases will affect debt service).
v. Currency exchange rate fluctuations (will affect operating expenses).
vi. World new building and scrapping capability (reductions will encourage speculative ordering).
vii. Oil prices (will affect operating expenses).

These are the most common variables for dry cargo vessels. Special variables will apply to different vessel types.

Whether shipping finance takes the form of conventional loan finance, leasing or equity participation, the rates of return can be immensely profitable in the form of:

- arrangement or "front-end" fees
- prepayment or "tail-end" fees
- margins on lending or "spreads"
- commitment fees for making the funds available over a long period (e.g. for multiple advances) and
- profit – sharing in sale or insurance proceeds.

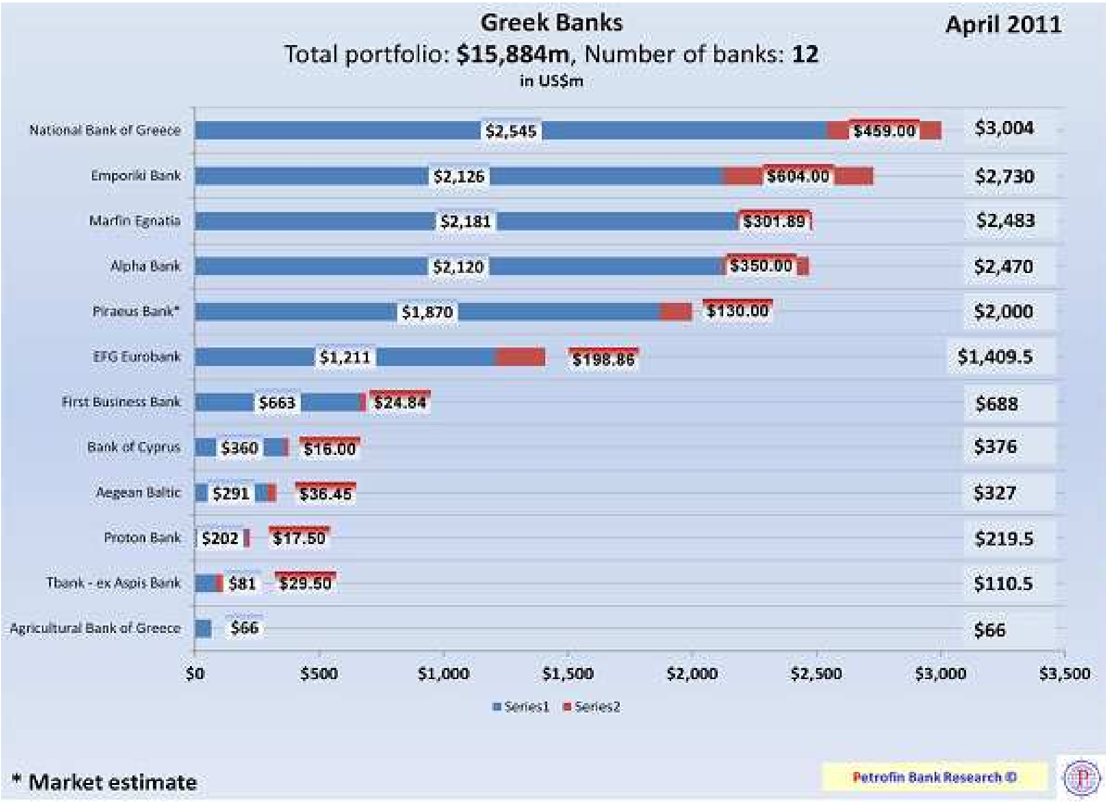
Generally, spreads are inextricably linked to the availability of funds on domestic and interbank markets and, more recently, to the capital adequacy rules imposed by the Basle Convergence Agreement. The Basle agreement requires banks to hold at least 8% of their assets as capital. The assets are weighted according to their perceived risk. Shipping loans have a risk weighting of 100% (compare this with house mortgage loans which are 50%). Though, if the borrower does not have a rating above BB-, then he will have a higher risk weighting of 150%.

Borrowers with good reputations are offered better terms than new, untried borrowers. Equally, heavily capitalized entrants who are prepared to inject a large percentage of their own funds on a recourse basis (with guarantees), deserve better terms than those who want to borrow on a non-recourse basis. It depends on the policy of each bank to choose, whether lending to customers that will give the rates of return it desires, or whether a mix of customers in its portfolio is preferable. Timing can also be crucial, as banks should look for opportunities of lending into a market coming out of recession. Moreover, banks seek to secure their financial exposure. They search for projects that will remain stable over the full length of the loan. They examine the performance of the shipping company, the shipowner and the employment of the fleet. The past record and the viability of the client in adverse market situations will also be taken into account.

1.2 Greek Shipfinance

In Greece, shipping banks are trying to reduce the risk when financing a shipping company and to find the right relation between risk and return. The common method of finance is the cash flow finance since the leasing finance it is not so widespread. The Greek shipping industry is mainly comprised of secondhand vessels which were built in foreign yards.

The Greek banking sector has remained steady in the number of banks that comprise it. Last year's first-time reduction in ship finance exposure, in the order of -4.74% has been trimmed this year to -1.59%, to an amount of $15,884 million. The growth in leaps and bounds of 115.59% of 2007 decelerated dramatically in 2008 (+6.97%) and went into negative growth for the first time in 2009. Considering the difficulties associated with the Greek economy and the position of Greek banks within it, as well as the overall liquidity problems and rising provisions faced by Greek banks, the decline in 2010 is remarkably small. This may be explained by the high regard in which Greek banks hold Greek shipping, as one of the country's main industries, as well as the willingness of Greek banks to co-operate with their clients to streamline loan repayments in line with shipping market conditions and obtain higher yields.



The National Bank of Greece continues to be the leader. Emporiki is ranked number 2. Marfin, the new number 3, has a marginally higher drawn portfolio than Emporiki, but a substantial lower level of commitments. Alpha bank has dropped from 2nd to 4th place. The Greek market is characterised by being a 20tier market, the top tier consisting of 6 banks of over $1billion threshold and the 2nd tier of another 6 banks below the $1billion threshold.

Moreover, from the total Greek shipfinance portfolio as of end 2010, it is noted that for the second consecutive year in a row the overall portfolio provided to Greek shipping was reduced, even though by a much lesser percentage than the year before. This demonstrates that, in balance terms, the banks held back from relending the funds realised from the repayment of their loan portfolios. Despite the above, the levels of 2010 still represent a substantial increase over Greek ship lending compared to 5 years ago.

In conclusion, as we mention before, the main reason why the shipping sector was chosen in order to implement this analysis is mainly attributed to the fact that there is no previous bibliography about credit risk in shipping loans and because shipping is an area of continuously growing economic significance. It is a fact that investors seem to show increasing interest, so an attempt to perform credit risk analysis for the shipping sector would be quite considerable. Finally, Greek shipping companies play a leading part in the global market.

2. LITERATURE REVIEW

Over the last 20 years credit risk measurement has evolved dramatically. The significant increase in the number of bankruptcies and in the number of highest quality and larger borrowers, along with the upcoming competition in loan margins and the participation of more risky assets in borrowers' portfolios which increased their risk exposure, have made the measurement of credit risk more important than ever before.

Moreover, in the late 1990's, discussions regarding the design of the new international bank capital accord, commonly known as Basel II, generated a renewed interest in credit risk modeling. The new capital accord (Basel Committee on Banking Supervision, 2004) proposes the use of credit risk models to determine banks' capital requirements. Banks can use internal (or external) rating models to classify borrowers according to their risk. Capital requirements can then be determined based on such credit exposure, instead of being constant per credit type, as under the previous accord. Under this new regulatory framework, it becomes crucial to accurately measure credit risk. On the one hand, banks must reserve enough capital to mitigate risks for depositors and to reduce insolvency risks. On the other hand, holding excessive capital is costly and limits efficiency.

In this section are presented some relative studies about the determinants of credit risk over the past two decades.

➢ **Expert systems and subjective analysis**

Twenty years ago most Financial Institutions (FIs) relied exclusively on subjective analysis or the so-called banker "expert" systems to assess the credit risk on corporate loans. Essentially, bankers only used information on various borrower characteristics to come up with a subjective judgment whether to approve the loan or not, based on the key points of credit - dominantly referred to as the five "C's" of credit.

Character: Implies the reputation of the company (shipowner) and its behavior on former loans.

Capital: The amount of equity capital used and the level of company's leverage as well. The probability of default is greater for higher levels of leverage.

Capacity: The firm's ability to take profitable decisions and to generate earnings in order to repay debt claims.

Collateral: The extent up to which company's creditors are covered in case default occurs. It depends on the market value of the underlying collateral: the loan becomes less risky as the market value of the collateral increases.

Conditions: How business cyclicality can affect company's performance.

- **Accounting based credit scoring systems**

In univariate accounting based credit scoring systems, the FI decision maker compares various key accounting ratios of potential borrowers with industry or group norms. Conversely, in a multivariate model key accounting variables are combined and weighed to produce a credit risk score or a probability of default measure. Where that score is assigned a value above a certain benchmark the loan is rejected or subjected to increased scrutiny. In terms of sheer number of articles and tests, models in this area have dominated the credit risk measurement literature in scholarly journals. Moreover, models have been globally developed in more than 25 countries. There are 4 methodological approaches to develop a multivariate credit scoring system:

i. Linear probability model
ii. Logit model
iii. Probit model
iv. Discriminant analysis model

Discriminant analysis, followed by logit analysis, claims the largest percentage of articles published in the *Journal of Banking & Finance*.

