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Polytomous Response Financial Distress Models: The Role of Accounting, Market and Macroeconomic Variables

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ABSTRACT

We apply polytomous response logit models to investigate financial distress and bankruptcy across three states for UK listed companies over a period exceeding 30 years and utilising around 20,000 company year observations. Results suggest combining accounting, market and macroeconomic variables enhances the performance, accuracy and timeliness of models of corporate credit risk. Models produced contribute to the prediction and early warning systems literature by investigating the distress/failure process with enhanced granularity. We employ marginal effects to assess individual covariates' impact on the probability of falling into each state. The new insights on individual risk factors are confirmed by analysis of vectors of changes in predicted probabilities of falling into a state of financial distress and corporate failure following changes in the level of individual covariates. Resulting models provide a better understanding of different risk factors and can help practitioners detect financial distress and failure in a timely fashion.

Keywords:
JEL: Bankruptcy Prediction; Financial Distress; Listed Companies

1. Introduction.

Models for the prediction of corporate financial distress/bankruptcy have attracted considerable interest amongst academics as well as practitioners over the last four decades. Lenders and other investors value timely information regarding the probability of corporate default. In order to develop effective Internal Rating Systems, banks are required to produce models based upon default probabilities tailored to the features of different firm types (e.g., quoted firms, private firms, Small and Medium firms), which take account of both the state of the macro-economy and data availability. Furthermore, as discussed by Jones and Hensher (2004), financial distress prediction models are used for many purposes including: "monitoring of the solvency of financial and other institutions by regulators, assessment of loan security, going-concern evaluations by auditors, the measurement of portfolio risk, and the pricing of bonds, credit derivatives, and other securities exposed to credit risk." (p. 1011). However, the financial crisis of 2007-2008 demonstrated the flaws of risk management standards, highlighting the need for richer and more accurate prediction models. Specifically, there is a need to develop more dynamic risk scores where default probabilities adjust to the dynamic macro-economic setting.

Previous studies typically offer models that focus on the prediction accuracy of bankrupt/financially distressed companies versus financially sound firms and incorporate a binary outcome as the independent variable[1]. However, in practice, this binary representation fails to take account of the complexities inherent in the nature of financial distress and bankruptcy and logit coefficients do not provide a clear indication of the contribution of the individual covariates to default risk.

The novelty of this paper, is that we build our current research work on the proposition that it is more realistic and of more value to users of failure prediction models to recognise firms as falling into more than two categories (e.g. financially sound and bankrupt), which, in addition, is formally tested in this study. This approach is shown to be useful to understand the contribution of individual risk factors to each of the states that constitute corporate failure. One of the crucial contributions of our study is that it shows that the effects of the variables that enhance the accuracy of the models are not the same for financial distress and failure. Therefore, according to the objectives of the academician or practitioner, the models can be calibrated to increase in prediction accuracy and can thus act as a superior early warning system relative to models that are composed of only two states (healthy and financially distressed firms). At the very least, three distinct possible financial states can be identified: 1) firms in a financially sound position; 2) firms in financial distress and thus at risk of failing, but which remain viable entities at the present time; and 3) firms which have failed. While the

[1] Altman et al. (2010) state that, from a statistical standpoint, "logit regression seems to fit well with the characteristics of the default prediction problem, where the dependant variable is binary (default/non-default) and where the groups are discrete, non-overlapping and identifiable. The logit model yields a score between 0 and 1, which conveniently gives the client's probability of default. Lastly, the estimated coefficients can be interpreted separately as the importance or significance of each of the independent variables in the explanation of the estimated probability of default." (p. 8)

use of the multinomial logit model allows for 3 (or more) states to be considered simultaneously, to date such an approach has not been extensively used when examining failure prediction[2].

Leclere (1999) argues that a potential reason for the underutilisation of these types of models "is that the interpretation of the model coefficients in a bivariate probit or logistic regression already differs substantially from OLS regression. When the models move from a dichotomous to an n-chotomous dependent variable, the interpretation becomes more complex." (p714) Neither the magnitude nor the sign of the parameters possess a natural meaning that can be directly interpreted. While a few studies have employed multinomial regression logit to examine financial distress, they focus almost exclusively on the predictive accuracy of their models relative to other research works. Occasionally, multinomial coefficient estimates are also presented to infer the nature of the relationship of individual variables with respect to the probability of falling into a certain outcome. In other words, through the signs of the multinomial function coefficients, previous research tries to ascertain whether this relationship is positive or negative. However, the signs of multinomial function coefficients from logit models can be misleading, as shown by the unexpected and counterintuitive signs that can be found in previous empirical multinomial research (e.g., Lau, 1987).

Furthermore, there are no studies to date that deal with the issue of the economic magnitudes of individual effects on the (predicted) probabilities of falling into each of the specified outcomes. For example, Lau (1987) is one of the first (and very few) studies that applied the multinomial logit methodology to the field of predicting financial distress by utilising five possible states "to approximate the continuum of corporate financial health." (p. 127). The multinomial function coefficients obtained are interpreted according to their respective signs. Even though the model yielded a high predictive accuracy, its coefficients' signs showed a number of inconsistencies. In order to account for and provide a solution to this coefficient-inconsistency problem, we compute average marginal effects[3] and show that they are a substantially more reliable and useful measure to investigate the effects of individual covariates in a multinomial logit model. In this way, we are able to overcome the interpretation issues identified by Leclere (1999), addressing thus a critical gap in the literature. Similarly, Johnsen and Melicher (1994) develop a multinomial logit model for predicting corporate bankruptcy and financial distress. They use a 3-state model and test the value added by multinomial logit regression methodologies. Their study reports multinomial function coefficients and, through classification accuracy tests, finds that the multinomial model significantly reduces

[2] There have been a number of studies that use polytomous response models in areas outside the field of failure prediction: In relation to human capital theory, Boskin (1974) empirically tests hypotheses about the variables influencing occupational choice; Lawrence and Arshadi (1995) analyse problem loan resolution choices using a multinomial logit model in the field of banking; Leclere (1999) develops and explains numerous ways in which coefficients in polytomous response models can be interpreted and applies them to accounting models; McFadden and Train (2000) provide evidence suggesting that mixed multinomial logit models provide a computationally practical method for economic discrete choice that stems from utility maximisation; Ward (1994) develops an ordinal four-state polytomous logit model to test the extent to which the naïve operating cash flow measure of Beaver can make accurate predictions; and more recently, Jones and Hensher (2004), tests the incremental ability of a three state mixed logit model to predict firm financial distress.

[3] Estimated as the partial derivative of the probability of falling into the financial distress/failure category with respect to a specific individual covariate.

misclassification errors. However, the magnitudes of the effects of individual variables are not investigated.

In this study, we consider corporate default as a dynamic process by including three possible states (financially sound; firms in financial distress; and failed firms) in a generalised or polytomous logit regression model. Moreover, our study provides graphic representations of the changes produced in the vectors of predicted probabilities by a change in the level of a specific covariate (holding other variables constant at their means), a methodology employed, for the first time, in the context of the financial distress default prediction literature. This allows us to further analyse the individual effects of the covariates included in the models (which can be further classified into accounting, market, and macroeconomic covariates), providing additional insights into their patterns of behaviour and most importantly, into the differences in their individual effects with respect to each of the outcome categories[4].

Prior polytomous response financial distress/bankruptcy prediction models include only accounting measures as independent variables. However, we have strong grounds to believe that such models would benefit from utilising the information contained in market (Das et al, 2009; Charitou et al., 2013) and macroeconomic (Bruche and González-Aguado, 2010; Tang and Yan, 2010) variables. The former provide information on how markets perceive the health of a firm, while the latter are relevant for the business environment in which firms are operating. As predicted, we demonstrate that the combination of information contained in market variables, accounting ratios, and macroeconomic indicators, is capable of enhancing the overall performance and prediction accuracy of financial distress models.

Finally, unlike previous studies, we adjust for outlying observations in the accounting and market variables by transforming the distribution of our ratios using the hyperbolic tangent (TANH) function. This addresses the problems caused by outlying values having an atypical effect on the fitted maximum likelihood linear regressors (and on the magnitude of the residuals), while allowing us, at the same time, to retain data from observations that would otherwise be eliminated from the sample and that could potentially add useful information to our models.

This paper, therefore, makes three major contributions to the financial distress/bankruptcy prediction literature. First, we build multinomial logit models to examine financial distress and bankruptcy across three states in a large data sample for the UK, which provides a fertile ground for this area of research given its dynamic corporate sector. We compute average marginal effects and graph the changes in the vectors of predicted probabilities following changes in individual covariates (from their minimum to their maximum values) in order to provide new insights on the differences in the effects of individual effects of covariates on the probability of falling into the financial distress and corporate failure categories. Second, we use a range of accounting, market and macroeconomic

[4] Additionally, the changes in the vectors of predicted probabilities following a change in the level of an individual covariate provide supplementary information and support to the interpretation of the average marginal effects.

variables as possible predictors of bankruptcy and financial distress, providing a more complete analysis of the factors and interactions that affect firm failure and financial distress. This results in prediction models with increased performance and prediction accuracy that can be, in addition, calibrated to suit academicians' and practitioners' requirements for the construction of early warning systems to detect financial distress and failure in a timely manner. Third, we use a robust and reliable methodology to address a number of shortcomings in previous research in terms of definition of firm states, adjustment for bias in our models, sample selection and the way in which outliers are taken into account. The rest of the paper proceeds as follows: the next section sets out the outcome definitions; this is followed by a discussion of the method used in this study. The independent variables are explained in the fourth section, together with the hypotheses to be tested. Results are then presented and discussed and the final section provides a conclusion.

2. Outcome Definition & Data.

A specific definition is required for each of the three potential outcomes: Non-financial distress/failure (NFD), Financial distress (DIS), and Corporate failure (FAI), which can be appropriately regarded as the outcome of a process. Our study presents ex-ante models for predicting financial distress and failure. Therefore, it is necessary to employ compelling criteria that are capable of differentiating the potential outcomes, as required by the polytomous response logit methodology.

Previous multinomial financial distress prediction models employ juridical definitions of default that are not exempt of shortcomings. For example, firm bankruptcy can be a drawn-out process and the legal default date and the date of the 'economic' or the 'real' failure episode may be very different. As shown in Hernandez Tinoco and Wilson (2013), substantial lags are evident (as much as 3 years, with the mean period being 1.17 years) from the start of financial distress (the event which triggered default) to the legal date of bankruptcy. In line with these findings, Theodossiou (1993) reports for US firms that accounts are not produced for about two years before the legal event of bankruptcy (filing). Furthermore, it is also feasible that a financially distressed firm does not change its formal status to bankrupt following the 'economic' or 'real' event of default. (Balcaen and Ooghe, 2004). Referring to the classic binary default prediction models, Ooghe et al. (1995) and Charitou et al. (2004) argue that the legal definition of failure is commonly employed because, on the one hand, it is an objective means by which to divide the sample into two distinct populations, and on the other, it allows the moment of failure to be objectively dated. In order to create a well-defined classification method that yields three financial states clearly separated from each other, we follow Barnes (1987), Barnes (1990) and Pindado et al. (2008) and present a finance-based firm distress definition that is dependent upon the level of a firm's EBITDA relative to its financial expenses and the changes in the firm's market value through time. Additionally, the present study follows Christidis and Gregory (2010) and offers a proxy for corporate failure whose observation date reflects the economic or real event of failure: a technical definition of corporate failure based on the London Share Price Database (LSPD) 2012.

