Assessing the probability of financial distress of UK firms

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First version: June 12 2008

This version: January 15 2009

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Preliminary and incomplete. Comments welcome.

Abstract

We assess whether the Taffler Z-score conveys sufficient information about the probability of financial distress for UK firms. Using a hazard model that includes the Z-score components, we find that half of its component ratios do not contribute to the corporate failure prediction. We also develop a hazard model that includes Z-score as the only predictor of bankruptcy. We compare these two models with two hazard models based on Shumway (2001). The first model considers accounting and market-related variables whereas the second model is based on market-driven variables. Our results show that both models suggested by Shumway are significantly more informative of financial distress prediction than the model of Z-score components and the univariate hazard model that includes Z-score. When we incorporate Z-score as an additional covariate in the two models based on Shumway (2001) we provide evidence that Z-score is not related to the probability of financial distress. Out-of-sample prediction tests provide evidence that the model of Z-score components has the least predictive ability while the model of Shumway that combines accounting and market-driven variables is the most accurate. Overall, our findings suggest that Z-score needs to be treated with caution with respect to the prediction of financial distress.

1 Introduction

Since the pioneering research of Beaver (1966) and Altman (1968), there is considerable interest in assessing distress risk. Several models in the literature focus on accounting-based variables to predict bankruptcy; see, for example, Ohlson's (1980) O-score and Zmijewski(1984). The model that has been extensively used in empirical research and in practice is the Z-score model in Altman (1968).[1] Building on the work of Altman (1968), Taffler (1983) developed a Z-score measure that analyses the financial health of UK firms. To calculate Z-score, Taffler (1983) employs linear discriminant analysis and uses historic accounting data. This paper examines the accuracy and the contribution of Taffler Z-score with respect to the financial distress prediction for UK firms.

The accounting ratio-based models can be less informative than the market-based models with respect to bankruptcy prediction for the following reasons. First, accounting-based models use information from the financial statements, which present the past performance of a firm and may not convey information about its future status. Second, some accounting conventions (e.g., historical cost, conservatism and money measurement) the book value of assets is understated.[2] Third, accounting data provide a snapshot of the value of the company at a specific point in time while market data market dynamically reflect the value of the company. Most of the accounting ratios based on UK financial statements are available only on an annual basis whereas market data have a forward looking perspective as the latter are available on a daily or monthly basis.

Shumway (2001) develops a hazard model for forecasting bankruptcy that combines both accounting and market data. He argues that well-established bankruptcy prediction models in the literature, such as Altman's (1968) Ohlson's (1980) and Zmijewski's(1984) are not correctly specified as they do not consider all the available firm-year observations. This can induce a bias of the estimated coefficients of the variables related to bankruptcy, leading to incorrect statistical inferences. In contrast to these models, a hazard model takes into account all the available observations for the bankrupt and non-bankrupt firms. Shumway (2001) shows that the inclusion of these additional observations produces efficient and consistent estimates of the coefficients. In addition to this, he documents that using a discrete hazard model half of the accounting ratios incorporated in Altman's (1968) and Zmijewski's accounting-based models are not statistically significant for predicting bankruptcy. He proposes a hazard model that uses both accounting ratios and market-driven variables, which outperforms these two accounting-based models in out of sample forecasts.

Recent papers use Shumway's methodological approach to develop corporate bankruptcy prediction models either based on accounting information or based on market information. Hillegeist Keating, Cram and Lundstedt (2004) use discrete hazard models to compare accounting-based measures of the probability of bankruptcy with the market-based probability of default

[1]Some of the studies that utilize the Z-score include Dichev (1998), Griffin and Lemmon (2002), Graham (2000) and Byoun(2007).

[2]The book value of assets is understated as many items are not recognized in the balance sheet (e.g. management skills and competence, reputation for quality, customer loyalty etc) and the book values of recognized assets are frequently biased downwards through write downs and impairments.

implied by the Black-Scholes-Merton (BSM) distance to default model. Their results suggest that the market-based BSM measure provides significantly more information about the probability of bankruptcy than Z-score and O-score measures. However, they find that the BSM model cannot explain much of the variation in the probability of bankruptcy across firms. Beaver, McNichols, and Rhie (2005) use a hazard model to explore the ability of financial statements to predict bankruptcy over time. Similar to Shumway (2001), Campbell, Hilscher and Szilagyi (2008) estimate a reduced-form model that incorporates both accounting and market-driven variables, extending the horizon of failure prediction and directly predicting failure for different horizons. They also find that the probability of default derived from the structural approach of the Merton model has little predictive ability after accounting for the accounting and market-based predictors incorporated in the reduced-form model. Bharath and Shumway (2008) assess the Merton distance to default (DD) model and find that it does not produce a sufficient statistic for the probability of default. They construct a naive probability of default as an alternative to the classical Merton DD model. Their findings suggest that this naive alternative predictor of default outperforms the Merton DD model.

