Predicting corporate failure for Listed Shipping Companies

ABSTRACT

The shipping industry has unique financial characteristics: it is capital intensive, faces highly volatile freight rates and ship prices and exhibits strong cyclicality and seasonality. It is a sector which has a unique corporate structure as it is normally highly geared and relies extensively on debt financing. Shipping is also a conservative sector favouring traditional finance and tapping the global capital market much later than other industries. In this sense, the shipping industry deserves its own enquiry into its financial characteristics. This paper considers worldwide listed shipping companies in terms of their overall financial performance. While default against individual financial instruments can represent early phases of corporate failure, predicting overall failure at the firm level is worth investigating. This paper studies corporate failure and financial performance in globally listed shipping firms, examining the different characteristics of financial risks and investigating how these characteristics vary over time. A new technique, the Receiver Operating Characteristic (ROC) Curve, is introduced to compare the overall accuracy of various models for predicting binary outcomes. The findings in respect of shipping finance for listed shipping companies can benefit both shipowners and investors.

Keywords: Shipping Finance; Financial Performance; Financial Risk; Logit Model; Regression

INTRODUCTION

There are many unique aspects to the shipping industry, which make financial and business forecasting difficult and, it has been suggested, leave the industry with a poor forecasting record. However, a paradox exists in that most sectors of the industry continue to try and make forecasts as, difficult and unpredictable though it may be, successful predictions can lead to substantial profits (Stopford, 2009). The shipping industry is known for being highly capital intensive, the sale of one merchant ship is a large capital transaction generally involving millions of US dollars. In the shipping industry as a whole, investment in the building and purchasing of ships involves billions of dollars every year; for example in 2017 the global total sales was $19.5 billion (Clarksons, 2018).

Shipping carries large volumes of traded raw materials and products, with around 80 per cent of global trade by volume and 70 per cent by value being carried by sea. For developing countries these proportions are even higher (UNCTAD, 2016). At the same time, shipping is an industry that is both highly volatile and high risk in nature for both operators and investors, known for wide fluctuations in demand and inertia of supply. Further, there are no firm cyclical patterns in shipping markets, although they are tightly linked to the general business cycle. Returns on investment are generally poor in terms of low financial returns and high risks (Albertijn et al, 2011).

However, at the same, the high-risk nature of shipping markets does attract investors. Due to the highly capital intensive nature of shipping markets, successful investment can generate large profits, while conversely failed investments can lead to substantial losses. The distinctive nature of the shipping industry also makes shipping finance unique, particularly in today's capital market environment, i.e. the late exposure to capital markets and the largely unique corporate structure. They are often highly geared - the leverage ratio (defined as the ratio of interest-bearing debt to total assets) can be twice as high compared to other industries (Syriopoulos and Tsatsaronis, 2011).

In earlier eras, much of ship finance was provided through individual owners funding their own companies. However, more recently shipowners have sought finance from the capital markets with up to 75% of finance being provided by banks. Starting from the 1990s, shipping companies began to turn to global capital markets to raise finance, through either equity or debt (Albertijn et al, 2011). During the period 2004 – 2007 there was an increased number of Initial Public Offerings (IPOs), secondary offerings, and issuance of high-yield bonds related to the shipping industry. However, following the financial crisis of 2008, bankruptcy amongst firms operating in the shipping industry was a familiar theme. The financial crisis also created capital, credit, and bailout problems for banks specialising in shipping. In 2009 the volume of syndicated shipping loans fell by more than 60% and the number of active shipping banks fell with those remaining restructuring existing loans rather than offering new finance (Albertijn et al, 2011). Corporate finance is therefore an important consideration within the shipping industry, which remains in a precarious situation. This has brought additional pressures in terms of shipping companies establishing sound and rigorous, as well as transparent, financial practices (Syriopoulos and Tsatsaronis, 2011).

While issues such as corporate failure and financial performance have been extensively researched in the accountancy and finance fields, their consideration within the shipping industry has been limited. The spotlight has been on loans (Kavussanos and Tsouknidis, 2016; Mitroussi et al, 2012; 2016), high-yield bonds (Grammenos et al, 2007; 2008) or IPOs (Grammenos and Papapostolou, 2012a). To date, no study has discussed the insolvency of shipping firms at a company level, leaving a significant research gap. There remain many unanswered questions, for example, how do shipping firms reach the point of failure/bankruptcy? How can the financial performance of shipping firms be evaluated more effectively?, and what can they do in the future to mitigate financial crisis?

In light of the above discussion, for the first time we look at worldwide listed shipping companies in terms of their overall financial performance, rather than that of individual financial instruments. In the literature no papers exist on corporate failure related to financial failure at the firm level in the shipping industry. Although various instruments have been studied, each individually indicating failure might occur, there is no analysis related to overall failure. While default against individual financial instruments can represent early phases of corporate failure, predicting overall failure at the firm level is worth investigating. This paper explores corporate failure and financial performance in globally listed shipping firms.

While previously there would have been limited access to financial data on shipping companies, it is now more easily available for analysis through various public databases (e.g. Bloomberg) and market information. The dataset used in this study consists of 40 globally listed shipping companies selected from the marine transport sector and available from the Bloomberg database. These companies either survived or failed between 2007 and 2014. Data were collected in order to assess whether failure can be predicted over a range of time horizons prior to failure: half year, one year, one and a half years, two years, two and a half years and three years. The results are unique in the ship finance literature. By means of econometric models for predicting corporate failure, this paper identifies possible predictors for financial risk associated with listed shipping companies. It also examines the different characteristics of financial risks in shipping and investigates how these characteristics vary over time. It then evaluates how accurate these models are, as well as the robustness of their implications. The findings will be of interest to traders and investors in shipping markets, as well as banks and shipowners in the ship finance sector.

