# Polytomous Response Financial Distress Models: the role of Accounting, Market and Macroeconomic Variables

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**ABSTRACT**

This paper uses polytomous response logit models to investigate financial distress and bankruptcy across three states for listed companies over a period in excess of 30 years and utilising over 20,000 company year observations. Our results suggest that combining accounting, market and macroeconomic variables enhances the performance, accuracy and timeliness of models explaining corporate credit risk. Additionally, we show the usefulness of employing marginal effects to assess the impact of individual covariates on the probability of falling into each of the states. These results were confirmed by the analysis of vectors of changes in predicted probabilities that follow a change in the level of individual covariates.

Keywords:
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## 1. Introduction.

Models for the prediction of corporate financial distress/bankruptcy have attracted considerable interest amongst academic as well as practitioners over the last four decades. Lenders and other investors value timely information regarding the probability of corporates 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 macroeconomy and the time at which data is available. 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. The relative advantages of binary logit models have been widely discussed since Efron's (1975) seminal theoretical paper. Jones (1987) provides a discussion of their application in the field of bankruptcy prediction, and Maddala (1991) has reviewed the role of logit, probit, and discriminant analysis in accounting research. 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." (p8) However, in practice, this binary representation fails to take account of the complexities inherent in the nature of financial distress and bankruptcy.

This paper builds upon the findings of Hernandez Tinoco and Wilson (2013), where a binary logit regression model is employed to enhance the accuracy of financial distress prediction models. The parsimonious character of their previous model finds justification in the stated objective of having utility for practitioners (and academics) to easily detect early signs of financial distress in order to avoid the costs of advanced states such as firm bankruptcy. However, the present study takes a different approach. The novelty of this paper, relative to Hernandez Tinoco and Wilson (2013) as well as to other research works in this field, 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). 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 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.[1]

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 works try 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 works (e.g., Lau, 1987).

Furthermore, there are no studies to date that deal with the issue of the *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

[1] 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.

coefficients obtained are interpreted according to their respective signs. The model yielded a high predictive accuracy, even though the coefficients' signs showed a number of inconsistencies. The most likely reason is that marginal effects (which do not necessarily yield the same signs as the coefficients) are a substantially more reliable measure to interpret the effects of individual covariates in a multinomial logit model. Similarly, Johnsen and Melicher (1994) develop a multinomial logit model for predicting corporate bankruptcy and financial distress. They us 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 misclassification errors. However, again the magnitudes of the effects of individual variables are not considered.

In this study we consider corporate default as a dynamic process by including the above three possible states (financially sound; firms in financial distress; and failed firms) in a generalised or polytomous logit regression model. Unlike previous studies, by estimating and examining marginal effects, derived from the output of the polytomous response model, we are able to overcome the interpretation issues identified by Leclere (1999) and address a critical gap in the literature. Moreover, 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) are presented. This allows us to further analyse the individual effects of all types of variables in the models, providing additional insights into their patterns of behaviour, as well as additional support to the interpretation of the marginal effects.

Additionally, in prior polytomous response financial distress/bankruptcy prediction models only accounting measures have been included as independent variables. However, there are strong grounds for believing that such models would benefit from utilising the information contained in market (e.g. abnormal return and market capitalisation) and macroeconomic (e.g. inflation and interest rates) 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. We demonstrate that the combination of information contained in market variables, financial statements, and macroeconomic indicators is capable of enhancing the performance of financial distress models.

Our study formally presents the methodology for the estimation of marginal effects and then employs the resulting output in order to perform an original comparative analysis relative to the coefficient estimates obtained from a polytomous response (three-state) generalised logit procedure. Given the interpretation of the formal development of marginal effects derived from the generalised logit methodology, our empirical results indicate that marginal effects are more useful and reliable (from a statistical point of view) than the coefficient estimates to effectively detect and predict financial distress and failure from financial stability.

Furthermore, 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 (Taffler, 1982; and 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.

It is also the case that 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) and 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 is employed.

Finally, unlike previous studies we adjust for outlying observations in the accounting variables by transforming the ratios using the 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.

This paper, therefore, makes three major contributions to the financial distress/bankruptcy prediction literature. First not only do we utilise the multinomial logit model to examine financial distress and bankruptcy across three states, but also we provide the first analysis of marginal effects of a range of variables on bankruptcy and financial distress prediction. Second, we use a range of accounting, market and macroeconomic variables as possible predictors of bankruptcy and financial distress, providing a more realistic analysis of factors and interactions that affect firm failure. Third, we address a number of shortcomings in the prior literature in terms of definition of firm states, 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 section 4, together with the hypotheses to be tested. Results are presented and discussed in section 5 and section 6 provides a conclusion.

## 2. Outcome Definition.

### 2.1 Outcome Definition

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 (especially for financial distress and failure), as required by the polytomous response logit methodology. The main reason is that a major purpose of this study is not only to provide a timely and accurate financial distress prediction model, but also to investigate the behaviour of the probabilities of falling into one of the three mutually exclusive states in the presence of different values for the regressors included in the models (accounting, market and macroeconomic variables). Therefore, 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 in the present study. 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[2] 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*[3].

The definition of corporate failure employs the 2012 London Share Price Database (LSPD) and is based on Christidis & Gregory (2010). A firm is classified as failed if its status is suspended, in liquidation or voluntary liquidation, when its quotation has been suspended for more than three years, when 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.

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**

The paper investigates the impact of the different types of variables (individually and as groups) on the outcome probabilities of falling into one of the mutually exclusive three-states. We investigate how the independent variables impact on the changes in predicted probabilities from one state to another conditional on a base outcome. This is important for academics as well as practitioners, as it provides new insights on practical and theoretical issues such as: what is the effect of a negative change of magnitude $z$ of the accounting ratio $x$ (while keeping the levels of all other independent variables constant) on the probability that a corporation will be in a state of failure in the future *given* that it is now in a state of financial distress (or conditional upon already

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

facing a perilous financial situation[4])?; or even, what is the *magnitude* of the effect of variable $x$ on this probability *relative* to variable $y$? Through the answers to these questions, practitioners can focus on the variables that deserve particular attention in order to understand what leads a firm to advance to a more serious state of financial distress, with failure being the most extreme and costly outcome. Marginal effects derived from the output of the polytomous response model are estimated and reported. Furthermore, vectors of predicted probabilities are plotted to confirm the effects of all types of variables in the models and to provide additional support to the interpretation of the marginal effects.

Additionally, we evaluate the contribution of non-accounting variables to the accuracy of financial distress models for listed firms. It is investigated whether the combination of accounting and market variables enhance the goodness-of-fit of the models by estimating an 'Accounting only model,' a 'Market only' model and a 'Comprehensive' model that includes accounting, market and macroeconomic data (using information one and two years preceding the event of interest). The performance of these regressors in dynamic financial distress models has been assessed in a very small number of prior research works. Furthermore, our models include controls for changes in the macroeconomic environment. It is of relevance to investigate the potential role of market variables in a generalized or polytomous response logit model, since they are likely to complement the role played by accounting information. Given the real costs associated with financial distress and corporate failure, market data is included in order to highlight the timeliness and, therefore, the practical value of the models.