The determination of a linear function, of both accounting and market variables, which distinguishes the potential borrowers into two categories Repayment and non-Repayment, is the foundation of discriminant analysis. This requires an analysis of a set of variables to maximize the group variance while minimizing the within group variance among these variables. In a similar way, logit analysis, based on asset of accounting variables calculates the probability of a borrower default assuming that this probability is logistically distributed i.e. the cumulative probability of default takes a logistic functional form and is, by definition, constrained to fall between 0 and 1. In 1968 a famous discriminant model was first presented, called Z-score, which is still used nowadays.

Altman's Linear Discriminant Model (1968). Journal of Banking and Finance

Altman aimed to assess the analytical quality of ratio analysis. A set of financial ratios was combined in a multiple discriminant analysis approach to the problem of corporate bankruptcy prediction. The theory was that ratios, if analyzed within a multivariate framework, would take on greater statistical significance than the common technique of sequential ratio comparisons.

According to Altman the discriminant function is as follows:

- $Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$ where:

X_1 - Working Capital/Total Assets: This ratio is the most valuable liquidity ratio. Working capital is defined as the difference between current assets and current liabilities. Liquidity and size characteristics are explicitly considered. Ordinarily, a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets.

X_2 - Retained Earnings/Total Assets: A firm's retained earnings is the proportion of earnings reinvested over its entire life. It is a measure of profitability over time and it is often argued that older firms are appeared to be superior to younger ones. This is because cumulative profitability will be greater for an older firm. This ratio is often used as an indicator of leverage. If a firm appears to have high Retained Earnings/Total Assets ratio it has probably financed its activities mostly through retained earnings and not through external debt.

X_3 - Earnings before Interest and Taxes/Total Assets: It is a measure of the true productivity of the firm's assets, abstracting from any tax or leverage factors. Since a firm's ultimate existence is based on the earning power of its assets, this ratio appears to be particularly appropriate for studies dealing with corporate failure.

X_4 - Market Value of Equity/Book Value of Total Debt: In this ratio the market value of equity consists of the value of both common and proffered stock and liabilities refer to both current and long term debt. This measure shows how much the firm's assets can decline in value (measured by market value of equity plus debt) before the liabilities exceed the assets and the firm becomes insolvent.

X_5 - Sales/Total Assets: This ratio illustrates the sales generating ability of the firm's assets. It is one measure of management's capability dealing with competitive conditions.

The critical value that characterize whether a firm will go bankrupt or not, is Z = 1.81. All firms having a Z score of greater than 2.99 clearly fall into the "non-bankrupt" sector, while those firms having a Z below 1.81 are all bankrupt. The area between 1.81 and 2.99 will be defined as the "zone of ignorance" or "gray area" because of the susceptibility to error classification (we can not make a classification in that case).

Both logit and discriminant methods have been used to predict bank defaults in the 1975-1976 period and both models came to similar predictions to failure identification. The economic condition of Credit Institutions was later on attempted to be quantified using logit model along with factor analysis calculating a probability of becoming problem banks. It is of interest to say that the factors identified by the logit model were similar to the CAMEL[1] rating components used by bank examiners. Another use of the logit model was to verify that corporate bankruptcy is better predicted by accounting ratios. In general, models correlating industry characteristics work better than unadjusted models. Discriminant analysis models based on relative accounting ratios provide similar findings. A logit model has also been used to identify the set of variables that contribute to the most accurate prediction on a loan moving towards a default situation. This model was based on a Markov model of default probabilities.

Nevertheless as noted earlier, most multivariate accounting credit scoring models are based on discriminant analysis. Altman et al (1977) studied the performance of a 7-variable model, one of the variables being market value of equity. This model known as ZETA followed the 5-variable model presented in 1968. Scott (1981) compared a variety of these empirical models with a theoretically sound approach. He came to the conclusion that the ZETA most closely approaches his theoretical bankruptcy construct.

- **<u>Newer models</u>**

Diana Bonfim (2009). Journal of Banking and Finance

As Bonfim (2009) shows, default probabilities are influenced by several firm-specific characteristics and when these characteristics were taken into account together with

[1] An international bank-rating system where bank supervisory authorities rate institutions according to six factors. The six factors are represented by the acronym "CAMELS" with C - Capital adequacy, A - Asset quality, M - Management quality, E – Earnings, L – Liquidity, S - Sensitivity to Market Risk

macroeconomic variables, the results of the models improved considerably. More specifically, Bonfim examined an extensive dataset with detailed financial information for more than 30,000 Portuguese firms, which also included their loan default record. By modeling default probabilities with discrete choice models, combining different parameters every time, the results obtained suggest that default probabilities are influenced by several firm-specific characteristics, such as their financial structure, profitability and liquidity, as well as by other factors as well. Sales growth displays a negative coefficient, suggesting that firms with stronger sales growth rates should have lower default probabilities. Profitability exhibits also a negative coefficient, as should be expected (more profitable firms have a more solid financial situation and, consequently, display lower default probabilities). The solvency ratio also suggests that firms with healthier financial conditions are less likely to default on their loan commitments. Moreover, firms with stronger investment rates show lower default probabilities. In fact, it seems reasonable to admit that firms under financial pressure are not expected to engage in large investment projects. Furthermore, the liquidity ratio has a negative impact on default probabilities, implying that firms facing stronger liquidity constraints may have higher difficulties in paying their debt commitments. Bonfim also concluded that firm age does not seem to be statistically significant under a regression analysis framework. Furthermore, the firm's default history should be taken into account in the assessment of its credit risk, given that firms which recorded loan defaults in the recent past seem to display much higher default probabilities than other firms. Finally, when macroeconomic variables were taken into account together with the firm-specific information, the results of the models improved considerably. From the results it is concluded that macroeconomic factors can explain why firms default.

Hsien - Hsing Liao et al (2009). Journal of Banking and Finance

This study investigates the effects of agency and information asymmetry issues embedded in structural form credit models on bank credit risk evaluation, using American bank data from 2001 to 2005. Findings showed that both the agency problem and information asymmetry significantly cause deviations in the credit risk evaluation of structural form models from agency ratings. They proved that five independent factors explain a deviation of 42.6% – 78.3% and should be incorporated into future credit risk modeling. The factors include "management-equity agency effect-free cash flow", "debt-equity agency effect", "information asymmetry", "debt-equity agency effect-reverse wealth transfers” and “management-equity agency effect cost efficiency”. Both the effects of information asymmetry and debt-equity agency relate positively to the deviation while that of management-equity agency relates to it negatively. Finally, was suggested that adding more parameters to existing models, which incorporate the views of both debt and equity holders, could be a way of fixing current models.

3. DATA

3.1 Data Collection

The aim of this analysis is to estimate a credit scoring model with high statistical significance and forecasting ability. This model should be able to assess the default risk of a new shipping loan request with the highest possible accuracy. The estimation of the model involves estimating weights for each variable that we have collect, according to its relevance, to assess default risk before granting a shipping loan. For that reason, we addressed to the ship finance department of a Greek bank in order to collect 32 variables, which are not only quantitative but also qualitative.

The dataset, which consists of historical data, originate from the aforementioned shipping bank's database and represents a major part of the bank's portfolio, consisting of 132 loans granted to 63 shipping companies. The period of the data that was analyzed referred to December 2002 until September 2011. For each loan were collected the following variables: financial ratios of the shipping companies and some key elements of the loan. As for the financial ratios, were included ratios such as Current Ratio, Leverage, Interest Cover Ratio, Profit Margin, Cash Reserves, Debt Coverage Ratio and Revenue Volatility.

Moreover, were collected supplementary variables, which are categorized below:

1. <u>Bank-related Variables</u>: The bank's internal rating of the shipowner's creditworthiness, the total fees, forecast of the market, credit officer, margin charged.
2. <u>Loan-related Variables</u>: Life to final maturity of the loan, amount of loan, purpose of the loan, type of financed vessels, Clarksea Index of financed vessel, size of financed vessel in Dead Weight Tonnage (dwt), newbuilding or secondhand vessel, age of the financed vessel, Asset Coverage Ratio (ACR) Contractual, ACR Actual, Loan to Value (LTV) ratio, balloon payment/amount of the loan, employment of the fleet (timecharter or voyage charter).
3. <u>Obligor-related Variables</u>: Age of firm, fleet characteristics, years of cooperation with the bank, years of operation to repay the debt outstanding.

In addition, the dataset displays information on whether the shipping company, was finally able to meet its loan obligations or whether has defaulted (the definition of default is provided analytically in the following lines). This information along with all the historical data that were collected will help to understanding the major determinants of credit risk.

3.2 Variable Definition

It worth to mention that the variables presented in this analysis, along with the respective rationale for each one, are developed under the consideration of the following sources:

1. The academic literature on corporate bank loans.
2. The standard practice of banks when assessing a new loan request as provided by internal documents and discussions with executives in the banking industry.
3. The standard practice of banks when assessing a new shipping loan request as provided by internal documents and discussions with Greek's bank senior executives.
4. The documents of how credit rating agencies rate the creditworthiness of shipping companies (Moody's and Fitch).
5. Greek's bank management beliefs and insight.