The states of financial distress and corporate failure are created as two distinct outcomes for analysis. First, in regard to the definition of financial distress (DIS), the capacity of a corporation to pay back its financial commitments (Asquith et al., 1994) plays a special role. The definition of financial distress follows Pindado et al. (2008) and incorporates two conditions which must be met for a firm-year observation to be classified as such: thus, a firm is allocated to the financially distressed[5] group whenever i) its financial expenses are greater than its EBITDA for two successive years and; ii) its market value decreases for two successive years[6].

A firm is classified as failed if any of the following holds: its status is suspended; in liquidation or voluntary liquidation; its quotation has been suspended for more than three years; the firm is being held by a receiver (in receivership), in administration or in administrative receivership; or when there has been a cancellation or suspension of the firm. Finally, non-financial distress relates to those firms that did not enter either the financial distress state or the corporate failure category.

The panel of data employed in this study consists of 23,218 annual firm observations of industrial listed companies in the United Kingdom. Information regarding corporate failure was taken from the 2012 LSPD, accounting data was obtained from Thomson Reuters Worldscope and Thomson One, and market variables were taken from the Bank of England, Datastream and the LSPD 2012. In order to arrive at the final database, a thorough merge of the information was performed based on individual identifiers (e.g., ISIN, SEDOL, etc.) of companies listed in the United Kingdom. Moreover, whenever any inconsistencies between companies and/or identifiers were detected, the firms in question were individually verified and the data manually treated to ensure the highest degree of accuracy and reliability of our final dataset. In line with prior research (Bharath and Shumway, 2008), financial companies were excluded from our main sample (SIC codes 6021, 6022, 6029, 6035, 6036). This resulted in a database that consists of industrial public listed companies that covers, to the best of our knowledge, the largest period employed in the area of risk modelling and credit scoring in the UK. The period investigated extends over more than 30 years of data: from 1980 to 2011. There are 21,964 firm-years classified as non-financially distressed/failed companies, 869 firm-years identified as financially distressed, and 385 firms classified as failed. As Table 1 shows, the percentage of non-financially distressed/failed companies is 94.6, while that of financially distressed firm-years and failed companies is equal to 3.74 and 1.66 respectively.

INSERT TABLE 1 ABOUT HERE

[5] A firm is deemed to be financially distressed in the year immediately following both criteria being met.
[6] See Hernandez Tinoco and Wilson (2013) for a detailed explanation of the reasoning behind the use of these two conditions.

Additionally, prior studies utilising the multinomial logit methodology to examine financial distress suffer from other shortcomings that are addressed in the current study. For example, Balcaen and Ooghe (2006), referring to the classic statistical models of failure prediction, argue that, "…if a classic statistical failure prediction model is eventually to be used in a predictive context, the estimation samples of failing and non-failing firms should be representative of the whole population of firms (Ooghe and Joos, 1990). Nevertheless, in the great majority of the classic failure prediction models, non-random samples of firms with available annual accounts are used." (p. 75).

It has been documented that if the estimation sample is not random, the function estimates as well as the predicted outcome probabilities are biased, which leads to an alteration of the overall classification accuracy (Manski and Lerman, 1977; Zmijewski, 1984). Indeed, non-random samples can give rise to biases usually stemming from failing companies being over-sampled (Zmijewski, 1984; and Platt and Platt, 2002), from matching the number of financially sound and failed firms (Ohlson, 1980; Scott 1981; Platt and Platt, 2002), or from employing a 'complete data' sample selection criterion (Declerc et al., 1992), resulting in a misleading classification accuracy that cannot be generalised (Piesse and Wood, 1992). By contrast, the present study employs a sample for the estimation of the model that is designed to reflect the distribution of the whole population of United Kingdom public companies.

This study provides a novel and flexible methodology to measure the classification accuracy of a three-state financial distress logit model using an unbalanced panel that is intended to approximate the real proportions of financially distressed/failed quoted companies in the United Kingdom. The final model in this study is tested using the entire database with the original proportions of outcomes, and a novel and flexible approach for the construction of biased-adjusted classification tables is presented.

Finally, in order to take into account potential correlation problems among variables included in all the models that could cause multicollinearity issues (resulting in imprecise coefficient estimates and artificially large standard errors), correlation matrices and direct multicollinearity diagnostic tests[7] were computed. These (unreported) results suggest that multicollinearity is not a problem in this study[8].

3. Methods: Polytomous Response Logit Model Specifications.

Given the three-state classification, the statistical analysis of the panel of data requires a generalisation of a binary logistic regression model in order to include more than two outcomes. A multinomial logistic methodology is appropriate for the analysis.[9] This type of model can be referred

[7] Tolerance value and its reciprocal, variance inflation tests are computed as $1 - R_k^2$ and $1/(1 - R_k^2)$ respectively, where R_k^2 is the determination coefficient for regression of the ith regressor on all the other regressors. The VIF values of all the independent variables in the study are below 5, suggesting that multicollinearity is not an issue in our models.

[8] Results are available upon request.

[9] For details of the development and specification of the underlying model, see the references cited in this section.

to as a multinomial logit model because the probability distribution for the response variable is assumed to be a multinomial distribution (Agresti, 1990; Hosmer and Lemeshow, 2000; Long and Freese, 2003, Allison, 2012). A problem with the results obtained from multinomial logit models is that neither the magnitude nor the sign of the parameters of the coefficients possess a natural meaning that can be directly interpreted (Hosmer and Lemeshow, 2000). Nevertheless, the relevant estimations can be obtained using appropriate transformations of the coefficients (Bartus, 2005; Long and Freese, 2006; Cameron and Trivedi, 2010; Williams, 2012). Therefore, marginal effects are computed for each individual regressor. The marginal impact can be defined as the partial derivative of the event probability with respect to the relevant predictor. Marginal effects are thus a more appropriate measure to assess the effect of the explanatory variable on the response variable for discrete response variable models, such as the multinomial logit model.

We test a three-state financial distress/failure model based on a polytomous response logit regression model, where the Response possible outcomes are: NFD or Non-financially distressed companies, DIS or Financially distressed companies, and FAI or Failed firms. In other words, a firm-year observation can fall into one of the following categories: Non-financial distress (Response = 1), Financial distress (Response = 2) and Corporate failure (Response = 3). Thus, the multinomial function coefficients reflect the effects of a specific variable on the probability of a firm-year observation falling into one of the three outcomes conditional upon a base outcome.

To test empirically the formal assumptions, the multinomial function coefficients for the three possible non-redundant combinations of outcomes are estimated: Non-financial distress versus Financial distress, Corporate Failure versus Financial distress, and Corporate Failure versus Non-financial distress. To obtain the coefficient estimates, as well as average marginal effects (AMEs) for the first two pairs of outcomes, the category Financial distress is selected as the base outcome, as this category can be considered as a transition point between two extremes in a process. In order to obtain the coefficient estimates (as well as AMEs) for the third pair of categories, FAI versus NFD, which further tests the extent to which the model variables discriminate between two potential outcomes, a second multinomial logit function is fitted specifying the category NFD as the base outcome. It is expected that, among these possible combinations, the model will produce better performing estimates for the prediction of pairs of outcomes that involve extreme or opposite categories. In other words, more reliable coefficient estimates (involving higher statistical significance and correct expected signs), should be expected for the pairs DIS versus NFD and FAI versus NFD than for the pair DIS versus FAI. The reason is that, concerning the latter pair of categories (where the outcomes are closer or more similar), DIS can be considered as a stage in a process that involves a deterioration of the characteristics of a firm (and its macroeconomic environment) that can ultimately lead to the most extreme outcome of the financial distress-failure process: FAI. Three sets of coefficient estimates are thus obtained for each model for the estimates using information one year before the observation of the event of interest (financial distress and corporate failure) (t-1), as well as two years before the relevant event (t-2).

Marginal effects are presented as an appropriate means for interpreting the effect of each variable on the response variable (for the discrete dependent variable model) and compared with the coefficient estimates. Additionally, standard errors (obtained employing the Delta-method), significance statistics, and 95 per cent confidence intervals are reported. In this manner, a comparison between ex-ante propositions/expectations, coefficient estimates, and AMEs is performed in order to provide evidence supporting the adequacy of marginal effects, while providing new insights on the individual effects of the regressors. Further, the study presents biased-adjusted classification accuracy tables for all the models.

4. Independent Variable Specifications.

The selection of the variables retained in the final multinomial logit models is based on prior studies, theory and empirical evaluations. Furthermore, scrupulous cleaning and testing of the data was undertaken and an original method to deal with outliers was tested for the first time in financial distress models. Extensive testing was undertaken and univariate and multivariate methodologies were applied to obtain the final choice of regressors[10]. This section explains the role of each variable in the models and discusses their relevance in the polytomous response logit regression models. We estimate the probability of financial distress/failure in the year preceding the relevant event (t-1) as well as two years in advance (t-2). Thus, for the t-1 models, the accounting ratios, market variables and macroeconomic indicators discussed below are based on employing their values in the year preceding the event date. The same procedure is employed to estimate coefficients and average marginal effects for the period t-2. For consistency and in order to provide a satisfactory solution to the problem of potential outliers in our sample without losing observations, all of the variables[11] were transformed employing the tangent hyperbolic (TANH) function for the following reasons: first, to provide a solution to the problem of outliers that could have an atypical effect on the fitted maximum likelihood linear regressors and on the magnitude of the residuals produced by the binary logistic regression; and second, because contrary to applying trimming and/or winsorizing to our sample, the TANH transformation allows us to retain useful data points identified as outliers by transforming the data distribution instead of arbitrarily setting all outliers to a specific percentile of the data sample. By following this methodology, data corresponding to outliers could be retained in our training set, as it

[10] In addition, the model was built and tested, following a 70-30% "estimation-holdout sample", in order to verify its robustness against different samples and time horizons.
[11] With the following exceptions: the two macroeconomic variables (for which the problem of outliers is not relevant), and the market variables PRICE and SIZE (which are generated, in line with previous research, by applying a logarithmic transformation).

can “carry some useful information on rare data points.”[12] The real line of the variables can be mapped onto [-1, 1] following the TANH transformation.