Furthermore, given the continuous availability of market data, it is expected that market variables are relevant to the timeliness of the output obtained from the models by providing early warnings about financial stress (therefore allowing corporate managers to take preventive actions to avoid failure, as well as corrective actions to tackle financial distress at early stages to avert the costs related to these events).

Furthermore, 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 few previous research studies based on the multinomial logit methodology for the construction of financial distress prediction models, employed almost symmetric (or balanced) panels of data consisting of either an approximately equal number of observations for each category, or an extremely small number of observations. The sample size as well as the proportions of the different outcomes relative to the database size and to the

[4] Defined by two conditions: a lower level of EBITDA relative to financial commitments, and a decrease in market value (both for two consecutive years), which could put the normal operations of the firm at serious risk.

proportions among outcomes results in alterations to individual observations' predicted probabilities (Zmijewski, 1984). 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[5] were computed. These (unreported) results suggest that multicollinearity is not a problem in this study[6].

## 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. This type of model can be referred to as a multinomial logit model because the probability distribution for the response variable is assumed to be a multinomial distribution. The development of the model is as follows. Suppose that there are $J$ categorical outcomes, with the running index $j$ = 1, 2,…, $J$. Next, let $p_{ij}$ be the probability that observation $i$ falls into outcome $j$. The model is thus given by

$$ln\frac{p_{ij}}{p_{iJ}} = \boldsymbol{\beta}_j\mathbf{x}_i' ,$$

Where $\mathbf{x}_i'$ is a column vector of independent variables describing observation $i$, and $\boldsymbol{\beta}_j$ is a row vector of coefficients for outcome $j$. These equations are solved to yield

$$\text{Prob}(Y_i = j|\mathbf{x}_i) = P_{ij} = \frac{\exp(\beta_k\mathbf{x}'_i)}{1+\sum_{k=2}^{J}\exp(\beta_k\mathbf{x}'_i)}$$

where $j$ = 1, 2,…, $J$

Now, given that the probabilities for all $J$ outcomes must sum to 1,

$$P_{ij} = \frac{1}{1+\sum_{k=2}^{J}\exp(\boldsymbol{\beta}_k\mathbf{x}_i')}$$

[5] 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 $i$th regressor on all the other regressors. The VIF values of all the independent variables in the study are below 5, suggesting that multicollinearty is not an issue in our models.
[6] Results are available upon request.

therefore, in the general form of the model, only *J* parameter vectors are required to determine the *J*+1 probabilities.

Next, in a multinomial logit model, each outcome is compared to a base outcome, so assuming that there are *J* categorical outcomes and – without loss of generality – the base outcome is defined as 1 (still with *j*=1,2,…,*J*), then the probability that the response for the *i*th observation is equal to the *j*th outcome is

$$\text{Prob}(Y_i = j|\mathbf{x}_i) = P_{ij} = \begin{cases} \dfrac{1}{1+\sum_{k=2}^{J}\exp(\boldsymbol{\beta}_k\mathbf{x}_i')}, & if\ \ i=1 \\ \dfrac{\exp(\boldsymbol{\beta}_j\mathbf{x}_i')}{1+\sum_{k=2}^{J}\exp(\boldsymbol{\beta}_k\mathbf{x}_i')}, & if\ \ i>1 \end{cases}$$

This methodology was employed in the present study to solve the equations for different base outcomes.

The log-likelihood is derived by defining, for each individual (observation), $d_{ij} = 1$ if outcome *j* is occurring for observation *i*, and 0 otherwise, for the *J+1* possible outcomes. Thus, for each observation *i*, one and only one of the $d_{ij}$'s is 1. The log-likelihood is thus a generalisation of that for the binomial logit (and probit) model.

$$\ln L = \sum_{i=1}^{n}\sum_{j=1}^{J} d_{ij}\ln\text{Prob}(Y_i = j|\mathbf{x}_i)$$

where $d_{ij} = \begin{cases} 1\,, & if\ y_i = j \\ 0, & otherwise \end{cases}$

We employ the Newton-Raphson maximum likelihood optimisation algorithm.

However, the coefficient parameters of a multinomial logit model are difficult to interpret. In a linear model, they can be directly interpreted as marginal effects of the predictor variables on the outcome variable. For instance, in a linear model of the form

$z = \beta_0 + \beta_1\mathbf{x}_1 + \beta_2\mathbf{x}_2 + \cdots + \epsilon$

$\beta_1$ can be taken as capturing the impact of a one-unit increase in $\mathbf{x}_1$on $z$. Nevertheless, $\beta_1$ is just the marginal effect of $z$ with respect to $\mathbf{x}_1$, following

$$\frac{\partial_y}{\partial \mathbf{x}_k} = \beta_k$$

From this equation, it can be observed that the effect of $\mathbf{x}$ on $z$ is a derivative. Hence, the natural interpretation of a linear regression model's marginal effects through derivatives stems from the linearity of the model: in this example the marginal effect of $\mathbf{x}_k$ on $z$ is given by $\beta_k$. This is true regardless of the values of $\mathbf{x}_k$ or $z$ under consideration or the values of other variables in the model.

This is not the case for polytomous response logit models. Neither the magnitude nor the sign of the parameters possess a natural meaning that can be directly interpreted. Nevertheless, the relevant estimations can be obtained using appropriate transformations of the coefficients. 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.

Formally we can express marginal effects as follows. First, let the probability of outcome *j* in response to a change in a specific variable $\mathbf{x}$, specific to outcome *j* be denoted by

$$\frac{\partial P_j}{\partial \mathbf{x}_j} = \left(1 - P_j\right) P_j \boldsymbol{\beta}_j$$

Next, taking into account that an identical change in the specific variable will occur for all outcomes in which the variable appears as an outcome specific variable, it is necessary to employ the cross-derivative of the probability of outcome *j* occurring in response to a change in the variable, specific to outcome *k*

$$\frac{\partial P_j}{\partial \mathbf{x}_k} = -P_j P_k \boldsymbol{\beta}_k$$

the sum over all outcomes $k \neq j$ is thus

$$\sum_{k \neq j} \frac{\partial P_j}{\partial \mathbf{x}_k} = -P_j \sum_{k \neq j} P_k \boldsymbol{\beta}_k$$

finally, the sum over all outcomes including *j* is denoted by

$$\frac{\partial P_j}{\partial \mathbf{x}_k} = P_j(1 - P_j)\boldsymbol{\beta}_j - \sum_{k \neq j} P_j P_k \boldsymbol{\beta}_k$$

$$= P_j \boldsymbol{\beta}_k - \sum_{k=1}^{J} P_j P_k \boldsymbol{\beta}_k$$

$$= P_j \left[ \boldsymbol{\beta}_j - \sum_{k=1}^{J} P_k \boldsymbol{\beta}_k \right]$$

$$= P_j [\boldsymbol{\beta}_j - \overline{\boldsymbol{\beta}}]$$

where $\overline{\boldsymbol{\beta}}$ is the probability weighted average of the outcome specific variable parameters.

Notice that the marginal effect of an independent variable $\mathbf{x}_i$ on the occurrence of outcome *j* incorporates the parameters of *k* as well as the parameters of all the other outcomes: it is shown that the derivative of the probability with respect to a change in a variable equals the probability times the amount by which the variable's coefficient for that outcome exceeds the probability weighted average variable coefficient over all outcomes. Furthermore, it is necessary to highlight that – without loss of generality – for any individual $\mathbf{x}_{ik}$, $\frac{\partial P_{ij}}{\partial \mathbf{x}_{ik}}$ need not display the same sign as $\boldsymbol{\beta}_{jk}$.

