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ABSTRACT

For the past 30 years, there has been continuous effort to explain and predict financial distress from finance, economics and accounting perspectives. Managers of businesses and business owners are constantly under stress to surge this turbulent and unpredictable economic environment. Modelling financial distress provides an early warning of future deviations from budgeted targets and it will help for the mitigation and prevention of these downturns. This study examines the multiple states of financial distress by applying a multinomial logistic regression on a panel sample of 161 companies listed on the FTSE AIM for the period 2002 to 2009. We use the stock-based and flow-based insolvency to categorize our sample into three independent states. Using the multinomial logistic technique, we analyse the impact of accounting ratios, market-based variables, activity and company characteristics, state dependence on entering these three states of financial distress. It has been found that profit margin, cash flow to total assets, change in net income, total liabilities to total assets, EBIT to share capital, dividend per share, dividend yield and most importantly state dependence are the key factors that drives companies into a situation of financial distress. The findings from the internal and external validations shows from the proposed model provide an accuracy of 81.20% and 69.54% respectively at forecasting the states of the companies in the following year.

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1. INTRODUCTION

Over the past three decades, the modelling of financial distress prediction has been one of the most popular areas of research in corporate finance. There exists evidence of notable corporate collapses, including WorldCom, Enron, and Tyco. In the United Kingdom (UK), in the first quarter of 2011, according to McGaph [53], 186,554 firms have experienced a significant or even a critical financial distress compared to 161,601 in the same quarter in 2010, indicating a 15% increase. The corporate health of firms is of a considerable concern to various stakeholders, such as investors, managers, policy makers and industry participants. Nowadays, businesses possess major apprehension, despite their nature of operation and size, in the significant threat of insolvency. There are several reasons for this strong attention for the prevention and mitigation of a corporate downturn.

It is importance to have build models that may, even approximately, predict future business failures. Corporate failures affect many stakeholders and parties; it involves both direct and indirect costs. Indeed the research around this topic has been motivated by both private agents, who ultimately would like to be aware of financial distress models and thus enable them to take corrective and preventive approaches to avoid failure on their own companies and Government, thus aiming to identify poor performing companies [46]. Laitinen and Kankaanpaa [48] asserted that this could result in 'contagion effects' whereby the costs of the business failure with a large network of related companies could result into a downward spiral for the whole economy of a country. Zopounidis and Dimitras [75] claimed that the number of corporate failures is an important element for the economy of a country. It can further be treated as an index for the development and robustness of the economy. The firm's failure could inflict negative shocks for each of the stakeholders and, consequently the total economic and social costs of that failure could be significant.

Hence stakeholders should consider financial collapse not as an individual point of view, but rather by encapsulating the societal and economical point of view. Furthermore auditors bear the threat of potential lawsuit if they fail to provide an early warning in the procedure of issuing qualified audit opinions, i.e. going concern opinion. See [13], [41], [48].

1.1. Financial Distress Cycle

Wruck [74] defines financial distress as “a situation where a firm's operating cash-flows are not sufficient to satisfy current obligations and the firm is forced to take corrective action”. Companies enduring financial distress pass through several separate stages, all of which contribute differently to corporate failure. Each stage, as described by Outecheva [58], has unique attributes and contributes differently to corporate failure. The company does not reside in the same state, i.e. it is time varying. Financial distress comprises of following stages: (1) early impairment - it sends very weak signals of the commencement of financial trouble, (2) deterioration of performance – it starts with the first signs of slight deterioration in performance, (3) failure - the company does not meet the a desirable or intended objective, (4) insolvency – it is unable to meet its current debt obligations, (5) default – the debt matures but the company is unable to reimburse, (6) bankruptcy – the company cannot pay the debts it owes to its creditors and it is filed for bankruptcy, (7) trouble debt-restructuring – it is designed to avoid remedy default and allows the company to remain alive until the financial health of the company reaches a particular threshold and (8) recovery – overcome financial difficulties and recover without defaulting. This is the so-called financial distress cycle.

One may question the early signs of financial distress. According to Outecheva [58], it is quite difficult to measure the length of the stages due to the complexity in the onset of financial distress. Platt and Platt [69] stated that ex-ante approaches for predicting bankruptcy failed to forecast three or more years in advance. Altman [4] with his Z score model demonstrated that there is a negative correlation between accuracy and the number of years. One important element is to distinguish between financial distress and insolvency. During the first stages of financial distress, the company suffers a reduction in its liquid resources, but it is not necessarily in a state of solvency, i.e. the company albeit bearing a liquidity problem is still able to meet its financial obligations in due time. Indeed liquidity ratios would capture this event, however solvency ratios would not. As the performance becomes aggravated, a further decline in its liquidity position triggers the next stage. As suggested by Hill and Perry [33], the solvency position at that point in time could be indicated by the investigation of change in cash flows in relation to the total assets. Deterioration and failure affects the profitability of the company, while the insolvency and default shapes its liquidity position. The outcome of each stage can be either positive or negative; a positive outcome implies that the company breaks the downward trend while a negative one indicates continuing deterioration.

Furthermore, Miller [54] stated that companies facing an early impairment result in attempting to reduce their comparative advantages; would put the future success potential of the company at risk. In the financial distress cycle, failure causes the company to suffer from continuously declining profitability, while the company's return is below the index's return; not temporarily but permanently.

Different models are designed for different time horizons. This can be demonstrated in the financial stress cycle. In the early stages, the future bankruptcy manifests differently in the financial statements compared to the near-term bankruptcy. In the early impairment, the managers can improve the appearance of the financial statements for a period of time through window dressing. Nevertheless, they can eventually solve the issue of financial trouble by selling fixed assets, cutting expenses and selling inventories at a reduced price. This would result in a rise of revenues and a reduction in cost of goods sold. Through the later stages of financial distress, near-term resources compromise of current assets while near-term obligations compromise of current liabilities.

1.2. FTSE Alternative Investment Market (AIM)

The FTSE Alternative Investment Market (AIM) was created by the London Stock Exchange in 1995. The AIM is a low cost exchange and is the leading equity exchange for small and mid caps companies. The characteristic of the firms listed on the AIM tends to be less liquid, less diversified, riskier, smaller, high-growth and small trading float [51]. Kearns and Young [44] have analysed the results of the questionnaire survey of UK Smaller Quoted Companies (SQC)[1] from a sample of CBI (Confederation of British Industry) members and of liaison meetings with some companies. Their findings were that the main reasons why

[1] Smaller quote companies (SQCs) are listed on the AIM exchange, have full listing on the London Stock Exchange or listed a non-regulated exchange. They falls below the FTSE 350 in terms of market capitalisation. Kearns and Young [44].

companies had no easy access to funds were due to their small size and the absence of a formal credit rating. The companies faced major difficulties in raising equity finance and bond markets. There are also suggestions that banks are less willing to extend small companies long-term loans unless on a secured basis (3:1 basis).

1.3. Objectives

Most financial distress and bankruptcy models have been derived primarily on large companies rather than on small companies. In general, the probability of failure of small companies is far higher than large ones. Hence, the objective of this paper is to derive an ex-ante near-time bankruptcy model based on small companies, more exactly on the companies that are listed on the FTSE AIM. Such a model will be more beneficial to small companies as well as its stakeholders for numerous reasons, for instance, one prominent reason would be the access to more funds. Small companies are always confronted with several difficulties for funding – due to their size which arouse mistrust and prejudices on financial transactions (loans, leasing, etc.), supply chain, customer relationships or other kinds of partnerships, especially strategic ones. The research will help these firms to enhance their capacity to raise capital more easily with less personal guarantee and have the same facilities and services as other bigger firms.

The aim of modelling financial distress is to gain an early insight of financial vulnerability in the near future and hence to have more time to respond. It can be argued that this study is the first attempt to apply the multinomial logistic regression on the FTSE AIM exchange for modelling three states of corporate financial health. The three states are: State 0 (zero) healthy companies; State 1 (one) flow-based distress; and State 2 (two) flow-based and stock-based distress. This research will introduce five models sequentially to ascertain how accounting based variables, market-driven variables, company characteristics and industry effects can improve the reliability and predictive power of the model. The research also attempts to model the state dependence across the three states by including dummy lagged dependent variables. Subsequently we will test the robustness of the proposed model through some post-estimation techniques. Afterwards, we compare the accuracy of the proposed model a forecasting horizon of one year and two years. Finally we validate the model by means of a holdout sample.

2. LITERATURE REVIEW

This chapter reviews existing literature pertaining to the field of financial distress prediction. The first section deals with various definitions of financial distress. The second section investigates the recent approaches regarding the modelling of financial distress in the UK. Finally, the third section elaborates on the literature regarding the multiple states of a financial distress model.

3.1. Definitions of Financial distress

Overall, many studies concentrate towards a bankruptcy prediction model rather than a financial distress model. Platt and Platt [63] suggested that one possible reason for this lack of financial distress prediction models is due to the unavailability of a theoretical definition for financial distress. There is no start date or end date for financial distress. Conversely, a formal bankruptcy is where there is a court sanction and it has a definite start date. Previous pieces of research have adopted a variety of financial distress definitions. In their working paper, Platt and Platt [63] have provided the different definitions employed in the past:

- Evidence of layoffs, restructurings, or missed dividend payments [49].
- Cash flow less than current maturities of long-term debt [73].
- The change in equity price or a negative EBIT [39].
- Negative net income before special items [35].