In contrast to the US literature, UK literature is adding little to the assessment of the probability of financial distress in the UK. Agarwal and Taffler (2007) evaluate the performance of Taffler Z-score model. They conclude that the UK-based Z-score model has the ability to predict distress risk for UK firms. Agarwal and Taffler (2008) compare the Taffler Z-score with the market based BSM model used in Hillegeist et al. (2004) and the naive market-based model used in Bharath and Shumway (2008). They find that both the Z-score and market-based models play an important role in the prediction of failure. However, they provide evidence that neither the market-based models nor the Z-score is a sufficient statistic for the corporate failure prediction. We follow two different and independent approaches to that of Agarwal and Taffler (2008) in examining the accuracy and the contribution of the Taffler Z-score. First, we examine the extent to which the components of the Taffler Z-score convey information related to the financial distress prediction. Second, we explore whether Z-score is a sufficient predictor for bankruptcy in ways that differentiate from those followed by Agarwal and Taffler (2008).

We investigate these two approaches above in five ways. We use a hazard model that incorporates the four accounting-based components of Taffler Z-score, i.e., profitability, working capital position, financial risk and liquidity. We also estimate a hazard model that includes only Z-score for the prediction of bankruptcy. We compare these two models with two reduced-form hazard models documented in Shumway (2001). The first model uses a combination of accounting and market-related information to predict bankruptcy while the second model predicts bankruptcy using only market-driven information. We further examine whether the Z-score can be replaced by the set of accounting or market-driven variables used in Shumway (2001). Finally, we perform out-of-sample tests to explore the predictive ability of the forecasting models.

We find that half of the components of the UK-based Z-score are not related to the prediction of financial distress. Also, a comparison of each model's pseudo-R^2 shows that the model based on Shumway (2001) outperforms the model of Z-score components and the univariate hazard model that includes Z-score. When we incorporate Z-score in the two models suggested by Shumway, the coefficient of Z-score becomes statistically insignificant. Overall, our results suggest that Z-score contains little information about the financial distress prediction for the UK firms as it does not remain a statistically significant financial distress predictor when we incorporate other variables in the hazard model. In addition to this, the out-of -sample prediction tests demonstrate that the two hazard models proposed in Shumway (2001) clearly dominate the model of Taffler Z-score components and the model that uses only Z-score to forecast bankruptcy. Also, consistent with the findings of the two models of Shumway we find that the model that combines accounting and market-driven variables outperforms the market-based model of bankruptcy.

Finally, we interact firm-specific covariates with time-varying macroeconomic variables to explore the contribution of macroeconomic factors to the financial distress prediction for UK firms. However, we find no evidence on the association between macroeconomic factors, i.e., the annual bankruptcy rate, the GDP growth rate and the three-month UK Treasury bill, and the prediction of financial distress. The layout of the paper is as follows. Section 2 discusses how financial distress prediction is empirically investigated. Section 3 describes our data and reports the descriptive statistics. Section 4 presents the results concerning the information content and the predictive ability of models that include accounting or market-related variables. Section 6 concludes.

2 Modeling the probability of financial distress

Several academics have used a variety of estimation techniques to develop default forecasting models. Beaver (1966) uses a multiple regression model to predict corporate failure with financial ratios. Altman (1968) employs a multivariate discriminant analysis to derive the Z-score measure for predicting bankruptcy. Taffler (1983) uses the same technique to generate the UK-based Z-score. Altman et al. (1977) use quadratic discriminant analysis to identify bankruptcy risk of firms. Ohlson (1980) applies a conditional logit model to predict corporate default (known as "O-score"), which consists of seven accounting-based explanatory variables.[3] Zmijewski (1984) performs a probit model incorporating three bankruptcy predictors, i.e., firm performance, leverage and liquidity. Lau (1987) recognizes more than two states of financial distress using a multinomial logit model.