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. As required by the statistical software used to estimate this type of generalised logit model, individual identifiers were assigned to each of these three potential outcomes of the Response variable: the state of Non-financial distress is denoted by the identifier Response = 1, the state of Financial distress by the identifier Response = 2, and the state of Corporate failure by the identifier Response = 3. In other words, a firm-year observation can fall into one of the following categories: Non-financial distress, Financial distress and Corporate failure. The multinomial function coefficients resulting from the three-level response logit model 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* that can be selected among the options depending on the objectives of the analysis.

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 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 was selected as the base outcome of the multinomial logit regression, as this category can be considered as a transition point between two extremes in a process. And in order to obtain the coefficient estimates (as well as AMEs) for the third pair of categories, FAI versus DIS, which further tests the extent to which the model variables discriminate between two potential outcomes, a second multinomial logit function was 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 a 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*). Also, information two years before the relevant event (*t-2*) is utilised.

Marginal effects are presented as a more appropriate means for interpreting the effect of the 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 primary premise that the latter are a more appropriate measure to evaluate and interpret polytomous response logistic regression models, 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 and Ex-ante Hypotheses.

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. This section explains the role of each variable in the models and discusses their relevance in the polytomous response logit regression models.

### 4.1 Accounting Ratios.

Four accounting variables were retained in the final models: Total Funds from Operations to Total Liabilities, Total Liabilities to Total Assets, the No Credit Interval, and Interest Coverage. The first ratio, Total Funds from Operations to Total Liabilities (TFOTL) is reflects the capability of a firm to repay its financial commitments from its operations. Therefore, a firm with a higher the value of TFOTL is less likely to be in a state of financial distress/failure. The second ratio Total Liabilities to Total Assets (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 firm's financial risk and, therefore, the lower its probability of financial distress/failure. The third variable, the No-credit interval (NOCREDINT) 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, Interest Coverage (COVERAGE), 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. Further, all of the above accounting ratios were converted by employing the TANH function 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. The real line of the variables can be mapped onto [-1, 1] following the TANH transformation.

### 4.2 Market Variables.

Four market variables were retained in the multinomial logit final models 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[7]. The first market variable is the price of the firm's

[7] 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.

equity (PRICE). 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 lagged cumulative abnormal return (ABNRET). To incorporate this variable in a financial distress model, the past abnormal return for each firm in year *t* was computed as the difference between the cumulative monthly return for the twelve months preceding the year where financial distress occurred, and the cumulative monthly return on the FTSE All Share Index during the same period (the same procedure was replicated for both periods *t-1* and *t-2*). In line with the findings of previous empirical studies[8], 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). 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 Market Capitalisation to Total Debt (MCTD). It is expected that a low level of this variable should result in a high probability of financial distress/failure.

### 4.3 Macroeconomic Indicators.

Two macroeconomic indicators were retained in all 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, both measured on an annual basis. The RPI 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 Short Term Treasury Bill Rate Deflated (SHTBRDEF), which reflects the annualised 'real' short-term rate of UK Treasury Bills. This variable is captures the impact of the 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.

### 4.4 Implications for the Comparison of Response categories in the Models.

The variables incorporated in the models can be further classified into those that have a negative impact on the likelihood of state NFD occurring and a positive effect on the likelihood

[8] See Dichev (1998), Shumway (2001) and Hernandez Tinoco and Wilson (2013).

of falling into category DIS and FAI, on the one hand, and those having the opposite effects, on the other. Consequently, to better understand and present the effects of individual regressors on the possible combinations of outcomes (NFD versus DIS, FAI versus DIS, and FAI versus NFD) it is useful to simplify this additional classification of variables into those that decrease (negatively affect) the likelihood of falling into the financial distress (DIS) and corporate failure (FAI) categories, and those that increase (positively affect) the likelihood of falling into the DIS and FAI categories. All types of variables included, the first group is composed by: TFOTL, NOCREDINT, COVERAGE, PRICE ABNRET, SIZE, and MCTD. And the second group includes the variables: TLTA, RPI, and SHTBRDEF.

**INSERT TABLE 2 ABOUT HERE**

**INSERT TABLE 3 ABOUT HERE**

**INSERT TABLE 4 ABOUT HERE**

Tables 2 to 4 present summary statistics for Model 1 (financial statement 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)[9].

Variables are chosen to be included in each of the models to allow us to meet the main objectives of our study: on the one hand, the aim is to present new insights on the effects of the individual variables on the vectors of transition predicted probabilities of a firm reaching a particular state *conditionally* on being in a different one, as well as on each variable's marginal effect of the on the probability of falling into one of the three categories; and, on the other hand, to test whether the combination of accounting, macroeconomic and market variables is able to increase the goodness-of-fit and overall performance (to correctly discriminate and predict outcomes). Table 5 presents tests to assess the fit of the model: it reports 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 conditionally on non-financial distress) on the three models, all of which include macroeconomic

[9] 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.

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. The tests displayed in Table 5 are performed for periods *t-1* and *t-2*, using information one and two years preceding the relevant outcome.

**INSERT TABLE 5 ABOUT HERE**

Panels A-C of Table 5 show likelihood-ratio test results to confirm the significance of the predictors to the model: the $\chi^2$ can be interpreted as an overall statistic that provides relevant information on which independent variables significantly predict the outcome category. It tests the null hypothesis that a given individual variable does not affect the outcome of the Response variable. This test shows that, in *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. Panel D, on the other hand, reports linear hypothesis results that test the null hypothesis that all 10 pairs of coefficients for financial distress (DIS) and corporate failure (FAI)[10] conditionally on nonfinancial distress (NFD) are equal. It yields a Wald $\chi^2$ equal to 181.2717 with 10 degrees of freedom, producing a *p*-value equal to 0.0001. It can be concluded that the coefficients for DIS (versus NFD) and FAI (versus NFD) are not the same. Had this test 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. The rejection of this supports our decision to use three possible states for analysis.

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 6 to 8. Three *ex-ante*

[10] 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.

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 6 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 financial statement ratios only. Table 7 reports results for Model 2 or the 'Market' model. Finally, Table 8 reports results for the 'Comprehensive' model or Model 3, which combines both types of variables in a single logit model of financial distress/failure. Furthermore, all three models incorporate proxies for the macroeconomic environment in order to control for macro dependent dynamics: RPI and SHTBRDEF.

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 were based on employing their values in the year preceding the event date. The same procedure was employed to estimate coefficients and average marginal effects for the period *t-2*.