4.1. Accounting Ratios.

Four accounting variables were retained in the final models: Total Funds from Operations to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), and Interest Coverage (COVERAGE). The first ratio, TFOTL, reflects the capability of a firm to repay its financial commitments from its operations. Therefore, a firm with a higher value of TFOTL is less likely to be in a state of financial distress/failure. The second ratio, TLTA, is generally employed to estimate the financial leverage of a firm by computing the ratio of the assets financed through short and long-term debt. The rationale for including this ratio is as follows: the lower the leverage, the lower is a firm’s financial risk and, therefore, the lower its probability of financial distress/failure. The third variable, NOCREDINT[13], can be defined as “an estimate of the length of time that a company could finance the expenses of its business, at its current level of activity, by drawing on its own liquid resources and on the assumption that it made no further sales” (Graham 2000, p. 86). The ratio is generally employed to evaluate a firm’s liquidity position. Higher, positive values of NOCREDINT signal lower financial distress/failure probability. The last accounting ratio, COVERAGE[14], measures the capability of a firm to meet interest payments on its outstanding financial obligations. An increasing value of this ratio reflects an enhanced capacity of a company to make interest payments, which should result in a decreased probability of financial distress/failure.

4.2 Market Variables.

Four market variables were retained to assess whether they contain additional information regarding the likelihood of financial distress and corporate failure that can increase the goodness-of-fit and performance (discriminating and predicting ability) of accounting only models[15]: the log of the firm’s equity price (PRICE), abnormal returns (ABNRET), firms’ scaled market capitalization (SIZE), and the ratio Market Capitalization to Total Debt (MCTD). The first market variable is

[12] Kordos (2008), in M. Köppen et al (Eds.), p. 455. This methodology, the TANH function is frequently employed in Neural Network architecture with the same purpose as described above.

[13] The NOCREDINT accounting ratio was generated as follows: (Quick assets – Current liabilities) / (Daily operating expenses). Quick Assets represent the assets that can be quickly and easily converted into cash or are already in cash form. The variable Quick assets is estimated by subtracting Inventories to Current Assets. Daily operating expenses are calculated by subtracting Depreciation to the difference between Sales and Earnings Before Interest and Taxes (EBIT) and dividing the result by 365 days (Sales – EBIT – Depreciation) / 365.

[14] The Interest Coverage ratio was generated by dividing the variable Earnings before interest, taxes and depreciation (EBITDA) by the variable Interest charges or Interest expense on debt, which reflects the service charge for the use of capital before the reduction for interest capitalised.

[15] A positive finding would suggest that market variables (which already incorporate information based on financial ratios) act as complements to accounting information. In addition, they are potentially very useful to enhance the timeliness of models relying exclusively on annual accounts.

PRICE, which was estimated following Campbell et al. (2008), as the log price per share of the firm. Market prices are employed as proxies for investor's forecasts of future cash flows and earnings. Therefore, to the extent that the financial stance affects a firm's earnings, there will be a negative relation between price levels/movements and the probability of distress/failure. The next market variable employed is ABNRET[16], which is estimated as the lagged cumulative abnormal return of individual firms. In line with the findings of previous empirical studies[17], it is assumed that a low level of a firm's abnormal returns relative to those of the FTSE All Share Index will result in a higher probability of falling into the financial distress/failure category. Firm market capitalisation relative to that of the FTSE All Share Index, is the next market variable included in our models (SIZE)[18]. This is included to capture the magnitude of a discount in a firm's market value of equity produced by a negative assessment of investors regarding the financial state of the firm relative to the market as a whole. Thus, it is expected that a large or increasing level of this variable will lead to a decrease in the likelihood of a firm falling into the financial distress/failure category. The last market variable is the ratio MCTD. It is expected that a high level of leverage of the company relative to its market capitalization should result in a high probability of financial distress/failure.

4.2. Macroeconomic Indicators.

Two macroeconomic indicators were retained in the models in order to incorporate macro dependent dynamics: The Retail Price Index (RPI), and the UK Short Term (3-month) Treasury Bill Rate Deflated (SHTBRDEF), both measured on an annual basis. The RPI[19] measures changes in prices of consumption goods and services in the UK. It is expected that a high RPI should increase the likelihood of distress/failure. The next macroeconomic indicator is the SHTBRDEF[20], which reflects the annualised 'real' short-term rate of UK Treasury Bills. This variable captures the impact of the

[16] Each firm's past residual return in year t was calculated as the cumulative monthly return of the twelve months prior to the year where the financial distress event was observed, minus the FTSE All Share Index cumulative monthly return for the same period ($t - 1$). Also, in line with the accounting and macroeconomic variables, and in order to confirm its predictive ability, the ABNRET variable was computed as the cumulative monthly returns two years prior to the observation of the financial distress event ($t - 2$).

[17] See Dichev (1998), Shumway (2001).

[18] This variable was generated as the log of the market capitalization of the company divided by the total market capitalization of the FTSE All Share Index (to make size static). Negative values result from the fact that the logarithmic form of a small number yields a negative sign, which is particularly relevant for companies whose size, compared to the market capitalization of the FTSE All Share Index, is very small.

[19] The Retail Price Index indicator (used on an annual basis and Base = 100), a measure of inflation, was taken from the Office for National Statistics, and can be defined as 'an average measure of change in the prices of goods and services bought for the purpose of consumption by the vast majority of the households in the UK.'

[20] The Short Term Treasury Bill Rate Deflated (SHTBRDEF) represents the 'real' short-term rate of 3-month United Kingdom Treasury Bills on an annual basis. Two main sources were used to construct this indicator: from the Bank of England website, the level of the discount rate from 1985 to 2011 was obtained; and from Datastream, the inflation rate employed in order to deflate the discount rate for the same period. Treasury Bills are defined as 'bearer Government Securities representing a charge on the Consolidated Fund of the UK issued in minimum denominations of £5000 at a discount to their face value for any period not exceeding one year". Treasury Bills are typically considered as the least risky investment available. They are much more liquid than gilts (with maturity ranging between 0 and 15 years) and therefore the yield rate on treasury bills is normally lower than on longer-term securities. The present study included the annualised level of the 91 days (3-month) discount rate in order to test another measure intended to capture the state of the macro- economic environment that could potentially have an effect on the probability of financial distress of industrial companies.

rate of interest. It is assumed that a high level of interest rates (a high or increasing level of SHTBRDEF) will affect positively firms' likelihood of falling into the financial distress/failure category.

Tables 2 to 4 present summary statistics for Model 1 (accounting variables, and macroeconomic variables), Model 2 (market and macroeconomic variables), and Model 3 (the comprehensive model including all three types of variables), respectively. Summary statistics are shown for the full dataset (Panel A), as well as for each of the three states employed in the study: non-financially distressed firms (Panel B), financially distressed firms (Panel C) and failed firms (Panel D)[21].

INSERT TABLE 2 ABOUT HERE

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INSERT TABLE 4 ABOUT HERE

In order to assess the goodness of fit we performed likelihood ratio tests to evaluate the effects of the predictors on the outcome variable, as well as linear hypothesis tests to estimate the overall effects of all 10 pairs of coefficients (financial distress and corporate failure conditional on non-financial distress) on the three models, all of which include macroeconomic indicators in order to account for the models' macro dependent dynamics: the 'Accounting' model (Model 1), the 'Market' model (Model 2), and the 'Comprehensive' model (Model 3) which combines accounting and market variables as well as macroeconomic indicators. These tests revealed that, for t-1 and for all of the models, the hypothesis that all coefficients relating to the individual variables are simultaneously equal to zero can be rejected at the 99 per cent level. As for t-2, the tests performed on Model 3 show that the null hypothesis is not rejected for the accounting variable TLTA and the market variable SIZE (although the latter is significant at the 10% level), which is a very modest proportion relative to the total number of variables. This is not surprising since the tests were estimated using information two years prior to the relevant event. However, given that, overall, for all coefficients the null hypothesis is rejected, all variables were kept in the final models. Moreover, we apply Wald tests as well as likelihood ratio tests to all three possible pairs of outcomes in order to verify whether any of the pairs should be combined into a single outcome. If none of the explanatory variables is able to affect the probabilities of any potential pair of outcomes (e.g., DIS V FAI) [22], then the pair of outcomes would be indistinguishable relative to the variables in the model. If this is the case, more efficient coefficient

[21] The number of observations varies amongst the models because a higher number of variables in a given model necessarily reduces the number of observations containing all of the information required in the logit equations for the estimation of coefficients and predicted probabilities.

[22] The test was applied to these particular outcomes as it could be argued that, because of their potential proximity, they could be combined into a single category in order to satisfy the polytomous response logit models' requirement that the outcome categories be clearly distinct.

estimates can be obtained by collapsing the pair of outcomes into a single one (e.g., DIS and FAI could be combined into FAI). Thus, the following null hypothesis is tested: All coefficients except intercepts associated with a given pair of alternatives are 0 (i.e., alternatives can be collapsed). The resulting p-values (all with $p < 0.0001$) for both Wald and likelihood ratio tests for all 3 models allowed us to conclude that the coefficients for DIS (versus NFD) and FAI (versus NFD) are not the same. Had these tests produced a high p-value (e.g., $p > 0.05$), the null hypothesis could not have been rejected, which would have suggested that the categories of financial distress and corporate failure could be combined into a single category. This result is crucial, since it strongly supports our decision to use three possible states for analysis.

5. Results.

To assess the impact of individual covariates on the three-state outcome variable, the multinomial coefficient estimates are compared with the average marginal effects. Coefficients obtained through the multinomial logit methodology are presented in tables 5 to 7. Three ex-ante models are used to determine the probability of financial distress and to examine the usefulness of market indicators to the performance of accounting ratios based models. Table 5 reports results from multinomial logit regressions of the three-level Response variable on the predictor variables for Model 1 or the 'Accounting' model, which incorporates accounting ratios only. Table 6 reports results for Model 2 or the 'Market' model. Finally, Table 7 reports results for the 'Comprehensive' model or Model 3. All three models incorporate proxies for the macroeconomic environment in order to control for macro dependent dynamics: RPI and SHTBRDEF.

5.1. Multinomial Function Coefficients.

Table 5 reports the estimates from the multinomial logistic regressions of the 3-state Response indicator for the 'Accounting' model. It can be observed that, as to the comparison of the Corporate failure (FAI) category versus the Non-financially distressed (NFD) category, all of the coefficients (accounting variables as well as macroeconomic indicators) in t-1 are significant at the 1% level and possess the expected signs. This is consistent with expectations, as it displays the coefficients resulting from the comparison of the extreme outcomes contained in the Response indicator. Therefore, it is unsurprising that all of the covariates have the ability to reliably discriminate between corporate failure and financial distress. Similarly, the coefficients for the pair Non-financial distress (NFD) versus Financial distress (DIS) display the expected signs and, with the exception of NOCREDINT (which is significant at the 5% level), are significant at the 1% level, suggesting that all of them are able to reliably discriminate between the pair of categories. Again, this is in line with expectations, given that, although not as extreme as the previous comparison, this pair includes two strongly contrasting response levels. On the other hand, the results obtained from the comparison Corporate failure (FAI) versus Financial distress (DIS) are less unequivocal: two covariates - one accounting ratio and one macroeconomic indicator - are not statistically significant. However, even if the number of covariates that reliably discriminate and predict between these two outcomes is reduced, there are still three financial ratios and one macroeconomic indicator that are statistically significant. This suggests that even for more similar outcomes, the accounting model presented in this study displays sound performance. However, the coefficient COVERAGE (concerning the pair FAI versus DIS) is not of the expected sign: as it was previously posited that an increasing level of this covariate would have a negative effect on the likelihood of falling into the FAI category versus falling into the DIS category. The coefficients obtained when the model was estimating using information at t-2 show a similar pattern.