The remaining sections are organised as follows. Section 2 reviews the relevant literature on corporate failure and particularly financial distress in shipping; Section 3 explains the econometric model employed; the data and financial ratios are discussed in Section 4; Section 5 analyses the results and discusses the predictive abilities of our models; and finally, Section 6 provides the conclusions.

LITERATURE REVIEW

Corporate Failure

A significant threat for many businesses, irrespective of company size or the business field in which they operate is corporate failure. Business failures are economically costly and the market value of distressed firms generally declines in the period leading up to collapse (Warner, 1977; Charalambous et al, 2000). In such circumstances, not only are the company and its employees directly affected but, so more broadly, are the suppliers of capital, investors and creditors (Charitou et al, 2004). The identification of companies which are likely to fail is thus of interest to a range of stakeholders, and predicting corporate failure has been a theme of economic research for several decades (Aharony et al, 1980; Morris, 1997). Corporate failure indicates that resource misallocation is likely to have occurred, which is undesirable, and identifying in advance if it is likely to occur would enable measures to be taken to prevent such an occurrence (Lev, 1974). Further, financial distress as a concept has been used to explain how some companies have a higher probability of failure in situations where they cannot meet their financial obligations (Chan and Chen, 1991; Fama and French, 1996; Campbell et al, 2008).

Argenti (1976) identified causes of corporate failure to originate either from internal factors related to poor management, or external factors over which a company has much less control. In the former, various manifestations exist including: a lack of responsiveness to change, poor communication, improper conduct by employees, weak cost control, poor financial management and the placing of the organisation in a highly leveraged position. Of these, the latter can play a very important role in the event of an economic downturn, as an organisation may not then be able to service their exposure to debt. In respect of external factors, the role of organisations such as unions; government regulation, and natural events including disasters and demographic change can all play a role in failure. (Dambolena and Khoury, 1980).

Capital markets, and the need for good corporate governance, have been discussed by a range of authors (see for example Jensen and Meckling, 1976; Gompers et al, 2003; Giroud and Mueller, 2011; Brown et al, 2011; Syriopoulos and Tsatsaronis, 2011). However, even with the rigour applied by corporate governance mechanisms, for a wide variety of reasons many companies still fail. In the wider economy, the provision of credit represents a major risk that banks are concerned with, and will seek to mitigate it through credit analysis, loan structuring and the monitoring of a loan throughout its duration. Literature exists on default risk for corporate credit loans and a number of factors, such as information asymmetry and the financial structure of firms have been recognised as being of significance (Bonfim, 2009). Credit risk assessment accuracy requires assessment mechanisms that can identify whether a company is likely to repay or default on credit (Yurdakul and Ic, 2004). Thus market conditions and the dynamics of a sector, both operational and financial, need to be considered in determining credit risk (Gavalas and Syriopoulos, 2015).

Evidence prior to the 2008 – 2009 economic crisis showed that in the 1980s and 1990s business failures occurred at their highest rates since the early 1930s (Charitou et al, 2004). Business failures during the more recent economic crisis from 2007 onwards have also been very high. During the 2008 – 2009 period, a large number of financial institutions collapsed or were bailed out by governments. This collapse led to a freeze of global credit markets and required government interventions worldwide (Erkens et al, 2012). The knock-on effect was the impact on individual firms, with many finding themselves in difficulty or failing completely.

When economic crises occur, there are a wide range of factors which can lead to business failure, deriving from both macroeconomic and firm specific aspects. Macroeconomic causes which increase the probability of corporate failure were identified by Altman (1968) and include tight monetary policy, negative investor expectations and the state of economy. These can lead to high interest rates, reduced profits and high debt burdens. Industry and firm-specific aspects, including government regulation and the nature of operations, can also contribute to a firm's financial distress (Charitou et al, 2004).

Financial Issues in Shipping

In relation to the maritime sector, globalisation of the world economy, increased competition and technological progress in freight transport have led to changes in how the shipping industry is financed (Andreou et al, 2014). Traditionally the shipping industry was financed through private capital, but from the 1990s public offerings and corporate lending have been used to fund investment (Grammenos and Papapostolou, 2012b). This has led to sources of corporate failure which did not previously exist (Syriopoulos and Theotokas, 2007; Syriopoulos and Tsatsaronis, 2011). With the shipping industry being capital-intensive, a wide range of capital sources have traditionally been used to finance newbuildings and secondhand sale and purchase (S&P). Three principal sources of finance exist: equity finance, mezzanine finance and debt finance Historically, the largest cumulative amount raised has come from the third source, in the form of internally generated funds and bank debt. By using internally generated finance and debt that is close to default-risk-free a company avoids the cost of financial distress and maintains financial slack in the form of reserve borrowing power. (Grammenos and Papapostolou, 2012b). However, more recently shipping companies have adopted financing strategies that have moved them towards external financing. The financial crisis of 2008 - 2009 meant that bank finance became limited and many shipping companies had to seek alternative methods of financing. Overall this puts many shipping companies in a more vulnerable financial position.

Drobetz et al (2013) showed the way cyclicality on the asset side of a shipping company's balance sheet translates to its liability side and how it affects financing and capital structure decisions. In relation to equity finance, Grammenos and Marcoulis (1996) identified that an increasing number of shipping companies were accessing the capital market. With regard to debt finance, Grammenos et al (2008) argued that bankruptcy and default on a debt instrument represent different phases of financial distress.

Methodology

The research analyses corporate failure and financial risk in globally listed shipping firms using binary logit models. Through constructing corporate failure prediction models, this paper identifies evaluation indicators of financial risk associated with listed shipping companies. It further examines the different characteristics of financial risks in shipping through marginal effect analysis and different cut-off points through ROC analysis. Finally we apply In and out of sample analysis to test the robustness of our model.