However, Shumway (2001) argues that these bankruptcy forecasting models are misspecified as they do not properly account for the length of time that a healthy firm has survived. In particular, such models are static because they use only a single firm-year observation for a non-bankrupt firm, which is randomly selected from the available firm-years. For a bankrupt firm the firm-year observation is not randomly selected and corresponds to the year before bankruptcy. His study also shows that ignoring all the available set of observations can produce inconsistent and inefficient estimates of the coefficients of the variables included in the model. To properly address time for predicting the likelihood of bankruptcy, Shumway (2001) adopts hazard analysis. The hazard rate is the probability of the firm to go bankrupt at time t, conditional upon having survived at time t. Therefore, in a hazard model firm's probability

[3] These variables are size, three measures of financial structure, two measures of profitability and one measure of liquidity.

of default changes through time and its health is a function of its latest financial data. This not only allows researchers to take advantage of all the available firm-year observations but also to include covariates that vary over time. Shumway (2001) explicitly demonstrates that a multi-period logit model can be used to examine the effect of time-varying covariates on the hazard rate taking into consideration the risk of bankruptcy in multiple years for firms that do not default.

A general form of the hazard model is:

$$ln[\frac{h_i(t)}{(1-h_i(t))}] = \alpha(t) + \beta'\mathbf{x}_{i,t} \tag{1}$$

where $h_i(t)$ represents the hazard of bankruptcy at time t for firm i, conditional on survival to t; $\alpha(t)$ is the baseline hazard; $\beta'\mathbf{x}_{i,t}$ the vector of coefficients of the covariates that vary over time. The hazard model econometrically is equivalent to a discrete time multi-period logit model described by the following equation:

$$P_{i,t} = \frac{1}{1+e^{(-\alpha+\ \ '\mathbf{x}_{i,t-1})}} \tag{2}$$

where $P_{i,t}$ is the probability that firm i will be in financial distress at time t; β' is the coefficient vector and $\mathbf{x}$ is a vector of explanatory variables.

The primary question we address in this paper is whether Taffler Z-score conveys information with respect to the prediction of financial distress for UK firms. To construct the Z-score, Taffler (1983) uses linear discriminant analysis and factor analysis to identify four accounting ratios; profitability (PROF), working capital (WCAP), financial risk (FRISK), and liquidity (LIQUID). In particular, the UK-based Z-score is of the following form:

$$Z - score = 3.20 + 12.18 * PROF + 2.50 * WCAP - 10.68 * FRISK + 0.029 * LIQUID \tag{3}$$

Using a multi-period logit model, presented above, that allows to use all the available firm-year observations for each firm i we explore whether PROF, WCAP, FRISK, and LIQUID are related to forecasting corporate distress in the UK. Also, we use a univariate discrete hazard model using only Z-score to predict corporate bankruptcy. Z-score is calculated following Equation (3). We compare the performance of these two models with the performance of two recently documented models in Shumway (2001) . Following Shumway (2001), we use profitability (EBITDA_TA), leverage (BLEV), relative size (REL_SIZE), excess past returns (EXPR), and variability of stock returns (σ) to predict financial distress for UK firms. Along with this model, Shumway also uses a market-based version of the above model for the prediction of bankruptcy. In line with Shumway (2001), we use REL_SIZE, EXPR and σ to predict bankruptcy. There are mainly four categories where firms exit the market due to financial distress. These are: bankruptcy, default, failure and mergers/acquisitions. The scope of this study is restricted to bankruptcy. According to the UK insolvency law administration, company voluntary arrangement (CVA), receivership, liquidation and dissolution constitute insolvency. The dependent variable in Equation (2) is a dummy that equals zero, if the firm is healthy. If the firm goes bankrupt, then the dependent variable equals one only for its last firm-year observation; zero otherwise.

3 Data and descriptive statistics

The sample consists of 3,459 (alive and dead) UK listed firms over 1980–2006 with 32,257 firm-year observations excluding financial firms and utilities. We obtain the accounting data from Datastream and most of the market data from London Share Price Database (LSPD). We also use LSPD to identify 310 bankrupt firms providing 2,378 firm-year observations and 3,149 non-bankrupt firms providing 29,879 firm-year observations from 1980 through 2006.[4] The average annual failure rate over the period 1980-2006 is less than 1% (310/32,257). Table 1 describes the sample size of the bankrupt and non-bankrupt firms for each year from 1980–2006. The frequency of distressed firms corresponds to the number of distressed firms whereas the frequency of non-distressed firms corresponds to the number of firm-years provided by the non-distressed firms.

