Jane Jing Haider, Zhirong Ou, Stephen Pettit

Cardiff Business School, Cardiff University, UK

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. Although various instruments in shipping finance have been studied 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 for the first time studies corporate failure and financial performance in globally listed shipping firms. It examines the different characteristics of financial risks in shipping and investigates how these characteristics vary over time. Shipowners and investors can benefit from some unique findings in respect of shipping finance for listed shipping companies.

Keywords: Corporate Failure, Logit Model, Listed Shipping Companies, Shipping Finance

1. INTRODUCTION

In earlier eras much of ship finance was provided through individual owners funding their own companies. However, more recently ship owners have sought finance from the capital markets. Starting from the 1990s, shipping companies began to turn to the global capital markets to raise finance, through either equity or debt. During the period 2004 – 2007, it can be observed that there was an increased number of Initial Public Offerings (IPOs), secondary offerings, and issuance of high-yield bonds related to the shipping industry. However, since the financial crisis of 2008, bankruptcy amongst firms operating in the shipping industry has been a familiar theme. 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. While previously there would have been limited access to financial data about shipping companies, now it has become available through public databases and market information. While the financial data is still to some extent limited, valuable insights can be obtained from analysing that, which is available, e.g. the Bloomberg Database.

While issues such as corporate failure and financial performance have been well researched amongst those in the accountancy and finance field, its consideration within the shipping industry has been limited. The spotlight has been on loans (Kavussanos and Tsouknidis, 2011; Mitroussi et al, 2012), high-yield bonds (Grammenos, et al, 2008) or IPOs (Grammenos and Papapostolou, 2012). To the best of our knowledge, no study discusses 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 best evaluated?; and what can they do in the future to avert financial crisis?

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 about corporate failure related to financial failure at the firm level in the shipping industry. Although various instruments have been studied, and which each individually indicate that 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. 484 globally listed shipping companies were selected from the marine transportation sector available from the Bloomberg database, of which 158 were delisted, between 1992 and 2014. Data was collected in order to assess whether failure can be predicted over a range of time horizons prior to failure occurring: 3 years, 2.5 years, 2 years, 1.5 years, 1 year and 6 months. The results are unique in terms of ship finance literature. Through constructing corporate failure prediction models, this paper identifies evaluation indicators for financial risk associated with listed shipping companies. It further examines the different characteristics of financial risks in shipping and investigates how these characteristics vary over time. The findings will be of interest to traders and investors in shipping markets, as well as banks and shipowners in the ship finance sector.

2. LITERATURE REVIEW

2.1. Financial distress and 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 (Charalambous 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, 1980; Morris, 1997). Corporate failure indicates that resource misallocation is likely to have occurred which is undesirable, and identifying 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 an increased probability of failure in situations where they cannot meet their financial obligations (Chan and Chen, 1991; Fama and French, 1996; Campbell et al, 2008).

2.2. Financial distress in shipping

The shipping industry is known for its family run business in favour of traditional financing tools. The industry is fragmented and consists of a large number of smaller firms with concentrated ownership (Stopford, 2009; Tsionas et al., 2012), lack of transparency and limited access to the capital markets. Only since the 1990s have ship owners sought financing from the global capital markets (Grammenos et al., 2007; Merikas et al., 2009). As maritime companies have increasingly turned to the financial markets to raise capital they have come under closer scrutiny by investors and shareholders. They have strengthened their corporate structure, and they have become larger in size, due to their growth strategies through mergers and acquisition. A generation of younger shipowners began to raise finance by itilising international capital markets, particularly during the 1993–1997 and 2004–2007 periods. There are many ways of financing ships, from traditional bank lending to private placements and public issues of debt and equity. They are all associated with different risks and the investor/lender has to make a decision based on the return in order to justify exposure to the risk.