Further recent definitions are:

- Filed for bankruptcy and operational cash flows are lower than financial expenses and market value persistently falls [61].
- Debt Service Coverage (DSC)[2] is less or equal to 1.2 [64], developed by Ruster [66].
- Flow based insolvency and Stock based insolvency [8], developed by Westerfield and Jaffe [65].

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[2] $DSC = (EAT + (Depr. + Amort) + Interest\ and\ or\ Coupon - Tax)/(Principal + Interest\ and\ or\ Coupon)$

In their book “Corporate Finance”, Ross, Westerfield and Jaffe [65] segregated company insolvency into stock based insolvency and flow based insolvency. Their definition of stock based insolvency is whenever the company’s total liabilities are greater than its total assets; while flow based insolvency occurs when a company’s operating cash flow cannot meet its routine obligations.

Ansell and Andreeva [8] have focused their research on 445 small UK businesses and they introduced different risk rating models by applying an accounting based approach. They developed a standard credit scoring modelling tool, i.e. binary logistic regression. They classified companies into four distinct groups: (1) Insolvent, (2) Flow-Based and Stock-Based Distress, (3) Flow-Based Distress and (4) Healthy.

3.2. Review of the prediction of UK models

On a worldwide perspective, the UK is considered as a major player in the economic market. Taffler [70] claimed that the United Kindgom provides the ideal platform for successful development of statistical models. It could alleviate the assessment of company performance and solvency. As of June 2011, the London Stock Exchange had a market capitalisation of US$3.8 trillion, making it the third largest stock exchange in the world by measurement and also the largest in Europe [72].

However most failure prediction models have utilised US data and attempted to extend Beaver’s [10] univariate approach and Altman’s [5] linear multiple discriminant analysis model, so-called MDA. The MDA’s popularity had a significant influence on the British failure prediction studies. The late 1970s and 1980s, several MDA models were developed in the UK. Charitou et al. [17] argued that despite the statistical advancements that occurred in this area, the MDA still remains the most popular and widely used technique for financial distress prediction in the UK. Moreover, Morris [55] claimed that the linear discriminant analysis developed by Taffler [70] is the best-known technique employed in the UK.

The work of Peel et al. [60] appeared to be the earliest attempt of applying logit analysis in the UK. They added non-conventional ratios and variables to the standard accounting based model.

Keasey and Watson [45] predicted small company failure and incorporated various qualitative indicators, such as the average submission lag[3], the number of directors, prior year audit qualifications and the presence of bank secured loans. They also illustrated that the cause of improvement in the predictive power of their model is mainly due to the inclusion of more years of financial data.

Keasey and Watson [45]and Peel and Peel [59] applied the multi-logit models on the conventional failing and non-failing dichotomy for a number of reporting periods prior to the failure. Keasey and Watson [46] further explored the limitations and usefulness of methods used in this research area; they claimed that logit analysis is as useful as any other technique for the user.

Lennox [50] applied the logit and probit models on a sample of 90 bankrupt firms. This revealed that the variables with the highest predictive power were leverage, profitability and cash flow variables. He also claimed that his model performed better than the typical MDA approach.

Charitou et al. [17] applied the logistic regression analysis and neural networks on a 51 matched-pairs[4] using the conventional failing and non-failing dichotomy over the period 1988 to 1997. They developed a corporate insolvency prediction models for one, two and three years prior to failure.

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[3] In a period of financial distress, the failing firms tend to delay the submission of their annual accounts.

[4] Matched pair is a form of analysis whereby each observation in a category is paired with each of those in the comparison group.

Agarwal and Taffler [2] assess the distress risk of the Taffler Z-score model over a 25-year period. They concluded that their model had the ability to forecast distress risk for the companies in the UK. Following that study, Agarwal and Taffler [3] compared their model with the market-based BSM model developed by Hillegeist et al. [34] and the one by Bharath and Shumway [12]. Their conclusion is that the Z-score and market-based models both have the ability to predict failure.

Chrisitidis and Gregory [20] employed the Shumway [67] and Chava and Jarrow [18] dynamic logit model. They provide two models for the companies in the UK: pure accounting based and accounting and market based models. They extended the work of Campbell et al. [15] by incorporating the macro-economic factors. They concluded that the inclusions of the term structure of interest rates, risk free rate of interest and inflation rates, are all significant variables. Furthermore, consistent with Chava and Jarrow [18], they added the industry effect to their model. They found that this increases the predictive power, as the industry effects appear more important than the other variables.

3.3. Multiple States of Financial Distress

Financial distress does not always result into the firm's death. Bankruptcy is only one extreme, the other extreme is a successful restructuring. According to Johnsen and Melicher [40], financial distress "is best depicted as a continuum ranging from being 'financially weak' to bankrupt, with the possibility of various degrees of financial weakness". In the financial distress cycle, the company ranges from being financial weak, such failure or insolvency, to being bankrupt. Previous corporate failure prediction models developed used the conventional failing and non-failing dichotomy [10], 17, [57],[67]]. However this dichotomy provides an impaired representation of the financial stress that companies face in reality.

Lau [49] was the first one to introduce a model that has five financial states to approximate the continuum of corporate financial health. He used the multivariate logit analysis to estimate the probability of a firm entering in each of the five ranked states[5]. However the model faced some limitations. Two of them were the inability to conform to the Independent and Identically Distributed (IID) data and Independence for Irrelevant Alternatives (IIA) assumptions.

Johnsen and Melicher [40] built upon the former of the multinomial logit models for predicting and explaining corporate bankruptcy. They identified three states for their research: State 0 (zero), non-bankrupt; State 1 (one), financially weak; and State 2 (two), bankrupt. They demonstrated that through the inclusion of a 'financially weak' state, it reduces the misclassification error of the three states, which appear to be independent. They used the multinomial logistic models to evaluate the value of information on the prediction of bankruptcy. Catering for the IID and IIA assumptions, the three states of financial health appeared to be independent.

Hensher and Jones [31] examined the listed companies in the Australian Stock Exchange and he argued through the inclusion of multiple states, it provides a prospect to examine carefully the explanatory variables across the various stages in the financial distress cycle. They illustrated the reliability of a mixed logit model and introduced a three state financial distress model: State 0 (zero), non-failed firms; State 1 (one), insolvent firms; and State 2 (two), firms filed for bankruptcy or appointed insolvency, liquidators, administrators or receivers.

Andreev [7] used the multinomial logistic regression on a panel data, consisting of 16,902 observations, which belong to a total of 1,667 Spanish firms over a period of 12 years. He employed a three state model: State 0 (zero), healthy; State 1 (one), voluntarily insolvent;

[5] The considered five ranked states are: State 0 (zero), financially healthy; State 1 (one), Firms with reduced dividend; State 2 (two), Firms filed for protection under Chapter X/XI or had C-rated bonds; State 3 (three), Bankrupt firms from WSJI list; and State 4 (four), Chapter X/XI firms.

State (2), necessarily insolvent. He validated that the hypothesis, which proposed a higher long-term liability of the firms that enter in judicial proceedings compulsory.

Hensher, Jones and Green [32] claimed that a model that incorporates multiple states of financial distress better reflect the real word by providing various distress stages. They extended the study of Hensher and Jones [31] and discovered that the error component logistic model and nested logistic model possess the capability of offering a better explanatory power over a standard logistic specification. Hence the robustness of the model allowed for an improved power of probability for predicting financial collapses.

Chancharat et al. [16] also examined the determinants of various states of financial distress by incorporating competing-risks model on a sample of 1,081 publicly listed Australian non-financial companies from 1989 to 2005. They defined financial distress in three unordered mutually exclusive states: State 0 (zero), active companies; State 1 (one), distressed external administration companies; and State 2 (two), distressed takeover, merger or acquisition companies. They concluded that there are significant differences in the variables that determine the stages of financial distress that a company is facing.

3. METHODOLOGY

3.1. Multinomial Logistic Regression

Logistic regression analysis has the ability of extending beyond the simple (binary) dichotomous analysis to the analysis of categorical dependent outcomes with more than two levels. Scholars have denoted this resulting model as polychotomous, polytomous or multinomial logistic regression (MNL) models, which is sometimes abbreviated to 'multinomial logit' or 'mlogit'. MNL belongs to the class of statistical techniques called categorical data analysis and was developed by McFadden [52]. MNL analyses the "relationship between a non-metric dependent variable and metric or dichotomous independent variables" (Andreev, 2006). It contrasts the different levels through a combination of binary logistic regressions. Peel and Peel [59] suggested that MNL is a dynamic approach to examine several periods of data prior to failure to discriminate between bankrupted, healthy or firms with financial embracement for several reporting periods prior to failure. When the categorical outcome is unordered, the MNL is one often-used strategy. MNL reduces misclassifications and accounts for a greater portion of the variance of the criterion variable [43].

For three categorical outcomes, the MNL computes a set of coefficients for each of the two outcomes, while the coefficients of the reference group are normalised to zero. The reference group is equivalent to the comparison for a dummy-coded dependent variable. The decision of choosing which category to set a reference group is arbitrary. It will not affect the overall fit of the model but it may prove difficult to interpret.