First of all, in our analysis, we have to define the term "default". The criterion used for the classification of a loan in the "default" category is critical for a study in credit risk. Generally, three "default" definitions are used in the literature:

1. A loan is classified as "doubtful" as soon as "full payment appears to be questionable on the basis of the available information".
2. A loan is classified as in "distress" as soon as a payment (interest and/or principal) has been missed.
3. A loan is classified as in "default" when a formal restructuring process or bankruptcy procedure is started.

In this analysis, default is a dummy variable taking the value of 1 if a missed payment over 90 days has occurred. Under this definition, only 7 are the defaulted loans in the sample of 132 loans and this will probably affect the results of this study. Thus, alternative definition of default (1) and (2) will be considered. Under the alternative definition of default (1), the default is a dummy variable taking the value of 1 not only when a missed payment over 90 days has occurred, but also when a change in the repayment schedule, the balloon payment and the margin of the loan has occurred.

Under the alternative definition of default (2), the default is a dummy variable taking the value of 1 when a missed payment over 90 days has occurred and when any change in the terms of a loan has changed.

Bank-related Variables

1. Internal Bank Rating: This represents the estimation of the bank concerning the credibility of the shipowner and the shipping company, by taking into account its reputation in the market, its past financial performance, its characteristic of fleet. The bank rating used by the bank for this purpose is the following: 1 = "Excellent" applies in circumstances where the shipping company and the shipowner are considered very powerful and trustworthy and there is no uncertainty about the repayment of the loan. It is the highest rating that a company can achieve. Under the same logic, 2 applies for "Very Strong" companies, 3 for "Strong", 4 for "Very Good" and 5 for "Good" companies. Codification 6 = "Satisfactory" and 7 = "Acceptable" applies for companies that are in satisfactory and acceptable levels. There is no codification for "Non acceptable" as we get information only for companies that have taken already a loan and not for the full list of shipping companies that have applied to the bank for a loan. So the rejected companies are not in our dataset.
2. Total fees (in $): The total fees the bank makes from the agreement as computed by the sum of the arrangement fee and participation fee. This variable will indicate if the pricing policy of the bank reflects the default risk entailed in each loan agreement. It is a crucial part of the risk-return relationship this project is trying to establish.
3. Forecast of the market: The bank's forecast of the specific shipping subsector where the financed vessel will be employed (1 = "Strong", 4 = "Poor"). The forecast of the market is based on the available information from news, shipping reports and personal judgment. The forecast of the market by the bank for the specific subsector that the financed vessel will be employed is introduced into the model in order to assess its relevance regarding the default behavior of shipping bank loans.
4. Credit Officer: The credit officer who conducted the report. This variable will be a dummy variable and account for the fact that different credit officers may

have different views and different subjective judgment regarding a company's creditworthiness for the proposed credit facility.

5. Margin Charged: The margin over the LIBOR charged. This variable is introduced in order to identify whether the pricing of each loan reflects the credit risk related with the specific loan. The margin charged must account for two facts:
    a. The capital markets effect, which means that the margin charged is conditional upon the current market conditions regarding the liquidity of the banks and the availability of the money into the market. If high interest rates are determined by the regulatory authorities and/or the market then a margin may be high because of the existing conditions of the money market and not due to the riskiness of the loan agreement under consideration.
    b. The shipping markets effect, which means that a high margin may reflect the bad economic conditions of the shipping market as indicated for example by low freight rates and/or low vessel values. However, in this case a high margin may not imply higher default risk for a specific loan agreement.

Loan-related Variables

1. Life to final maturity (Tenor of the loan): The number of years from the initiation of the agreement until the final maturity of the loan. This variable investigates if a default event is more probable at the start or at the end of a loan agreement.
2. Amount of Loan: The total amount of the loan granted by the bank and the other participants of the syndicated loan. This variable is introduced in order to assess whether a larger loan value is more risky than a smaller loan value.
3. Type of financed vessels: A qualitative variable indicating the type of the financed vessel (e.g. tanker, dry, chemical etc.). This variable accounts for the type of the financed vessel in order to examine whether the subsector of shipping in which the financed vessel operates, increases the default risk of the granted loan.

4. Size of financed vessel in dwt: This variable accounts for the fact that as shown in the literature larger ships are more risky regarding their cash-flow generation ability.
5. Clarksea Index of financed vessel: The Clarksea Index is a weighted average of earnings for all the main vessel types (tanker, bulker, container, chemical) where the weighting is based on the number of vessels in each fleet sector.
6. Purpose of the loan: This variable can take the following values: acquisition (newbuilding or secondhand), working capital and mixed. This variable accounts for possible differences in the default risk assessment of a facility for acquisition purpose versus a working capital facility or a mixed facility.
7. Newbuilding (dummy variable): It takes the value of 1 if the purpose is for a newbuilding and 0 otherwise. This variable accounts for possible differences in the default risk assessment of a newbuilding project to a secondhand one. For example, a newbuilding entails higher default risk because of the fact that it has a larger economic life and thus the operator is exposed to the fluctuations of the market for a greater period.
8. Age of the financed vessel: The year the credit report was produced minus the year of built for the vessel. The age of the financed vessel affects its current value and its cash flow generation ability.
9. Asset Coverage Ratio (ACR) Contractual: The Market value of the ship over the amount of loan. The contractual ratio defined by the bank as a threshold which should be always smaller than the ACR Actual.
10. ACR Actual: It is computed using the market value of the ship as estimated by ship-brokers or internal sources above the amount of the loan. It changes each time the market value of the ship changes (because the amount of loan is steady). The ACR contractual ratio indicates how many times the market value of the vessel covers the loan exposure. However, the ACR ratio is subject to the business cycle of the shipping industry since a value of e.g. 123% could be high during a bull market[2] in shipping but low during a bear[3] market.

[2] A financial market of a group of securities in which prices are rising or are expected to rise. The term "bull market" is most often used to refer to the stock market, but can be applied to anything that is traded, such as bonds, currencies and commodities.
[3] A financial market of a group of securities in which prices are falling or are expected to fall. The term "bear market" is most often used to refer to the stock market, but can be applied to anything that is traded, such as bonds, currencies and commodities.

11. Loan to Value (LTV) ratio: The amount of the loan over the market value of the vessel at the time of the agreement.
12. Balloon payment/Amount of the loan: This variable is defined as the final payment of the repayment schedule named the balloon payment as a percentage of the total amount of the loan. The balloon can also indicate the default risk of a loan agreement. For example, a loan for a newbuilding usually carries a larger balloon payment. This variable will control for the fact that the bank may have the option to alter the breakeven rate by changing the regular installment or the balloon payment.
13. T/C or Voyage Employment (T/C=1, Voyage=0): This will be a dummy variable indicating whether the employment of the financed vessel will be based on a T/C or a voyage charter.

Obligor-Related Variables

1. Age of firm: The years of operation of the shipping company from its origination until the year of the credit report. The age of the firm is used in order to account for the market power of the firm into the industry. Higher values are expected to be associated with lower default risk for a specific obligor.
2. Fleet Characteristics
    a. Profile of fleet: The type of majority of the vessels (e.g. tankers, dry, chemicals, diversified, etc.). The profile of fleet indicates in which sub-sector of the shipping industry a specific obligor is more exposed.
    b. Aggregate market value of the existing fleet: The total market value of the existing fleet based on estimates from several sources (i.e. Internal, Clarkson's, etc.). This variable also reflects the quality of fleet along with the average age of existing fleet.
    c. Number of vessels: The total number of vessels for the existing fleet. The number of vessels is an indicator of the size of the shipping company.
    d. Fleet ACR = Aggregate MV of the fleet / Aggregate Leverage: This variable will indicate the Asset Coverage Ratio for the fleet. If the current MV of the fleet exceeds in a large percentage the aggregate

leverage, then it is expected that the proposed transaction will entail lower default risk.

3. Years of cooperation with the bank: This is the total number of years from the initiation of the relationship between the bank and the obligor. The longer the cooperation between the bank and the obligor the higher the trust and creditworthiness.
4. Years of operation to repay the debt outstanding = [Average age of fleet + (Total Debt / EBITDA)]: This variable indicates how many years of operation (with the same market conditions) are needed for the obligor to cover the debt outstanding. The more the years to cover the debt outstanding the higher the default risk of the proposed transaction.
5. Financial Ratios:
    a. Current Ratio = Current Assets / Current Liabilities.
    This ratio measures the liquidity of a company. It shows the ability of a company to repay its current liabilities. Generally, anything greater than 1 is considered healthy. In our model we expect the coefficient of this variable to be negative, meaning that when the Current ratio increases, the default probability decreases.
    b. Leverage = Debt / Equity.
    This ratio is a measure of a company's financial leverage calculated by dividing its total debt by stockholders' equity. It indicates what proportion of equity and debt the company is using to finance its assets. A high debt / equity ratio generally means that a company has been aggressive in financing its growth with debt. This can help company to generate more earnings than it would have without this outside financing. However, the cost of this debt financing may outweigh the return that the company generates on the debt through investment and business activities and become too much for the company to handle. This can lead to bankruptcy.
    c. Interest Cover Ratio = EBITDA / Interest Expenses.
    This ratio shows the ability of a company to meet its debt obligations through profits. It indicates the euros/dollars of earnings available for each euro/dollar of required interest payment. In our model we expect the coefficient of this variable to be negative meaning that when the

Interest Cover ratio increases, the default probability decreases since the company will probably repay the loan.

d. Profit Margin = EBITDA / Revenues

   Profit margin is a profitability ratio, with its value expressed in percentage. It indicates how profitable a company has been in the sales that has made. Higher profit margin indicates higher revenues which may be due to low competition or a successful product policy, and correspondingly indicates low default risk. However, the relation between profit margin and default may not be always negative, because higher profit margin indicates higher revenues which are often associated with high cash requirements (for advertising and inventories) and higher risk.

e. Cash Reserves = Cash and Cash Equivalents/Total Assets

   The Cash reserves ratio measures the liquidity of a firm. It is an indication of the firm's ability to have cash immediate in case of an emergency.

f. Revenues Volatility (average change in growth rate over last 3 years).