**INSERT TABLE 6 ABOUT HERE**

**4.5 Multinomial Function Coefficients.**

Table 6 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 the *ex-ante* assumptions, 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 almost all of them are able to reliably discriminate between the pair of categories. Again, this is in line with the *ex-ante* assumptions of the study, given that, although not as extreme as the previous comparison, this pair includes two 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 similar outcomes (there is more proximity or similarity between the pair Corporate failure and Financial distress than between either of the other pairs of outcomes), the accounting model presented in this study displays a sound performance. Further, it is interesting to note that, for both pairs NFD versus DIS and FAI versus DIS, COVERAGE exhibits the highest coefficient in magnitude followed by TLTA, TFOTL, and NOCREDINT, in order of importance. This rank is not the same for the pair that compares the most extreme categories (FAI versus NFD). In this case the coefficient with the highest magnitude is TLTA, followed by TFOTL, COVERAGE and NOCREDINT, suggesting that the importance of the coefficients depends on the specific comparison pair, and that TLTA is more powerful in discriminating between extreme outcomes than COVERAGE, which performs better when the outcomes to be compared are more similar. However, the fact that the sign of the variable COVERAGE (concerning the pair FAI versus DIS) does not display the expected sign must be highlighted: in contrast with these results, it was previously posited that an increasing level of this covariate would have a negative effect on the likelihood of falling into the Corporate failure category versus falling into the Financial distress category. Finally, the coefficients obtained when the model was estimating using information at *t-2* show a similar pattern.

**INSERT TABLE 7 ABOUT HERE**

The multinomial function coefficient estimates for the 'Market' model (Model 2) are shown in Table 7. 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 correct 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, only the macroeconomic indicator SHTBRDEF displays lower statistical significance (5%).

The marginal decrease in performance (suggested by the lower statistical significance of the proxy for interest rates) reflects the fact that the outcomes' proximity is increased. This comparison indicates that 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. 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 failure category versus falling into the financial distress category. In the case of RPI it was assumed that an increase in inflation would have a positive effect on the likelihood of failure, given a current strained financial condition. From this analysis, it can be concluded that the accounting model discriminates better between this pair of categories. On the other hand, an analysis of the magnitudes of the coefficients shows that, for the pair NFD versus DIS, ABNRET can be ranked in first place followed by MCTD, SIZE and PRICE. This order is different for the pair FAI versus NFD: MCTD has the largest coefficient in absolute terms followed by ABNRET, PRICE, and SIZE, suggesting that residual returns might have an important role in discriminating between extreme outcomes. Unsurprisingly, the statistical significance of some of the variables decreases when the model is estimating using information at *t-2*.

**INSERT TABLE 8 ABOUT HERE**

Table 8 presents results for the 'Comprehensive' model. As expected, 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. An assessment of the coefficient magnitudes reveals that, for this comparison pair, the market variable MCTD can be ranked in first position followed by TLTA, TFOTL, ABNRET and NOCREDINT, which might indicate the order of importance of individual variables to discriminate between failed and financially sound companies. 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.

Unsurprisingly, the pair that combines the categories FAI and DIS yields only 6 statistically significant variables: the market variables PRICE, ABNRET, and SIZE (all of them at the 1% level), and 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 this study's *ex-ante* assumptions: 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. An analysis of the magnitude of the coefficients based on their absolute values reveals that the top five is composed by the accounting variable COVERAGE (although with an unexpected sign), followed by TLTA, ABNRET (also displaying an unexpected sign), TFOTL and MCTD.

The above analysis of the multinomial function coefficient 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.

Before moving on to the analysis of the average marginal effects, we formally assess the goodness-of-fit of individual models, employing a set of measures as shown in Table 9.

**INSERT TABLE 9 ABOUT HERE**

### 4.6 Model Fit Statistics.

Table 9 reports model fit statistics. To evaluate the goodness-of-fit of each model used, a set of complementary measures is employed. First we consider Cox and Snell's R-squared and Nagelkerke's Max-rescaled R-squared. For both, the higher the value, the better the model's goodness-of-fit[11]. Next, this is the first study on financial distress/failure models that employs measures using the Akaike's information criterion and the Schwartz's Bayesian criterion in order to compare fit statistics between models[12]. These criteria are useful in cases where the main objective is to compare models (with different sets of regressors) for the same data. The methodology used is the following: First, for both criteria (Akaike and Schwartz information criteria), statistics are estimated for an intercept only model and for a model that incorporates the relevant independent variables. Next, given that a lower value of the 'intercept plus predictors' statistic relative to the 'intercept only' statistic indicates a better fit of a given model[13], the difference is calculated and presented in the tables. Therefore, the higher this difference (shown in Table 9) the greater the improvement of the goodness-of-fit resulting from the inclusion of the specific model's independent variables. The chi-square statistics is the result of the likelihood ratio test and tests the *joint* effect of the independent variables included. Thus, small *p*-values (e.g., $p<0.05$) reject the null hypothesis that all slope parameters equal zero ($H_0\colon \boldsymbol{\beta} = \mathbf{0}$). Finally, Deviance and Pearson statistics are also reported. For both tests, large *p*-values suggest the null hypothesis that the model fits should not be rejected.

An analysis of the measures shown in Table 9 indicates that, overall, the 'Comprehensive model' or Model 3, that includes the three types of variables (accounting, market, and macroeconomic), yields the best goodness-of-fit statistics: Model 3 displays the highest Cox and Snell's R-squared and Nagelkerke's Max-rescaled R-squared statistics, as well as the highest differences between the 'intercept plus predictors' statistic and the 'intercept only' statistic in both the Akaike information and the Schwartz Bayesian criteria, which indicates that Model 3 contains the set of independent variables that produces the largest improvement of goodness-of-fit statistics. Furthermore, the $\chi^2$ statistic has a small *p*-value ($p<0.0001$), indicating that there is enough evidence for rejecting the null hypothesis of all slope parameters being equal to zero. In other words, it unambiguously suggests that the overall impact of the independent variables is different from zero. Moreover, with regard to the Deviance and Pearson statistics, the tests' large *p*-values (e.g., $p<1.0000$) suggest that the null hypothesis that the model fits the data well should not be rejected. This analysis applies when Model 3 is estimated in both periods *t-1* and *t-2*, although a marginal decrease in the levels of the statistics can be perceived, which is not unexpected, given that, in *t-2*, the models are estimated using information two years before the event of interest. A similar analysis of Models 1 and 2 (the Accounting and Market models,

[11] See Cox and Snell (1989) and Nagelkerke (1991).

[12] The Akaike information criterion and the Schwartz's information criterion are two distinct approaches to adjust the -2 Log L statistic for the number of terms in the model and the number of observations employed.

[13] In other words, a lower value of the 'intercept plus predictors' statistic relative to the 'intercept only' statistic indicates the model with predictors is superior to the 'intercept only' model.

respectively) shows that there is sufficient evidence to conclude that they both have positive goodness-of-fit statistics. The differences in model fit statistics are only marginal, with Model 1 showing slightly higher levels for the first four measures (Cox and Snell's R-squared is an exception, as Model 2 displays a marginally higher value) when the model is estimated using information one as well as two years preceding the observation of the relevant event. Nevertheless, Model 1 shows lower magnitudes for the Deviance and Pearson statistics in both *t-1* and *t-2*, even though their respective *p*-values provide clear evidence suggesting that both models fit the data. In summary, through the comparison of the Accounting and the Market model's statistics it can be concluded that both models fit the data well; however, the evidence is insufficient to positively ascertain the superiority of one over the other.