In relation to equity finance, Grammenos and Marcoulis (1996) were the first to document that an increasing number of shipping companies were accessing the capital market. Grammenos and Marcoulis (1996) and Grammenos and Arkoulis (1999) were amongst the first papers to analyse the performance of shipping IPOs in the equity capital markets. Cullinane and Gong (2002) studied IPOs underpricing in the transportation sector in the Chinese mainland and Hong Kong markets. Merikas et al. (2009 &2010) studied global shipping IPOs underpricing using US-listed Shipping IPOs. Grammenos and Papapostolou (2012) were the first to test the different theories that explain the underpricing phenomenon. They examined the impact of market information on US shipping IPOs through analysing 51 shipping US IPOs that took place in the period 1987–2008. They indicated that there is no asymmetry of information between participants in shipping IPOs and the probability of underpricing can be predicted by employing variables available to all IPO participants prior to the issue.

In relation to debt finance, Grammenos et al (2008) argued that bankruptcy and default on a debt instrument represent different phases of financial distress. Grammenos and Arkoulis (2003) studied debt finance for shipping companies for the first time. They investigated determinants of the primary pricing of shipping company high yield bond issues. In line with Fridson and Garman (1998), they argued that when studying the pricing of new high yield bonds, it would be better to categorise the bonds by industry in order to avoid biased results. Using 30 high yield bond offerings issued by shipping companies in the US market during the period 1993–1998 they identified a set of potential determinants, with credit rating being the major determinant of the price spread of bond offerings. Financial leverage and shipping market conditions also account for a significant part of the price variability. Grammenos et al (2007) studied factors affecting the dynamics of yield premia on seasoned high yield bonds of shipping companies. They found the explanation factors to be: credit rating; term-to-maturity; changes in earnings in the shipping market, as well as in the yield on 10-year Treasury bonds; and the yield on the Merrill Lynch single-B index. Grammenos et al (2008) estimated the probability of default for shipping high yield bond issues. They also suggested that shipping high yield bonds should be studied separately as an industry due to its cyclical, volatile and capital intensity characteristics. In addition to the financial ratios employed in previous models, they used two industry specific variables and another financial ratio. They found the best estimates as: the gearing ratio, the amount raised over total assets ratio, the working capital over total assets ratio, the retained earnings over total assets ratio and an industry specific variable (shipping market sector).

While default against individual financial instruments can represent early phases of corporate failure, predicting overall failure at the firm level is worth investigating.

3. METHODOLOGY

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 f(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 f(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.

4. DATA

4.1. Data description

The data were extracted from the Bloomberg database for the period 1992 to 2014. 484 globally listed shipping companies were selected under the marine transportation sector available from the Bloomberg database, of which 158 were delisted. We apply the criteria that the company must have had at least three years of full financial data prior to its formal failure year. The application of this criteria resulted in a sample of 20 delisted shipping companies. We then chose to match these delisted companies with 20 companies that survived in the same periods and with similar size of total assets. The final dataset thus consists of 40 shipping companies that either survived or failed between 2007 and 2014.

A large number of financial ratios were employed and tested to ascertain whether corporate failure of listed shipping companies could be predicted. These ratios can be categorised into six groups: gearing, liquidity, profit, activity, cash flow and market. We further chose three industrial specific variables (dummy variables) in order to reflect the main business of the shipping companies: ship-owning, tramp and wet. Ship-owning is used to describe whether the company owns any ships, Tramp is used to select the companies with tramp trades as their main business, and lastly, Wet is used to select the companies with oil products as their main business. All the ratios are 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 before the year of failure.

4.2. Financial ratios

Ratio analysis evaluates various aspects of an organisations operating and financial performance, e.g. efficiency, liquidity and profitability. For most ratios, an acceptable level is determined by its comparison to ratios of companies in the same industry. Such ratios are generally of two types: comparison of items between years or a comparison between items in the same year. The number of ratios that can be calculated is large and the multiplicity of available ratios means that it is important that the correct ratios are chosen. For the purposes of this paper the ratios considered covered gearing, liquidity, profit, activity, cash flow and market and are detailed in Table 1. (Tamari, 1978; Investopedia, 2015a).