   It measures the change in revenues over the last 3 years. High revenue volatility indicates higher risk.

g. Debt Coverage Ratio = Total Debt / EBITDA.

   This ratio is a common metric used by credit rating agencies to assess the probability of defaulting on issued debt. A high debt/EBITDA ratio suggests that a firm may not be able to service their debt in an appropriate manner and can result in a lowered credit rating. Conversely, a low ratio suggests that a firm can take on more debt, if needed, and it often warrants a relatively high credit rating.

4. METHODOLOGY

In general, several factors can affect a borrower's default probability. A scoring model specifies how to combine the different pieces of information in order to get an accurate assessment of default probability, thus serving to automate and standardize the evaluation of default risk within a financial institution.

In this study, we specify and use a scoring model by using a statistical technique called *logistic regression* or simply *logit*. Specifically, this amounts to coding information into a specific value (e.g. measuring leverage as total liabilities / total assets) and then finding the combination of factors that does the best job in explaining historical default behavior. At first, we will clarify the link between scores, default probability and observed default behavior.

A score summarizes the information contained in factors that affect default probability. Standard scoring models take the most straightforward approach by linearly combining those factors. Let x denote the factors (their number is K) and b the weights (or coefficients) attached to them; we can represent the score that we get in scoring instance i as:

$$\text{Score}_i = b_1 x_{i1} + b_2 x_{i2} + \ldots + b_K x_{iK} \qquad (1.1)$$

It is convenient to have a shortcut for this expression. Collecting the b's and the x's in column vectors $\mathbf{b}$ and $\mathbf{x}$ we can rewrite (1.1) to:

$$\text{Score}_i = b_1 x_{i1} + b_2 x_{i2} + \ldots + b_K x_{iK} = \mathbf{b}'\mathbf{x}_i, \quad \mathbf{x}_i = \begin{bmatrix} x_{i1} \\ x_{i2} \\ \vdots \\ x_{iK} \end{bmatrix}, \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_K \end{bmatrix} \qquad (1.2)$$

If the model is to include a constant b_1, we set $x_{i1} = 1$ for each i.

If, we have already agreed on the choice of the factors $\mathbf{x}$ we have to determine the weight vector $\mathbf{b}$. Usually, it is estimated on the basis of the observed default behavior[4]. We have collected data on shipping loans with factor values and default behavior. The default information is stored in the variable y_i. It takes the value 1 if the firm defaulted in the year following the one for which we have collected the factor values and 0 otherwise. The overall number of observations is denoted by N. The scoring model should predict a high default probability for those observations that defaulted and a low default probability for those that did not. In order to choose the

[4] In qualitative scoring models, however, experts determine the weights.

appropriate weights **b**, we first need to link scores to default probabilities. This can be done by representing default probabilities as a function F of scores:

$$\text{Prob (Default}_i\text{)} = F\text{ (Score}_i\text{)} \tag{1.3}$$

Like default probabilities, the function F should be constrained to the interval values ranging from 0 to 1; it should also yield a default probability for each possible score. The requirements can be fulfilled by a cumulative probability distribution function. A distribution often considered for this purpose is the logistic distribution. The logistic distribution function $\Lambda(z)$ is defined as $\Lambda(z) = \exp(z)/(1+\exp(z))$. Applied to (1.3) we get:

$$\text{Prob (Default}_i\text{)} = \Lambda\text{ (Score}_i\text{)} = \frac{\exp(\mathbf{b'x_i})}{1+\exp(\mathbf{b'x_i})} = \frac{1}{1+\exp(-\mathbf{b'x_i})} \tag{1.4}$$

Models that link information to probabilities using the logistic distribution function are called *logit* models.

Having collected the factors **x** and chosen the distribution function F, a natural way of estimating the weights **b** is the maximum likelihood method (ML). According to the ML principle, the weights are chosen such that the probability (= likelihood) of observing the given default behavior is maximized. (The first step in maximum likelihood estimation is to set up the likelihood function.) For a borrower that defaulted (Y_i =1), the likelihood of observing this is:

$$\text{Prob (Default}_i\text{)} = \Lambda\ (\mathbf{b'x}_i) \tag{1.5}$$

For a borrower that did not default (Yi =0), we get the likelihood:

$$\text{Prob (No default}_i\text{)} = 1 - \Lambda\ (\mathbf{b'x}_i) \tag{1.6}$$

We can combine the two formulae into one that automatically gives the correct likelihood, be it a defaulter or not. Since any number raised to the power of 0 evaluates to 1, the likelihood for observation i can be written as:

$$L_i = (\Lambda(\mathbf{b'x_i}))^{y_i}\,(1-\Lambda(\mathbf{b'x}_i))^{1-y_i} \tag{1.7}$$

Assuming that defaults are independent, the likelihood of a set of observations is just the product of the individual likelihoods:

$$L = \prod_{i=1}^{N} Li = \prod_{i=1}^{N}\ (\Lambda(\mathbf{b'x_i}))^{y_i}\,(1-\Lambda(\mathbf{b'x}_i))^{1-y_i} \tag{1.8}$$

For the purpose of maximization, it is more convenient to examine ln L, the logarithm of the likelihood:

$$\ln L = \sum_{i=1}^{N} y_i \ \ln(\Lambda(\mathbf{b}'\mathbf{x_i})) + (1\text{-}y_i) \ln(1-\Lambda(\mathbf{b}'\mathbf{x}_i)) \tag{1.9}$$

This can be maximized by setting its first derivative with respect to **b** to 0. This derivative (like **b**, it is a vector) is given by:

$$\frac{\partial \ln \mathbf{L}}{\partial \mathbf{b}} = \sum_{\mathbf{i}=1}^{\mathbf{N}} \ (y_\mathrm{i} - \Lambda(\mathbf{b}'\mathbf{x}_\mathrm{i}))\mathbf{x_i} \tag{1.10}$$

Newton's method does a very good job in solving equation (1.10) with respect to **b**. To apply this method, we also need the second derivative, which we obtain as:

$$\frac{\partial^2 \ln \mathbf{L}}{\partial \mathbf{b} \partial \mathbf{b}'} = -\sum_{\mathbf{i}=1}^{\mathbf{N}} \ \Lambda(\mathbf{b}'\mathbf{x}_\mathrm{i})(1 - \Lambda(\mathbf{b}'\mathbf{x}_\mathrm{i}))\ \mathbf{x_i}\ \mathbf{x_i}' \tag{1.11}$$

At this point we analyze how to estimate logit coefficients in Excel. Since Excel does not contain a function for estimating logit models, we sketch how to construct a user-defined function that performs the task. Our complete function is called LOGIT. The syntax of the LOGIT command is equivalent to the LINEST command: LOGIT(*y*, *x*, [const], [statistics]), where [] denotes an optional argument.

The first argument specifies the range of the dependent variable, which in our case is the default indicator *y*; the second parameter specifies the range of the explanatory variable(s). The third and fourth parameters are logical values for the inclusion of a constant (1 or omitted if a constant is included, 0 otherwise) and the calculation of regression statistics (1 if statistics are to be computed, 0 or omitted otherwise). The function returns an array, therefore, it has to be executed on a range of cells and entered by [Ctrl]+[Shift]+[Enter].

The LOGIT function requires the input data to be organized in columns, not in rows. For the estimation of scoring models, this will be standard, as the number of observations is large. However, we could modify the function in such a way that it recognizes the organization of the data. The LOGIT function maximizes the log likelihood by setting its first derivative to 0, and uses Newton's method to solve this problem. Required for this process are: a set of starting values for the unknown parameter vector **b**; the first derivative of the log-likelihood (the gradient vector *g*() given in (1.10)); the second derivative (the Hessian matrix *H*() given in (1.11)). Newton's method then leads to the rule:

$$b_1 = b_0 - \left[\frac{\partial^2 \ln L}{\partial b_0 \partial b_0{}'}\right]^{-1} \frac{\partial \ln L}{\partial b_0} = b_0 - H(b_0)^{-1} g(b_0) \tag{1.12}$$

The logit model has the nice feature that the log-likelihood function is globally concave. Once we have found the root to the first derivative, we can be sure that we have found the global maximum of the likelihood function. A commonly used starting value is to set the constant as if the model contained only one constant, while the other coefficients are set to 0. With one constant only, the best prediction of individual default probabilities is the average default rate, which we denote by $\bar{y}$; it can be computed as the average value of the default indicator variable *y*. We should not set the constant b_1 equal to $\bar{y}$ because the predicted default probability with a constant only is not the constant itself, but rather $\Lambda(b_1)$. To achieve the desired goal, we have to apply the inverse of the logistic distribution function:

$$\Lambda^{-1}(\bar{y}) = \ln\left(\frac{\bar{y}}{1-\bar{y}}\right) \tag{1.13}$$

To check that it leads to the desired result, we examined the default prediction of a logit model with just a constant that is set to (1.13):

$$Prob\ (y = 1) = \Lambda(b_1) = \frac{1}{1+\exp(-b_1)} = \frac{1}{1+\exp(-\ln(\frac{\bar{y}}{1-\bar{y}}))} = \frac{1}{1+(\frac{1-\bar{y}}{\bar{y}})} = \bar{y} \tag{1.14}$$

Afterwards, we illustrate how the regression statistics are computed in the LOGIT function. To assess whether a variable helps to explain the default event or not, one can examine a *t*-statistic ratio for the hypothesis that the variable's coefficient is zero. For the *j*th coefficient, such a *t*-statistic ratio is constructed as:

$$t_i = \frac{b_i}{SE(b_i)} \tag{1.15}$$

where SE is the estimated standard error of the coefficient. We take *b* from the last iteration of the Newton scheme and the standard errors of estimated parameters are derived from the Hessian matrix. Specifically, the variance of the parameter vector is the main diagonal of the negative inverse of the Hessian at the last iteration step.