Table 2 provides descriptive statistics for our variables. PROF, WCAP, FRISK and LIQUID are the accounting ratios on which the UK-based Z-score is measured.[5] EBITDA_TA, BLEV, REL_SIZE, EXPR, and σ are the bankruptcy predictors used in Shumway (2001).[6] In the Appendix we provide detailed information about the construction of the variables used in the analysis. The independent variables are lagged to ensure that the data are observable prior to the event of financial distress. Following Agarwal and Taffler (2008), we winsorize Z-score to be bounded between $\pm$ 18.4207. To avoid outliers for the remaining independent variables, I truncate them, apart from REL_SIZE as it is normally distributed, at the 1% level in either tail of the distribution.[7] The summary statistics reported in Table 2 are calculated after the truncation.

[4]LSPD gives information about the type of death for the UK listed firms. Specifically, firms whose LSPD death type is liquidation, voluntary liquidation, receiver appointed/liquidation, in administration/administrative receivership, and cancelled assumed valueless are considered bankrupt.

[5]Note that in the table of descriptive statistics LIQUID is expressed as a ratio of liquidity. However, to calculate Taffler Z-score, LIQUID reflects the number of days the company can trade if it can no longer generate revenues as the denominator of LIQUID is divided by 365; see Appendix for details.

[6]Unlike our study, Shymway (2001) measures profitability as net income to total assets and leverage as total liabilities to total assets.

[7]The results are similar when we also winsorize REL_SIZE.

4 Results

4.1 Multi-period logit models

Table 3 presents the results from five maximum likelihood multi-period logit models. Using all the available firm-year observations for a particular firm can result in understated standard errors as the logit estimation considers erroneously these observations independent. Following Shumway (2001), to control for this effect we divide the test statistic by the average number of firm-year observations per firm. The ZCOMP model produces the estimates of the coefficients of the accounting -based components of Taffler Z-score. If Z-score is a powerful predictor of financial distress, we would expect all of its component ratios to predict financial distress. The ZCOMP model shows that half of the accounting ratios that have been used to calculate the UK-based Z-score are not related to the prediction of bankruptcy. In particular, while PROF and FRISK are statistically significant WCAP and LIQUID are not statistically significant predictors of default for UK firms. This indicates that the predictive ability of Z-score derives from firms' profitability and financial risk. The ZSCORE model yields the estimate of the coefficient of Z-score. Using Z-score as the only predictor of bankruptcy, we show that Z-score is strongly associated with the prediction of financial distress.

The SHUM model is based on the accounting and market-based predictors used in Shumway (2001). The results in SHUM model demonstrate that BLEV and σ are positively related to financial distress forecast whereas REL_SIZE and EXPR are negatively related to financial distress forecast. In line with Shumway (2001), we also find that the coefficient of EBITDA_TA is statistically insignificant when market-driven variables are included in the model. Unlike Shumway (2001) we find that σ is strongly related to the prediction of corporate failure for UK firms when it is also combined with the accounting ratios. The remaining findings of SHUM model are consistent with those of Shumway (2001). The SHUM-Z model incorporates the Taffler Z-score as an additional predictor of corporate financial distress. In this model we observe that the coefficient of Z-score becomes statistically insignificant. This suggests that Z-score can be replaced by other accounting and market-based factors that convey more information about the prediction of corporate distress in the UK. Also, we observe that when we include Z-score in the model, BLEV becomes statistically in significant. This is possibly because Z-score and BLEV are correlated.[8]

The SHUM_MV model is based on the market-related predictors proposed by Shumway (2001). As in the SHUM model, the coefficients of REL_SIZE and EXPR are negative and significant whereas the sign of σ is positive and significant. The SHUM_MV-Z model includes Z-score as an additional covariate for the prediction of financial distress. The results from this model show that Z-score is statistically insignificant when incorporating the three market-driven variables, i.e., REL_SIZE, EXPRET and σ. This is similar to the evidence from the SHUM-Z model. Therefore, we provide evidence that Z-score is not a sufficient predictor for bankruptcy as it can be replaced by a set of market-based predictors.

[8] In particular, one of the components of Z-score is FRISK, which is highly correlated with BLEV.