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

Gearing measures financial leverage and shows the extent to which businesses activities are funded by owner's versus creditor's funds. Liquidity is the ability of an organisation to meet its short term financial obligations without the need, for example, to liquidate long term assets. In the short term this could mean, for example, that there would be the need to defer payments on interest on loans. 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. Cash Flow ratios measure whether current liabilities are covered by cash flow generated from an organisation's operations. Cash flow is in some cases considered a better indicator of a company's financial health because cash flow is both harder to manipulate than net income and because a company that doesn't generate cash is likely to fail (Wayman, 2015). Market ratios measure the reaction of investors to an organisations performance, for example by comparing the market value of shareholder equity to actual shareholder equity (Seitz, 1979).

5. Empirical results

5.1. Trend analysis

The trends of the financial ratios were compared for both active and delisted companies three years prior to the failure of the delisted companies. Figure 1 shows the equally weighted means of three representative financial ratios for the two groups of companies.

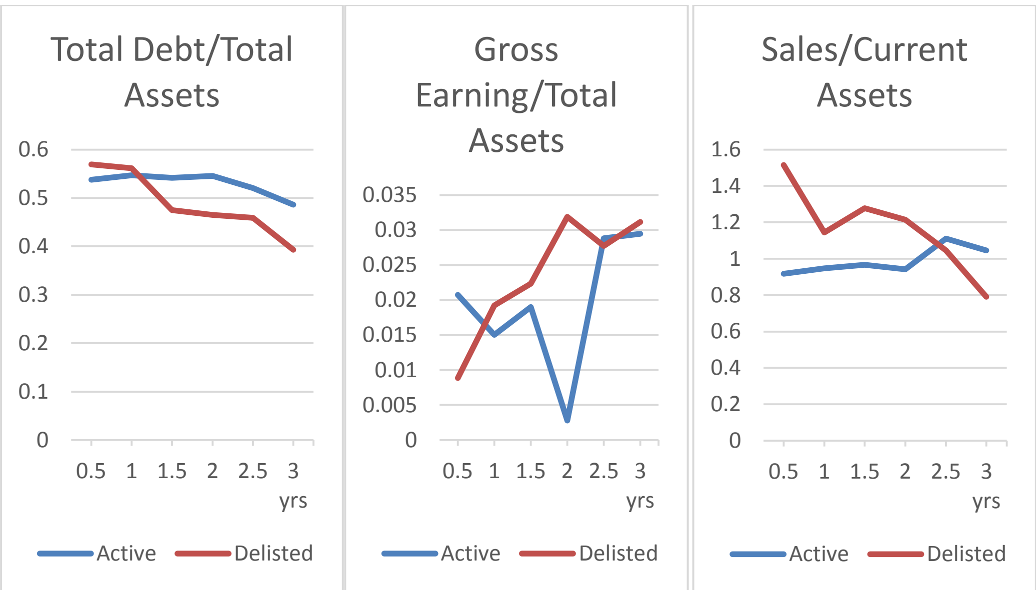

Figure 1. Trend of representative financial ratios

Distinct differences can be observed between the two groups of companies. The total debt/total assets ratio increases for the delisted 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. The gross earning/total assets ratio shows a decreasing trend for delisted shipping companies, while it doesn't follow any specific pattern for the active companies. This observation is also consistent with the previous literature, where profitability measures are inversely related to the probability of failure. The sales/current assets ratio remains relatively stable for the active companies, while it reveals an increasing trend for the delisted companies. This can be explained by a decrease in the value of current assets before failure which leads to an increasing overall ratio.

5.2. Univariate analysis

To examine the predictive ability of the financial ratios, the significance of the individual variables was tested through univariate logistic regression, to uncover which of these variables might be empirically important in explaining corporate failure before they might be considered simultaneously for multivariate analysis. For convenience only the significant variables in this screening stage are reported.