Before the MNL model is applied, there is a need to develop some notation. Consider a dataset with N companies $i = 1,2,\dots,N$. Let C takes the categories $1, 2, \dots, K$ for the financial distress and the elements of this set is indexed by c. The dependent variable Y_i can take any of K values. Let the number of observations be n_i for company i. The total sample size is then $\sum_{i=1}^{N} n_i = M$.

Denote y as a matrix with N rows, with each row representing a company with $C-1$ columns and C is fixed as the reference group. The probability that Y_i can take any c values can be represented as $P(Y_i = c) = P_{i,c}$ with $\sum_{c-1}^{C} P_{i,c} = 1$.

Denote the number of independent variables as the set R indexed by r. The matrix of independent variable X comprises of N rows with $R+1$ columns. The intercept being the first element of each row takes the value of one, $x_{i0} = 1$. Since our categories are independent, each x_i is a multinomial random variable.

The set of coefficients is represented by the matrix β with $R+1$ rows and $C-1$ columns. Each element of the set is a unique value depicting the parameter estimate of a variable r^{th} for a particular category c^{th}.

Let ω be a matrix representing the probability of i^{th} company being in the c^{th} category. ω has the same dimension as the matrix y.

$$log\left(\frac{\omega_{ic}}{\omega_{iK}}\right) = log\left(\frac{\Pr(Y_i = c)}{\Pr(Y_i = K)}\right) = \sum_{r=0}^{R} x_{ir}\beta_{rc}$$

where $i = 1, 2, \dots, N\ and\ c = 1, 2, \dots, K-1$ and K is fixed as the reference group. Hence it can be equated that the linear component and model the log odds of c^{th} category with the reference category K.

Now solving for the probability of each category ω_{ic}, we have:

$$\omega_{ic} = \frac{e^{\sum_{r=0}^{R} x_{ir}\beta_{rc}}}{1 + \sum_{c=1}^{K-1} e^{\sum_{r=0}^{R} x_{ir}\beta_{rc}}}. \qquad c < K$$

$$\omega_{iK} = \frac{1}{1+\sum_{c=1}^{K-1} e^{\sum_{r=0}^{R} x_{ir}\beta_{rc}}}.$$

In this example, consider outcome 0 (zero), 1 (one) and 2 (two). The outcome is set to 0 (zero) as the reference group. Based on the interpretation of Hosmer and Lemeshow [37], Andreev [7] denoted the two functions as:

$$\mathrm{h_1(x)} = \ln\left(\frac{\mathrm{P(y=1|x)}}{\mathrm{P(y=0|x)}}\right) = \beta_{10} + \beta_{11}\mathrm{x}_1 + \beta_{12}\mathrm{x}_2 + \beta_{13}\mathrm{x}_3 + \ \ldots + \beta_{1\mathrm{r}}\mathrm{x}_\mathrm{r} = \mathrm{x}'\beta_1.$$

$$\mathrm{h_2(x)} = \ln\left(\frac{\mathrm{P(y=2|x)}}{\mathrm{P(y=0|x)}}\right) = \beta_{20} + \beta_{21}\mathrm{x}_1 + \beta_{22}\mathrm{x}_2 + \beta_{23}\mathrm{x}_3 + \ \ldots + \beta_{2\mathrm{r}}\mathrm{x}_\mathrm{r} = \mathrm{x}'\beta_2.$$

Where $\mathrm{h_t(x)}$ with represents the log of odds compared to the reference group and β_{ir} is the coefficient of the independent variables. As it can be seen, the logs of the odds of one state relative to others remains a linear function of the matrix of independent variables.

Now to represent the probability of c^{th} category:

$$\omega_{i0} = \mathrm{P(y = 0|x)} = \frac{1}{1+e^{h_1(x)}+e^{h_2(x)}}\,.$$

$$\omega_{i1} = \mathrm{P(y = 1|x)} = \frac{e^{h_1(x)}}{1+e^{g_1(x)}+e^{g_2(x)}}\,.$$

$$\omega_{i2} = \mathrm{P(y = 2|x)} = \frac{e^{h_2(x)}}{1+e^{h_1(x)}+e^{h_2(x)}}\,.$$

$$\mathrm{P(y = 0|x) = 1 - P(y = 1|x) - P(y = 2|x)}$$

and the general formula for three outcomes case is:

$$\omega_{ic} = \mathrm{P(y = c|x)} = \frac{e^{h_c(x)}}{1+\sum_{t=1}^{2} e^{h_t(x)}}\,.$$

The equations above are utilised to compute the probability of each outcome. The equation with the highest probability is the case predicted for that observation i. From the equations above, we can see that the set of coefficients start with β_{10} as the reference group also has a set of coefficients β_1 to β_9 and they are normalised to zero.

3.2. Evaluation of the model

There are a number of issues to consider when evaluating the results obtained from the MNL. Firstly the estimated coefficients should be interpreted as the effect of one unit change in an independent variable upon $\log\,[\mathrm{P_t}/(1-\mathrm{P_t})]$ and not upon the probability $\mathrm{P_t}$ where $\mathrm{P_t}$ represents the probability that the c^{th} state will occur [40]. Secondly, the final estimation is the probability of a particular state to occur change depending on the values of the independent variables. It is the probability that a particular state will have the greatest gains over the other states [7]. Thirdly an important concern is the implications of the restrictive assumption of independence present in the MNL model. This may be a serious weakness when at least two of the states are close substitutes [30], [42], [47]. Johnsen and Melicher [40] argued that the model with five states introduced by Lau [49] endured a risk of close substitutes in context of the MNL model, this would lead to bias estimated probabilities.

The independence assumption of MNL called Independence of Irrelevant Alternatives (IIA) can be tested with the Hausman's specification test. This is a statistical test in econometrics named after Jerry A. Hausman. Hausman and McFadden [30] claimed that if a subset of choice of alternatives is irrelevant, i.e. close substitutes, it could be omitted from the sample without changing the remaining parameters systematically. The MNL assumes that the odds for any pair of outcomes are determines independent without any dependence on the other outcomes in the model.

Freese and Long [24] outlined the steps of the Hausman-type test:

- Estimate the unrestricted model with all the categories and keeping the estimates in $\hat{\beta}_U$.
- Estimate a restricted model by eliminating one or more outcome categories and keeping the estimates in $\hat{\beta}_R$.
- After eliminating coefficients not estimated in the restricted model, let $\hat{\beta}_U^*$ be a subset of $\hat{\beta}_U$. The Hausman test of IIA is defined as:

$$\mathrm{H}_{\mathrm{IIA}} = \left(\hat{\beta}_{\mathrm{R}} - \beta_{\mathrm{U}}^*\right)' \left[\widehat{\mathrm{Var}}\left(\hat{\beta}_{\mathrm{R}}\right) - \widehat{\mathrm{Var}}(\beta_{\mathrm{U}}^*)\right]^{-1} \left(\hat{\beta}_{\mathrm{R}} - \beta_{\mathrm{U}}^*\right)$$

$\mathrm{H}_{\mathrm{IIA}}$ is asymptotically distributed as chi-square with degrees of freedom equal to the rows of $\hat{\beta}_{\mathrm{R}}$ if the IIA is true. The IIA assumption is violated when there are significant values of $\mathrm{H}_{\mathrm{IIA}}$.

According the null hypothesis, i.e. IIA holds, omitting the irrelevant outcomes will lead to consistency, however efficient parameter estimates $\hat{\beta}_{\mathrm{R}}$ while the parameter estimates $\hat{\beta}_{\mathrm{U}}$ of the will be consistent yet inefficient. Under the alternative, if the alternatives are close substitutes, only the parameter estimates of the unrestricted model $\hat{\beta}_{\mathrm{U}}$ will be consistent.

4. SELECTION OF CANDIDATES FOR PREDICTIVE VARIABLES

According to Andreev [7], all financial distress models share a common static methodology, whereby it performs statistical analysis to distinguish between financial states on the last year prior to failure. Essentially almost all of them have converged toward the conclusion that distressed companies differ significantly from healthy ones for the referred period. Similar to the unavailability of a clear definition of financial distress, there is also no unified theoretical justification of both theory and set of indicators for the prediction of financial vulnerability. Andreev [7] further stated, “in the absence of a theory that provides testable hypothesis, each empirical result has to evaluated to its own merit”. The previous research has outlined some common significant variables such as total liabilities to total assets and change in net income. Normative theories tend to explain the reasons for corporate failures, i.e. deductive reasoning, while positive theories explain why in practice they do fail, i.e. inductive reasoning. Charitou et al. [17] allege “although the majority of bankruptcy studies were conducted in line with the positivistic paradigm, very few researchers clearly identified an underlying theory”.

Therefore to ensure a theoretical justification of the selection of predictive variables, in line with Christidis and Gregory [20], the accounting variables need to be grouped into a number of categories, whilst a rationalisation of selecting these categories is also required. Additionally an explanation of the reasoning of selecting the other predictive variables is then required. In this paper, the variables are chosen based on intuition, popularity and predictive power demonstrated in previous studies. Table 1 shows the selected predictive variables for this study. Explanations of each variable are provided in the Appendix.