In this paper, Logit Model, which has been widely applied in various disciplines including transportation, finance and manufacturing, is used. It is a form of regression analysis used for predicting fundamentally different response variables, such as 0, 1. 1 reflects the existence of the qualitative factor, and 0 represents the absence. Barniv et al. (2002) indicated that logit analysis has been the most commonly used technique in the recent literature. In the shipping finance literature, Logit Model has rarely been applied (Grammenos et al 2008; Kavussanos and Tsouknidis (2011).

Similar to linear regression, Logit Model (sometimes called logistic regression) is used to model a relationship between a dependent variable Y and one or more independent variables X. The probability of a "yes/success" outcome is influenced by an exogenous set of predictor variables (Christensen, 1997). Logistic regression models make use of the logistic transformation, which is employed as the response variable in the logistic regression model to ensure that the model cannot predict outside the range of (0, 1).

The dependent variable, Y, is a discrete variable that represents a choice, or category, from a set of mutually exclusive choices or categories. The dependent variable for a Binary Logit Model has a binomial outcome, which can be obtained from grouped data (multiple experimental units observed on the binary outcome variable), or panel data (multiple observations on the same experimental unit over time). In this paper, grouped data have been collected; we use 1 for all the shipping companies that have been delisted and 0 for all the shipping companies that continue to operate.

The independent/predictor variables X can be continuous or discrete; they describe the various attributes of the choices to be causal or influential in the decision or classification process (McCullagh and Nelder, 1989).

The logit Model begins with a Logistic transformation:

$y = f(z) = \frac{e^z}{e^z + 1} = \frac{1}{1 + e^{-z}}$, and

y = 1 if the shipping company has failed.
y = 0 if the shipping company has not failed.

The logistic function, like probabilities, always takes on values between zero and one. The input is z and the output is ƒ(z). Logistic transformation confines the output to values between 0 and 1. The variable z represents the exposure to same set of independent variables, while ƒ(z) represents the probability of a particular outcome, given that set of explanatory variables. The variable z is a measure of the total contribution of the set of independent variables, it is defined as:

$$z = \beta_0 + \beta_1 \chi_1 + \beta_2 \chi_2 + \beta_3 \chi_3 + \cdots + \beta_K \chi_K$$

where ($\chi_1 \ldots \chi_K$) are the independent variables (financial ratios in this paper), β_0 is the constant and ($\beta_1 \ldots \beta_K$) are called the coefficients of ($\chi_1 \ldots \chi_K$) respectively. Each of the regression coefficients describes the size of the contribution of the independent variable.

DATA

Data description

Data were extracted from the Bloomberg database, which provides market data to financial practitioners. The database is accessed through a computer software system known as the Bloomberg Terminal. Specifically data were extracted for globally listed shipping companies selected under the marine transportation sector, for the period between 1992 and 2014. We required companies to have had at least three years of full financial data prior to the year of failure. This criterion resulted in a sample of 20 failed shipping companies that were then matched with 20 companies that survived in the same period and with similar size of total assets. A final data sample of 40 companies that either survived or failed between 2007 and 2014 was thus derived.

A large number of financial ratios were employed and tested to ascertain whether corporate failure of listed shipping companies could be predicted. These ratios were categorised into six groups: 'gearing', 'liquidity', 'profit', 'activity', 'cash flow' and 'market'. In addition to these, we also allowed for three industry-specific variables — 'ship', 'bulk and 'wet' — to examine whether a company's main business played a role, where 'ship' specifies whether a company owns ships (i.e. a company can also choose to operate ships through chartering), 'bulk denotes whether a company in engaged in dry bulk goods transport , and 'wet' represents companies with oil products as their main business (i.e. oil tankers). All the ratios were collected through six time horizons prior to failure: half year, one year, one and a half years, two years, two and a half years and three years.

Financial ratios

Financial ratios reflect various aspects of an organisation's operating and financial performance, such as efficiency, liquidity and profitability. For most ratios, an acceptable level is determined by comparing them to the same ratios of other companies within the industry. Such comparisons are generally of two types: comparison of the same items over different years, or comparison of different items in the same year.

While a large number of financial ratios may be chosen, this paper focuses on gearing, liquidity, profit, activity, cash flow and market ratios as defined in Table 1. Gearing measures financial leverage and shows the extent to which business activities are funded by creditors versus owners' own funds. Liquidity measures the ability of an organisation to meet its short term financial obligations without the need, for example, to liquidate long term assets. Profitability ratios measure the profitability of an organisation, which is the ability of an organisation to turn sales into profits and earn profits on assets. Activity ratios measure both the level of assets committed and the extent of asset usage, thus giving an indication of the efficiency of asset usage. (Finally, cash Flow ratios measure whether current liabilities are covered by cash flow generated from an organisation's operations. (Tamari, 1978; Seitz, 1984; Wayman, 2015).

Table 1 here

Financial Ratios Trends

The financial ratio trends were compared for both active and failed companies three years prior to the failure. Figure 1 shows the weighted means of financial ratios, with the weights being the total assets of companies in the sample. Distinct differences can be observed between the two groups of companies. The total debt/total assets ratio increases for the failed shipping companies as the year of failure approaches, while it remains relatively stable for the active companies. This observation is in line with the previous corporate failure findings, where gearing is positively related to the probability of failure (e.g. Charitou et al, 2004). The gross earning/total assets ratio shows a decreasing trend for failed shipping companies, while it does not follow any specific pattern for the active ones. This observation is also consistent with the previous literature, where profitability measures are inversely related to the probability of failure (e.g. Mitroussi et al, 2016). The sales/current assets ratio remains relatively stable for the active companies, while it reveals an increasing trend for the failed ones. This can be explained by a decrease in the value of current assets before failure which leads to an increasing overall ratio.