INSERT TABLE 5 ABOUT HERE

The multinomial function coefficient estimates for the 'Market' model (Model 2) are shown in Table 6. The pattern reflected by the analysis of the pairs of comparisons FAI versus NFD and NFD versus DIS is similar to the one observed for the 'Accounting model': regarding the first pair, all of the market variables are significant at the 1% level and display the expected signs, suggesting that they are able to reliably discriminate between the most extreme potential outcomes of the Response indicator. For the next comparison, NFD versus DIS, all coefficients are significant at 1%, with the exception of the macroeconomic indicator SHTBRDEF, which is significant at 5%.

This comparison indicates that the market model contains useful information for the classification of financially healthy versus financially distressed companies. In contrast, three variables obtained from the comparison pair FAI versus DIS display signs that are at odds with the study's expectations, namely, ABNRET, SIZE and RPI, although the last of these is insignificant. It was expected that an increase in both the level of residual returns and the size of the company would lead to a decrease in the likelihood of the firm falling into the FAI category versus falling into the DIS category. In the case of RPI it was assumed that an increase in inflation would have a positive effect on the likelihood of FAI, given a current strained financial condition. From this analysis, it can be concluded that the accounting model discriminates better between this pair of categories. Unsurprisingly, the statistical significance of some of the variables decreases when the model is estimating using information at t-2.

INSERT TABLE 6 ABOUT HERE

Table 7 presents results for the 'Comprehensive' model. Again, all of the coefficients resulting from the comparison FAI versus NFD possess the expected signs and display statistical significance at the 1% level, providing additional evidence suggesting that all of the variables contain information that is useful to discriminate between these extreme states. In other words, unambiguous differences in individual characteristics between the Corporate failure and the Non-financial distress categories can be found in every single accounting, market and macroeconomic variable incorporated in the 'Comprehensive' model. With regard to the comparison NFD versus DIS, despite the fact that all of the covariates show the expected signs, only two accounting variables are statistically significant, while three out of four market variables (ABNRET, SIZE, and MCTD) and all of the macroeconomic indicators remain statistically significant at the 1% level. Furthermore, an ordering of the variables based upon the magnitude of their coefficients reveals that the top five is composed of three market variables and two financial ratios: COVERAGE, ABNRET, MCTD, TFOTL, and SIZE, in order of importance. Unlike in the previous comparison, these results confirm the importance of the effects of market variables on the likelihood of falling into category NFD versus falling into category DIS.

While, the comparison of the categories FAI and DIS yields fewer statistically significant variables, six are significant: the market variables PRICE, ABNRET, and SIZE (all of them at the 1% level), the accounting ratios COVERAGE, NOCREDINT (at the 1% level), and TLTA (at the 5% level). Interestingly, when the model is estimated using information at time t-2, the macroeconomic indicators and the market variable MCTD are statistically significant, suggesting a difference in the performance (or in the amount of useful information relevant to the prediction of each outcome) of the variables that is dependent upon the period of analysis. Furthermore, the market variables ABNRET and SIZE and the accounting variable COVERAGE display signs at odds with expectations: a negative relationship would have been expected instead for the three covariates suggesting that the higher is each individual variable, the lower the likelihood of falling into the FAI category versus falling into the DIS category.

INSERT TABLE 7 ABOUT HERE

The above analysis of the multinomial function coefficients is useful in order to be aware of the predictors of the three levels of the response variables, which are of potential use given a base outcome. It also provides hints regarding the overall performance of the model by displaying the number of variables that are statistically significant for each pair of variables. The above analysis is, nevertheless, most useful as a benchmark to make comparisons relative to what this study posited to be the most appropriate tool to interpret the individual impact of each regressor on the different levels of the Response indicator for Polytomous response logit models: marginal effects.

5.2. Marginal Effects and Changes in Predicted Probabilities.

This section presents the output of the estimation of marginal effects of individual covariates and graphic depictions of predicted probabilities of distressed and failed firms. Vectors are employed to represent the changes in the predicted probabilities of falling into the DIS and FAI categories when the variation in the level of an individual covariate ranges from its minimum to its maximum, while maintaining all the other variables constant at their means.

Table 8 presents marginal effects (on a percentage basis) of the variables included in Model 1 (panel A), 2 (panel B) and 3 (panel C). Significance statistics, and standard errors obtained employing the Delta method are also presented. The analysis of marginal effects for the 'Accounting model' (Model 1) reveals a similar pattern with regard to the previously reported coefficient estimates; the individual average marginal effects relative to the probabilities of falling in to the NFD (Response = 1) and DIS (Response = 3) categories are consistent with their respective coefficients (NFD versus DIS and FAI versus NFD), in terms of the expected signs. However, with regard to the probability of falling into the FAI category (Response = 2), there is one important difference to highlight: the AME for the variable COVERAGE displays the expected negative sign, in contrast with the sign displayed by the respective coefficient estimate (for the pair FAI versus DIS). An analysis of Model 2 (panel B), shows that the probabilities that Response =1 and Response = 2 are 'sign-consistent' relative to the coefficients for the pairs NFS versus DIS and FAI versus DIS. However, there is a crucial difference to highlight with regard to the probability that Response =3: the signs for ABNRET, SIZE, and RPI, are as expected (negative, negative, and positive), unlike the signs of the corresponding coefficient estimates (for the pair FAI versus NFD).

Panel C presents marginal effects (on a percentage basis) of the covariates in Model 3, the comprehensive model. The analysis reveals the following: all of the individual average marginal effects (AME) relative to the probability of falling into the NFD category (Response = 1) display the expected signs and are statistically significant at 1%. Next, the procedure to estimate AMEs corresponding to the probability of falling into the DIS category (Response = 2) yields again the expected signs for all variables, with NOCREDINT being the only exception (however, the AME is not statistically significant, which provides the estimation procedure with a high degree of reliability). Moreover, significance at the 1% level is found for seven out of ten covariates in the model. Finally, with regard to the probability of a firm falling into the FAI category (Response = 3), seven out of ten of the Comprehensive model's covariates are significant at 1%, which indicates again a high degree of reliability of the AMEs estimates. Crucially, all of the AMEs for the FAI category display the expected signs.

The resulting AMEs obtained using information at time t-2, confirm the results obtained when the models are estimated with t-1 data: regardless of the expected marginal decrease in the number of covariates that are statistically significant, AMEs estimated for the period t-2 display similar behaviour patterns to those estimated for t-1. Likewise, all of the individual AMEs that are statistically significant, show the expected signs, and the entirety of those few (six, all categories comprised) AMEs that display an unexpected sign, are not statistically significant at any standard level. This observation provides further evidence that confirms the directionality as well as the magnitude of the effects of the estimated AMEs, which further corroborates the validity and usefulness of the marginal effects estimation method employed in this study.

INSERT TABLE 8 ABOUT HERE

Overall, the estimation and analysis of all covariates' AMEs incorporated in the three models provides a solution to an important gap in the literature: the lack of a measure of the individual instantaneous impact of changes to a covariate on the polytomous (3-state) outcome variable (NFD, DIS, FAI), while maintaining all the other predictors constant.

Given the high costs associated with financial distress (DIS) and corporate failure (FAI), and the cost-minimisation behaviour of practitioners such as banks and investment companies, this study presents a comparison of the vectors of predicted probabilities that reflect the impact of a change of individual variables on the likelihood of falling in the DIS and FAI categories. The advantage of such vector representations is that they inform practitioners as well as academics on the predicted probability of falling into one of the two categories for a level of the specific covariate that varies between the minimum and maximum possible values.

In figure 1, we plot the vectors reflecting the behaviour of predicted probabilities for Financial Distress and Corporate Failure resulting from individual changes in the levels of the accounting ratios. The plot was built including all the variables in the comprehensive model, and the predicted probabilities were computed using the minimum and maximum approximate values of each of the accounting variables. This figure corroborates the directionality and the magnitude of the effects of the financial ratios. The visible differences in magnitude, reflected by the steepness of the slopes, suggest that the same individual accounting covariates in the model have different effects on the probability of Financial distress and Corporate failure, consistent with our prior expectations.

INSERT FIGURE 1 ABOUT HERE

5.3. Classification Accuracy Tables.

To evaluate the classification accuracy of the three polytomous response (three-state) logit models, a generalisation of the bias-adjusted classification accuracy tables for the binary logistic models is employed (Fleiss et al. 2003, p. 578-598; SAS/STAT(R) 9.22 User's Guide, The Logistic Procedure, Classification Table[23]). This method has the advantage of testing the accuracy of the models to differentiate (and predict) among all the possible non-redundant comparison pairs of response outcomes. Most importantly, this methodology was selected to perform prediction accuracy tests as it has the advantage of being able to incorporate distinct cut-off points that allow the

[23] https://support.sas.com/documentation/cdl/en/statug/63347/HTML/default/viewer.htm#statug_logistic_sect044.htm.

academic/practitioner to calibrate the model taking into account the costs associated with each outcome (financial distress, bankruptcy) in order to obtain better results for a desired outcome.

Furthermore, this technique allows the inclusion of very close approximations of the actual proportions of an outcome relative to the one it is being tested against, which is very important as they can be used as cut-off points in an unbalanced panel (such as the one used in this study, that approximates the actual proportions observed in the United Kingdom), thus providing the researcher with realistic and reliable results as well as a high degree of accuracy. Predicted probabilities from three possible non-redundant combinations of outcomes through binary logit regressions are estimated to build the bias-adjusted classification tables. Thus, equation 1 computes the predicted probabilities for the pair of outcomes Non-financial distress and Financial distress, equation 2 estimates the probabilities for the pair Non-financial distress and Corporate failure, and equation 3 computes the probabilities for the pair Financial distress and Corporate failure.

Figures 2 and 3 present the respective vectors for market and macroeconomic indicators respectively.

INSERT FIGURE 2 ABOUT HERE

INSERT FIGURE 3 ABOUT HERE

This procedure is performed using data from period t-1 and period t-2 separately[24], using information one and two years in advance of the date of the event of relevance. In this way, the predictive ability of the models can be assessed. Next, from a range of probability levels, those that closely approximate the real proportions of the pairs of events and that, at the same time, minimise the difference between sensitivity and specificity, are selected for comparison. In this manner, the study provides a consistent point of comparison. Finally, the numbers of correct and incorrect classifications for each of the above equations are incorporated into a single table that presents the classification accuracy (in percentages) of the models built up using a panel of data that, unlike previous multinomial logit financial distress/corporate failure prediction models, is representative of the population of UK quoted companies.

Analysis of Table 9 unambiguously indicates that the combination of accounting and market variables yields the highest classification accuracy among the three polytomous response logit models. Model 3 results in overall classification accuracy of 85 %, while Model 1 and Model 2 produce similar accuracy results: 80% and 79% respectively, which suggest that the performance of

[24] In order to save space, the table containing all the details regarding the prediction accuracy of our models in t-2 was omitted; a summary of the main findings is included below. Results available on request.

accounting and market variables is not highly dissimilar: the accounting model is only marginally superior to the market model.