Table 1: Selected predictive variables

Accounting-based Ratios			Market-driven variables	Activity and Company characteristics	State Dependence
Profitability	Liquidity	Leverage			
EBITDA Margin	Working Capital to Total Assets	Total Liabilities to Total Assets	Dividend per share	Log of Total Assets per Employee	Lagged Dummy Dependent variable
EBIT to Share Capital	Cash Flow over Total Assets	Debt to EBITDA	Dividend Yield	Size using Log Assets	
Profit Margin	Cash Flow from Operation to Sales			Size using Log Turnover	
EBIT Growth	Cash Ratio			Industry	
Change in net income					

4.1. Accounting Ratios

Green [29] argued that ratio analysis was regarded as a barometer for the financial health of a firm and also acts as indicators of liquidity, leverage, activity, profitability and its future prospect of success. Gardiner [25] also concluded that the ratio analysis continues to represent one of the most powerful and versatile tools in the financial world.

PROFITABILITY

Profitability ratios indicate the ability of the company to control its expenses and generate a return out of the resources committed in the business. Most research explicitly illustrated how profitability ratios are crucial in the prediction of financial distress. In his book, the 'Early Warnings Indicators Corporate Failure', Morris [55] explained how low profitability eventually leads to an increase in gearing and impaired liquidity. Various scholars also showed these ratios were the most significant variables in their studies [5], [10], [17], [70]. In most cases, in prior years before corporate failure, profitability ratios tend to subsequently decrease in magnitude, affecting the whole company in terms of cash flow from operations and working capital, leading to a faster transition to failure.

LIQUIDITY

Liquidity refers to the company's aptitude to meet its short-term debt obligations in due time. It also refers to how cheaply and quickly assets can be converted into cash and the prospective of generating working capital funds. Christidis and Gregory [20] explained that companies have a tendency to invest excessively into productive assets, so called illiquid assets[6]. They can consequently impair the company from meeting its debt obligations. Although the company may have enough funds, in terms of illiquid assets, to match its debt payments, the latter may have to resort to liquidating these illiquid assets, such as stocks; this can lead to additional costs such as hastily selling the assets at low value. Hence the proportion of liquid assets maintained by the company is an indicator of the ability to meet expected or unexpected payments. Baskin [9] reported that on a sample of 338 major US corporations, 9.6% of the capital invested[7] was held in cash and marketable securities in 1972. Also that amount was surprisingly equal to one-third of total outstanding debt.

LEVERAGE

Leverage ratios, also referred to as gearing ratios, are the most relevant ratios for financial distress in the literature. It measures the ability of the company to meet its long-term financial obligations, alongside its capability to raise additional capital borrowing. Leverage ratio in itself provides an overall picture of the financial health, as well as the financial risk of the company. In the case a company being highly geared, in a period of growth, its profitability would be high. However in a period of severe conditions, the company may bear severe losses due to the high interest payments. Hence, low geared companies would be less prone to bearing a financial distress than high geared ones. Gepp and Kumar [26] showed that financial leverage was the variable which possessed the most impact on corporate failure for their financial distress prediction model. Long-term debts, always

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[6] Illiquid assets are assets that cannot be readily converted into cash.
[7] Capital invested is the book value of the debt and equity

known as hard contracts[8], require payments on specific dates. Failure to do so would result into the company being in violation of the contract and eventually the debt holders can seek, specified and unspecified, legal recourses to enforce the contract.

4.2. Market Variables

Under the weak form of efficiency of the Efficient Market Hypothesis[9] (EMH), the existing share price always reflect and incorporates all relevant information of the company. It reflects all the information learnt from the financial statement, as well as the any information available of the market. This implies that any information about the future activities or events, both favourable and unfavourable, known by the market but not yet reflected in the financial statements would be incorporated in the share prices. Hence market variables should be considered as an important predictive variable for predicting the probability of being in financial distress.

Furthermore, there is an issue of timeliness, since accounting data is out-dated, while simultaneously there is a tendency of late reporting by distressed firms [50], [57]. Ultimately, there is time lag between the end of the financial year and the published financial reports. Accounting data alone cannot be used as a reliable predictor. Hence combining accounting data with information in market prices may help to increase the reliability of the prediction. Numerous scholars have understood the importance of market variables. [3], [5], [10], [14], [31], [67]. Beaver et al. [11] signifies that “market prices reflect a rich and comprehensive mix of information, which includes financial statement data as a subset.”

[8] A hard contract is a coupon debt contract, which specifies periodic payments by the firm to its bondholders.

[9] EMH is an investment theory ,which stipulates that it is impossible to beat the market because the share prices always reflect and incorporate all relevant information of the share. There are three forms of EMH: weak, semi-strong and strong.

4.3. Activity and Company characteristics

Many researchers have incorporated the indicators that reflect the characteristics of a company, such as size and industry group. A model with the conventional failing and non-failing dichotomy may be distinguished between large and small firms, or between certain industries. Taffler [70] and Foster [23] argued that matching firms by size and industry eliminates the predictive power of these variables. They stated that this could lead to a restricted model rather than a general model for prediction corporate failure. Ohlon [57] found that the firm size was inversely correlated with bankruptcy, i.e. bankrupt firms tend to be smaller than non-bankrupt firms. Furthermore Jones [41] commentated "bankrupt firms are often disproportionately small and concentrated in certain known failing industries." Chava and Jarrow [18] investigated the forecasting accuracy of hazard rate models for bankruptcy on companies in the US from 1962 to 1999. They concluded that industry effects are important in predicting bankruptcy. Industry groupings were found to be affecting both the slope and the intercept of the covariates in the forecasting equations.

Furthermore, the company's economic activity could be described using accounting variables in relation to its number of employees. Employee ratios can indicate the productivity of the company's employees. In a period of severe conditions, relatively good employee ratios within the industry type could help the company to evade financial distress. Ecaterina et al. [22] found that employee ratios can aid in the classification of the conventional failing and non-failing dichotomy.

4.4. State Dependence

The presence of state dependence[10] through the inclusion of a lagged dependent variable among the covariates in situations of financial vulnerability can be further tested. A healthy firm is less likely to experience financial distress in the next period compared to a firm already bearing financial distress. According to Table 2 below, it can be seen the transition

[10] State dependence is a dynamic fundamental property of time series whereby the state at a given point in time depends on the previous state or states of the system.

probability from healthy (State 0) to the two levels (State 1 and 2) of distress is only 0.13. It can be further noticed that the probability on average of a firm staying in the same state in the next period is 0.70. Chortareas et al. [19] allowed for the presence of a binary lagged dependent variable in their dynamic probit specification. It takes the value of one in the case that a financial crisis episode is detected. In their findings, they suggest that the use of the lagged dependent variable can considerably improve the predictive power upon the in-sample performance of a static model.

However there may be some criticism of including a lagged dependent variable. Achen [1] explains how the inclusion of the lagged dependent variable can suppress the explanatory power of other independent variable. He claims that the lagged dependent variable can be statistically significant and improves the fit dramatically, while the other substantive coefficients tend to collapse to implausibly small and insignificant values, or can even take the wrong sign.

Table 2: Transition Probabilities

		To		
		0	**1**	**2**
From	**0**	0.8725	0.1144	0.0131
	1	0.2878	0.6475	0.0647
	2	0.2273	0.1818	0.5909

5. SAMPLE SELECTION

The data set used for this research consists of companies listed on the FTSE AIM from various industry classifications including: Oil, Mining, Industrials, Support Services, Consumer goods, Healthcare, Consumer Services, Telecommunication, Financials and Technology. Financial statements comprising of income statements, cash flow statements and balance sheets as well as the market variables were sourced from the database 'Datastream' for the period 2001 to 2009. Most companies are audited by one of the Big Four[11] firms, thus it can be expected the data is unbiased and reliable. The dataset also includes companies, which were delisted from the exchange in 2010. The reasons for a company to be declared as delisted by the exchange are: voluntary delisting, takeover delisting, involuntary delisting (suspension), transferred to the main market, merger and acquisition. Hoque [36] analysed the FTSE AIM and found that not all the delistings are due to bad operating performance of the company. Hoque alleged that most of them are due to mergers. A total of 42 delisted companies were included in the sample, only if they experienced involuntary delisting, particularly 'continued suspension and expected cancellation' and they had more than three years of continuous financial statements prior to delisting, i.e. 2010. One could suggest including companies that were delisted for other reasons, such as voluntary delisting as category. Due to the fact that the covariates of a healthy company and a voluntary delisting company might be the same, this will violate the IIA assumption of the multinomial logistic regression. Initially there were 1648 observations for 240 companies. Due to missing data, the data finally compose an unbalanced CSTS[12] panel data, consisting of 633 observations, which belong to total of 161 companies with a maximum of 7 years and minimum two years of accounting data prior to 31st December 2009.

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[11] The Big Four firms are the four largest accountancy and professional firms, which form an oligopoly in the large auditing sector. They handle an enormous number of audits for both publicly traded companies and private companies. These Big Four firms are: Deloitte Touche Tohmatsu, PwC, Ernst & Young and KMPG.

[12] CSTS is an acronym for cross sectional dominant data

6. APPROACH TO MODEL ESTIMATION

6.1. Data manipulation

Firstly the data manipulation was performed using Matlab. This stage involved extracting the financial statements and market data from Excel sheets into Matlab, calculating the various ratios and other variables, cleaning the data and categorising the data into three distinct groups.