Among the possible financial variables the only variable that is found to have a significant impact on explaining corporate failure is 'gearing', as measured by the total debt/assets ratio. Table 2 shows that regardless of the choice of the data quoted in terms of the time before the delisted companies are 'dead' (with an exception of the choice of '3 years before' where none of these variables is found to be significant). The estimated coefficients for this variable all have the expected (positive) sign that indicates that a rise in the debt-to-assets ratio tends to imply a higher probability of failure as omened by exacerbated financial burden. The McFadden R-squared and H-L statistics are both within reasonable boundaries for this baseline model to be considered acceptable.

While previous literature shows that financial leverage/gearing variables provide the highest univariate classification accuracy (Charitou et al, 2007), this finding seems to distinguish itself from many existing findings in the literature that corporate failure might also be predicted by many other factors besides gearing, such as liquidity, profitability and cash flow (see Charitou et al, 2004 and Grammenos et al, 2008 for examples). At this point it can be concluded that the gearing ratio shows a consistent and robust significance in prediction corporate failure of listed shipping firms.

Table 2. Univariate regressions

	Time before failure						Exp sign
Regressors	6 mths	1 yr	1.5 yrs	2 yrs	2.5 yrs	3 yrs	(failure=1)
Gearing							
TD/TA	4.408**	3.815**	3.521**	3.423**	4.16**	2.33	**(+)**
	(2.001)	(1.68)	(1.657)	(1.678)	(1.845)	(1.672)	
Constant	-1.86**	-1.617**	-1.671**	-1.489*	-2.11**	-1.279	
	(0.902)	(0.804)	(0.782)	(0.77)	(0.928)	(0.783)	
McFadden R^2	0.153	0.131	0.135	0.109	0.155	0.053	
H-L statistic	6.258 [0.618]	7.633 [0.469]	7.697 [0.464]	3.029 [0.933]	5.549 [0.698]	8.8176 [0.358]	
Obs:	34	34	35	32	30	29	

5.3. Univariate analysis with dummy variables

In order to capture sector-specific factors in the shipping industry, three variants of the baseline model above were tested, by adding to it in each case a shipping industry-specific dummy, representing the main business of the shipping companies, to see if any of these would improve the model's fit. The three dummy variables considered were 'ship-owning', 'tramp' and 'wet', where 'ship'=1 represents the case in which the company owns ships, 'tramp'=1 means the company is involved with tramp trades as their main business and 'wet'=1 means the company is involved with oil products as their main business

Table 3 reports the results with 'ship-owning' added to the benchmark case. 'Ship' is shown to have a negative sign in all cases, suggesting whether a company owns ship matters, and a negative sign means owning ships reduces the probability of failing. It clearly improves the model's fit when '6 months before' data are used for predicting corporate failure, as the McFadden R-squared almost doubles (increases from 0.15 to 0.31) while the H-L statistic is nearly halved (reduced from 0.62 to 0.39); it also yields more significant estimate of the impact of the debt-to-assets ratio while it is itself a significant variable.

The inclusion of 'ship' turns 'activity', as measured by total revenue/current assets ratio, to be significant at 1%, though such an improvement is only seen in the '6 months before' category. It shows a negative impact of 'activity' to the probability of failure, this is in line with previous studies, as the higher the ratio of total revenue over current assets is, the less likely the shipping company would fail. The second dummy variable 'tramp' was tested as shown in Table 4. The results show that the 'profit' factor, measured by gross profit over total assets is significant if the model is estimated with data quoted in '6 months before'. It has a negative sign which shows the more profitable the shipping company is the less likely it is going to fail. The 'tramp' is in itself a significant factor under the perspective of '6 months before', and the negative sign indicates that if a shipping company is involved in tramp trade as its main business, the less likely they are going to fail. Lastly 'wet' was added as the third dummy variable but it is not possible to gauge the impact of 'wet' on the probability of failure by evaluating the variable's sign since none of these is significant.