### 4.7 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. Predicted probabilities were produced by plotting vectors that represent the changes in the predicted probabilities of falling into the financial distress and corporate failure 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 10 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 that there is a strong similarity with regard to the previously reported coefficient estimates: the individual average marginal effects (AME) relative to the probability of falling into the FAI category (Response = 3) display the same ranking (as the coefficients for the pair Corporate failure versus Non-financial distress) based on their absolute levels or magnitude. The same analysis can be applied to the marginal effects corresponding to the probability of falling into the NFD category (Response = 1) relative to the coefficients obtained for the pair NFD versus DIS. With respect to the marginal effects for the probability of falling into the DIS category (Response = 2) - apart from a change of ranking of the variables NOCREDINT and SHTBRDEF from the 4$^{th}$ and 5$^{th}$ places to the 5$^{th}$ and 4$^{th}$ places, respectively – 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). Next, a similar conclusion can be obtained for the analysis of Model 2 (panel B): The ranking of the variables based on the magnitude of the AMEs is very similar for the probability that Response = 1 (relative to the pair

NFS versus DIS) and Response = 2 (relative to the pair FAI versus DIS). As to the probability that Response = 3, it can be observed that PRICE occupies first place in the ranking followed by MCTD, ABNRET, and SIZE. Most importantly, 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 DIS).

**INSERT TABLE 10 ABOUT HERE**

Panel C presents marginal effects (on a percentage basis) of the covariates in Model 3, the comprehensive model. From the analysis of the average marginal effects it can be observed that the ranking, based on their absolute magnitude, is somewhat different relative to the previously reported ranking based on the multinomial function coefficient estimates. The individual average marginal effects (AME) relative to the probability of falling into the NFD category (Response = 1) are highest for the market variable MCTD, which is followed by COVERAGE, ABNRET, TFOTL, TLTA and SIZE. There is an equal number of market and accounting variables in the first six places of the ranking, with two macroeconomic variables entering the top three. Moreover, it is very important to highlight the fact that all variables display the expected signs and are statistically significant at 1%. Next, an analysis of the average marginal effects corresponding to the probability of falling into the DIS category (or Response = 2), yields the following ranking (also based on the absolute magnitudes of the AMEs): the accounting variable COVERAGE possesses the highest value of the AME, followed by the market variables ABNRET and MCTD. TFOTL, SIZE and TLTA occupy the next places. Again, two market variables entered the top three, suggesting that ABNRET and MCTD contain a high degree of information useful to estimate the probability of a firm falling into the NFD as well as DIS categories. Above all, the procedure employed to estimate AMEs yields 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), the analysis of the absolute magnitudes of the AMEs yields the following ranking: MCTD occupies the first place followed by TLTA, TFOTL, NOCREDINT, ABNRET and PRICE. In this category there are three accounting variables in the top four, which suggests that financial ratios contain a high degree of useful information to predict FAI (corporate failure). Furthermore, seven out of ten of the comprehensive model's covariates are significant at 1%, which indicates a high degree of reliability of the AMEs estimates. Importantly, 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 decrease of 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 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 of the marginal effects estimation method and the usefulness of the AMEs reported in the present study.

Figure 1 shows a graphical representation of the average marginal effects for each covariate in the comprehensive model (Model 3) on the probability of the Response variable being equal to NFD (Response = 1), DIS (Response = 2), and FAI (Response = 3), respectively, in period (*t-1*)[14]. Each plot contains vertical lines dividing the figures into Accounting (Acc), Macroeconomic (Mac) and Market (Mkt) variables, where Acc1 = TFOTL, Acc2 = TLTA, Acc3 = NOCREDINT, Acc4 = COVERAGE, Mac1 = RPI, Mac2 = SHTBRDEF, Mkt1 = PRICE, Mkt2 = ABNRET, Mkt3 = SIZE and Mkt4 = MCTD. Additionally, the horizontal line divides the figures into positive and negative AMEs on the respective response indicator. The purpose of Figure 1 is to facilitate the analysis of the directionality and magnitude (by category) of the AMEs in Model 3 by presenting a graphic representation of the effects of individual AMEs. In this way it is possible to make a direct comparison between the effects of the individual variables incorporated in Model 3 on the three outcome categories. Furthermore, figure 1 provides 95% confidence limits (Cl) for each level of the AME.

**INSERT FIGURE 1 ABOUT HERE**

Overall, the estimation and analysis of all covariates' AMEs incorporated in the three models provided 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-

[14] The graph displaying the AMEs for Model 3 estimated using information at *t*-2 are not shown, as they are show very similar patterns, as previously discussed.

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 varies between the minimum and maximum possible values.

In figure 2 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 financial statement 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 analysis shows that, concerning the DIS category (Response = 2), a positive change in the value of TFOTL, NOCREDINT, and COVERAGE leads to a decreased predicted probability of falling into the financial distress category. Likewise, a positive change in the level of the proxy for leverage, TLTA, yields a positive variation (increase) in the likelihood of financial distress, as previously suggested by the estimation of average marginal effects. Furthermore, the accounting variable COVERAGE produces the steepest slope of the financial ratios, suggesting that a given variation in the magnitude of this covariate should have the largest effect on the predicted likelihood of falling in the financial distress category. Similarly, with regard to the FAI category (Response = 3), the analysis confirms that a positive change in the magnitude of TFOTL should have the largest (negative) impact on the likelihood of falling into the corporate failure category, as this accounting variable generated the steepest slope relative to the other financial ratios (especially in the range -1.0 to 0.0). Moreover, as expected, the directionality of the vectors related to the Corporate failure category follows the same directionality patterns as those related to the Financial distress category. 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 expectations.

**INSERT FIGURE 2 ABOUT HERE**

Figures 3 and 4 present similar vectors for market and macroeconomic indicators respectively. Analysis of figure 3 indicates that all market indicators display a negative relationship with the estimated probabilities of Financial distress (Response = 2) and Corporate Failure (Response = 3). The only difference lies in the magnitudes of the changes of the predicted probabilities that correspond to the changes in the covariate levels. Thus, it can be observed that, concerning the DIS category, the variable SIZE produces the vector with the steepest slope, suggesting that a positive change in the value of this market indicator should have the highest negative impact in the probability of falling into the Financial distress category, followed by ABNRET, MCTD, and PRICE. As to the vectors corresponding to the Corporate failure category, figure 3 shows that the covariate PRICE generates the vector with the steepest slope, which seems to indicate that an increase (decrease) in its level should produce the highest decrease (increase) in the likelihood of a firm falling in to the Corporate failure category (particularly in the range -5.0 to 5.0). The market indicators MCTD, SIZE, and ABNRET are next in the list (based upon their respective impact on the likelihood of Corporate failure).

**INSERT FIGURE 3 ABOUT HERE**

Finally, it can be seen from figure 4 that a positive change in the level of both indicators (RPI and SHTBRDEF) result in a positive variation in the predicted probability of a firm's likelihood of falling into the Financial distress and the Corporate failure categories. Overall, the changes in predicted probabilities are very useful as they confirm the validity of the results obtained through the estimation of marginal effects. However, it should be emphasized that the differences in ranking (based on the magnitude of the impact of individual variables on the likelihood of falling into one of the three possible categories) between marginal effects and the changes in predicted probabilities stem from the specific characteristics and definitions of each. The identification of these subtle differences, far from being a disadvantage, can instead be employed by the academic/practitioner as an additional source of information to enhance their analysis.