Nenide et al. [56] provides a clear description of the numerous inconsistencies of ratio computation with large databases for prediction models. Therefore one cannot assume that the sample collated is error free. It is absolutely necessary to assess for accuracy to avoid inaccurate findings and conclusions. Two problems were dealt with in the sample, these being zero divisors and outliers influence. The zero divisors caused ratios to be either positive or negative infinity. Hence these values were replaced with zero. The impact of the outliers needs to be analysed to ensure that these outliers are representative of the actual population of the companies. Consistent with the recommendations of Nenide et al. [56] and various other scholars, data was winsorized at five percent to bring the mean and medians closer together [21], [28]. This also reduces the standard deviation resulting in a better representation of the population. Winsorization at five percent replaces the data below the 5th percentile to the 5th percentile and data above the 95th percentile to the 95th percentile. The key advantage of this method is that the number of financial statements and data points is unchanged.

To account for industry effects on our study, the firms are divided into nine industry groupings: (1) Oil; (2) Mining; (3) Industrials; (4) Support Services; (5) Consumer Goods; (6) Healthcare; (7) Consumer Services, (8) Telecommunication (9) Financials; and (10) Technology. See Table VI in the Appendix.

The current paper follows the Ansell and Andreeva [8] approach to classify the data set into three groups. The categories are assumed to be independent and unordered. The flow based insolvency and stock based insolvency identifications were utilised.

Flow based insolvency is identified using Interest Coverage as follows:

$$Interest\ Coverage = \frac{Earnings\ before\ interest, taxes, depreciation\ and\ amortization}{Interest\ expense\ on\ debt}.$$

A value of less than one for the interest coverage indicates the company does possess enough funds to pay the interest on the outstanding debts and this signals a flow-based financial distress.

A stock based insolvency is identified using Insolvency Ratio as follows:

$$Insolvency\ Ratio = \frac{Shareholders\ Fund}{Total\ Assets}.$$

$$Shareholders\ Fund = Total\ Assets - Current\ Liabilties - Long\ term\ Debt$$

It measures the ratio of both secured and unsecured liabilities in relation the assets owned by the company and acts as confidence factor for unsecured creditors. If the ratio is too low, it indicates a dependency on outside finance for long-term financial support. If the insolvency ratio has a negative value, this would indicate that the total liabilities of the company exceed its total assets and therefore it signals a stock based insolvency.

The companies were classified into three groups as illustrated in Table3 below: State 0 (zero), healthy companies; State 1 (one) flow-based distress; and State 2 (two) flow-based and stock-based distress. In this paper, it is assumed that the states are unordered and mutually exclusive.

Table 3: States of Financial Health

States			No of observations
State 0 (zero)	Healthy	Listed healthy	407
State 1 (one)	Flow-based Distress	Interest Coverage<1	191
State 2 (two)	Flow-based and Stock-based Distress	Insolvency Ratio<0 and Interest Coverage<1	35

6.2. Data analysis

According to the objective of this paper, five models are introduced sequentially to assess how the models increase in terms of predictive power and reliability.

- Model 1 - purely accounting-based model.
- Model 2 - accounting ratios; and market-driven variables.
- Model 3 - accounting ratios; market-driven variables; and activity and company characteristics.
- Model 4 - accounting ratios; market-driven variables; and activity and company characteristics and industry effects.
- Model 5 - accounting ratios; market-driven variables; and activity and company characteristics and dummy lagged dependent variables.

The data analysis was carried out using Stata. Note that the dependent variable takes the value of zero, one and two to coincide with the corresponding states. Also, all the covariates are lagged one by one year except Net_incom. Such a lag eventually lowers the predictive power of the models. Alternatively, it adds to the practical value for decision makers by giving them enough time for the prevention and mitigation of future possible downturns. Net_incom is a binary variable, which takes the value of one if the net income was negative for the two previous years, or it is otherwise zero.

Following previous studies, the log functional form has been applied on some on the covariates. Sori et al. [68] showed that data transformation provides a mean to correct normality violations and the natural log transformation outperforms the other techniques.

From a candidate list of predictive variables, the following elements are included in the multinomial logistic regression:

- EBITDA Margin (EBITDA_marg)
- Profit Margin (Profit_marg)
- Working Capital to Total Assets (WCap_TA)
- Cash Flow to Total Assets (CFlow_TA)
- Change in Net Income (Net_Incom)

- EBIT Growth (EBIT_growth)
- Cash Flow from Operations to Sales (CFlow_Sales)
- Cash Ratio (Cash_ratio)
- Total Liabilities to Total Assets (TLiab_TA)
- Debt to EBITDA (Debt_EBITDA)
- EBIT per Share Capital (EBITSHARE)
- Dividend per share (Div_share)
- Dividend Yield (Div_yield)
- Log of Total Assets per Employee (Log_TA_emp)
- Log of Total Assets (Log_assets)
- Log of Turnover (Log_turn)

The *mlogit* command was used to perform the multinomial (polynomous) logistic regression. Two variance estimators are also used, robust and cluster. The variance estimators are called 'sandwich estimators'. The robust standard errors are robust for some types of misspecification, as long as the three categories are independent. It accounts for serial correlation and heteroskedasticity[13]. The cluster standard errors accounts for intragroup correlations. It specifies that the observations are independent across the three categories, but not necessarily within the categories. See Thiprungsri [71] for the benefits of clustering of accounting data. Hence the two variance estimators result in a less biased estimation of variation and statistical significance. StataCorp LP [69] provides a detailed explanation of these two commands.

[13] Heteroskedascticity means when the standard deviation is time varying, i.e. when observed on a time period t is non-constant. The standard deviation varies with the distributions and independent variables.

7. ANALYSIS AND DISCUSSION OF EMPIRICAL RESULTS

In this chapter, the five models will be analysed using the multinomial logistic regression with three states to determine the interaction of the independent variables. The number of observations for each state is 407, 191 and 35 respectively. This sample represents the true population, as there is no sampling bias in terms of matched pairing procedure[14]. For all the five models, the block of healthy companies - State 0 (zero) is set as the reference group.

7.1. Comparison of the five models

MODEL 1

The predictive power of the pure accounting-based model is initially demonstrated. Table 4 below displays the characteristics of the variables of the accounting based model. Since it is not possible to interpret the sizes of the coefficients, the relative risk ratios were utilised using the rrr command on Stata. The relative risk is the ratio of probability of a company being in either State 1 (one) or State 2 (two) over the probability of being in the reference category, i.e. State 3 (three). This is sometimes referred to as odds.

For example, Profit_mar for State 1 (one) is the relative risk or odds of one unit increase in Profit_mar for State 1 (one) relative to State 0 (zero) given *ceteris paribus*. If Profit_mar were to increase by one unit, the relative risk of the company failing in State 1 (one), flow-based distress rather than being in State 0 (zero) healthy, would be expected to decrease by a factor of 0.89 *ceteris paribus*. Therefore, if the profit margin were to decrease by 1%, the relative risk of bearing flow-based distress would be 1.13 times more likely *ceteris paribus*. The same interpretation applies for State 2 (two). If the profit margin were to

[14] When bankruptcy studies are based on matched pairs, for example 60 failed and 60 paired non-failed companies, it leads to sampling bias. It is unreasonable to assume that “there is an equal 50:50 per cent probability of any firm selected from the wider population of companies being a potential failure” [55]

decrease by 1%, the relative risk of suffering both flow and stock based distress would be 1.22 times more likely *ceteris paribus*.

There are two common significant ratios amongst State 1 (one) and State 2 (two), which distinguishes them from the State 0 (zero). The two ratios are CFlow_TA and TLiab_TA. In the block of State 1 (one), there are two more significant ratios: Profit_marg and Cash_ratio. The percentage of correct classifications among the three groups is 79.77%.

Table 4: Multinomial Logistic Regression on Accounting-based variables

	State 1	State 2
Accounting-based ratios		
EBITDA_mar	1.07	1.25
	(0.11)	(0.23)
Profit_mar	0.89***	0.82**
	(0.04)	(0.08)
WCap_TA	0.65	0.90
	(0.54)	(1.11)
CFlow_TA	0.00***	0.00***
	(0.01)	(0.00)
Net_incom	1.38	1.15
	(0.37)	(0.72)
EBIT_growth	1.03	0.84
	(0.06)	(0.11)
CFlow_Sales	1.02	0.86
	(0.16)	(0.16)
Cash_ratio	1.24***	0.77
	(0.09)	(0.37)
TLiab_TA	0.17***	145.87***
	(0.10)	(190.03)
Debt_EBITDA	0.86*	0.89
	(0.07)	(0.10)
EBITSHARE	0.15***	0.03***
	(0.08)	(0.02)
Constant	0.93	0.00***
	(0.41)	(0.00)

*** p<.10, ** p<.05, *** p<.01 and standard errors are in parentheses**

However the model tends to misclassify 16.84% of State 0 (zero) as State 1 (one); additionally there is anomaly in the standard errors of TLiab_TA for State 2. According to

Table I in the Appendix, the model's accuracy has a low accuracy for State 1 (one) and it tends to misclassify State 1 (one) as State 2 (two). On a standalone basis, it is apparent that a pure accounting-based model has a high degree of predictive power.