INSERT TABLE 9 ABOUT HERE

Unreported results reveal that the classification accuracy obtained using information two years in advance of the event of relevance confirms the superiority of the predictive accuracy of the 'Comprehensive' model relative to Model 1 and Model 2 by revealing a very similar pattern to the models estimated for period t-1: Model 3 displays the highest overall classification accuracy (82%), followed by Model 1 (79%), and Model 2 (75%), which suggests that accounting models might perform better than market models in period t-2. What is more, even though the percentages decreased in period t-2, as expected, the models still show high classification accuracies, which confirm the robustness of the models. Unsurprisingly, the monotonic decrease in classification accuracy observed by response category can be explained by the monotonic decrease in the respective observations for each outcome, which affect accordingly the predicted probability estimations. Nevertheless, it must be emphasized that even the individual accuracies remain high.

6. Conclusions.

This study presents new financial/distress corporate failure models for listed firms in the UK using a polytomous response (three-state) logit methodology. It contributes to the literature, first, by creating a three-state response variable that comprises a finance-based definition of the Financial distress category, a technical definition of the Corporate failure category, and a category that captures on-going firms assumed to be in a financially sound position. Unlike previous work, this study builds up a large dataset by combining information from a range of sources that are widely available and employed in academia and in industry in order to estimate generalised logit models based on a sample whose distribution is representative of the whole population of listed firms in the United Kingdom.

Second, we test whether the inclusion of accounting and market variables in a single multinomial logit model is able to outperform models including only either market or accounting data. The reported results unambiguously indicate that this is the case: model performance statistics, not previously used in a financial distress/corporate failure model, invariably show a considerable increase in the goodness-of-fit of the 'Comprehensive model' relative to the 'Accounting only' model and the 'Market only' model. Additionally, adequate bias-adjusted classification accuracy tables provide evidence corroborating these results: for data from period t-1, the 'Comprehensive model' yields an 85% overall classification accuracy, whereas the 'Accounting' and 'Market' models yield an overall classification accuracy of 80% and 79%, respectively. As expected, the accuracy of the models decreased when the models were estimated using data two years in advance of the observation of the event of relevance; nevertheless, similar patters confirming the ascendancy of a comprehensive model can be observed. Furthermore, the classification accuracy of the models for t-2 remains high: for the ‘Comprehensive’ model being equal to 82%. (79% for the ‘Accounting’ model and 75% for the ‘Market’ model).

Third, through the estimation of marginal effects and changes in predicted probabilities, the study compares the relative individual as well as collective contributions of accounting and market variables to the performance of the models, while controlling for the macroeconomic environment. Unlike previous research, this study considers the difficulties of interpretation of the coefficients obtained through multinomial logistic regressions; it posits that marginal effects, defined as expected instantaneous changes in the outcome variable resulting from changes to a particular predictor variable (other covariates held constant), are a more appropriate means by which to determine the effects of individual covariates on the likelihood of falling into one of the three pre-defined financial states/outcomes. The reported results confirm this hypothesis: apart from the advantage of their direct interpretation, the estimation of average marginal effects yields the expected signs for all the variables and outcomes, unlike some of the multinomial function coefficients. In practice, these results can be used to determine the individual effects of the different covariates on the probability of a firm falling into financial distress or corporate failure with a high degree of reliability. In other words, marginal effects are an appropriate measure to determine the relative importance of individual variables based on their relative magnitudes. In this manner, practitioners are able to rank and target the specific aspects or characteristics of a company that require special attention given the large costs inherent in financial distress and bankruptcy.

Finally, as a complement to these findings as well as to the usefulness and robustness of the model, the study provides graphical representations of the vectors that reflect the changes in predicted probabilities of falling into a state of financial distress or corporate failure produced by changes in the levels of individual covariates (ranging from their minimum to their maximum possible values), all other variables held constant at their means. The graphical representations, in addition, are designed to directly compare the differences in the magnitude of the effects of an individual variable on the probabilities of reaching a state of financial distress and corporate failure, respectively.

References.

Agresti, A. (1990). Categorical Data Analysis. Wiley, Inc., New York.

Alexander, C., & Kaeck, A. (2008). Regime Dependent Determinants of Credit Default Swap Spreads. Journal of Banking & Finance, 32, 1008-1021.

Allison, P. D. (2012). Logistic Regression Using SAS. Theory and Application. 2nd Ed. SAS Institute Inc. North Carolina.

Altman, E. I., Sabato, G., & Wilson, N. (2010). The Value of Non-Financial Information in Small and Medium-Sized Enterprise Risk Management. The Journal of Credit Risk, 6**,** 1-33.

Asquith, P., Gertner, R., & Scharfstein, D. (1994). Anatomy of Financial Distress: An Examination of Junk-Bond Issuers. The Quarterly Journal of Economics, 109**,** 625-658.

Balcaen, S., & Ooghe, H. (2004). 35 Years of Studies on Business Failure: An Overview of the Classic Statistical Methodologies and their Related Problems. Vlerick Leuven Gent Working Paper Series, 15.

Balcaen, S., & Ooghe, H. (2006). 35 Years of Studies on Business Failure: An Overview of the Classic Statistical Methodologies and their Related Problems. The British Accounting Review, 38, 63-93.

Barnes, P. (1987). The Analysis and Use of Financial Ratios: A Review Article. Journal of Business Finance & Accounting, 14**,** 449-461.

Barnes, P. (1990). The Prediction of Takeover Targets in the U.K. by Means of Multiple Discriminant Analysis. Journal of Business Finance & Accounting, 17**,** 73-84.

Bartus, T. (2005). Estimation of Marginal Effects Using Margeff. Stata Journal, 5: 309-329.

Boskin, M. J. (1974). A Conditional Logit Model of Occupational Choice. Journal of Political Economy, 82, 389-398.

Bharath, S. T., & Shumway, T. (2008). Forecasting Default with the Merton Distance to Default Model. Review of Financial Studies, 21**,** 1339-1369.

Black, F., & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. Journal of Political Economy, 81, 637-654.

Bruche, M., & González-Aguado, C. (2010). Recovery rates, default probabilities, and the credit cycle. Journal of Banking & Finance, 34(4), 754–764.

Cameron, A. C., & Trivedi, P. K. (2010). Microeconometrics Using Stata. Rev. Ed. College Station, TX: Stata Press.

Charitou, A., Dionysiou, D., Lambertides, N., & Trigeorgis, L. (2013). Alternative bankruptcy prediction models using option-pricing theory. Journal of Banking & Finance, 37(7), 2329–2341.

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

Christidis, A., & Gregory, A. (2010). Some New Models for Financial Distress Prediction in the UK. Xfi Centre for Finance and Investment Discussion Paper No. 10.

Cox, D. R., & Snell, E. J. (1989). The Analysis of Binary Data. London: Chapman and Hall.

Das, S. R., Hanouna, P., & Sarin, A. (2009). Accounting-based versus market-based cross-sectional models of CDS spreads. Journal of Banking & Finance, 33(4), 719–730.

Declerc, M., Heins, B., & Van Wymeersch, C. (1992). The Use of Value Added Ratios in Statistical Failure Prediction Models: Some Evidence on Belgian Annual Accounts. Cahiers Economiques de Bruxelles, 353-378.

Dichev, I. D. (1998). Is the Risk of Bankruptcy a Systematic Risk? The Journal of Finance, 53, 1131-1147.

Efron, B. (1975). The Efficiency of Logistic Regression Compared to Normal Discriminant Analysis. Journal of the American Statistical Association, 70, 892-898.

Fleiss, J. L., Levin, B., & Cho Paik, M. (2003). Statistical Methods for Rates and Proportions. 3rd Ed., Wiley Series in Probability and Statistics.

Freund, R. J., & Littell, R. C. (2000). SAS System for Regression. New York, Chichester: Wiley, Carey.

Hernandez Tinoco, M., & Wilson, N. (2013). Financial Distress and Bankruptcy Prediction Among Listed Companies Using Accounting, Market and Macroeconomic Variables, International Review of Financial Analysis, 30, 394-419.

Hillegeist, S. A., Keating, E. K., Cram, D. P., & Lundstedt, K. G. (2004). Assessing the Probability of Bankruptcy. Review of Accounting Studies, 9, 5-34.

Hosmer, D. W., Lemeshow, S., (2013). Applied Logistic Regression. 3rd Ed, Wiley Series in Probability and Statistics.

Johnsen, T., & Melicher R. W. (1994). Predicting corporate bankruptcy and financial distress: Information value added by multinomial logit models. Journal of Economics and Business, 46, 269-286.

Jones, F. L. (1987). Current Techniques in Bankruptcy Prediction. Journal of Accounting Literature, 6, 131-164.

Jones, S., & Hensher, D. A. (2004). Predicting Firm Financial Distress: A Mixed Logit Model. The Accounting Review, 79, 1011-1038.

Köppen, M., Kasabov, N., Coghill, G. (Eds.). (2008). 15th International Conference. Advances in Neuro-Information Processing, ICONIP 2008, Auckland, New Zealand, November 25-28, Revised Selected Papers, Part II.

Lau, A. H.-L. (1987). A Five-State Financial Distress Prediction Model. Journal of Accounting Research, 25, 127-138.

Lawrence, E. C., & Arshadi, N. (1995). A Multinomial Logit Analysis of Problem Loan Resolution Choices in Banking. Journal of Money, Credit and Banking, 27, 202-216.

Leclere, M. J. (1999). The Interpretation of Coefficients in N-Chotomous Qualitative Response Models. Contemporary Accounting Research, 16, 711-747.

Long, J. S., Freese, J. (2003). Regression Models for Categorical Dependent Variables Using Stata, College Station, Texas, Stata Press.

Maddala, G. S. (1991). A Perspective on the Use of Limited-Dependent and Qualitative Variables Models in Accounting Research. The Accounting Review, 66, 788-807.

Manski, C. F., & Lerman, S. R. (1977). The Estimation of Choice Probabilities from Choice Based Samples. Econometrica, 45, 1977-1988.

Mare, D. S. (2012). Contribution of Macroeconomic Factors to the Prediction of Small Bank Failures. Paper presented at 4th International IFABS Conference, Valencia, Spain 18/06/12 – 20/06/12.

McFadden, D., & Train, K. (2000). Mixed MNL Models for Discrete Response. Journal of Applied Econometrics, 15, 447-470.

Merton, R. C. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. The Journal of Finance, 29**,** 449-470.

Nagelkerke, N. J. D. (1991). A Note on a General Definition of the Coefficient of Determination. Biometrika, 78**,** 691-692.

Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. Journal of Accounting Research, 18**,** 109-131.

Ooghe, H., & Joos, P. (1990). Failure Prediction, Explanation of Misclassifications and Incorporation of other Relevant Variables: Results of Empirical Research in Belgium. Working Paper, Department of Corporate Finance, Ghent University.