**INSERT FIGURE 4 ABOUT HERE**

### 4.8 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. 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. But 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 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. This procedure is performed using data from period *t-1* and period *t-2* separately, 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 11 unambiguously indicates that the combination of accounting and market variables yields the highest classification accuracy among the three polytomous response logit models built in this study. Model 3 results in overall classification accuracy of 85 %, while Model 1 and Model 2 produce extremely similar accuracy results: 80% and 79% respectively, which suggest that the performance of accounting and market variables is not highly dissimilar: the accounting model is only marginally superior to the market model by approximately one percentage point.

**INSERT TABLE 11 ABOUT HERE**

The classification accuracy results obtained using information two years in advance of the event of relevance (Table 12) confirm 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.

**INSERT TABLE 12 ABOUT HERE**

## 5. 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. Second, 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. Third, 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, novel 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).

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.

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

Panel A reports summary statistics for the whole sample. NFD stands for Non-financially distressed firms, DIS for firms in a state of financial distress, and FAI indicates those firms classified as failed.

| Classification of annual 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.' 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.' 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**
**Likelihood-ratio and linear hypothesis testing results**

This table reports likelihood-ratio tests to evaluate the effects of the independent covariates on the Response variable for the 'Accounting plus macroeconomic indicators' model (Model 1), the 'Market plus macroeconomic indicators' model (Model 2), and the 'Comprehensive' model (Model 3) in Panel A, B and C, respectively. The likelihood ratio tests were estimated with accounting market and macroeconomic information one and two years prior to the observation of the event of interest (for periods *t-1* and *t-2*). The test is used to confirm the significance of the predictors to the model. Additionally, Panel D reports linear hypothesis testing results for the null hypothesis that all ten pairs of coefficients are equal for states DIS and FAI.

| Effect | DF | Chi-Square (Pr>ChiSq) | Chi-Square (Pr>ChiSq) |
|---|---|---|---|
| *Panel A: Model 1* | | *t-1* | *t-2* |
| TFOTL | 2 | 37.686 (<.0001) | 31.828 (<.0001) |
| TLTA | 2 | 75.154 (<.0001) | 19.422 (<.0001) |
| NOCREDINT | 2 | 38.460 (<.0001) | 20.040 (<.0001) |
| COVERAGE | 2 | 639.078 (<.0001) | 652.672 (<.0001) |
| RPI | 2 | 80.485 (<.0001) | 40.647 (<.0001) |
| SHTBRDEF | 2 | 54.266 (<.0001) | 42.175 (<.0001) |
| *Panel B: Model 2* | | | |
| PRICE | 2 | 62.548 (<.0001) | 35.661 (<.0001) |
| ABNRET | 2 | 313.185 (<.0001) | 590.850 (<.0001) |
| SIZE | 2 | 248.434 (<.0001) | 102.040 (<.0001) |
| MCTD | 2 | 78.609 (<.0001) | 48.367 (<.0001) |
| RPI | 2 | 23.085 (<.0001) | 21.213 (<.0001) |
| SHTBRDEF | 2 | 16.156 (<.0001) | 6.738 (0.034) |
| *Panel C: Model 3* | | | |
| TFOTL | 2 | 34.180 (<.0001) | 31.695 (<.0001) |
| TLTA | 2 | 13.079 (0.001) | 2.655 (0.265) |
| NOCREDINT | 2 | 23.849 (<.0001) | 6.028 (0.049) |
| COVERAGE | 2 | 304.970 (<.0001) | 356.000 (<.0001) |
| RPI | 2 | 20.424 (<.0001) | 14.938 (0.001) |
| SHTBRDEF | 2 | 18.024 (<.0001) | 15.564 (<.0001) |
| PRICE | 2 | 35.368 (<.0001) | 23.095 (<.0001) |
| ABNRET | 2 | 117.757 (<.0001) | 224.161 (<.0001) |
| SIZE | 2 | 63.715 (<.0001) | 4.894 (0.087) |
| MCTD | 2 | 59.550 (<.0001) | 18.371 (<.0001) |
| *Panel D: Linear Hypothesis Testing Results – Model 3* | | | |
| ALL VARIABLES TESTED | 10 | 181.2717 (<.0001) | 224.9170 (<.0001) |

**Table 6**

**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 or non-failed firms), financial distress (DIS or financially distressed companies), and failure (FAI or failed firms). Model 1 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 parenthesis. * denotes significant at 10%, ** denotes significant at 5%, and *** denotes significant at 1%.

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

**Table 7**
**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 or non-failed firms), financial distress (DIS or financially distressed companies), and failure (FAI or failed firms). 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 parenthesis. * denotes significant at 10%, ** denotes significant at 5%, and *** denotes significant at 1%.

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

**Table 8**
**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 or non-failed firms), financial distress (DIS or financially distressed companies), and failure (FAI or failed firms). 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 parenthesis. * denotes significant at 10%, ** denotes significant at 5%, and *** denotes significant at 1%.

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

**Table 9**
**Comparative Model Fit Statistics**

This table reports model performance statistics. Panel A displays measures for the three models estimated data at *t-1* and Panel B shows the same measures for all of the models estimated using data in *t-2*. Model 1 is the 'Accounting plus macroeconomic variables' model, Model 2 is the 'Market plus macroeconomic variables' model, and Model 3 is the 'Comprehensive' model, including accounting, market and macroeconomic variables. The first two measures are Cox and Snell's R-squared and Nagelkerke's Max-rescaled R-squared, which provide a gauge to compare the substantive significance of the 3 models; in addition Akaike information criterion and Schwartz's Bayesian criterion statistics, the models' Chi-squared, and the deviance and Pearson statistics are also presented.

| Measure | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| *Panel A: models' fit statistics in t-1* | | | |
| Cox & Snell's $R^2$ | 0.1071 | 0.1100 | 0.1555 |
| Nagelkerke's Max-rescaled $R^2$ | 0.2854 | 0.2819 | 0.4028 |
| Akaike Information Criterion | 2023.246 | 1675.399 | 2247.175 |
| Schwartz's Bayesian Criterion | 1929.622 | 1584.352 | 2096.923 |
| $\chi 2$ Chi-square (12, 12, 20) | 2047.246 ($p<.0001$) | 1699.399 ($p<.0001$) | 2287.175 ($p<0.0001$) |
| Deviance | 6453.086 ($p<1.0000$) | 5514.040 ($p<1.0000$) | 4315.100 ($p<1.0000$) |
| Pearson | 26842.865 ($p<1.0000$) | 22898.823 ($p<1.0000$) | 19082.679 ($p<1.0000$) |
| | | | |
| *Panel B: models' fit statistics in t-2* | | | |
| Cox & Snell's $R^2$ | 0.1122 | 0.0914 | 0.1458 |
| Nagelkerke's Max-rescaled $R^2$ | 0.2796 | 0.2241 | 0.3617 |
| Akaike Information Criterion | 1845.295 | 1254.999 | 1899.099 |
| Schwartz's Bayesian Criterion | 1753.355 | 1165.015 | 1750.744 |
| $\chi 2$ Chi-square (12, 12, 20) | 1869.294 ($p<.0001$) | 1278.999 ($p<.0001$) | 1939.099 ($p<.0001$) |
| Deviance | 6189.397 ($p<1.0000$) | 5713.619 ($p<1.0000$) | 4409.522 ($p<1.0000$) |
| Pearson | 24879.178 ($p<1.0000$) | 22705.242 ($p<1.0000$) | 17163.792 ($p<1.0000$) |