MODEL 2

Table VII in the Appendix shows the results of the accounting-based and market-driven model. The variables Profit_mar, CFlow_TA and TLiab_TA and EBITSHARE are significant for both states. Cash_ratio and Debt_EBITDA are still significant for State 1 (one) while the standard errors of TLiab_TA still remain relative high. As we can observe, the market variables Div_share and Mkt_value are significant for State 2 (two) and the model's accuracy is 79.62%. Table II in the Appendix shows that adding market variables have slightly increased the accuracy at predicting State 0 (zero) while decreasing the accuracy for State 1 (one). We can further see that the market variables have no effect on State 2 (two).

MODEL 3

Now we include activity and company characteristics to our model. According to Table B in the Appendix, the four ratios Profit_mar, CFlow_TA, TLiab_TA and EBITSHARE remain significant for State 1 (one) and State 2 (two). Debt_EBITDA continue to remain significant for State 1 (one). A company characteristic variable which is significant for State 2 (two) is Log_turn . The predictive power of the remains almost the same with a score of 78.99% and the standard errors for TLiab_TA still remain relatively high. See Table VIII in the Appendix. The inclusion of activity and company characteristics has reduced the precision of the model for State 0 (one) and State 1 (one). See Table III in the Appendix.

MODEL 4

For this model, ten dummy variables were introduced for the industry, i.e. the industry dummy variable take the value of one if the observation falls in that industry, or it is otherwise zeroed. Due to multicollinearility[15], there is a requirement to drop one of the industry dummies. By selecting the Consumer Services, this leads to the other dummies to capture variation to the Consumer Services industry. It was found that the industry dummies are jointly significant for the model. The accuracy has slighted increased to 79.14%. However Table IX in the Appendix illustrates the coefficients of the industry dummies are almost zero for State 2 (two) and they have absolutely no effect at distinguishing State 2 (two) from State 0 (zero). Hence it can be concluded that for this particular sample, industry dummies are inefficient at improving the model. See Table C in the Appendix

MODEL 5 – PROPOSED MODEL

Finally extending previous models, we propose a model which incorporates state dependence. Knowing that industry dummies are not reliable for this sample, we include dummy lagged dependent variables to capture state dependence. We want to capture the state dependence across the three categories. Again to avoid multicollinearity, we only generate two dummy variables: Dep1 and Dep2. Dep1 takes the value of one if the company was in State 1 (one) in the previous year and zero otherwise. Dep2 takes the value of one if the latter was in State 2 (two) in the previous year and zero otherwise.

Table 5 shows that the variables which are significant for both states with reference to State 0 (zero) are: CFlow_TA, TLiab_TA and Ldep2. Also the variables Net_incom, Ldep1 are significant for State 1 (one) while the variables Debt_EBITDA and EBITSHARE are

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[15] Multicollinearity is an undesirable situation whereby two or more predictor variables are high correlated. In this case, multicollinearity arises if there is failure to omit one category.

Table 5: Multinomial Logistic Regression on Accounting-based, Market variables, Activity and Company characteristics and State Dependence

	State 1	State 2
Accounting-based ratios		
EBITDA_mar	1.11	1.28
	(0.12)	(0.27)
Profit_mar	0.92*	0.85
	(0.04)	(0.09)
WCap_TA	0.82	2.57
	(0.59)	(3.22)
CFlow_TA	0.02***	0.01**
	(0.02)	(0.02)
Net_incom	1.60*	1.29
	(0.44)	(0.93)
EBIT_growth	0.98	0.84
	(0.06)	(0.12)
CFlow_Sales	1.18	0.99
	(0.18)	(0.17)
Cash_ratio	1.11	0.52
	(0.08)	(0.29)
TLiab_TA	0.16***	22.16**
	(0.09)	(31.01)
Debt_EBITDA	1.01	0.88
	(0.07)	(0.07)
EBITSHARE	0.62	0.02***
	(0.37)	(0.02)
Market-driven variables		
Div_share	0.95	0.59*
	(0.08)	(0.17)
Div_yield	0.99	1.82**
	0.95	0.59*
Activity and Company Characteristics		
Log_TA_emp	1.10	0.95
	(0.12)	(0.27)
Log_assets	0.91	1.30
	(0.08)	(0.40)
Log_turn	0.99	0.78
	(0.07)	(0.12)
State Dependence		
Dep1	7.53***	1.08
	(3.31)	(1.31)
Dep2	6.20**	21.83***
	(5.32)	(24.36)
Constant	0.61	0.00**
	(0.64)	(0.01)

*** p<.10, ** p<.05, *** p<.01 and standard errors are in parentheses**

significant for State 2 (two). As we can observe, the standard errors of TLiab_TA has vastly improve. The model is able to correct classify 514 companies and it have reached an accuracy of 81.20%. Table V in the Appendix suggests that the incorporate of state dependence in our model has improved the accuracy for both State 1 (one) and State (2). We can see which variables have the highest or lowest odds ratio. Also we can compare the variables between the two states. For example, if we take the variable Log_turn, we can see that the odds for State 1 (one) are higher than State 2 (two). Hence if the company's size decreases, we can see the relative odds of falling in either a flow based or both a flow and stock based distress.

7.2. Evaluation of proposed model

Based on the results, we can say that the main factors that lead to both a situation of flow-based and a situation of flow-based and stock-based distress are: (i) a decrease in the cash flow in relation to total assets; (ii) and if the company was already experiencing a flow-based and stock-based distress. Cash flow in relation to total assets being a liquidity ratio shows us how liquidity is extremely important to avoid distress. If the company was already experiencing harsh financial distress, it is in a downward spiral and hence more prone to be experiencing the same distress in the following year. Even if the company manages to break that downward spiral, it is probable that the company will still suffers from a flow-based distress.

In addition, the statistically significant factors that specifically drive the company towards a flow-based (interest coverage) distress are: (i) a decrease in profit margin, (ii) if the company has suffered negative income in the previous two years; (iii) a decrease in the total liabilities and total assets; (iv) and if the company was experiencing a flow-based distress in the previous year. The decrease in profit margin supports the claims of many scholars and including Morris [55] who stipulated that a low profitability eventually leads to both an increase in gearing and impaired liquidity. Previous studies showed the significance of the negative change in net income in their studies. In this study, we demonstrate that a negative change in income in the preceding two periods drives the company towards a flow-based distress. If the net income was negative in the previous years, it is probable that in the current year, the company's interest coverage is low or even less than one. It is surprising to find that a decrease in total liabilities to total assets leads toward a flow-based distress. A possible explanation is that a decrease in this ratio is due to either a decrease in liabilities or an increase in total assets. Consistent with Christidis and Gregory (2010), companies tends to invest into illiquid assets and their liquidity ability declines. Hence they suffer from poor liquidity and this may trigger a flow-based distress. Lastly if the company was suffering from a flow-based distress in the previous year, it is probable that the company is still in the same state.

Furthermore we can observe the statistically significant factors that cause flow-based and stock-based distress. The factors are: (i) an increase in the liabilities in relation to total assets; (ii) a decrease in EBIT in relation to share capital, (iii) a decrease in dividend per share; (iv) and an increase in dividend yield. The first factor could be explained by either an increase in liabilities or a decrease in the assets; in either case, it eventually leads to a decrease in shareholders' funds. Secondly a decrease in the ratio of EBIT over share capital means that there has been an increase the share capital. This could signal there has been an issue of share capital throughout the year and hence a higher dependency on outside finance. We can see that both market variables are significant. A decrease in dividend per share may signal that the company's performance has fallen on hard times and this triggers distress. Lastly an increase in dividend yield may be considered to be evidence that either the stock price is under priced or most importantly the company's performance has declined and future dividends might not be high as previous ones. Furthermore in search of capital company can use a high dividend yield as a marketing tool to attract new investors.

The odds ratio of Ldep1 is higher than Ldep2 for State 1 (one). This means that if the company was in State 1 (one) the preceding year, the company is 7.53 more likely to remain in State 1 (one) relative to State 0 (zero) compared to fall in State 2 (two) that year. Furthermore for State 2 (two), the relative risk of being in State 2 (two) this year is much higher if the company was already in State 2 (two) the previous year. If we replace the dummy variable Ldep1 by a dummy dependent variable for State 0 (zero) and assign State 1 (one) as reference group, we can see that the company is 5.95 more likely to be in State 0 (zero) this year if it was already in State 0 (zero) the preceding year[16]. This clearly shows the state dependence across three groups. Hence we can conclude, a company's current year performance mostly depend on its previous years' performance.

7.3. Postestimation and IIA assumption testing

Some postestimation techniques were performed when analysing with Stata developed by Freese and Long [24]. Firstly the Likelihood ratio can be calculated for the indepndet variables. The likelihood ratios test is used to compare the fitness of two model: the null model compared with the alternative one. It uses the likelihood ratio which computes the number of times that the data is under one model rather than the alternative. The results can be found in Table X in the Appendix. The findings suggest that the variables CFlow_TA, Liab_TA, EBITSHARE, Dep1 and Dep2 are significant across the equations and thus, the other variables can be dropped.

Secondly it is plausible to further test whether it is possible to combine the two states of the dependent variable, i.e State 1 (one) and State 2 (two). The findings reveal that the independent variables jointly can differentiate between the two categories. See Table XI in the Appendix.