Ooghe, H., Joos, P., & Bourdeaudhuij, C. D. (1995). Financial Distress Models in Belgium: The Results of a Decade of Empirical Research. The International Journal of Accounting, 30, 245-274.

Piesse, J., & Wood, D. (1992.) Issues in Assessing MDA Models of Corporate Failure: A Research Note. The British Accounting Review, 24, 33-42.

Pindado, J., Rodrigues, L., & De La Torre, C. (2008). Estimating Financial Distress Likelihood. Journal of Business Research, 61**,** 995-1003.

Platt, H. D., & Platt, M. B. (2002). Predicting Corporate Financial Distress: Reflections on Choice-based Sample Bias. Journal of Economics and Finance, 26, 184-199.

Reisz, A. S., & Perlich, C. (2007). A Market-Based Framework for Bankruptcy Prediction. Journal of Financial Stability, 3**,** 85-131.

Scott, J. (1981). The Probability of Bankruptcy: A Comparison of Empirical Predictions and Theoretical Models. Journal of Banking & Finance, 5, 317-344.

Shumway, T. (2001). Forecasting Bankruptcy More Accurately: A Simple Hazard Model. Journal of Business, 74, 101-124.

Tang, D. Y., & Yan, H. (2010). Market conditions, default risk and credit spreads. Journal of Banking & Finance, 34(4), 743–753.

Theodossiou, P. T. (1993). Predicting Shifts in the Mean of a Multivariate Time Series Process: An Application in Predicting Business Failures. Journal of the American Statistical Association, 88, 441-449.

Vassalou, M., & Xing, Y. (2004). Default Risk in Equity Returns. The Journal of Finance, 59, 831-868.

Ward, T. J. (1994). An Empirical Study of the Incremental Predictive Ability of Beaver's Naive Operating Flow Measure Using Four-State Ordinal Models of Financial Distress. Journal of Business Finance & Accounting, 21, 547-561.

Williams, R. (2012). Using the Margins Command to Estimate and Interpret Adjusted Predictions and Marginal Effects. Stata Journal, 12: 308-331.

Zmijewski, M. E. (1984). Methodological Issues Related to the Estimation of Financial Distress Prediction Models. Journal of Accounting Research, 22, 59-82.

Table 1
Summary Statistics of the Annual Observations. Financially and Not Financially Distressed Firms

The table reports summary statistics for the whole sample of UK companies, corresponding to the period 1980 – 2011. NFD stands for Non-financially distressed firms, DIS for firms in a state of financial distress, and FAI those firms classified as failed.

Classification of observations into Non-financially distressed, Financially distressed, and Failed companies.				
Response	Freq.	Per cent	Cumulative Freq.	Cumulative Per cent
NFD	21964	94.60	21964	94.60
DIS	869	3.74	22833	98.34
FAI	385	1.66	23218	100.00

Table 2
Summary Statistics for Model 1

This table presents summary statistics for Model 1, the 'Accounting' (plus macroeconomic variables) model. Panel A provides summary statistics for the whole dataset, Panel B for financially healthy firms, Panel C for financially distressed firms, and Panel D for failed firms.

Variable	TFOTL	TLTA	NOCREDINT	COVERAGE	RPI	SHTBRDEF
Panel A: Entire data set						
Mean	0.067493	0.485921	-0.118042	0.525922	178.39851	2.048426
Std. Dev.	0.339813	0.189284	0.986466	0.822947	32.220261	2.427929
Min	-1	-0.432123	-1	-1	94.59	-4.69551
Max	1	1	1	1	235.18	7.7407
Observations	18,070					
Panel B: Non-financially distressed firms						
Mean	0.088319	0.482455	-0.109658	0.589027	177.75165	2.068698
Std. Dev.	0.325357	0.184057	0.987328	0.781256	32.427066	2.442916
Min	-1	-0.432123	-1	-1	94.59	-4.69551
Max	1	1	1	1	235.18	7.7407
Observations	17,143					
Panel C: Financially distressed firms						
Mean	-0.385525	0.524583	-0.136795	-0.866796	193.10239	1.437297
Std. Dev.	0.369959	0.279639	0.987389	0.379827	24.667725	2.117728
Min	-1	-0.302382	-1	-1	115.21	-4.69551
Max	0.99792	1	1	0.751412	235.18	7.1745
Observations	612					
Panel D: Failed Firms						
Mean	-0.185767	0.599386	-0.537879	-0.202545	185.03432	2.132532
Std. Dev.	0.33396	0.208933	0.837612	0.916257	25.739411	1.983302
Min	-1	0.005761	-1	-1	115.21	-4.69551
Max	0.796339	1	1	1	235.18	7.1745
Observations	315					

Table 3
Summary Statistics for Model 2

This table presents summary statistics for Model 2, the 'Market' (plus macroeconomic variables) model. Panel A provides summary statistics for the whole dataset, Panel B for financially healthy firms, Panel C for financially distressed firms, and Panel D for failed firms.

Variable	PRICE	ABNRET	SIZE	MCTD	RPI	SHTBRDEF
Panel A: Entire data set						
Mean	4.392914	-0.111672	-10.10087	0.911268	177.87621	2.075157
Std. Dev.	1.720131	0.388324	2.238356	0.191682	32.877633	2.52962
Min	-3.912023	-0.999988	-18.762915	0.002019	94.59	-4.69551
Max	14.151983	0.999996	-2.374161	1	235.18	7.7407
Observations	14,578					
Panel B: Non-financially distressed firms						
Mean	4.495108	-0.088945	-9.965482	0.920038	177.18654	2.097117
Std. Dev.	1.646194	0.376547	2.197184	0.17782	33.115608	2.549583
Min	-3.912023	-0.999829	-18.762915	0.002019	94.59	-4.69551
Max	14.151983	0.999996	-2.374161	1	235.18	7.7407
Observations	13,780					
Panel C: Financially distressed firms						
Mean	2.652963	-0.566576	-12.605192	0.790393	192.29895	1.491971
Std. Dev.	1.982396	0.318766	1.464687	0.304776	24.90328	2.135678
Min	-3.912023	-0.999988	-16.602146	0.002877	115.21	-4.69551
Max	10.266393	0.560483	-7.427867	1	235.18	7.1745
Observations	522					
Panel D: Failed Firms						
Mean	2.580608	-0.384036	-12.118752	0.701029	184.95234	2.088227
Std. Dev.	2.012367	0.450497	1.642173	0.334435	26.553931	2.041848
Min	-3.912023	-0.996655	-16.581148	0.00588	115.21	-4.69551
Max	10.96388	0.949759	-5.641377	1	235.18	7.1745
Observations	273					

Table 4
Summary statistics for Model 3

This table presents summary statistics for the 'Comprehensive' model, or Model 3. Panel A provides summary statistics for the entire dataset, Panel B for financially healthy firms, Panel C for the firms in financial distress, and Panel D for failed firms.

Variable	TFOTL	TLTA	NOCREDINT	COVERAGE	RPI	SHTBRDEF	PRICE	ABNRET	SIZE	MCTD
Panel A: Entire dataset										
Mean	0.097363	0.497767	-0.19551	0.599672	178.08903	2.046149	4.427373	-0.108952	-10.046418	0.91036
Std. Dev.	0.27721	0.169538	0.973386	0.770045	32.874323	2.532696	1.702743	0.386299	2.22842	0.192053
Min	-1	-0.102771	-1	-1	94.59	-4.69551	-3.912023	-0.999988	-16.602146	0.002877
Max	1	1	1	1	235.18	7.7407	14.151983	0.999996	-2.374161	1
Observations	13,529									
Panel B: Non-financially distressed firms										
Mean	0.118203	0.492827	-0.184269	0.669078	177.4168	2.066005	4.526808	-0.086315	-9.913979	0.919151
Std. Dev.	0.258451	0.163083	0.975489	0.713444	33.102993	2.553595	1.630117	0.374557	2.189381	0.17828
Min	-1	-0.102771	-1	-1	94.59	-4.69551	-3.912023	-0.999829	-16.480853	0.006411
Max	1	1	1	1	235.18	7.7407	14.151983	0.999996	-2.374161	1
Observations	12,801									
Panel C: Financially Distressed Firms										
Mean	-0.332766	0.561524	-0.252689	-0.849951	192.32595	1.507206	2.708543	-0.563883	-12.555755	0.785255
Std. Dev.	0.335827	0.262972	0.963513	0.401609	25.028722	2.094824	1.964593	0.322238	1.428658	0.307795
Min	-0.999979	0.028495	-1	-1	115.21	-4.69551	-3.912023	-0.999988	-16.602146	0.002877
Max	0.724547	1	1	0.751412	235.18	7.1745	10.266393	0.560483	-7.427867	1
Observations	482									
Panel D: Failed firms										
Mean	-0.144323	0.629916	-0.668404	-0.171655	185.17427	2.068862	2.62093	-0.395512	-12.021421	0.698069
Std. Dev.	0.29425	0.187108	0.735512	0.921337	26.84074	2.07339	2.019445	0.43582	1.593138	0.331656
Min	-1	0.052458	-1	-1	115.21	-4.69551	-3.912023	-0.996655	-15.922758	0.00588
Max	0.49607	1	1	1	235.18	7.1745	10.96388	0.949759	-5.641377	1
Observations	246									

Table 5
Multinomial Logit Regression of 3-Level Response Variable on Predictor Variables Model 1 - Accounting + Macroeconomic Variables Model

This table reports results from multinomial logit regressions of the 3-level Response variable on the predictor variables for the 'Accounting' (plus macroeconomic variables) Model 1. The 3-level Response variable is composed of the following states: Non-financial distress (NFD), financial distress (DIS), and failure (FAI). Model 1 was computed for periods t-1 and t-2 to examine the stability over time of the displayed signs as well as the magnitude of the coefficients. The absolute value of z-statistics is reported in parentheses. *, **, *** denote significant at 10%, 5% and 1%, respectively.

Covariates	FAI V NFD		FAI V DIS		NFD V DIS	
	t-1	t-2	t-1	t-2	t-1	t-2
TFOTL	-1.0049***	-0.8865***	-0.3945	-0.3003	0.6103***	0.5862***
	(4.57)	(3.80)	(1.60)	(1.16)	(4.49)	(4.41)
TLTA	1.9573***	1.3100***	0.7940**	1.3846***	-1.1633***	0.0747
	(6.90)	(4.36)	(2.42)	(3.95)	(5.89)	(0.36)
NOCREDINT	-0.4337***	-0.3001***	-0.3160***	-0.2021**	0.1177**	0.0981*
	(5.65)	(4.08)	(3.49)	(2.27)	(2.21)	(1.81)
COVERAGE	-0.6384***	-0.4786***	1.3069***	1.5608***	1.9453***	2.0394***
	(7.23)	(5.11)	(10.06)	(11.50)	(19.73)	(20.11)
RPI	0.0226***	0.00772**	0.00241	-0.0115**	-0.0202***	-0.0192***
	(6.03)	(2.13)	(0.52)	(2.44)	(6.77)	(5.96)
SHTBRDEF	0.3001***	0.0951*	0.1570***	-0.1994***	-0.1431***	-0.2946***
	(5.80)	(1.71)	(2.61)	(2.76)	(4.22)	(6.02)
Intercept	-9.8282***	-6.1267***	-1.2830	1.7931	8.5451***	7.9198***
	(12.16)	(7.84)	(1.30)	(1.75)	(13.59)	(11.27)
Observations	18,070	15,703	18,070	15,703	18,070	15,703

Table 6

Multinomial Logit Regression of 3-Level Response Variable on Predictor Variables Model 2 - Market + Macroeconomic Variables Model

This table reports results from multinomial logit regressions of the 3-level Response variable on the predictor variables for the 'Market' (plus macroeconomic variables) Model 2. The 3-level Response variable is composed of the following states: Non-financial distress (NFD), financial distress (DIS), and failure (FAI). Model 2 was computed for periods t-1 and t-2 to confirm the stability over time of the displayed signs as well as the magnitude of the coefficients. The absolute value of z-statistics is reported in parentheses. *, **, *** denote significant at 10%, 5% and 1%, respectively.