Figure 1 here

Empirical analysis

Which financial ratios are statistically important?

The financial variables were subsequently tested to identify their capacity for predicting the failure of shipping companies in the sample. The initial stage of screening focused on the significance of individual variables, with separate logistic regressions, to uncover which of the financial ratios would be potentially useful in more advanced models with multiple factors and/or dummy variables, where categorical effects would be allowed for. This test was conducted using data recorded during different time periods prior to the time of failure; the regression results are summarised in Table 2.

This shows that, among the possible financial ratios, the only variable that is significant in explaining the failure of the shipping companies is the total debt/total assets ratio (TD/TA) under the 'gearing' tag. The estimated coefficients of TD/TA are all significant at the 5% level, and with the expected (positive) sign. This suggests that a rise in the debt-to-assets ratio would imply a higher probability of failing due to exacerbated financial burden, regardless of the choice of data (with an exception of the '3 years before' measurement with which none of the variables is shown to be significant). While these models' predictive ability is formally assessed in section 5.5, the McFadden R-squared values are mostly above 10%, indicating that these models – admittedly simple – do have reasonably good predictive power. The high p-values of the H-L statistic then shows that these model versions also have very good 'fit' to the data (although with small samples such as ours, this could also be an indication of 'overfitting' – a discussion on this issue is given at the end of the paper).

While our findings are broadly consistent with the literature, where financial leverage/gearing variables usually provide the highest univariate classification accuracy (Charitou et al, 2004), it is surprising that other financial factors, such as liquidity, profitability and cash flow that are found to have predictive power in many other businessesi, are not significant predictors for failure of shipping companies. This suggests that multivariate analysis that brings together these financial factors into one regression to allow for 'joint effect' would not provide any sensible evidence here, though the gearing ratio (as measured by TD/TA) is a robust predictor[ii]. Considering that shipping is such a special industry for the reasons discussed, and that factors that predict well for general industries fail to predict as well here, next, three industry-specific dummy variables are added to the baseline model with TD/TA, to assess if any of these could provide additional implication for future financial failure.

Table 2 here

The role of industry-specific factors

In order to capture sector-specific factors, shipping industry-specific variables were added as detailed in the 'Data' section, representing the main business of the shipping companies; 'Ship', 'Bulk and 'Wet'. These dummy variables were chosen to represent the market sector in which each company was operating (i.e. chartering, bulk, tanker), in order to evaluate the impact of the state of the market on the financial performance of each company. To avoid 'dummy variable trap', i.e. xxx, the dummy variables were added to the baseline model in turn. Both intercept dummy and slope dummy (i.e., cross-term) were allowed for in each case, but because the latter was proven insignificant in all model variants it was dropped from the final versions. The final results of this exercise are summarised in table 3.

Table 3 here

Starting from panel A, it can be seen that, while the data suggest 'ship' has negative sign in all horizon versions, indicating that owning ships generally reduces the probability of failing, such a statistical relationship is distinctly significant (at 5%) when the '6-month before' data are used. The inclusion of this dummy variable clearly improves the significance of the debt-to-assets ratio in this version (now being significant at 1%), as well as the model's predictive power (as the McFadden R-squared doubles to 0.31 from 0.15 in univariate analysis), without causing a clear loss in model fit (as the p-value of the H-L statistic remains high at 0.39). Hence, although on longer horizons whether a company owns ships does not seem to provide useful information for predicting possible failure in the future, within 6 months this factor is proven one that should not be neglected.

Turning to panels B and C, it can be seen that a company's main business (dry bulk or oil trades) is not as relevant, since neither 'bulk nor 'wet' is shown to be significant in any of the tested versions. For this reason, these dummy variables were not included in the finalised model versions.

The finalised model versions

Thus, to summarise what was ascertained in the screening exercise: financial ratios quoted three years before a shipping company's failure fail to establish a correlation with the probability of failure, so practically it is difficult to use these ratios to predict possible failure (or survival) of these companies for three years ahead. However for shorter time horizons (between six months and two and a half years as found here), the 'gearing' status, measured by the debt-to-assets ratio, would be a robust predictor, though in cases where prediction is made for six months ahead it also matters whether a company is a ship owner. This therefore constitutes the five benchmark model variants that predicts financial failure with the debt-to-assets ratio for different forecasting horizons on which the discussions in the rest of the paper are built[iii].

Marginal effect of the debt-to-assets ratio

Figure 2 plots the marginal impact of the debt-to-assets ratio on the probability of failure for each of the benchmark models. It shows that while higher debt ratio implies higher probability of failing, its marginal impact varies with the actual debt ratio. The most obvious example of this feature is from the ‘6-month before’ model version, where, for instance, when the debt ratio is close to 0, a 10% rise in the ratio would only cause the failure probability to rise by 4%; but when the debt ratio is over some ‘cautionary’ level, say 40%, a 10% rise would increase the failure probability substantially, by as much as 19%. The marginal effect then fades again when the debt ratio has passed some ‘critical’ point, at about 70%. This implies that a gearing ratio of 40% - 70% indicates a higher risk of corporate failure for shipping companies, especially in the short run.

Another feature shown by Figure 2 is that, (except for the ‘2.5-year before’ version) all the model variants generate a marginal effect curve that intersects the others when the debt ratio is near 40%; at this level the probability of failure is about 50%, which is usually taken as the threshold value in binary logistic analysis – See Birchenhall et al. (1999), Nyberg (2010) and Ng (2012) for examples. Here, these models seem to agree that a debt ratio of around 40% is notable. This happens to coincide with the earlier trend analysis (in Figure 1) where the average debt ratio of the delisted companies was mostly above 50%, while that of active firms was just above 30%. The ‘6-month before’ variant predicts much higher (lower) probabilities of failure beyond (below) this critical point compared to the other variants. The ‘2.5-year before’ variant suggests a somewhat higher critical point of debt ratio, at about 50%.