In the Logit model, the *t* ratio does not follow a *t* distribution as in the classical linear regression. Rather, it is compared to a standard normal distribution. To get the *p*-value of a two-sided test, we exploit the symmetry of the normal distribution:

$$p\text{-value} = 2 * (1 - \text{NORMDIST}(\text{ABS}(t))) \tag{1.16}$$

In a linear regression, we would report that R^2 is a measure of the overall goodness of fit.

In non-linear models estimated with maximum likelihood, one usually reports the Pseudo-R^2 suggested by McFadden. It is calculated as 1 minus the ratio of the log-likelihood of the estimated model (ln L) and the one of a restricted model that has only a constant (ln L_0):

$$\text{Pseudo-}R^2 = 1 - \frac{\ln L}{\ln L_0} \tag{1.17}$$

Like the standard R^2, this measure is bounded by 0 and 1. Higher values indicate a better fit. The log-likelihood ln L is given by the log-likelihood function of the last iteration of the Newton procedure, and is thus already available. Left to determine is the log-likelihood of the restricted model. With a constant only, the likelihood is maximized if the predicted default probability is equal to the mean default rate $\bar{y}$. We have seen in (1.14) that this can be achieved by setting the constant equal to the logit of the default rate, i.e. $b_1 = \ln(\bar{y} / 1 - \bar{y})$.

For the restricted log-likelihood, we then obtain:

$$\text{Ln } L_0 = \sum_{i=1}^{N} y_i \ln(\Lambda(\mathbf{b'x_i})) + (1\text{-}y_i)\ln(1 - \Lambda(\mathbf{b'x_i}))$$

$$= \sum_{i=1}^{N} y_i \ln(\bar{y}) + (1\text{-}y_i)\ln(1\text{-}\bar{y})$$

$$= N * [\bar{y}\ln(\bar{y}) + (1\text{-}\bar{y})\ln(1\text{-}\bar{y})] \tag{1.18}$$

The two likelihoods used for the Pseudo-R^2 can also be used to conduct a statistical test of the entire model, i.e. test the null hypothesis that all coefficients except for the constant are zero. The test is structured as a likelihood ratio test:

$$\text{LR} = 2(\ln L - \ln L_0) \tag{1.19}$$

The more likelihood is lost by imposing the restriction, the larger the LR statistic will be. The test statistic is distributed asymptotically chi-squared with the degrees of freedom equal to the number of restrictions imposed. When testing the significance of the entire regression, the number of restrictions equals the number of variables K minus 1. The function CHIDIST (test statistic, restrictions) gives the p-value of the LR test. The LOGIT command returns both the LR and its p-value.

The likelihoods ln L and ln L_0 are also reported, as is the number of iterations that was needed to achieve convergence.

Moreover, explanatory variables in scoring models often contain a few extreme values. These extreme values can have a large influence on coefficient estimates, which could impair the overall quality of the scoring model. A first step in approaching the problem is to examine the distribution of the variables. Excel provides the functions for the statistics we are interested in: arithmetic means (AVERAGE) and medians (MEDIAN), standard deviations (STDEV), skewness (SKEW) and excess kurtosis (KURT)[5], percentiles (PERCENTILE) along with minima (MIN) and maxima (MAX). A common benchmark for judging an empirical distribution is the normal distribution. The reason is not that there is an *a priori* reason why the variables we use should follow a normal distribution but rather that the normal serves as a good point of reference because it describes a distribution in which extreme events have been averaged out. Having identified the existence of extreme observations, a clinical inspection of the data is advisable as it can lead to the discovery of correctable data errors. In many applications, however, this will not lead to a complete elimination of outliers; even data sets that are 100% correct can exhibit bizarre distributions. Accordingly, it is useful to have a procedure that controls the influence of outliers in an automated and objective way. A commonly used technique applied for this purpose is winsorization, which means that extreme values are pulled to less extreme ones. We can also treat outliers by taking the physical logarithm of the variables that have extreme values (this treatment we use in our analysis).

In conclusion, the methodology that we use in our data can be summarized in the following steps:

1. From economic reasoning, a set of variables to capture factors that might be relevant for default prediction is compiled. To give an example: the Factor "Profitability" might be captured by EBIT / TA, EBITDA / TA, or Net Income / Equity.
2. The univariate distribution of these variables is examined (skewness, kurtosis, quantiles).
3. From step 2 it is determined whether there is a need to treat outliers and since there are extreme values, we treat them by taking their physical logarithm.
4. Based on steps 1 to 3, we run regressions in which each of the factors we believe to be relevant was represented by at least one variable. To select just

[5] Excess kurtosis is defined as kurtosis minus 3.

one variable out of a group that represents the same factor, first we considered the one with the highest Pseudo-R^2 in univariate logit regressions.

5. We rerun the regression with insignificant variables from step 4 being removed and we test the joint significance of the removed variables.

This methodology was implemented in our data and the results are presented in detail in the next section.

5. EMPIRICAL RESULTS

Initially, before the *logistic regression* model, we followed the first step of the procedure mention in the previous section. Since we had 32 variables, from economic reasoning, a set of variables to capture factors that might be relevant for default prediction was compiled. In models A, B and C we captured all financial ratios. More specifically, model A include ratios related to the debt of a shipping company in order to examine the relation between debt ratios and default, model B include ratios related to the liquidity and the profitability and model C include ratios related to the revenues of a shipping company. In model D we captured the bank related variables, in model E the loan related variables and in model F the obligor related variables.

We then moved to the second step by examining the univariate distribution of these variables (skewness, kurtosis, quantiles). All the quantitative variables were examined and as we mentioned in the previous section, a common benchmark for judging an empirical distribution is the normal distribution. Comparing the results with the normal distribution was found that all the quantitative variables contain a few extreme values and we went on by taking the physical logarithm of the variables.

After having completed the second step, logit function was applied to the models A – F with the logical values for constant and statistics both set to 1. From all the results were chosen the variables that had high Pseudo-R^2, which means that they interpreted better the default and the variables that were statistically significant at 5% level, which means that their p-values was below 5% and t-statistic higher than 1.96. These variables were: Interest cover ratio, Current ratio, Fleet ACR ratio, TC or Voyage employment of fleet, Forecast of the market, Clarksea Index of the financed vessel, Internal bank rating and Participation of Bank.

We applied again the logit function in only these statistically significant variables and from the eight models that we ran, we concluded in three models with the higher Pseudo-R^2. In Model 1 with 24.4% Pseudo-R^2 and 0.3% p-value, the variables were the Interest cover ratio, the Fleet ACR, the TC or Voyage employment of the fleet, the Forecast of the market and the Clarkesea Index. In Model 2 with 24.4% and 0.3% p-value, the variables were the Interest cover ratio, the Fleet ACR ratio, the TC or Voyage employment of the fleet, the Forecast of the market and the Internal bank rating. In Model 3 with 24.7% and 0.3% p-value, the variables are the Interest cover ratio, the Clarksea Index, the TC or Voyage employment of the fleet, the Forecast of the market and the Internal bank rating. The general model that was chosen was Model 1 because between 1 and 2, the variable's coefficients in Model 1 had better *p*-values. Moreover, since there was a slightly difference of Pseudo-R^2 between Model 1 and 3, we preferred Model 1 because our goal in this analysis is to propose a new internal bank rating procedure so we cannot have in our general model the internal bank rating as explanatory variable.

Table 1 presents the general Model 1.

Table 1

Model 1	**Constant**	**Interest Cover**	**Fleet ACR**	**TC or Voyage of fleet**	**Forecast of the market**	**Clarksea Index of financed vessel**
b	-5.604	-0.478	-0.712	-2.474	1.572	-0.074
SE(b)	1.582	0.276	0.719	1.008	0.583	0.085
t	-3.543	-1.728	-0.989	-2.455	2.697	-0.867
p-value	0.000	0.084	0.322	0.014	0.007	0.386
Pseudo R^2 / # iter	0.244	11.000	#N/A	#N/A	#N/A	#N/A
LR-test / p-value	17.846	0.003	#N/A	#N/A	#N/A	#N/A
$\ln L$ / $\ln L_0$	-27.679	-36.602	#N/A	#N/A	#N/A	#N/A

The dependent variable is the default (dummy variable) and we have set as explanatory variables the Interest cover ratio, the TC or Voyage employment of the fleet, the Forecast of the market, the Fleet ACR and the Clarksea Index. Starting with the statistics on the overall fit, the LR test implies that the logit regression is highly significant. The hypothesis H_0: "the five ratios add nothing to the prediction" can be rejected with a high confidence. From the three decimal points displayed in Table 1, we can deduce that the significance is better than 0.5%, since the p-value is 0.3%. So, we can trust that the regression model helps to explain the default events. Knowing that the model does predict defaults, we would like to know how well it does so. One usually turns to the R^2 for answering this question, but as in linear regression, setting up general quality standards in terms of a Pseudo-R^2 is difficult to impossible. A simple but often effective way of assessing the Pseudo-R^2 is to compare it with the ones from other models estimated on similar data sets. From the literature, we know that scoring models for listed US corporates can achieve a Pseudo-R^2 of 35% and more. In Model 1 we obtain a Pseudo-R^2 24.4% which is very high and means that these variables can interpret defaults. When interpreting the Pseudo-R^2, it is useful to note that it does not measure whether the model correctly predicted default probabilities – this is infeasible because we do not know the true default probabilities. Instead, the Pseudo-R^2 (to a certain degree) measures whether we correctly predicted the defaults.