Covariates	FAI V NFD		FAI V DIS		NFD V DIS	
	t-1	t-2	t-1	t-2	t-1	t-2
PRICE	-0.3019***	-0.2344***	-0.2132***	-0.1859***	0.0887***	0.0485*
	(7.65)	(5.85)	(4.62)	(3.96)	(3.05)	(1.70)
ABNRET	-0.7053***	-1.3269***	1.6494***	1.6941***	2.3548***	3.0210***
	(4.16)	(7.97)	(7.60)	(7.81)	(15.92)	(20.34)
SIZE	-0.2650***	-0.1845***	0.2291***	0.1052**	0.4941***	0.2897***
	(6.10)	(4.48)	(4.29)	(2.07)	(13.97)	(8.95)
MCTD	-1.8670***	-1.2337***	-1.3721***	-2.1018***	0.4949***	-0.8680***
	(9.18)	(5.43)	(5.58)	(6.97)	(2.86)	(3.87)
RPI	0.0103***	-0.00136	-0.00238	-0.0152***	-0.0127***	-0.0139***
	(2.68)	(0.37)	(0.51)	(3.26)	(4.16)	(4.45)
SHTBRDEF	0.1659***	-0.0198	0.0926	-0.1379**	-0.0733**	-0.1181**
	(3.44)	(0.37)	(1.64)	(1.97)	(2.14)	(2.48)
Intercept	-6.5980***	-3.8812***	4.8330***	6.8700***	11.4310***	10.7512***
	(6.88)	(4.15)	(4.09)	(5.70)	(14.71)	(13.14)
Observations	14,578	13,342	14,578	13,342	14,578	13,342

Table 7
Multinomial Logit Regression of 3-Level Response Variable on Predictor Variables Model 3 - Comprehensive Model

This table reports results from multinomial logit regressions of the 3-level Response variable on the predictor variables for the 'Comprehensive' Model 3. The 3-level Response variable is composed of the following states: Non-financial distress (NFD), financial distress (DIS), and failure (FAI). Model 3 was computed for t-1 and t-2 to confirm the stability over time of the displayed signs as well as the magnitude of the coefficients. The absolute value of z-statistics is reported in parentheses. *, **, *** denote significant at 10%, 5% and 1%, respectively.

Covariates	FAI V NFD		FAI V DIS		NFD V DIS	
	t-1	t-2	t-1	t-2	t-1	t-2
TFOTL	-1.2817***	-1.0780***	-0.4411	-0.2416	0.8406***	0.8364***
	(4.29)	(3.67)	(1.33)	(0.74)	(4.51)	(4.61)
TLTA	1.3217***	0.5879	1.0362**	0.6839	-0.2855	0.0960
	(3.58)	(1.54)	(2.46)	(1.55)	(1.07)	(0.35)
NOCREDINT	-0.4384***	-0.1936**	-0.4177***	-0.1480	0.0207	0.0456
	(4.59)	(2.36)	(3.82)	(1.49)	(0.33)	(0.72)
COVERAGE	-0.3469***	-0.1232	1.2631***	1.6784***	1.6100***	1.8016***
	(3.42)	(1.15)	(8.67)	(11.00)	(14.45)	(15.86)
RPI	0.0128***	-0.00126	0.000306	-0.0153***	-0.0125***	-0.0141***
	(3.12)	(0.32)	(0.06)	(2.94)	(3.57)	(3.75)
SHTBRDEF	0.1821***	-0.0276	0.0805	-0.2383***	-0.1017***	-0.2107***
	(3.50)	(0.48)	(1.31)	(3.07)	(2.58)	(3.73)
PRICE	-0.2425***	-0.2007***	-0.2069***	-0.1840***	0.0356	0.0167
	(5.87)	(4.76)	(4.42)	(3.80)	(1.19)	(0.57)
ABNRET	-0.5197***	-1.2226***	0.9834***	0.5839***	1.5031***	1.8065***
	(2.91)	(6.71)	(4.44)	(2.58)	(9.96)	(12.26)
SIZE	-0.1289***	-0.0959**	0.1823***	-0.1044*	0.3111***	-0.00848
	(2.77)	(2.15)	(3.08)	(1.83)	(7.45)	(0.22)
MCTD	-1.5780***	-1.1816***	-0.4365	-1.0814***	1.1416***	0.1002
	(6.58)	(4.41)	(1.50)	(3.06)	(5.36)	(0.38)
Intercept	-6.8379***	-3.4106***	2.5189*	3.5683***	9.3569***	6.9788***
	(6.42)	(3.24)	(1.93)	(2.61)	(10.47)	(7.24)
Observations	13,529	12,305	13,529	12,305	13,529	12,305

Table 8
Marginal Effects – Model 1, Model 2 and Model 3

This table reports marginal effects (in percentages) for the 'Accounting' (plus macroeconomic indicators) Model 1, for the 'Market' (plus macroeconomic indicators) Model 2, and for the 'Comprehensive' (including accounting plus macroeconomic plus market indicators) Model 3, in panels A, B, and C respectively. Columns 2 and 3 display the individual marginal effects of each variable on the likelihood that the response variable is equal to non-financial distress (j=1) one and two years prior to the observation of the event (t-1 and t-2, respectively). Columns 4 and 5 present the individual marginal effects of each variable on the probability that the outcome variable is equal to financial distress (j=2) in t-1 and t-2, respectively. Lastly, columns 6 and 7 display the individual marginal effects on the probability that the response indicator is equal to failure (j=3) in t-1 and t-2, respectively. Standard errors, obtained employing the Delta-method, are reported in parentheses. *, **, *** denote significant at 10%, 5% and 1%, respectively.

Panel A: Model 1 – Accounting model

	Pr (j = 1)		Pr (j = 2)		Pr (j = 3)	
	t-1	t-2	t-1	t-2	t-1	t-2
TFOTL	3.1273***	3.2490***	-1.5739***	-1.7531***	-1.5534***	-1.4958***
	(0.0051)	(0.0058)	(0.0039)	(0.0043)	(0.0037)	(0.0042)
TLTA	-6.0229***	-1.9115**	2.9924***	-0.4472	3.0304***	2.3584***
	(0.0071)	(0.0084)	(0.0056)	(0.0066)	(0.0049)	(0.0055)
NOCREDINT	0.9568***	0.7917***	-0.2600	-0.2694	-0.6968***	-0.5222***
	(0.0019)	(0.0021)	(0.0015)	(0.0017)	(0.0013)	(0.0013)
COVERAGE	6.1852***	7.0448***	-5.4805***	-6.5086***	-0.7051***	-0.5364***
	(0.0033)	(0.0038)	(0.0032)	(0.0036)	(0.0014)	(0.0016)
RPI	-0.0877***	-0.0716***	0.0540***	0.0609***	0.0338***	0.0108
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
SHTBRDEF	-0.8283***	-1.0601***	0.3573***	0.9361***	0.4709***	0.1241
	(0.0012)	(0.0018)	(0.0010)	(0.0016)	(0.0009)	(0.0010)

Panel B: Model 2 – Market model

	Pr (j = 1)		Pr (j = 2)		Pr (j = 3)	
	t-1	t-2	t-1	t-2	t-1	t-2
PRICE	0.7002***	0.5552***	-0.1961**	-0.1175	-0.5040***	-0.4378***
	(0.0011)	(0.0012)	(0.0009)	(0.0009)	(0.0007)	(0.0008)
ABNRET	7.5441***	11.7408***	-6.8496***	-9.7677***	-0.6948**	-1.9731***
	(0.0051)	(0.0059)	(0.0047)	(0.0055)	(0.0028)	(0.0031)
SIZE	1.7596***	1.2244***	-1.4109***	-0.9261***	-0.3488***	-0.2983***
	(0.0012)	(0.0013)	(0.0011)	(0.0011)	(0.0008)	(0.0008)
MCTD	4.1821***	-0.5926	-1.0534**	3.103***	-3.1285***	-2.5112***
	(0.0061)	(0.0085)	(0.0050)	(0.0074)	(0.0038)	(0.0044)
RPI	-0.0504***	-0.0411***	0.0354***	0.0562***	0.0150**	-0.0052
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
SHTBRDEF	-0.4523***	-0.3355	0.1809	0.3950**	0.2715***	-0.0594
	(0.0012)	(0.0018)	(0.0010)	(0.0016)	(0.0008)	(0.0010)

Panel C: Model 3 – Comprehensive model

	Pr (j = 1)		Pr (j = 2)		Pr (j = 3)	
	t-1	t-2	t-1	t-2	t-1	t-2
TFOTL	3.7638***	3.9531***	-1.8691***	-2.1635***	-1.8945***	-1.7895***
	(0.0064)	(0.0071)	(0.0048)	(0.0051)	(0.0050)	(0.0054)
TLTA	-2.5054***	-0.6939	0.3925	-0.3997	2.1127***	1.0934
	(0.0087)	(0.0101)	(0.0070)	(0.0078)	(0.0061)	(0.0069)
NOCREDINT	0.6558***	0.4331**	0.0652	-0.0894	-0.7209***	-0.3437**
	(0.0021)	(0.0022)	(0.0017)	(0.0018)	(0.0016)	(0.0015)
COVERAGE	4.2914***	4.9695***	-4.1569***	-5.1283***	-0.1347	0.1585
	(0.0031)	(0.0037)	(0.0031)	(0.0035)	(0.0016)	(0.0019)

RPI	-0.0472***	-0.0352***	0.0294***	0.0405***	0.0178***	-0.0053
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
SHTBRDEF	-0.4928***	-0.5136***	0.2187***	0.6188***	0.2741***	-0.0952
	(0.0012)	(0.0018)	(0.0010)	(0.0016)	(0.0009)	(0.0011)
PRICE	0.4198***	0.3679***	-0.0276	-0.0051	-0.3922***	-0.3627***
	(0.0010)	(0.0011)	(0.0008)	(0.0008)	(0.0007)	(0.0008)
ABNRET	4.2773***	6.7551***	-3.8271***	-4.9082***	-0.4503	-1.8470***
	(0.0044)	(0.0049)	(0.0039)	(0.0040)	(0.0029)	(0.0034)
SIZE	0.9149***	0.1322	-0.7864***	0.0447	-0.1285	-0.1768**
	(0.0012)	(0.0013)	(0.0011)	(0.0011)	(0.0008)	(0.0008)
MCTD	4.887***	2.1706**	-2.5830***	-0.0352	-2.3035***	-2.1352***
	(0.0065)	(0.0086)	(0.0055)	(0.0074)	(0.0041)	(0.0050)

Table 9

Bias-Adjusted Classification Accuracy Table in t-1

This table reports a biased-adjusted classification table for predicted frequencies in percentage for the 'Accounting' (plus macroeconomic indicators) Model 1, the 'Market' (plus macroeconomic indicators' model) Model 2, and the 'Comprehensive' Model 3 (that includes the three types of variables) in Panels A, B and C, respectively. The results are obtained using information one year prior to the observation of the event of interest (period t-1). The first column compares the observed responses with the first row of predicted outcomes. Thus, the diagonal line (replicated in the last column 'Correct') shows the three individual models' correct predictions for non-financially distressed/failed (NFD), financially distressed (DIS) and failed (FAI) companies. In addition, the table presents overall classification accuracy percentages by model in order to compare relative performances.