Figure 2 here

Predictive ability of the models

How well could these models predict the future failure or survival of shipping companies? The general practice taken in the literature for answering this question is to construct the so-called ‘confusion matrix’ (Rees, 1990), which compares the occurrence of an event to the times it was predicted to happen, based on a chosen threshold probability value discriminating between ‘predicted to happen’ and otherwise.

The confusion matrix

Any threshold probability could be chosen to manipulate the correction rates whenever a model's predictive ability is assessed. Nevertheless, if we follow the common practice of setting the cut-off point at 0.5 (i.e., we take that a model predicts 'fail' if the probability of failure is greater than or equal to 0.5, and 'survive' if otherwise), it is found that all these models indeed possess reasonably good predictive ability, as Table 4 indicates.

Table 4 here

As far as the total correction rate is concerned, Table 4 suggests that the '6-month before' model is the best predictor, with a correction rate reported to be 76.5%. Models using debt ratio measured 1 year to 2 years before the dates of failure predict almost equally well, compared to each other, but with slightly lower rates (all being around 70% nevertheless). The '2.5-year before' model predicts the least well among the five, but in total it still predicted 66.7% of the actual events successfully. Focusing particularly on the models' ability of predicting failure, it can be seen that the '6-month before' model and the '1-year before' model remain as good, having a correction rate of, respectively, 76.5% and 70.6%, while those of the other models have fallen to just over 50%. But, considering the models' ability of predicting survivals, these other models are, nevertheless, very successful predictors, even compared to the '6-month before' model and the '1-year before' model.

So how do these models compare to each other overall? Zavgren (1983) and Grammenos et al (2008) suggest that, since the total rate of correction by itself does not discriminate between a model's abilities in predicting the binary outcomes ('failure' and 'survival' in this context), ranking models based on 'total correction rate', without allowing for the trade-off between type I errors (predicting 'survival' when a company failed) and type II errors (predicting 'failure' when a company survived), could lead to mis-perception about the models' overall predictive ability. As an example, while there is hardly any difference between the '1-year before' model and the '2-year before' model according to their total correction rate, the '1-year before' model is shown to have equal abilities in predicting 'failure' and 'survival', with the rates of type I and type II errors both being 29.4%. This is very different from the '2-year before' model which outperforms in predicting 'survival' and so has a very low type II error rate (17.6%); but because it has particular difficulties predicting 'failure' it also incurred a high rate of type I errors (40%). Hence, to rank models on their overall predictive ability, one needs to evaluate not only their total predictive ability, but also the trade-off between their type I and type II errors.

But how should the two criteria be combined for an overall evaluation? Clearly, unless the models being compared happen to perform equally well in one aspect, so that they can be ranked based simply on the other (which is often not the case), simultaneous evaluation of the two criteria is usually tricky with just the information provided by the confusion matrix[iv]. Indeed, the fact that the confusion matrix is a function of the chosen cut-off point of the binary outcomes also adds to the difficulties, in that any ranking based on the former may well be altered should the latter be redefined. In order to compare the overall predictive ability of the benchmark models, taking into account both the trade-off between their strength and weakness, and the robustness of the models' ranking (which seems to not be taken as seriously in the literature), the investigation is extended to the less-well-known Receiver Operating Characteristic curve analysis discussed below.

The Receiver Operating Characteristic curves

While the approach may be less familiar to researchers in business studies, Receiver Operating Characteristic (ROC) curves have been widely used in biomedical science. The purpose is to compare the *overall* accuracy of different models, with all possible cut-off values chosen for prediction of binary outcomes[v].

For a given model, the ROC curve traces out the 'sensitivity'/type II error pairs, for different cut-off values chosen for the prediction exercise. 'Sensitivity' in this context is defined as one minus the type I error rate. Each 'sensitivity'/type II error pair indicates the correction rate of predicting one outcome, while the error rate of predicting the other is associated with a chosen cut-off value for the predictions – hence, the trade-off between type I and type II errors. When the chosen cut-off value shifts from one extreme (0) to the other (1), the ‘sensitivity’/type II error pair shifts, and traces out the whole ROC curve for the model being studied. The area under the ROC curve is known as the ‘area under curve’ (AUC), whose size measures the model’s overall ability of predicting the binary outcomes, with all possible choices of the cut-off point. Thus, by comparing the size of AUC generated by different models, one can rank these models’ overall predictive ability, without being biased by the choice of the cut-off value. The ROC curve also identifies the optimal model/threshold combination, which is the point on an ROC curve that lies nearest to the top left of the graph.

Figure 3 shows the ROC curves for all the five models, and reports the size of their respective AUC as a percentage of one. It show that the ‘6-month before’ model forms the largest AUC (83.4%), implying that the model is the best predictor overall. Following this it comes the ‘2.5-year before’ model (77.8%), the ‘1-year before’ and ‘1.5-year before’ models (74.1% and 74%, respectively), and finally the ‘2-year before’ model (71.8%), which remains to have similar predictive ability, but ranked quite differently compared to the earlier perception formed simply by comparing the confusion matrices.