Table 3: Regressions with dummy variable: Ship

	Time before failure						Exp sign
Regressors	6 mths	1 yr	1.5 yrs	2 yrs	2.5 yrs	3 yrs	(failure=1)
Gearing							
TD/TA	7.779***	4.711*	3.878**	4.396**	4.397**	2.477	**(+)**
	(2.98)	(1.996)	(1.778)	(1.999)	(1.928)	(1.714)	
Ship	-2.749**	-1.35	-0.955	-1.472	-1.002	-0.645	**(-)**
	(1.2)	(0.904)	(0.859)	(0.978)	(0.969)	(0.891)	
Constant	-1.439	-1.136	-1.15	-0.834	-1.482	-0.871	
	(1.004)	(0.872)	(0.877)	(0.854)	(1.047)	(0.946)	
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]	
Obs:	34	34	35	32	30	29	
Activity							
TR/CA	-0.711*	-0.426	-0.444	-0.401	-0.49	-0.46	**(-)**
	(0.43)	(0.368)	(0.402)	(0.319)	(0.431)	(0.455)	
Ship	-1.561*	-0.891	-0.725	-1.05	-1.125	-0.721	**(-)**
	(0.864)	(0.744)	(0.827)	(0.863)	(0.944)	(0.896)	
Constant	1.86	1.028	0.863	1.135	1.022	0.563	
	(0.941)	(0.763)	(0.87)	(0.879)	(0.976)	(0.902)	
McFadden R^2	0.187	0.077	0.086	0.09	0.103	0.071	
H-L statistic	3.258 [0.917]	16.38 [0.037]	4.039 [0.854]	9.002 [0.342]	1.814 [0.986]	3.664 [0.886]	
Obs:	37	37	35	32	31	28	

Table 4: Regressions with dummy variable: Tramp

	Time before failure						Exp sign
Regressors	6 mths	1 yr	1.5 yrs	2 yrs	2.5 yrs	3 yrs	(failure=1)
Gearing							
TD/TA	5.49**	4.068**	3.629**	3.507**	4.112**	2.242	**(+)**
	(2.361)	(1.797)	(1.698)	(1.722)	(1.86)	(1.692)	
Tramp	-1.452	-1.112	-0.565	-0.556	-0.174	-0.513	
	(0.89)	(0.8)	(0.774)	(0.795)	(0.85)	(0.796)	
Constant	-1.468	-1.089	-1.376	-1.184	-1.98	-0.948	
	(0.946)	0.871)	(0.863)	(0.87)	(1.11)	(0.927)	
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]	
Obs:	34	34	35	32	30	29	
Profit							
GP/TA	-19.93*	-0.722	-30.57	10.91	0.174	16.751	**(-)**
	(11.35)	(8.359)	(15.67)	(9.667)	(10.28)	(16.19)	
Tramp	-2.15*	-0.717	-1.96	-0.467	-0.909	-1.0721	
	(1.189)	(0.93)	(1.322)	(0.983)	(1.127)	(1.169)	
Constant	2.312*	0.731	2.446	0.223	0.905	0.376	
	(1.196)	(0.837)	(1.409)	(0.816)	(1.08)	(0.976)	
McFadden R^2	0.191	0.02	0.228	0.064	0.035	0.091	
H-L statistic	7.129 [0.523]	9.116 [0.333]	7.522 [0.482]	9.372 [0.312]	10.55 [0.229]	8.499 [0.386]	
Obs:	24	23	22	20	17	15	

Overall, the screening exercise suggests: Firstly, any analysis with data quoted as ‘3 years’ before failure fails to establish a correlation between the probability of corporate failure and normal financial variables. Hence we can conclude that it is difficult to predict failure for shipping companies three years ahead, it would only be sensible to use historical data with shorter time horizon (i.e. less than 3 years) to predict corporate failure in shipping companies. Secondly, the main business of the shipping company, i.e., whether a company owns ships or whether it operates in tramp trades, matters when it comes to financial failure, and they have the potential of improving the significance of some financial variables under the ‘6 months before’ category. Thirdly, gearing, measured as total debt-to-assets ratio is found to be significant and robust in different variants of model and it has the best goodness-of-fit under the ‘6 months before’ category with the inclusion of ‘ship’.