	Predicted				
Observed	NFD	DIS	FAI	Total	Correct
Panel A: Model 1					
NFD	80.83	8.15	11.02	100.00	80.83
DIS	8.42	75.25	16.34	100.00	75.25
FAI	15.56	17.62	66.83	100.00	66.83
		Overall Classification Accuracy			80.40
Panel B: Model 2					
NFD	79.25	9.65	11.11	100.00	79.25
DIS	8.48	73.81	17.71	100.00	73.81
FAI	12.64	18.13	69.23	100.00	69.23
		Overall Classification Accuracy			78.86
Panel C: Model 3					
NFD	85.45	5.46	9.09	100.00	85.45
DIS	5.39	80.29	14.32	100.00	80.29
FAI	10.98	14.02	75.00	100.00	75.00
		Overall Classification Accuracy			85.08

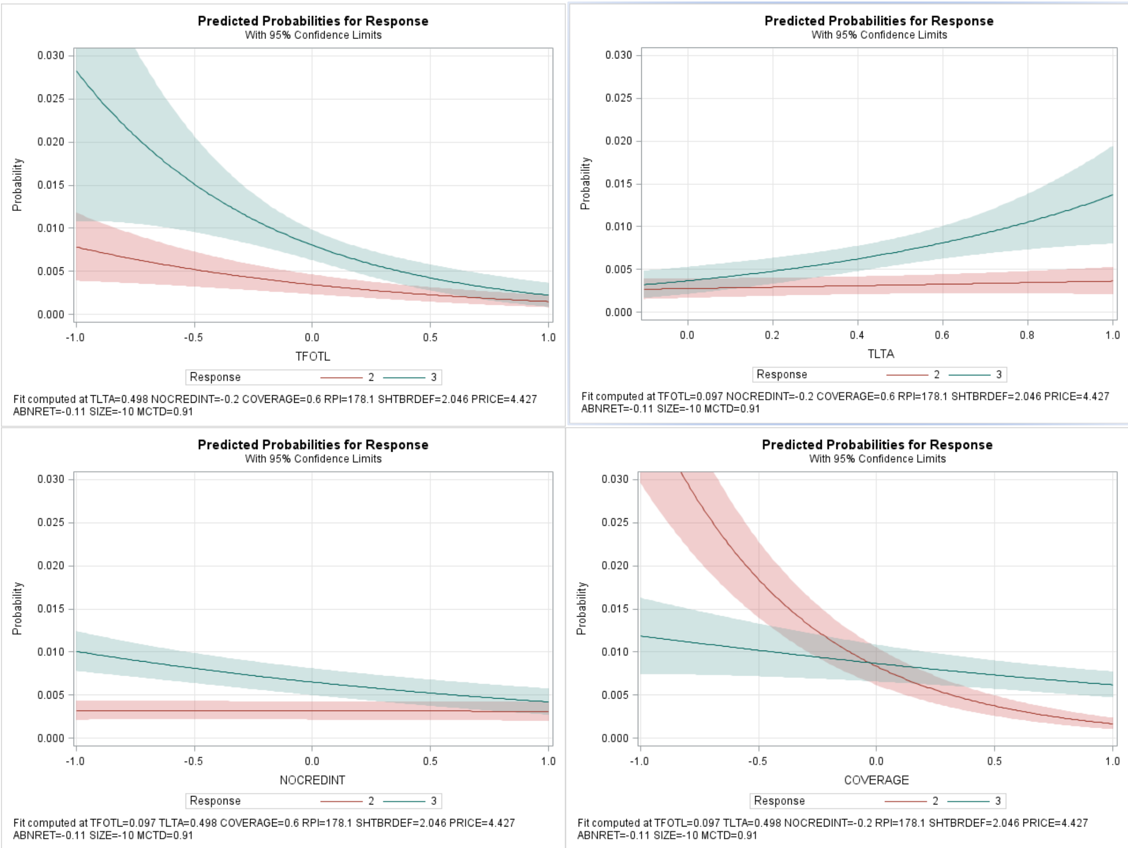

Figure 1

Changes in Predicted Probabilities – Accounting Ratios

The figure shows the vectors representing variations in predicted probabilities for Financial distress (Response = 2) and Corporate Failure (Response = 3) resulting from individual changes in the levels of the accounting ratios Total Funds from Operations to Total Liabilities (TFOTL), Total Liabilities to Total Assets (TLTA), the No Credit Interval (NOCREDINT), and Interest Coverage (COVERAGE), while keeping all the other covariates constant at their mean values.

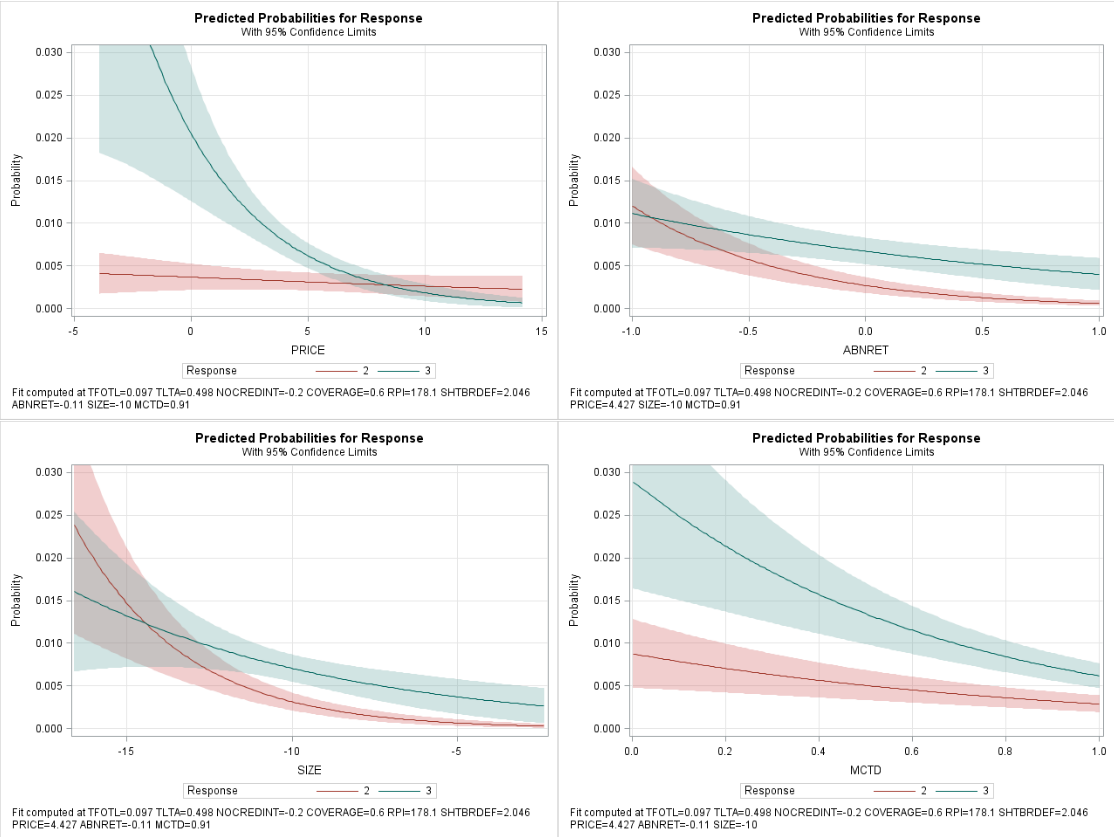

Figure 2

Changes in Predicted Probabilities – Market Variables

The figure shows the vectors representing variations in predicted probabilities for Financial distress (Response = 2) and Corporate Failure (Response = 3) resulting from individual changes in the levels of the market independent variables Share Price (PRICE), Abnormal Returns (ABNRET), the relative Size of the company (SIZE), and the ratio Market Capitalisation to Total Debt (MCTD), while keeping all the other covariates constant at their mean values.

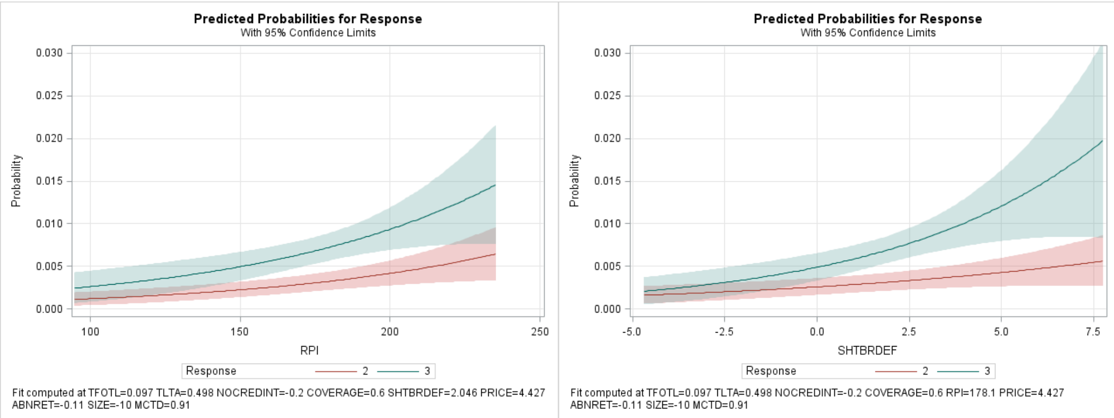

Figure 3

Changes in Predicted Probabilities – Macroeconomic indicators

The figure shows the vectors representing variations in predicted probabilities for Financial distress (Response = 2) and Corporate Failure (Response = 3) resulting from individual changes in the levels of the macroeconomic independent variables Retail Price Index (RPI), and the proxy for interest rates, the Deflated Short Term Bill Rate (SHTBRDEF), while keeping all the other covariates constant at their mean values.