Thirdly it is vital to test for the IIA assumption for the three states. A Suest-based test of IIA assumption is derived from the Hausman specification test. This is useful for the cross model and intermodel hypothesis. Following the Suest-based tests, it can be concluded that the null hypothesis of independent alternatives cannot be rejected. Hence the results

[16] These results are available upon request.

indicate that three states of the model are independent and are in line with the assumption of the multinomial logisitic technique. See Table XII in the Appendix.

7.4. Comparing forecasting horizons and Validation

We further test the robustness of the model by forecasting the states two years in advance (two year lag). On a sample of 476 companies for the period 2002 to 2010, we compare the accuracy between a lag of on year and a lag of two years. The findings suggest that the accuracy for a one year lag 82.44% while for a two year lag, it is 80.73%. Consistent with Altman [4], we found a negative correlation between accuracy and number of years. See Table XIII in the Appendix.

We can further test the model by trying to forecast three states two years The proposed model was derived from 161 companies for the period 2002 to 2009. Using the same companies, the model can be validated by forecasting the state of those companies in 2010. The hold out sample consists of 151 companies, State 0 (zero), State 1 (one) and State 2 (two) with of 90, 41 and 5 companies respectively. The findings suggest that the proposed model has an accuracy of 69.54%. Table XIV in the Appendix shows that the precision for State 1 (one) is 46.34% and State 2 (two) is 40.00%. The misclassficiations of State 2 (two) can be explained by the relatively low number of State 2 (two) observations in our sample. If we increase the sample size, the accuracy will amplify.

8. CONCLUSION AND FUTURE RESEARCH PERSPECTIVES

A financial distress prediction with wider range of distress scenarios better depicts the reality faced by companies. The main nuisances with such models are that there is no unified definition of financial distress and set of predictive variables. In this paper, the three financial states of corporate health have been based on the flow based and stock-based insolvency classifications. The set of candidates predictive variables were chosen based on intuition, popularity and predictive power showed in previous researches. This study provided an unordered three states of corporate financial health on a panel sample of 161 companies for the period 2002 to 2009 combining accounting ratios, market variables, company and activity characteristics and state dependence with a multinomial logistic technique.

Consistent with previous studies, we have found that change in net income and total liabilities to total assets were significant at distinguishing between the various states. In addition, the findings suggest that EBIT to share, dividend per share and dividend yield are also significant. We have also showed how state dependence statistically adds predictive power to the model. However findings suggest that industry effects were not appropriate for this study. Furthermore through the Hausman specification test, we have demonstrated that the three states proposed conform to the IIA assumption. The internal validation and external validation shows that our proposed model has an accuracy of 81.20% and 69.54% respectively at forecasting the state of the companies in the following year. Lastly we have seen the accuracy of the proposed for one year and two years horizon.

However a limitation of the model as well as all prior models is that accounting numbers are affected by the accounting conventions used with regard to the stock valuation and depreciation. Also most firms are multi-product in nature, hence the profit margin and EBITDA margin are a weighted average of each product. Hence as that sales mix vary over times, so will the overall margin [55]. Moreover the companies across the eleven industries adopt different organisational structures and the predictive variables have different significant in each industry.

A perspective for further research is to incorporate qualitative factors such financial control, industry experience, management experience, planning, professional advisor staffing and corporate governance. Qualitative factors contribute largely to success but these data are costly to acquire. Also another perspective is derive a duration model to analyze the expected failure on these companies and conduct panel data analysis for random effects. Also one could analyse companies which were restructured, spot the changes in factors and see which factors have contributed towards this successful restructuring.

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10. APPENDIX

10.1. Explanations of candidates variables

Profitability

1. EBITDA Margin (EBITDA_mar)

$$EBITDA\,margin = \frac{EBITDA_t}{EBITDA_{t-1}} - 1\,. \quad for\ t = 2, 3, \ldots, T$$

It is a measure of the operating profitability of a company and the proportion of operating expenses on the revenue. It provides cleaner view since it excludes non-cash items such as depreciation and amortization.

2. Profit Margin (Profit_mar)

$$Profit\ Margin = \frac{Pretax\ Income}{Operating\ Income}.$$

It is an indicator of the ability of the company to control its costs and the pricing strategies of the company. It measures how much of every pound of sales is kept in earnings. It is widely used to compare companies in similar industries.

3. EBIT Growth (EBIT_growth)

$$EBIT\ Growth = \frac{Earnings\ before\ interest\ and\ tax_t}{Earnings\ before\ interest\ and\ tax_{t-1}} - 1 \quad for\ t = 2, 3, \ldots, T.$$

It is the percentage of gain in EBIT over time. It is an indicator to measure the company's success and the motivating force for stock appreciation. Moreover it determines the demands of investors in terms of dividends, for a low or constant EBIT growth, the shareholders will demand more in demands to compensate for this steady stock appreciation.

4. Change in Net Income (Net_incom)

$$Change\ in\ net\ income = \begin{cases} 1, & net\ income_{t-1} < 0 \\ & net\ income_{t-2} < 0 \\ 0, & otherwise \end{cases} \qquad for\ t = 3, 4, \ldots, T.$$

Net income is the amount remaining after all operating expenses, interest, taxes and preferred stock dividends have been met and deducted. When the change in income is negative, it is may be due to many causes such as decreasing sales, poor management of expenses or low customer satisfaction.

Liquidity

1. Working Capital to Total Assets (WCap_TA)

$$Working\ Capital\ to\ Total\ Assets = \frac{Working\ Capital}{Total\ Assets}.$$

It measures the ability of the company to meet its short term obligations. It is a ratio which shows the percentage of liquid assets in comparison to the total assets.

2. Cash Flow to Total Assets (CFlow_TA)

$$Cash\ Flow\ to\ Total\ Assets = \frac{Cash\ Flow\ from\ Operations}{Total\ Assets}.$$

It is an indicator of the cash generated by the company in relation to its size. It provides an insight of whether the company is able to fund capital expenditures out of operating cash flows.

3. Cash Flow to Sales (CFlow_Sales)

$$Cash\ flow\ to\ Sales = \frac{Cash\ Flow\ from\ Operations}{Net\ Sales\ or\ Revenues}.$$

It measures the cash generating ability of the company in relation to its sales. It may be regarded as an indicator for productivity and creditworthiness. For example, a high ratio means that the company is able to finance its production using the cash flow generated from its sales and vice versa.

4. Cash Ratio (Cash_ratio)

$$Cash\ Ratio = \frac{Cash\ and\ Short\ term\ investments}{Current\ Liabilities}.$$

It measures the aptitude of the company to readily repay its short-term debt using only its cash and short term investments. A strong ratio is useful for assessing a company liquidity position on deciding the amount of debt the creditors would be willing to lend.

Leverage

1. Total Liabilities to Total Assets (TLiab_TA)

$$Total\ Liabilties\ to\ Total\ Assets = \frac{Total\ Liabilties}{Total\ Assets}.$$

It measures the financial risk of the company by examining the proportion of assets that have been finance by debt. A strong ratio suggests that low borrowing capacity of the company and hence lowers its financial flexibility. In extreme cases, the creditors could start asking for repayment of debt in fear of potential future inability to repay.

2. Debt to EBITDA (Debt_EBITDA)

$$Debt\ to\ EBITDA = \frac{Long\ term\ Debt}{EBITDA}.$$

It measures the ability of the company to pay its debt using its earnings before interest, taxes, depreciation and amortization. It gives an insight of the approximate amount of time (years) that the company needs to pay off its debt assuming same level of earnings.

3. Earnings per Share Capital (EBITSHARE)

$$EBITSHARE = \frac{EBIT}{Share\ Capital}.$$

This ratio quantifies the ability of the company cash generating ability relative to the capital it has invested in the company. When the ratio is greater than the cost of capital, the company is said to be creating value and when it is less, the company is destroying value.

Market-driven Variables

1. Dividend per Share or DPS (Div_share)

$$DPS = \frac{Dividends\ paid}{Number\ of\ shares\ in\ issue}.$$

The ratio is the amount of dividend paid off to for each share owned by its shareholders over an entire year (including interim dividends). DPS is the simplest way to communicate financial well-being and shareholder value. A regular DPS payout would indicate future prospects and performance.

2. Dividend Yield (Div_yield)

$$Dividend\ Yield = \frac{Most\ Recent\ full\ year\ dividend}{Current\ share\ price}.$$

This ratio shows how much the company pays out in terms of dividends relative to its current share price. It can be regarded at the return on investment for a stock. Investors usually look at the dividend yield to see which companies are worth investing in. Two companies may pay out the same dividends but this does not mean the same dividend yield.

Activity and Company characteristics

1. Logarithmised Total Assets to Employee (Log_TA_emp)

$$Log\ Total\ Assets\ to\ Employee = log\left(\frac{Total\ Assets}{Number\ of\ Assets}\right).$$

It measures the productivity of the employees of the company. It can be further used to examine the fluctuations within the same industry.

2. Logarithmised Assets (Log_assets)

$$Log\ Assets = \log(Total\ Assets).$$

The size of a company can be determined by the amount of assets held by that company.

3. Logarithmised Turnover (Log_turn)

$$Log\ Turnover = \log(Net\ Sales\ or\ Revenue)\ .$$

The size of the company can also be determined by the amount of the turnover made throughout the year.