Turning to the regression coefficients of Model 1, we can summarize that two out of the five variables (TC or Voyage of fleet and Forecast of market) have coefficients b that are significant on the 5% level or better, i.e. their *p*-values are below 0.05 and the t-statistics (|t|) higher than 1.96. If we reject the hypothesis that one of these coefficients is zero, we can expect to err with a probability of less than 5%. If we take a higher level of 10% we can, also consider the coefficient b of the Interest cover variable significant.

If we simultaneously remove two or more variables based on their *p*-values and *t*-statistic, we should be aware of the possibility that variables might jointly explain defaults even though they are insignificant individually. To statistically test this possibility, we can run a regression in which we exclude variables that were insignificant in the general Model 1 and then conduct a likelihood ratio test.

Table 2 presents the restricted Model 1a.

Table 2

Model 1a	**Constant**	**Interest Cover**	**TC or Voyage of fleet**	**Forecast of the market**
b	-6.152	-0.500	-2.525	1.548
SE(b)	1.473	0.255	0.961	0.543
t	-4.177	-1.963	-2.627	2.850
p-value	0.000	0.050	0.009	0.004
Pseudo R^2 / # iter	0.215	10.000	#N/A	#N/A
LR-test / p-value	15.727	0.001	#N/A	#N/A
$\ln L$ / $\ln L_0$	-28.739	-36.602	#N/A	#N/A

In Model 1a, we removed the variables Clarksea Index and Fleet ACR and we conducted the LR test which is presented in the next Table 3.

Table 3

LR - Test for b (Clarksea Index of financed vessel) = b (Fleet ACR) = 0 in Model 1	
LR	2.119
DF	2
p-value	0.347

We imposed the restriction that the coefficients on these two variables are zero. The likelihood ratio test for the hypothesis $b_{\text{Clarkesea Index}} = b_{\text{Fleet ACR}} = 0$ is based on a comparison of the log likelihoods ln L of the Models 1 and 1a and referred to a chi-squared distribution with two degrees of freedom because we impose two restrictions. The LR test leads to value of 2.12 with a p-value of 34.7%. This means that if we add the two variables Clarksea Index and Fleet ACR to Model 1, there is probability of 34.7% that we do not add explanatory power. The LR test thus confirms the results of the individual tests: individually and jointly, the two variables would be considered only marginally significant and we would probably consider not using them for prediction.

Table 4 presents the default probabilities of the seven defaulted loans for the eight models that we ran, together with the restricted model 1a.

Table 4

Default probabilities	Model 1	Model 1a	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Defaulted loan 1	7.61%	7.88%	12.93%	10.10%	8.76%	11.32%	2.10%	12.09%	3.82%
Defaulted loan 2	4.79%	10.28%	2.86%	7.29%	5.55%	2.72%	4.38%	6.06%	0.66%
Defaulted loan 3	2.40%	1.55%	4.36%	2.92%	1.54%	4.09%	1.20%	1.74%	3.54%
Defaulted loan 4	18.35%	30.46%	15.90%	18.11%	20.20%	14.68%	2.79%	17.44%	1.60%
Defaulted loan 5	0.33%	0.37%	0.11%	0.23%	0.50%	0.15%	1.11%	0.41%	1.60%
Defaulted loan 6	29.17%	18.10%	26.06%	32.76%	21.06%	23.95%	7.54%	24.53%	10.72%
Defaulted loan 7	4.56%	0.87%	4.77%	2.61%	3.27%	5.51%	13.13%	3.28%	6.79%
AVERAGE	**9.60%**	**9.93%**	**9.57%**	**10.57%**	**8.70%**	**8.92%**	**4.61%**	**9.36%**	**4.10%**

The observations shown in Table 4 contain defaulters for which we predict a default probability of 0.11% to 32.76%. The defaulted loan 5 has a law default probability. This should not be cause for alarm though, for two reasons: First, a borrower can default even if its default probability is very low. Second, even though a model may do a good job in predicting defaults on the whole, it can nevertheless fail at predicting some individual default probabilities.

From the default probabilities, we can confirm the result of the previous models meaning that model 1, 2 and 3 are these with the highest default probabilities and can interpret better the default. Moreover, from Table 4 we observe that the average of default probabilities of Model 3 is higher than the average of default probabilities of the general Model 1 but since there was a slightly difference of their Pseudo-R^2 and of their default probabilities, we prefer Model 1 because as we have mentioned, our goal in this analysis is to propose a new internal bank rating procedure so we cannot have in our final model the internal bank rating as explanatory variable. Finally, since the average of the default probabilities is higher in restricted Model 1a than in general Model 1 we confirm the results of the LR test in Table 3, meaning that the two variables Clarksea Index and Fleet ACR, will be considered only marginally significant.

5.1 Alternative Definition of Default (1)

As we mentioned in the data description, because the number of defaults in our sample is limited (seven defaulted loans), we will consider an alternative definition of default and a loan will be characterized as defaulted when a missed payment over 90 days has occurred and when any change in the margin of a loan or the repayment schedule or the balloon payment has occurred. So we reran the logit regression with 28 defaulted loan and from models A – F the variables that were statistically significant and interpreted better the default were: Interest Cover ratio, Profit Margin, Revenues, Age of firm, Fleet ACR ratio and TC or Voyage Employment of fleet. Table 5 presents the general model with the highest Pseudo-R^2 and the best *p*-values and *t*-statistics.

Table 5

Model 1	**Constant**	**Interest Cover**	**Profit Margin**	**Age of firm**	**TC or Voyage of fleet**	**Fleet ACR**
b	-0.117	-0.246	0.227	-0.450	-0.736	-0.532
SE(b)	0.786	0.125	0.185	0.253	0.426	0.336
t	-0.149	-1.968	1.223	-1.780	-1.728	-1.586
p-value	0.882	0.049	0.221	0.075	0.084	0.113
Pseudo R^2 / # iter	0.074	8.000	#N/A	#N/A	#N/A	#N/A
LR-test / p-value	15.818	0.007	#N/A	#N/A	#N/A	#N/A
lnL / lnL0	-99.062	-106.971	#N/A	#N/A	#N/A	#N/A

The dependent variable is the default (dummy variable) and we have set as explanatory variables the Interest cover ratio, the TC or Voyage employment of the fleet, the Age of firm, the Fleet ACR and the Profit Margin ratio. In Model 1 we obtain a Pseudo-R^2 7.4% which is low implying that the way the model was set up may not be ideal. However, from all the models that we ran is the highest Pseudo-R^2 that we obtained.

Turning to the regression coefficients, we can summarize that one out of the five variables (Interest Cover ratio) have coefficient b that is significant on the 5% level or better, i.e. its *p*-value is below 0.05 and the t-statistic (|t|) higher than 1.96. If we reject the hypothesis that the coefficient is zero, we can expect to err with a probability of less than 5%. If we take a higher level of 10% we can, also consider the coefficients b of the Age of firm and the TC or Voyage Employment of flee statistically significant.

If we simultaneously remove two or more variables based on their *p*-values and *t*-statistic, we should be aware of the possibility that variables might jointly explain defaults even though they are insignificant individually. To statistically test this possibility, we can run a regression in which we exclude variables that were insignificant in the general Model 1 and then conduct a likelihood ratio test.

Table 6 present the restricted model 1a.

Table 6

Model 1a	**Constant**	**Interest Cover**	**Age of firm**	**TC or Voyage of fleet**
b	-0.260	-0.252	-0.531	-0.980
SE(b)	0.820	0.126	0.265	0.412
t	-0.317	-1.997	-2.004	-2.379
p-value	0.751	0.046	0.045	0.017
Pseudo R^2 / # iter	0.053	8.000	#N/A	#N/A
LR-test / p-value	11.264	0.010	#N/A	#N/A
lnL / lnL0	-101.339	-106.971	#N/A	#N/A

Table 7

LR - Test for b (Fleet ACR) = b (Profit Margin) = 0 in model 1		
LR	4.554	
DF	2	
p-value	0.103	

Table 7 presents the results of the LR test. We impose the restriction that the coefficients of the two variables Fleet ACR and Profit Margin are zero and the LR test leads to value of 4,55 with a *p*-value of 10,3 %. This means that if we add the two variables Fleet ACR and Profit Margin to Model 1, there is probability of 10,3% that we do not add explanatory power. Since the probability is very low we might consider these two variables for prediction of default probabilities. Table 8 presents the average of the default probabilities for each model that we ran.