Figure 3 here

The optimal model/threshold combination is found when the ‘6-month before’ model is used, and the cut-off value is set to 0.5 (point A in Figure 3), which happens to be the ‘6-month before’ model version used above for analysing the marginal effect[vi]. Interestingly, the ROC curves now suggest the ‘2.5-year before’ model, although being the least accurate when the ‘convention’ of setting the cut-off value to 0.5 is followed, does predict as accurately as the optimal version when the cut-off value is tuned down to 0.4 (point E). Thus, by comparing the models’ ROC curves, the ‘optimal threshold’ that should be chosen for the best overall accuracy, when prediction is concerned with different times in the future, is also identified. What is found is that, unless prediction is made for 6 months ahead, it is always the best to set the cut-off value to 0.4, as summarised in Table 5.

Table 5 here

Validation of models

We now turn to the validation exercise as the final task, for checking the robustness of the models and their implication.As acknowledged earlier, models estimated with small samples could have been victims of the 'overfitting' problem, where 'noises' in the data are mistaken as 'signals', causing the models to fit (or 'predict') well *within* the samples, but when the same models are used for out-of-sample prediction, their predictive ability deteriorates significantly. In order to check whether the models we used above suffer the problem of overfitting, we follow the general practice of conducting a validation exercise here.

Specifically, we follow Grammenos et al (2008) to draw 80% of the full sample data randomly, and use them as the training data sample to estimate the models[vii]. The predictive ability of these models is then evaluated using the training data for their *in-sample* predictive ability to be found. The models' predictive ability is then evaluated again, using the remaining 20% observation held-out as the validating data[viii]. The process is repeated for 5,000 times; and for each model, we calculate and compare their average predictive abilities as found in- and out-of- sample to see if there is any sign of overfitting.

Table 6 below first summarises the models' in-sample estimates and compares them to the full-sample estimates. The purpose of this preliminary comparison is to ensure that the models used for the validation exercise are good approximation of their full-sample versions. We find that the full-sample estimates of all the models are well embraced by the empirical 95% boundary generated by their in-sample counterparts. This shows that in-sample model versions are suitable for the validation exercise.

Table 6 here

Table 7 reports the predictive abilities of the models evaluated in- and out-of-sample. The 'optimism' column (that measures the difference between the models' in-sample and out-of-sample predictive ability) suggests that overfitting could not have occurred, as none of the models is found to have a substantial change in its predictive ability, no matter the evaluation is based on a fixed cut-off value or based on an ROC curve. Since the in-sample models could not have overfitted the data and that they are all good approximation of the full-sample models, our validation exercise here verifies the robustness of the main results established in the foregone sections, albeit the use of a relatively small sample due to limited data availability.

Table 7 here

Conclusions

In this paper we analyse how financial and industry specific variables can be used to predict corporate failure in listed shipping companies through the use of binary logit models, and various analytical tools, particularly ROC analysis for model selection. While gearing, profit and activity are all found to be potential factors that may have predictive power, only the former is able to establish a robust correlation with corporate failure as in these models. We find that higher gearing ratio implies higher risk of failure from 6 months ahead to up to 2.5 years ahead. We further added three industry specific variables and in the short run, i.e., for a horizon up to 6 months ahead, companies that own ships themselves are less likely to fail compared to their rivals, ceteris paribus.

Our marginal analysis further reveals that a gearing ratio of above 40% is worth noticing, especially in the short run, as it seems to identify the critical point between survival and failure. Our ROC analysis then suggests the model is most accurate in predicting these events 6 months ahead of such a ratio is measured, but this also means that companies in the shipping industry would face greater time pressure to respond, should there be any indications of possible financial failure. Finally, by applying In-and-out-of-sample tests we validated the robustness of our models.

Our findings will be of interest to traders and investors in shipping markets, as well as banks and shipowners in the ship finance sector. The publicly available nature of the information used to compile this research means that traders and investors (both individual and corporate) are now able to use an easily accessible source of data to make their judgements about investing in the shipping industry. In addition, shipowners are able to identify the factors that they need to focus on in order to understand more effectively the financial performance of their company. In an academic context this research provides a new application of the ROC analysis, for comparing the overall predictive ability of different models in the field of corporate failure.

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Table 1. Financial ratios tested in the study

Category	Variable Definition
Gearing	*Current liabilities/total assets*
	Total debt/total assets
Liquidity	Current assets/current liability
	Current assets/total assets
	Working capital/total assets
Profit	Earnings before interest and taxes/total assets
	Net income/total assets (ROA)
	Net income/shareholder's equity (ROE)
Activity	Sales/total assets
	Sales/current assets
Cash flow	Cash flow/total assets
Market	Market value of equity/shareholder's equity

Table 2 see attached file

Table 3: 'gearing' with industry-specific dummy variables

	Time before failure					
Panel A: Gearing + Ship	**6 mths**	**1 yr**	**1.5 yrs**	**2 yrs**	**2.5 yrs**	**3 yrs**
TD/TA	7.779***	4.711*	3.878**	4.396**	4.397**	2.477
Ship	-2.749**	-1.35	-0.955	-1.472	-1.002	-0.645
Constant	-1.439	-1.136	-1.15	-0.834	-1.482	-0.871
McFadden R^2	0.307	0.185	0.162	0.166	0.182	0.067
H-L statistic	8.501 [0.386]	5.576 [0.695]	9.433 [0.307]	7.217 [0.513]	6.236 [0.621]	6.429 [0.599]
Panel B: Gearing + Tramp	**6 mths**	**1 yr**	**1.5 yrs**	**2 yrs**	**2.5 yrs**	**3 yrs**
TD/TA	5.49**	4.068**	3.629**	3.507**	4.112**	2.242
Tramp	-1.452	-1.112	-0.565	-0.556	-0.174	-0.513
Constant	-1.468	-1.089	-1.376	-1.184	-1.98	-0.948
McFadden R^2	0.217	0.175	0.147	0.12	0.156	0.064
H-L statistic	8.673 [0.371]	6.256 [0.619]	15.83 [0.045]	8.222 [0.412]	6.093 [0.637]	6.964 [0.541]
Panel C: Gearing + Wet	**6 mths**	**1 yr**	**1.5 yrs**	**2 yrs**	**2.5 yrs**	**3 yrs**
TD/TA	5.11**	3.993**	3.424**	3.388*	4.088**	2.298
Wet	-0.665	-0.269	0.143	0.059	0.243	0.187
Constant	-1.896	-1.602	-1.689	-1.5	-2.18	-1.338
McFadden R^2	0.166	0.133	0.136	0.109	0.157	0.054
H-L statistic	5.658 [0.686]	6.815 [0.557]	10.56 [0.228]	7.098 [0.526]	5.904 [0.658]	6.101 [0.636]