10.2. Models Accuracy

Table I: Model 1 Accuracy

		Prediction		
		0	1	2
Actual	0	0.9189	0.0713	0.0098
	1	0.3979	0.5707	0.0314
	2	0.1714	0.2000	0.6286

Table II: Model 2 Accuracy

		Prediction		
		0	1	2
Actual	0	0.9214	0.0713	0.0074
	1	0.4031	0.5602	0.0366
	2	0.1714	0.2000	0.6286

Table III: Model 3 Accuracy

		Prediction		
		0	1	2
Actual	0	0.9140	0.0762	0.0098
	1	0.4031	0.5550	0.0419
	2	0.2000	0.1714	0.6286

Table IV: Model 4 Accuracy

		Prediction		
		0	1	2
Actual	0	0.9017	0.0835	0.0147
	1	0.3979	0.5759	0.0262
	2	0.1714	0.1429	0.6857

Table V: Model 5 Accuracy

		Prediction		
		0	1	2
Actual	0	0.8919	0.0983	0.0098
	1	0.3037	0.6702	0.0262
	2	0.1714	0.1714	0.6571

Table VI: Industry Classifications

Industry	State 1 (one)	State 2 (two)	State 3 (0)	Total
1	26	37	1	168
2	41	31	6	202
3	59	21	3	174
4	69	19	8	192
5	44	12	2	105
6	24	2	0	96
7	54	21	3	195
8	7	5	0	24
9	20	20	6	174
10	63	23	6	201
Total	407	191	35	1531

10.3. Results from Multinomial Logistic Regression

Table VII: Multinomial Logistic Regression on Accounting and Market variables

	State 1	State 2
Accounting-based ratios		
EBITDA_mar	1.06	1.29
	(0.10)	(0.25)
Profit_mar	0.89***	0.83*
	(0.04)	(0.08)
WCap_TA	0.78	1.00
	(0.63)	(1.19)
CFlow_TA	0.01***	0.00***
	(0.01)	(0.00)
Net_incom	1.40	0.98
	(0.38)	(0.60)
EBIT_growth	1.02	0.84
	(0.06)	(0.11)
CFlow_Sales	1.03	0.86
	(0.16)	(0.16)
Cash_ratio	1.22***	0.77
	(0.09)	(0.38)
TLiab_TA	0.20***	183.60***
	(0.12)	(243.54)
Debt_EBITDA	0.86*	0.90
	(0.07)	(0.10)
EBITSHARE	0.16***	0.03***
	(0.08)	(0.02)
Market-driven variables		
Div_share	0.95	0.67*
	(0.09)	(0.14)
Div_yield	0.94	1.61*
	(0.14)	(0.42)
Constant	1.03	0.00***
	(0.44)	(0.00)

*** p<.10, ** p<.05, *** p<.01 and standard errors are in parentheses**

Table VII: Multinomial Logistic Regression on Accounting-based, Market variables, Activity and Company Characteristics

	State 1	State 2
Accounting-based ratios		
EBITDA_mar	1.05	1.32
	(0.10)	(0.26)
Profit_mar	0.90***	0.80**
	(0.04)	(0.09)
WCap_TA	1.04	3.19
	(0.97)	(4.01)
CFlow_TA	0.01***	0.01***
	(0.02)	(0.01)
Net_incom	1.48	0.96
	(0.42)	(0.59)
EBIT_growth	1.01	0.84
	(0.06)	(0.11)
CFlow_Sales	1.11	0.90
	(0.18)	(0.17)
Cash_ratio	1.14	0.51
	(0.09)	(0.34)
TLiab_TA	0.27*	267.38***
	(0.18)	(386.13)
Debt_EBITDA	0.87*	0.89
	(0.07)	(0.10)
EBITSHARE	0.16***	0.03***
	(0.08)	(0.02)
Market-driven variables		
Div_share	0.94	0.68*
	(0.08)	(0.15)
Div_yield	0.97	1.65*
	(0.14)	(0.45)
Activity and Company Characteristics		
Log_TA_emp	1.05	0.87
	(0.13)	(0.25)
Log_assets	0.91	1.15
	(0.10)	(0.34)
Log_turn	0.90	0.73**
	(0.07)	(0.11)
Constant	4.24	0.01*
	(5.46)	(0.03)

*** p<.10, ** p<.05, *** p<.01 and standard errors are in parentheses**

Table IX: Multinomial Logistic Regression on Accounting-based, Market variables, Activity and Company Characteristics and industry dummies

	State 1	State 2
Accounting-based ratios		
EBITDA_mar	1.04	1.39
	(0.10)	(0.28)
Profit_mar	0.89***	0.71**
	(0.04)	(0.11)
WCap_TA	1.08	5.21
	(0.99)	(7.58)
CFlow_TA	0.01***	0.01**
	(0.01)	(0.02)
Net_incom	1.52	0.56
	(0.43)	(0.42)
EBIT_growth	1.01	0.80
	(0.06)	(0.12)
CFlow_Sales	1.10	0.82
	(0.19)	(0.18)
Cash_ratio	1.11	0.53
	(0.08)	(0.42)
TLiab_TA	0.23*	775.55***
	(0.18)	(1303.03)
Debt_EBITDA	0.89	0.87
	(0.07)	(0.11)
EBITSHARE	0.19***	0.01***
	(0.10)	(0.01)
Market-driven variables		
Div_share	0.99	0.65**
	(0.09)	(0.14)
Div_yield	0.90	1.65
	(0.13)	(0.51)
Activity and Company Characteristics		
Log_TA_emp	1.00	0.70
	(0.12)	(0.21)
Log_assets	0.90	0.98
	(0.10)	(0.27)
Log_turn	0.90	0.77
	(0.07)	(0.13)

Industry dummies		
Ind1	31.58***	1.26e+07***
	(22.83)	(2.76e+07)
Ind2	20.16***	2.43e+07***
	(15.48)	(5.67e+07)
Ind3	19.04***	4.84e+07***
	(15.48)	(1.38e+08)
Ind4	9.30***	8.72e+07***
	(7.33)	(1.86e+08)
Ind5	28.88***	2.82e+08***
	(21.76)	(6.40e+08)
Ind7	31.18***	2.42e+07***
	(25.88)	(6.47e+07)
Ind8	69.88***	0.00***
	(69.75)	(0.00)
Ind9	37.86***	3.37e+08***
	(33.77)	(8.27e+08)
Ind10	23.03***	3.36e+07***
	(16.98)	(7.49e+07)
Constant	0.28	0.00
	(0.42)	(.)

*** p<.10, ** p<.05, *** p<.01 and standard errors are in parentheses. The industry groups represented by dummy variables are: Ind1 - Oil; Ind2 - Mining; Ind3 - Industrials; Ind4 - Support Services; Ind5 - Consumer Goods; Ind7 - Consumer Services, Ind8 –Telecommunication; Ind9 - Financials; and Ind10 - Technology.**

10.4. Postestimation and IIA Testing

Table X: Likelihood ratio tests for independent variables (N=633)

	chi2	df	p-value
EBITDA_mar	2.012	2	0.366
Profit_mar	5.930	2	0.052
WCap_TA	0.513	2	0.774
CFlow_TA	14.166	2	0.001
Net_incom	2.694	2	0.260
EBIT_growth	1.502	2	0.472
CFlow_Sales	2.130	2	0.345
Cash_ratio	4.012	2	0.134
Liab_TA	17.797	2	0.000
Debt_EBITDA	0.722	2	0.697
EBITSHARE	29.542	2	0.000
Div_share	3.530	2	0.171
Div_yield	3.230	2	0.199
Log_TA_emp	0.839	2	0.657
Log_assets	2.761	2	0.251
Log_turn	2.298	2	0.317
Dep1	39.208	2	0.000
Dep2	9.116	2	0.010

Table XI: Suest-based Hausman tests of IIA Assumption (N=633)

Omitted	chi2	df	P>chi2	evidence
State 1	21.244	19	0.323	for Ho
State 2	14.514	19	0.753	for Ho
State 0	14.512	19	0.753	for Ho

Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.

chi2 – chi square test; df – degrees of freedom; and P - probability

Table VIIIII: Likelihood ratio tests for combining alternatives (N=633)

Alternatives tested	chi2	df	P>chi2
State 1 – State 2	121.638	18	0.000
State 1 – State 0	301.873	18	0.000
State 2 – State 0	177.652	18	0.000

Ho: All coefficients except intercepts associated with a given pair of alternatives are 0 (i.e., alternatives can be collapsed).
chi2 – chi square test; df – degrees of freedom; and P - probability

10.5. Comparing forecasting horizons and Validation – 1 year and 2 years

Table IXIII: Comparing forecasting accuracy across horizons – 1 & 2 years

		Prediction		
		0	**1**	**2**
Actual	**0**	0.9006 [0.9006]	0.3178 [0.3333]	0.1538 [0.2692]
	1	0.0929 [0.0897]	0.6589 [0.6434]	0.1154 [0.2308]
	2	0.0064 [0.0096]	0.0233 [0.0233]	0.7308 [0.5000]

Table XIV: Validation year 2010

		Prediction		
		0	1	2
Actual	0	0.9333	0.0667	0.0000
	1	0.3415	0.4634	0.1951
	2	0.2000	0.4000	0.4000