5.4. Multivariate analysis

From the univariate analysis, it was found that the gearing ratio (total debt to total assets) is the best estimate for predicting failure of shipping companies. One activity ratio (total revenue to current assets) and one profit ratio (gross profit over total assets) were also proved to be useful in predicting failure. Two industrial-specific dummy variables – ship-owning and tramp were confirmed to contribute to the predictive ability of the models too.

The next stage was to investigate multivariate models and their forecasting ability by comparing different model versions: debt-to-assets ratio plus ship for '6 months before' were used as our baseline model, the significant variables as found in the univariate analysis above with the inclusion of dummy variables were then added. All the multivariate versions where possible were attempted. For example, both gearing (measured by debt-to-assets) and activity (measured by current assets) were included and they were both found significant with the inclusion of 'ship' as shown above in the '6 months before' category. But this immediately turns 'activity' to be insignificant (Table 5) thus returned the model to the baseline of gearing and ship.

Table 5: Multivariate regressions: Gearing + Activity + Ship

	6 mths before failure			
	TD/TA (gearing)	**TR/CA (activity)**	**Ship**	**Constant**
Exp sign (failure=1)	**(+)**	**(-)**	**(-)**	
Est. coeff.	9.108**	-0.738	-3.424**	-0.678
	(3.798)	(0.584)	(1.548)	(1.407)
McFadden R^2	0.451			
H-L statistic	7.02 [0.535]			
Obs:	**32**			

5.5 Marginal effect

Having identified five model variants that are robust in predicting corporate failure using the debt-to-assets ratio measured at different times with reference to the bankrupted firms' delisted dates, how the probability of failure varies can be evaluated, in each model variant, along with the variation in the debt-to-assets ratio, i.e., the marginal effect of debt-to-assets ratio on the firms' failure probability.

One important feature of the marginal effect in logistic regression analysis, compared to the usual linear regression analysis, is that the marginal impact of an explanatory variable on the dependent variable, as measured by the 'slope parameter' in linear regression analysis, is not fixed but a function of both the slope parameter and the values at which all the explanatory variables are measured, due to the non-linear relationship between the dependent and explanatory variable(s) as reflected by the logistic model structure. In other words, the non-linear relationship between the dependent and explanatory variable(s) determines that the change in the probability of failure would be different should the same amount of change in an explanatory variable be caused upon different starting levels.

This can be seen clearly from figure 2 below the probability of failure against the significant financial variable is plotted, the debt-to-assets ratio, as identified with data measured at the different reference points. It can be seen that while a higher debt-to-assets ratio leads to higher probability of failure in all cases (as determined by the positive coefficients of TD/TA as reported in Table 2 above), the varying slopes on each response function suggest the responsiveness of failure probability with respect to 'a unit change' in the debt-to-assets ratio varies at different gearing levels. The most obvious of these is when the model is estimated using data reported 6 months before the bankruptcy dates, where, for example, when the debt ratio is close to 0%, a 10% rise in the ratio would only cause a 4% rise in the failure probability, whereas when the debt ratio has reached a 'cautionary' level, say 40%, a 10% rise on top of this would cause the failure probability to rise significantly, by as much as 19%; the sensitive response then slows down again substantially when the debt level has passed a 'critical' point, at about 70% of the total assets. The other model variants, by the nature of the model setting, also display similar properties of varying responsiveness, although compared to the '6-month before' version their responsiveness is much more 'linear'; that is, they imply much less drastic changes in failure probability when the debt ratio varies.