TA: total assets; TD: total debt. *, **, ***: significant at 1%, 5% and 10%.

Numbers in square bracket are p-values.

Table 4: predictive ability of models (the 'confusion matrix')

Model version	Confusion matrix			Correction rates		
		Predicted failed	Predicted survived	Total	Correct total: 76.5%	
6 mths before	Actual failed	13	4	17	Correct failed: 76.5%	Type I error: 23.5%
	Actual survived	4	13	17	Correct survived: 76.5%	Type II error: 23.5%
		Predicted failed	Predicted survived	Total	Correct total: 70.6%	
1 yr before	Actual failed	12	5	17	Correct failed: 70.6%	Type I error: 29.4%
	Actual survived	5	12	17	Correct survived: 70.6%	Type II error: 29.4%
		Predicted failed	Predicted survived	Total	Correct total: 68.6%	
1.5 yrs before	Actual failed	9	7	16	Correct failed: 56.3%	Type I error: 43.8%
	Actual survived	4	15	19	Correct survived: 78.9%	Type II error: 21.1%
		Predicted failed	Predicted survived	Total	Correct total: 71.9%	
2 yrs before	Actual failed	9	6	15	Correct failed: 60%	Type I error: 40%
	Actual survived	3	14	17	Correct survived: 82.4%	Type II error: 17.6%
		Predicted failed	Predicted survived	Total	Correct total: 66.7%	
2.5 yrs before	Actual failed	7	6	13	Correct failed: 53.8%	Type I error: 46.2%
	Actual survived	4	13	17	Correct survived: 76.5%	Type II error: 23.5%

Predicted failure if prob(fail)⩾0.5.

Table 5: models and their 'optimal threshold'

Models	Optimal cut-off	Point on ROC curve (as in figure 3)	Correct total	Corret failed	Correct survived
6 mths before	0.5	A	76.5%	76.5%	76.5%
1 yr before	0.4	B	76.5%	88.2%	64.7%
1.5 yrs before	0.4	C	71.4%	70.5%	68.4%
2 yrs before	0.4	D	71.9%	80.0%	64.7%
2.5 yrs before	0.4	E	76.7%	76.9%	76.5%

Table 6: In-sample estimates vs full-sample estimates of models

	Full-sample estimate	In-sample mean	In-sample 2.5% LB	In-sample 97.5% UB
6 mths before				
Constant	-1.439	-1.488	-3.223	-0.384
TD/TA	7.779	8.223	5.703	13.31
ship	-2.749	-2.924	-4.361	-1.938
1 yr before				
Constant	-1.617	-1.672	-2.773	-0.942
TD/TA	3.815	3.96	2.391	6.831
1.5 yrs before				
Constant	-1.671	-1.737	-2.898	-1.063
TD/TA	3.521	3.673	2.225	6.304
2 yrs before				
Constant	-1.489	-1.553	-2.766	-0.786
TD/TA	3.423	3.576	1.881	6.28
2.5 yrs before				
Constant	-2.108	-2.197	-3.667	-1.439
TD/TA	4.16	4.341	2.75	7.407

Table 7: in-sample predictive ability vs out-of-sample predictive ability of models

Panel A: predictive ability based on fixed cut-off (0.5)			
	In-sample mean	**Out-of-sample mean**	**Optimism**
6 mths before			
Correct failed	75.9%	74.8%	1.1%
Correct survived	74.9%	69.8%	5.1%
Correct total	75.6%	71.5%	4.1%
1 yr before			
Correct failed	69.4%	69%	0.4%
Correct survived	71.6%	71.3%	0.3%
Correct total	71.1%	68.1%	3.0%
1.5 yrs before			
Correct failed	59.1%	58.6%	0.5%
Correct survived	77.4%	77.1%	0.3%
Correct total	69.3%	67.2%	2.1%
2 yrs before			
Correct failed	62.6%	61.5%	1.1%
Correct survived	77.8%	77.5%	0.3%
Correct total	71.2%	68%	3.2%
2.5 yrs before			
Correct failed	59.2%	59.5%	-0.3%
Correct survived	77.3%	76.2%	1.1%
Correct total	69.8%	67.7%	2.1%
Panel B: predictive ability based on ROC curve (AUC)			
	In-sample mean	**Out-of-sample mean**	**Optimism**
6 mths before	83.8%	80.3%	3.5%
1 yr before	74.1%	74.3%	-0.2%
1.5 yrs before	74.1%	74%	0.1%
2 yrs before	71.8%	71.8%	0.0%
2.5 yrs before	77.9%	77.7%	0.2%