Table 8

Default probabilities	Model 1	Model 1a	Model 2	Model 3	Model 4	Model 5	Model 6
AVERAGE	**9.94%**	**8.78%**	**9.29%**	**9.49%**	**9.87%**	**8.61%**	**9.37%**

From the default probabilities, we can confirm the result of the models we ran, meaning that Model 1 is that with the highest default probabilities and can interpret better the default. Moreover, from Table 8 we observe that the average of default probabilities of the restricted Model 1a is lower than the general model 1 by 1.16%. This confirms the result of the LR test in Table 7, meaning that the two variables Profit Margin and Fleet ACR, will be considered significant explanatory variables since together with the other three variables in Model 1 predict better the default probabilities.

5.2 Alternative Definition of Default (2)

As we mentioned in the data description, because the number of defaults in our sample is limited (seven defaulted loans), we will consider an alternative definition of default and a loan will be characterized as defaulted when a missed payment over 90 days has occurred and when any change in the terms of a loan has occurred. So we reran the logit regression with 36 defaulted loans and from models A – F the variables that were statistically significant and interpreted better the default were: Revenues, Revenues Volatility, Profit Margin, Age of firm, Fleet ACR ratio and Years of cooperation between the shipping company and the bank. Table 9 presents the general Model 1 with the highest Pseudo-R^2 and the best *p*-values and *t*-statistics.

Table 9

Model 1	Constant	Revenues	Revenue Volatility	Age of firm	Years of Cooperation with Bank	Fleet ACR
b	-0.047	-0.074	0.058	-0.405	-0.476	-0.555
SE(b)	0.789	0.037	0.026	0.238	0.275	0.298
t	-0.059	-2.024	2.242	-1.698	-1.728	-1.862
p-value	0.953	0.043	0.025	0.090	0.084	0.063
Pseudo R^2 / # iter	0.061	8.000	#N/A	#N/A	#N/A	#N/A
LR-test / p-value	15.564	0.008	#N/A	#N/A	#N/A	#N/A
lnL / lnL0	-120.393	-128.175	#N/A	#N/A	#N/A	#N/A

The dependent variable is the default (dummy variable) and we have set as explanatory variables the Revenues, the Revenues volatility, the Age of firm, the Fleet ACR and the Years of cooperation between the shipping company and the bank. In Model 1 we obtain a Pseudo-R^2 6,1% which is low implying that the way the model was set up may not be ideal. However, from all the models that we ran is the highest Pseudo-R^2 that we obtained. Turning to the regression coefficients, we can summarize that two out of the five variables (Revenues and Revenues Volatility) have coefficients b that are significant on the 5% level or better, i.e. their *p*-values are below 0,05 and the t-statistic (|t|) higher than 1,96. If we reject the hypothesis that the coefficient is zero, we can expect to err with a probability of less than 5%. If we take a higher level of 10% we can consider all the coefficients b of the five variables statistically significant.

If we simultaneously remove two or more variables based on their *p*-values and *t*-statistic, we should be aware of the possibility that variables might jointly explain defaults even though they are insignificant individually. To statistically test this possibility, we can run a regression in which we exclude variables with the higher *p*-values in the general Model 1 and then conduct a likelihood ratio test.

Table 10 presents the restricted Model 1a.

Table 10

Model 1a	**Constant**	**Revenues**	**Revenue Volatility**	**Fleet ACR**
b	-1.271	-0.086	0.046	-0.491
SE(b)	0.529	0.036	0.025	0.290
t	-2.404	-2.365	1.836	-1.692
p-value	0.016	0.018	0.066	0.091
Pseudo R² / # iter	0.036	8.000	#N/A	#N/A
LR-test / p-value	9.257	0.026	#N/A	#N/A
lnL / lnL0	-123.547	-128.175	#N/A	#N/A

Table 11

LR - Test for b (Age of firm) = b (Years of Cooperation with Bank) = 0 in model 1		
LR	6.307	
DF	2	
p-value	0.043	

Table 11 presents the LR test. We impose the restriction that the coefficients of the two variables Age of firm and Years of cooperation with the bank are zero and the LR test leads to value of 6.3 with a *p*-value of 4.3%. This means that if we add these two variables to Model 1, there is probability of 4.3% that we do not add explanatory power. Since the probability is lower than 5% level we will consider these two variables for prediction of default probabilities. In Table 12 is presented the average of the default probabilities for each model that we ran.

<u>Table 12</u>

Default probabilities	**Model 1**	**Model 1a**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
AVERAGE	**10.77%**	**9.28%**	**10.27%**	**10.11%**	**10.54%**	**10.70%**	**10.02%**

Finally, from the default probabilities, we can confirm the result of the models we ran meaning that Model 1 is that with the highest default probabilities and can interpret better the default. From Table 12 we observe that the average of default probabilities of the restricted Model 1a is lower than the general model 1 by 1.49%. This confirms the result of the LR test in Table 11, meaning that the two variables Age of firm and Years of cooperation with the bank will be considered significant explanatory variables since along with the other three variables in Model 1 predict better the default probabilities.

6. DISCUSSION

The aim of this dissertation is to estimate a credit scoring model with high statistical significance and forecasting ability. This model should be able to assess the default risk of a new shipping loan request with the highest possible accuracy. The estimation of the model involves estimating weights for each variable that we have collected, according to its relevance, to assess default risk before granting a shipping loan.

Three different definitions of default were considered. According to the first definition, a loan is characterized as defaulted when a missed payment over 90 days has occurred. According to the second definition, a loan is characterized as defaulted when a missed payment over 90 days has occurred and when the margin of the loan or the repayment schedule or the balloon payment has occurred. According to the third definition, a loan is characterized as defaulted when any term of it has changed and when a missed payment over 90 days has occurred.

In the **first definition of default**, we had 7 defaulted loans and the variables that interpreted better the model were: the Interest cover ratio, the Fleet ACR ratio, the TC or Voyage employment of the fleet, the Forecast of the market and the Clarksea Index.

The coefficients b of the Interest cover ratio is negative, meaning that there is a negative relation between Interest cover ratio and default probability. Increasing values of this variable reduce default probability or the opposite, decreasing values of this variable increase default probability. This result is what we expected, because when Interest cover ratio increases, the shipping company can meet its debt obligations through profits and thus the risk of not repaying the new loan decreases. The coefficient b of the TC or Voyage employment of fleet (dummy variable) is also negative, meaning that when shipping's company probability of having time chartered its fleet increases, the probability of default decreases (or the opposite). This is also what we expected, because with time charter the shipping company has secured for a certain long period its revenues. It is less risky than voyage employment of fleet where there is a fear of having laid-up ships. The coefficient b of the quantitative variable Forecast of the market is positive, implying that when the Forecast is not "Strong" the probability of default increases since the shipping company may not be able to repay the loan. The coefficient b of the Fleet ACR is negative, implying that increasing values of this variable reduce default probability. This is the result that we expected, because when Fleer ACR ratio increases, the market value of the fleet increases or the leverage of the fleet decreases. Each of these scenario is positive, concerning a new loan since the risk of not repaying it, is decreased. Last, the coefficient b of the Clarksea Index of the financed vessel is negative, implying the negative relation between Clarksea Index and default probability, because when the Clarksea Index of the financed vessel increases, the shipping company will have earnings from the employment of the financed vessel. So, the risk of not repaying the new loan is decreased.

From these five variables the Interest cover ratio, the TC or Voyage employment of the fleet and the Forecast of the market are statistically significant and the Fleet ACR and the Clarksea Index of the financed vessel are marginally significant since the combination of all leads to the highest Pseudo-R^2.

In the **alternative definition of default (1)**, we had 28 defaulted loans and the variables that interpreted better the model were: the Interest cover ratio, the TC or Voyage employment of the fleet, the Age of firm, the Fleet ACR and the Profit Margin ratio. Coefficients b of the Interest cover ratio, the TC or Voyage employment of the fleet and the Fleet ACR are negative, as in the previous model with the seven defaulted loan. The coefficient b of the Profit Margin ratio is positive, meaning that increasing values of this variable increase default probability. As we mentioned in the section of data description, Profit margin is a profitability ratio, with its value expressed in percentage. It indicates how profitable a company has been in the sales it has made. Higher Profit margin indicates higher revenues which may be due to low competition or a successful product policy, and correspondingly indicates low default risk. However, the relation between Profit margin and default may not be always negative, because higher profit margin indicates higher revenues which are often associated with high cash requirements (for advertising and inventories) and higher risk. This is the reason why in this model the coefficient b of the Profit margin ratio is positive. The coefficient b of the variable Age of the firm is negative, implying the negative relation between Age of firm and default probability. Age of the firm is used in order to account for the market power of the firm into the industry. Higher values are expected to be associated with lower default risk for a specific shipping company.

From these five variables the Interest cover ratio, the TC or Voyage employment of the fleet and the Age of the firm had low p-values, however, we consider significant all the five variables since altogether interpret better the default probability and leads to the highest Pseudo-R^2.

In the **alternative definition of default (2)**, we had 36 defaulted loans and the variables that interpreted better the model were: the Revenues, the Revenues volatility, the Age of firm, the Fleet ACR and the Years of cooperation with the bank. Coefficients b of the Age of firm and Fleet ACR are negative, as in the previous model with 28 defaulted loans. The coefficient b of the Years of cooperation with the bank is negative, meaning that increasing values of this variable reduce default probability .The longer the cooperation between the bank and the shipping company, the higher the trust and creditworthiness. The coefficient b of the Revenues is negative, implying that increasing values of this variable reduce default probability. High revenues growth is often associated with high cash requirements (for advertising and inventories. Thus, high revenues growth can also be symptomatic of high default risk. However, in our model the relation between default probability and revenues is negative. The coefficient b of the Revenues volatility is positive, meaning that as the volatility increases the default probability also increases. This is true, because high volatility indicate higher risk since is difficult for the shipping company to estimate its future revenues.