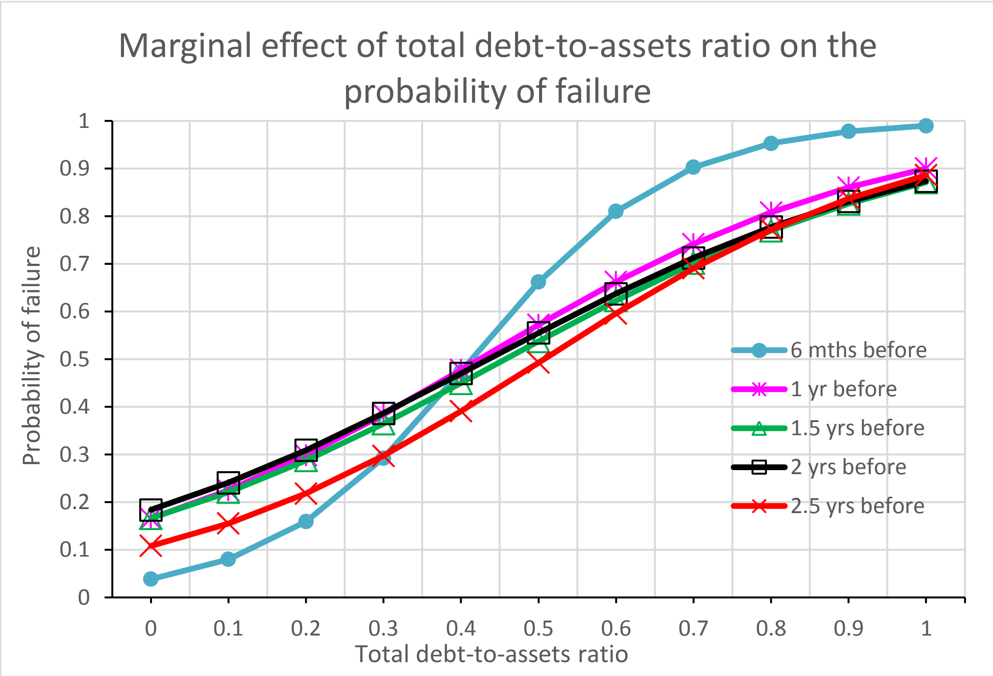

Figure 2. Marginal effect of debt-to-assets ratio on failure probability

Interestingly, Figure 2 shows all but the '2.5-year before' variant suggest a response function that intersects each other when the debt ratio is near 40%; at this level the probability of failure is about 50% which is usually taken as the threshold/critical point in binary logistic analysis. Here, these variants seem to roughly agree that a debt-to-assets ratio at around 40% is notable – this contrasts to our trend analysis (figure 1) where the average debt ratio of delisted firms was mostly kept 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 others whose predictions are not substantially different. The '2.5-year before' variant suggests a somewhat higher critical point, at about 50%; its prediction is otherwise fairly similar to the others' (except for that of the '6-month before' variant), although below such a critical point its predicted failure probabilities are consistently lower by some 8-10%.

While we have identified five model variants that are robust in predicting corporate failure, it should be noted that these logistic models were only estimated with limited observations.

Hence we have carried out In and out of sample tests to validate the robustness of our models. The results of In and Out of sample tests can be obtained on request.

5. CONCLUSIONS

In this paper we analysed how financial and industry specific variables can be used to predict corporate failure in listed shipping companies through the use of binary logit model. Through trend analysis, univariate and multivariate regressions, gearing, profit and activity were found to be useful in predicting corporate failure in listed shipping companies.

Higher gearing levels were found to be associated with a higher level of corporate failure, whereas profit, measured by gross profit / total assets and activity, measured by total revenue to current assets, are shown to have a negative impact on the possibility of failure. However ship finance models are more restricted in terms of the predictive ability of the variables. Gearing is the only robust variable which has been proven to be statistically significant among existing prediction models, whereas in other industries multiple predictors have been identified and used effectively. We further added three industry specific variables and found that shipowning companies are less likely to fail compared to non-ship owning companies operating in the marine transportation sector. Ship companies that are involved in the tramp trade are less likely to fail, reflecting the main business of such companies. We also conclude that it is difficult to predict failure 3 years prior to bankruptcy. The best time horizon to predict corporate failure in shipping is 6 months. Our paper further examines the different characteristics of financial risks in shipping through marginal effect analysis. If the gearing ratio increases to above 40% and remains in the 40% to 70% range it would appear that failure is more likely to occur. Finally, by applying In and out of sample tests we validated the robustness of our models.