Figure 1 see attached file

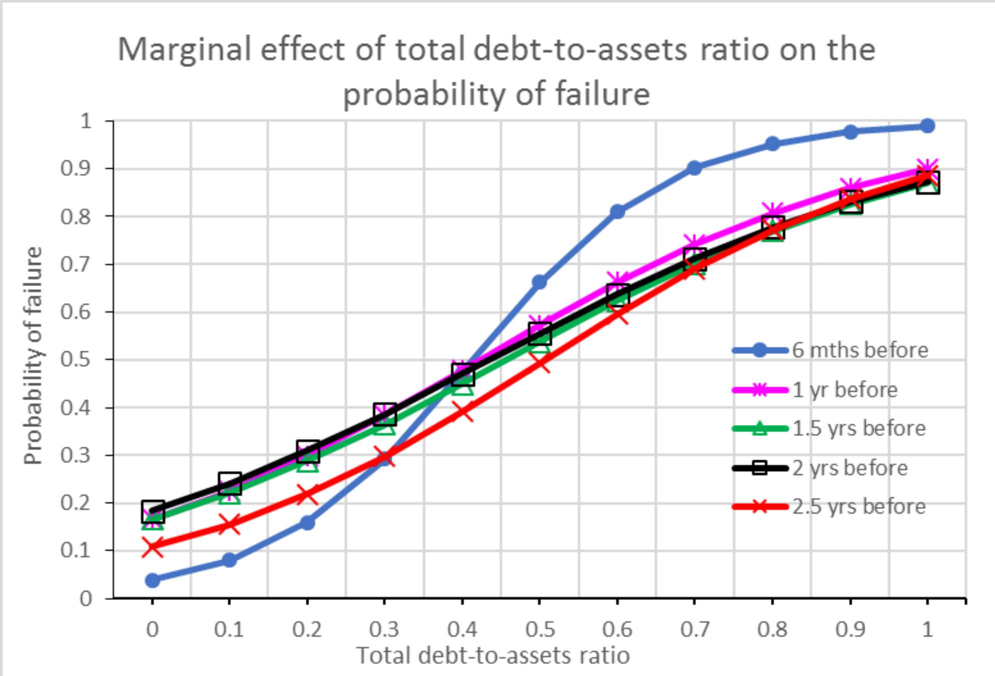

Figure 2. Marginal effect of debt-to-assets ratio on failure probability

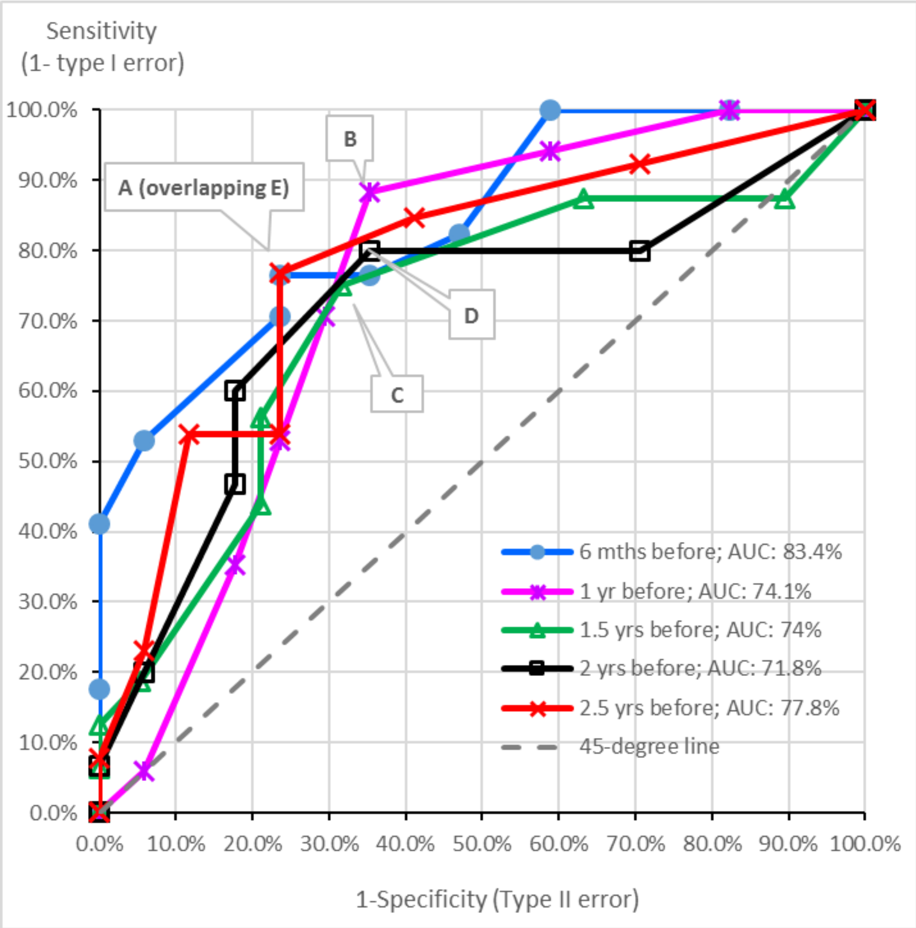

Figure 3: The Receiver Operating Characteristic curves

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[i] See Charitou et al. (2004) and Grammenos, et al. (2008) for examples.

[ii] Indeed, when these factors are included in the same regression, with different possible combinations of measurement, it is found that none of the financial ratios – except for TD/TA – is significant.

[iii] The '6-month before' version includes 'ship' as an intercept dummy.

[iv] This is mainly because the total correction rate does not discriminate between type I and type II errors, so the relationship between the total correction rate and the trade-off between type I and type II errors is quite independent over different cases.

[v] See Zweig and Campbell (1993) for a thorough illustration of the method.

[vi] Recall that this optimal version predicted 76.5% of the true failed cases and 76.5% of the true survived cases according to its confusion matrix – see Table 4.

[vii] The draws are conducted with the bootstrap technique.

[viii] Thus, the Pareto '80-20 principle' is followed when segmenting the sample.