**Table 10**
**Marginal Effects – Model 1, Model 2 and Model 3**

This table reports marginal effects (in percentages) for the 'Accounting plus macroeconomic indicators' model, or Model 1 for the 'market plus macroeconomic indicators' model, or Model 2, and for the comprehensive model (the 'accounting plus macroeconomic plus market indicators' model) in panel A, B, and C respectively. Columns 2 and 3 display the individual marginal effects of each accounting variable and macroeconomic indicator 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) one and two years prior to the observation of the event (*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) one and two years prior to the observation of the event (*t-1* and *t-2*, respectively). Standard errors, obtained employing the Delta-method, are reported in parenthesis. * denotes significant at 10%, ** denotes significant at 5%, and *** denotes significant at 1%

*Panel A: Model 1 – Accounting plus macroeconomic indicators 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 plus macroeconomic indicators 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 (accounting plus macroeconomic plus market variables) 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 11**

**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 (Model 1), the 'Market plus macroeconomic indicators' model (Model 2), and the 'Comprehensive model' (Model 3, that includes the three types of variables) in Panel A, B and C, respectively. The results were 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, this table presents overall classification accuracy percentages by model in order to compare their 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 |

**Table 12**

**Bias-Adjusted Classification Accuracy Table in *t-2***

This table reports a biased-adjusted classification table for predicted frequencies in percentage for the 'Accounting plus macroeconomic indicators' model (Model 1), the 'Market plus macroeconomic indicators' model (Model 2), and the 'Comprehensive model' (Model 3, that includes the three types of variables) in Panel A, B and C, respectively. The results were obtained using information two years prior to the observation of the event of interest (period *t-2*). 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, this table presents overall classification accuracy percentages by model in order to compare their relative performances.

| | Predicted | | | | |
|---|---|---|---|---|---|
| Observed | NFD | DIS | FAI | Total | Correct |
| *Panel A: Model 1* | | | | | |
| NFD | 79.39 | 7.90 | 12.71 | 100.00 | 79.39 |
| DIS | 7.74 | 78.18 | 14.09 | 100.00 | 78.18 |
| FAI | 20.45 | 13.75 | 65.81 | 100.00 | 65.81 |
| | Overall Classification Accuracy | | | | 79.09 |
| *Panel B: Model 2* | | | | | |
| NFD | 75.74 | 10.15 | 14.11 | 100.00 | 75.74 |
| DIS | 11.39 | 70.46 | 18.15 | 100.00 | 70.46 |
| FAI | 13.75 | 17.47 | 68.77 | 100.00 | 68.77 |
| | Overall Classification Accuracy | | | | 75.40 |
| *Panel C: Model 3* | | | | | |
| NFD | 82.26 | 6.04 | 11.71 | 100.00 | 82.26 |
| DIS | 5.92 | 82.35 | 11.73 | 100.00 | 82.35 |
| FAI | 14.64 | 11.72 | 73.64 | 100.00 | 73.64 |
| | Overall Classification Accuracy | | | | 82.09 |

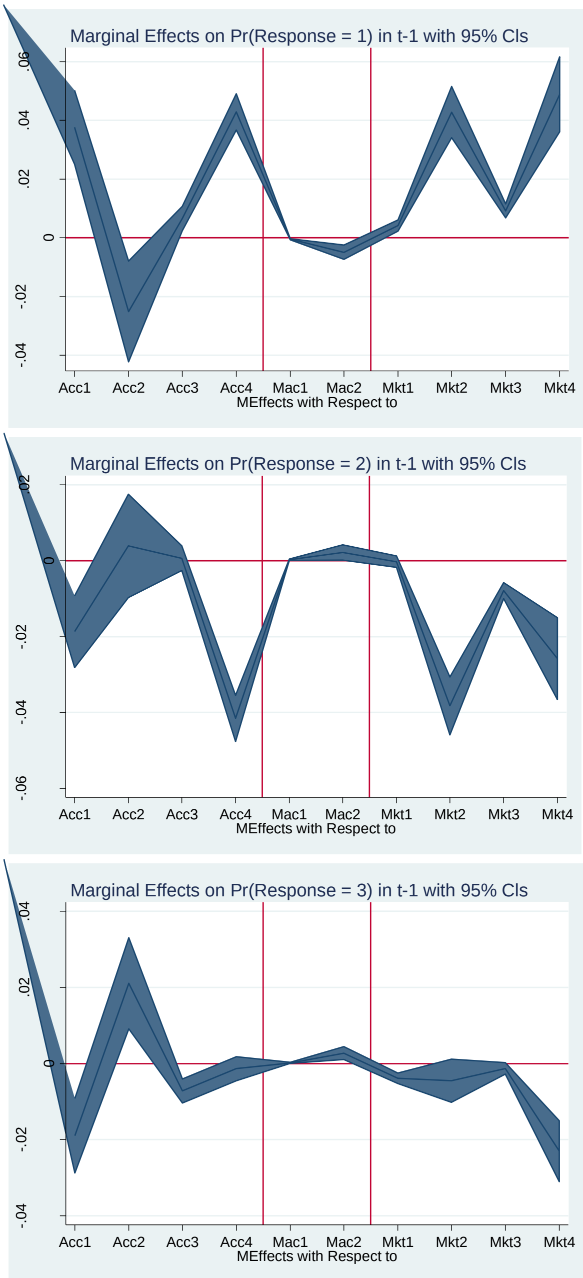


**Figure 1**
**Marginal effects on the Probabilities of Non-Financial Distress, Financial Distress and Corporate Failure in *t-1***
The figure plots the average marginal effects (AME) for each variable in the comprehensive model, or Model 3, on the likelihood that the Response variable is equal to Non-financial distress (Response = 1), Financial distress (Response = 2), and Corporate failure (Response = 3), respectively, one year prior to the observation of the relevant event (*t-1*). The vertical lines divide the figures into Accounting (Acc), Macroeconomic (Mac) and Market (Mkt) variables, where Acc1 = TFOTL, Acc2 = TLTA, Acc3 = NOCREDINT, Acc4 = COVERAGE, Mac1 = RPI, Mac2 SHTBRDEF, Mkt1 = PRICE, Mkt2 = ABNRET, Mkt3 SIZE and Mkt4 = MCTD. The horizontal line divides the figures into positive and negative AMEs on the respective response indicator. In addition, the coloured area indicates 95 per cent confidence limits (Cls) for each level of the AME.