In light of the above, these 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 ship owners are able to identify the factors that they need to focus on in order to understand more effectively the financial performance of their company.

REFERENCES

Aharony J, Jones CP, Swary I (1980) An Analysis of Risk and Return Characteristics of Corporate Bankruptcy Using Capital Market Data, The Journal of Finance , Vol 35 (4) pp 1001 – 1016

Campbell JY , Hilscher J, Szilagyi J (2008) In Search of Distress Risk The Journal of Finance, 63 (6) pp. 2899 – 2938

Chan, K. C., and Nai-fu Chen, 1991, Structural and return characteristics of small and large firms, Journal of Finance 46, 1467–1484.

Charitou A, Neophytou E, Charalambous C (2004) Predicting Corporate Failure: Empirical Evidence for the UK, European Accounting Review, 13 (3) pp. 465 – 497

Cullinane, K., Gong, X., 2002. The mispricing of transportation initial public offerings in the Chinese mainland and Hong Kong. Maritime Policy and Management 29 (2), 107–118.

Fama, EF., French KR (1996) Multifactor explanations of asset pricing anomalies, Journal of Finance 51, pp. 55–84.

Grammenos CT, G. Arkoulis AG (2003) Determinants of spreads on new high yield bonds of shipping companies, Transportation Research Part E 39 459–471

Grammenos, Costas Th, and Angelos G. Arkoulis. "Determinants of spreads on new high yield bonds of shipping companies. "*Transportation Research Part E: Logistics and Transportation Review* 39.6 (2003): 459-471.

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

Grammenos, Costas Th, Amir H. Alizadeh, and Nikos C. Papapostolou. "Factors affecting the dynamics of yield premia on shipping seasoned high yield bonds." *Transportation Research Part E: Logistics and Transportation Review* 43.5 (2007): 549-564.

Grammenos, C. T., & Papapostolou, N. C. (2012). US shipping initial public offerings: Do prospectus and market information matter? *Transportation Research Part E: Logistics and Transportation Review*, *48*(1), 276-295.

Grammenos, Th. C., Marcoulis, N.S., 1996. Shipping initial public offerings: a cross-country analysis. In: Levis, M. (Ed.), Empirical Issues in Raising Equity Capital. Elsevier, pp. 379–400.

Investopedia (2015a) Ratio Analysis,http://www.investopedia.com/terms/r/ratioanalysis.asp

Investopedia (2015b) Gearing Ratio, http://www.investopedia.com/terms/g/gearingratio.asp

Investopedia (2015c) Liquidity Ratio, http://www.investopedia.com/terms/l/liquidityratios.asp

McLachlan, Geoffrey J., Do, Kim-Anh and Ambroise, Christophe (2004), *Analyzing Microarray Gene Expression Data*, John Wiley and Sons Ltd, United States.

Merikas, A., Gounopoulos, D., Nounis, C., 2009. Global shipping IPOs performance. Maritime Policy and Management 36 (6), 481–505.

Merikas, A., Gounopoulos, D., Karli, C., 2010. Market performance of US-listed shipping IPOs. Maritime Economics and Logistics 12 (1), 36–64.

Mitroussi, K., Xu, J., Petttit, S., Tigka, N. (2012) "Performance drivers of shipping loans: An empirical investigation", Conference Proceedings, International Association of Maritime Economists Annual Conference, Taipei, 5-8 September 2012.

Seitz N (1979) Financial Analysis – a programmed approach, Reston Publishing, Virginia.

Tamari M (1978) Financial ratios. Pitman Press, Bath, 182pp.

Tsionas, M.G., Merikas, A.G., Merika, A.A., 2012. Concentrated ownership and corporate performance revisited: the case of shipping. Transp. Res. Part E: Logist. Transp. Rev. 48 (4), 843–852.

Wayman R (2015) Operating Cash Flow: Better Than Net Income? http://www.investopedia.com / articles/ analyst/03/ 122203.asp