It is observed from the three general models that even if the definition of default changes, some variables are still statistically significant. The variable Fleet ACR is an explanatory variable in each of the three definitions of default. In the first definition is consider only marginally statistically significant and in the other two definitions is consider statistically significant. The Interest cover ratio and the TC or Voyage employment of the fleet are statistically significant explanatory variables in the first definition of default and in the alternative definition of default (1). The Age of firm is statistically significant explanatory variable in the alternative definition of default (1) and (2). These four variables are very important, as a shipping company which is high-leveraged, its market value decreases, it cannot meet the debt obligations through profits, it operates in voyage market and it operates few years, is more likely to face problems in fulfilling its loan obligations.

Summing up the above mentioned, despite the fact that the variables Fleet ACR, Interest cover ratio, TC or Voyage employment of fleet and Age of firm are statistically significant in more than one general model, from the results of the three different definitions of default, it is concluded that all the variables discussed in this section are important when assessing the default risk in an individual shipping bank loan.

7. CONCLUSION

This dissertation focused on the determinants of credit risk in shipping loans which are relevant when assessing the default risk in an individual shipping bank loan. Our attempt to study the event of default in a sector like shipping is of great interest and value adding, since there was no previous bibliography about credit risk in shipping loans.

We tried to understand how the default behavior of a shipping loan and a shipping company could possibly be predicted by a bank providing a loan. We started by exploring the term credit risk and the shipping market. Moreover, we examined all the information taken into account by a bank, during its loan evaluation process. Information related to the bank, the loan and the obligor.

Afterwards, a dataset was compiled with detailed information for 132 shipping loans, which also includes their loan default record. The number of defaulted loans was very small. Consequently, we suggested three definitions of default. Under the first definition, default is a dummy variable taking the value of 1 if a missed payment over 90 days has occurred. Under the alternative definition of default (1), the default is a dummy variable taking the value of 1 not only when a missed payment over 90 days has occurred, but also when a change in the repayment schedule, the balloon payment and the margin of the loan has occurred. Under the alternative definition of default (2), the default is a dummy variable taking the value of 1 when a missed payment over 90 days has occurred and when any change in the terms of a loan has changed. The results obtained suggest that default probabilities are influenced by many factors, which are quantitative and qualitative.

More precisely, by studying the results of our research, from the first definition of default, we reached the conclusion that default probabilities are influenced by the TC or Voyage employment of the fleet, the Forecast of the market and the Interest cover ratio. However, we can consider two more variables marginally statistically significant, the Fleet ACR and the Clarksea Index of the financed vessel, since the combination of these five variables interpret better the default by giving the highest Pseudo-R^2 in the *logistic regression* model. In the alternative definition of default (1), we reached the conclusion that the default probabilities are influenced by the TC or Voyage employment of the fleet, the Age of the firm, the Interest cover ratio, the Fleet ACR and the Profit margin ratio. In the alternative definition of default (2), we reached the conclusion that the default probabilities are influenced by the Revenues, Revenues Volatility, Age of firm, Fleet ACR and Years of corporation between the bank and the shipping company. Generally, the obtained results of the three definition of default suggest that many factors affect the probability of default, especially, factors related to the shipping company and to the market where the shipping company operates.

Moreover, it is useful to note that, since our sample was relatively small and there was no previous bibliography about credit risk in shipping loans so as to compare the results of this study, the results may be misleading. Thus, more research must be done on this area.

In conclusion, we believe that credit risk analysis is of great importance as worldwide economies expand and develop. The assessment of credit risk and default behaviour of borrowers is an important matter for all Financial Institutions. In times of worldwide recession the study of the event of default and the evaluation of borrowers' credit risk is a crucial issue.

8. APPENDIX

A. Testing for Extreme Values

Table A1

	Leverage (TL/TA)	Debt Coverage Ratio = Long Debt / EBITDA	Debt Coverage Ratio = Current Debt /EBITDA	Debt Coverage Ratio=Total Liabilities/EBITDA	Years of operation to repay debt
Average	0,65	2,44	1,10	5,38	25,13
Median	0,55	1,92	0,58	3,57	24,69
Stdev	2,16	5,70	3,61	8,48	11,64
Skewness	21,28	-6,77	-2,53	0,81	1,03
Kurt	458,30	137,32	54,99	19,57	7,21
Quantiles / Extreme Values					
Min	0,00	-86,73	-35,77	-54,80	-25,80
0,50%	0,02	-3,65	-7,84	-34,88	-18,92
1,00%	0,05	0,00	0,00	0,03	3,02
5,00%	0,19	0,00	0,02	0,56	10,06
95,00%	0,94	7,15	5,59	16,08	42,97
99,00%	1,31	13,38	11,49	46,79	64,89
99,50%	2,03	28,91	19,07	48,72	82,40
Max	47,10	38,31	24,19	54,04	89,04

Table A2

	Current Ratio (CA/CL)	Interest Cover (EBITDA/Interest Expenses)	Profit Margin (EBITDA/ Revenues)	Cash Reserves (Cash and Cash Equivalents/TA)	Revenues	Revenues Volatility (last 3 yr.)
Average	3,57	15,24	0,43	0,10	93405221,96	30531612,95
Median	1,13	7,48	0,34	0,05	34578458	9700804,245
Stdev	21,35	80,72	0,69	0,13	163421522,6	65925010,83
Skewness	12,01	7,50	6,89	4,37	4,16	4,09
Kurt	155,79	92,34	56,40	33,80	22,52	18,41
Quantiles / Extreme Values						
Min	0,02	-399,00	-0,18	0,00	13415,00	9748,59
0,50%	0,02	-324,33	-0,02	0,00	17287,76	48274,44
1,00%	0,03	-0,64	0,00	0,00	27135,98	76268,93
5,00%	0,22	1,12	0,02	0,00	2278458,40	980260,57
95,00%	4,87	40,26	0,75	0,39	365053700,00	132566827,66
99,00%	51,11	133,08	4,40	0,60	775816000,00	382281818,35
99,50%	167,65	741,10	5,84	0,61	1137344780,00	423550847,26
Max	326,49	878,16	7,04	1,55	1331144000,00	424448283,48

Table A3

	Arrangement Fees	Participation Fees	Up-front Fees	Margin of the loan
Average	126697,24	25398,81	79770,85	0,06
Median	64750,00	15673,60	50250,00	0,02
Stdev	330200,05	28667,00	81349,98	0,36
Skewness	6,70	2,58	1,74	8,83
Kurt	45,66	6,07	2,19	76,38
Quantiles / Extreme Values				
Min	6000,00	1818,00	5000,00	0,01
0,50%	6000,00	1818,00	5350,00	0,01
1%	6525,00	1831,68	10000,00	0,01
5%	10000,00	2960,00	15000,00	0,01
95%	310000,00	120000,00	300000,00	0,04
99%	2500000,00	120000,00	333000,00	3,25
99,50%	2500000,00	120000,00	333000,00	3,25
Max	2500000,00	120000,00	333000,00	3,25

Table A4

	Amount of Loan	Life to Final Maturity	ACR Contractual	ACR Actual	Total Size of financed vessel	Age of financed vessel
Average	30593274,05	5,15	1,47	1,93	87531,94	12,20
Median	13850000	3,00	1,45	1,68	42310,00	11,00
Stdev	50205910,12	3,87	0,26	0,91	154550,46	11,18
Skewness	3,99	0,71	1,32	2,72	4,92	0,27
Kurt	19,21	-0,82	2,08	10,88	28,21	-1,36
Quantiles / Extreme Values						
Min	300000,00	0,30	1,15	0,06	2424,00	0,00
0,50%	300000,00	0,30	1,15	0,06	2424,00	0,00
1%	650000,00	0,47	1,15	0,06	2446,40	0,00
5%	1500000,00	1,00	1,20	1,22	3290,00	0,00
95%	110000000,00	12,00	2,00	3,37	280000,00	29,00
99%	310000000,00	13,34	2,00	5,30	1073466,00	35,00
99,50%	310000000,00	15,00	2,50	6,12	1073466,00	35,00
Max	353130000,00	15,00	2,65	7,61	1073466,00	35,00

Table A5

	LTV	Balloon payment / Amount of	Clarksea Index of financed vessel	Age of firm	Years of Cooperation with Bank
Average	0,82	0,27	22443,28	19,25	2,99
Median	0,60	0,23	20766,00	17,00	3,00
Stdev	2,07	0,17	11090,73	10,20	2,05
Skewness	8,27	1,39	0,30	0,95	0,74
Kurt	67,14	2,99	-0,95	0,60	-0,12
Quantiles / Extreme Values					
Min	0,13	0,00	3640,00	1,00	0,00
0,50%	0,16	0,00	5605,42	2,00	0,00
1%	0,19	0,00	6211,00	2,00	0,00
5%	0,30	0,05	7107,00	5,10	1,00
95%	0,82	0,63	42967,00	38,00	6,00
99%	18,18	0,90	44258,00	50,00	9,00
99,50%	18,18	0,90	44258,00	50,00	9,00
Max	18,18	0,93	44258,00	50,00	9,00

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