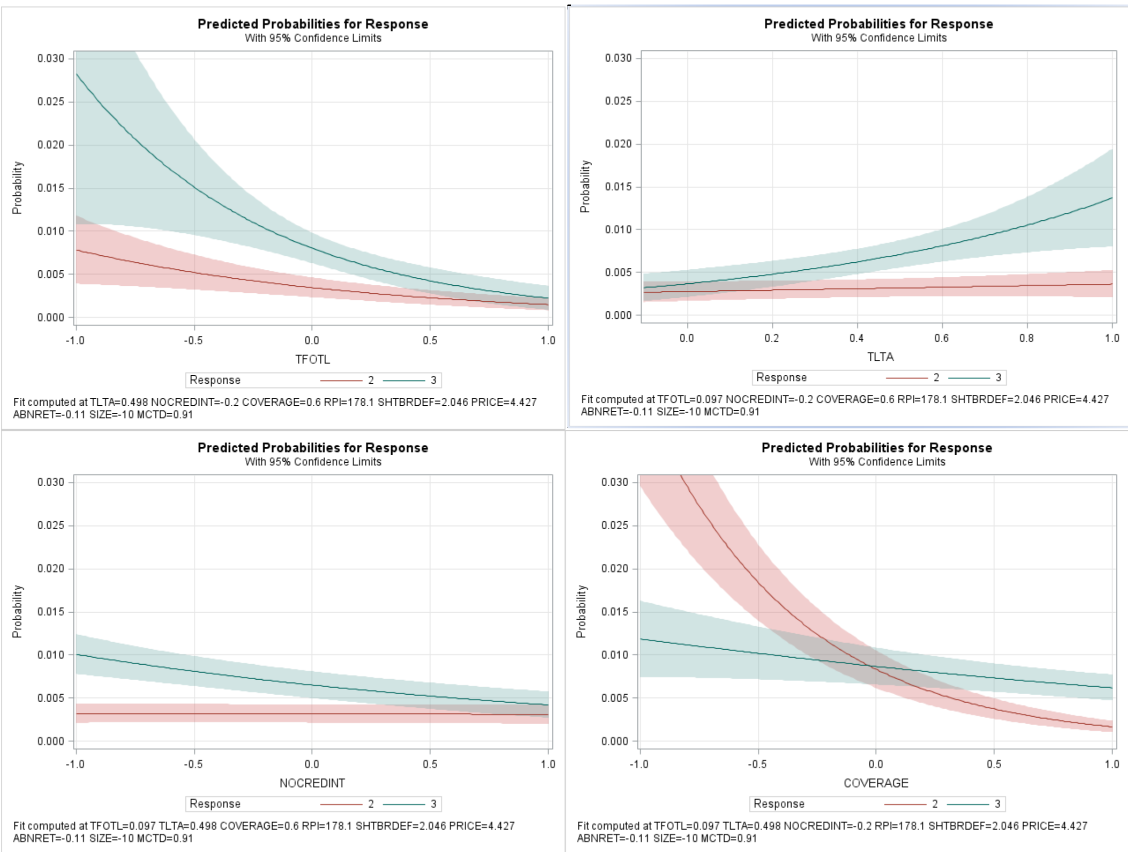


**Figure 2**

**Changes in Predicted Probabilities – Financial Statement 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 financial statement 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.

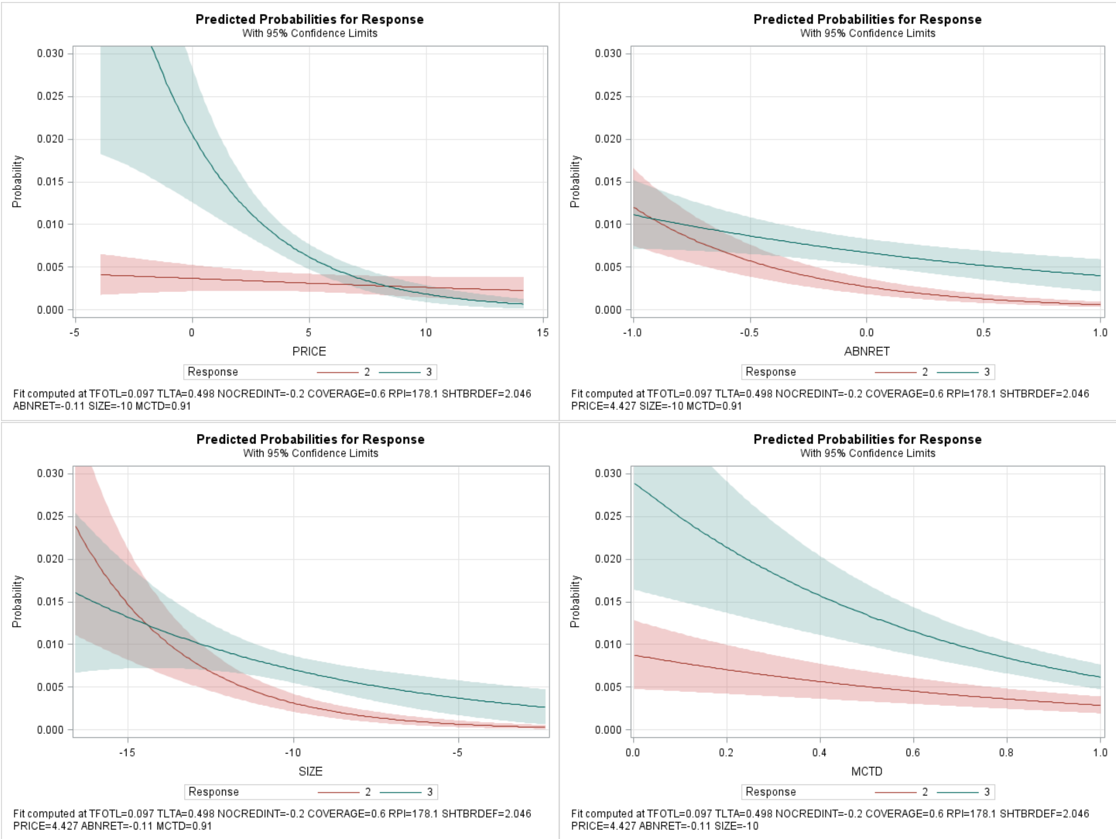


**Figure 3**

**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.

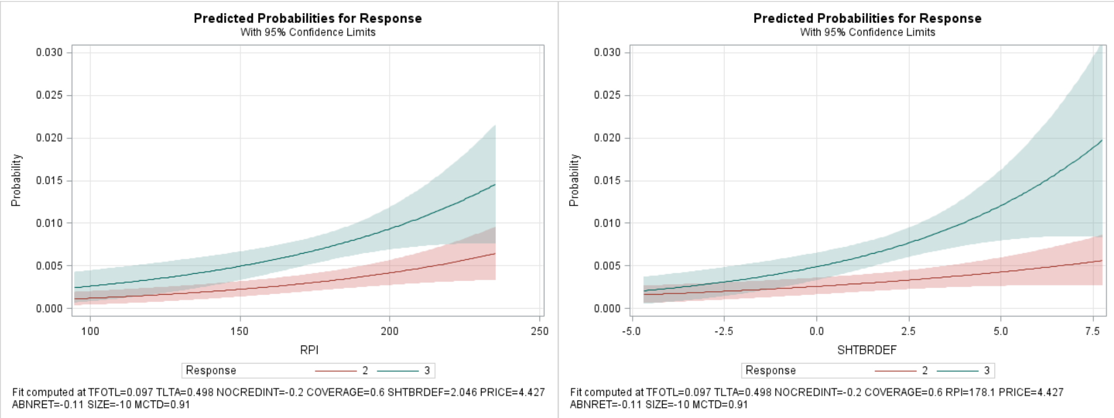


**Figure 4**

**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.