We report McFaddens pseudo R^2 coefficient for each specification, calculated as $1 - L_1/L_0$, where L_1 is the log likelihood of the estimated model and L_0 is the log likelihood of a null model that includes only a constant term. Concerning the pseudo R^2 of each model we observe that the SHUM model has the highest pseudo R^2 coefficient compared to that of the ZCOMP and ZSCORE model. In particular, while the pseudo R^2 coefficient in the ZCOMP model is 4% and in the ZSCORE model is 5%, the pseudo R^2 coefficient in the SHUM model is 10%. The pseudo R^2 coefficient in the SHUM_MV model is 9%. When we add Z-score, the pseudo R^2 coefficient slightly increases in the SHUM-Z model (11%) and in the SHUM_MV-Z model (11%). However, in fact these two models do not carry any additional information with respect to the bankruptcy prediction as Z-score is statistically insignificant.

4.2 Out of sample forecasts

We perform out-of-sample tests to assess of the predictive ability of four models for corporate financial distress prediction. We assess the forecast accuracy of ZCOMP model, which includes the accounting-based components on which Z-score is measured. We also explore the out-of-sample forecasting ability of ZSCORE model. Finally, we test the forecast accuracy of SHUM and SHUM_MV model. We do not examine the predictive ability of SHUM-Z model and SHUM_MV-Z model as Z-score is statistically insignificant in both of these models.

To examine the out-of-sample accuracy, we perform a multi-period logit regression in an earlier sub-period (1981-1990) and then use these parameter estimates to forecast corporate financial distress in a later sub-period (1991-2006). Table 4 reports the results of the out-of-sample prediction test of the four models. In particular, we sort UK firms from the sub-period 1991-2006 into deciles based on their estimated values of probability of financial distress. We estimate these probability values by using the coefficients from the sub-period 1981-1990. Table 4 presents the fraction (%) of UK financially distressed firms identified in each of the five highest probability deciles (Deciles 1-5). Table 4 also documents the percentage of financially distressed firms that are classified below the median probability of financial distress (Deciles 6-10).

As shown in Table 4, ZCOMP model identifies 201 corporate failures within the sub-period 1991-2006 classifying 57.7% of UK corporate defaults within the three highest probability deciles. Moreover, ZCOMP model classifies 26.87% of UK financially distressed firms below the median probability of corporate default (see, Deciles 6-10). ZSCORE model reveals 201 UK failed firms, classifying 66.7% of UK distressed firms within the three highest deciles and 19.90% of failed firms in the five lowest deciles. SHUM model observes 207 UK failed firms within the sub-period 1989-2002, classifying more than 70% of UK corporate failures within the three highest probability of corporate failure decile and 88% of UK distressed firms above the probability of corporate default median. SHUM model also classifies only 11% of UK defaulted firms in the five lowest deciles (see, Deciles 6-10). SHUM_MV model identifies 208 corporate defaults, classifying less than 70% of UK corporate failures within the three highest probability of corporate failure decile and 16% of UK bankrupt firms below the median probability of corporate financial distress. Taking together the results in Table 4, we argue that the SHUM model has the greatest predictive ability in comparison with the other three models. SHUM_MV model also outperforms the two accounting-based models, i..e, ZCOMP and ZSCORE model. Among these four models, the ZCOMP model has the least predictive ability, casting doubt on its effectiveness to predict corporate failures in the UK through time.

4.3 Combining macroeconomic factors with firm-specific covariates

We also interact firm-specific variables with macroeconomic variables to explore whether macroeconomic conditions are strongly related to the corporate financial distress prediction in the UK. Following Hillegeist et al. (2004) we incorporate in the five multi-period logit models the Annual rate (ANRATE), which is a proxy for the time-varying baseline hazard rate. The Annual rate is the ratio of the number of corporate bankruptcies to the total number of firms in our sample over the previous year and is expressed as a percentage. This ratio can reflect the general macroeconomic conditions that vary over time and cause cross-sectional dependence. We also include the annual UK real GDP growth rate in the previous year (GDPRATE, in percent) and the three-month UK treasury bill rate in the previous year (TB3M, in percent) as macroeconomic predictors of bankruptcy.

Table 5 reports logit regression results on the firm-specific and macroeconomic covariates for the five bankruptcy prediction models. We make the same adjustment to the test statistic derived from the logit regressions as in Table 3. Only in ZCOMP model ANRATE is positive and marginally significant. This suggests that the ANRATE provides additional information to the financial distress prediction that the components of the Z-score do not seem to capture. However, in all the other models models the coefficient on the ANRATE is positive but not statistically significant showing that the baseline hazard rate is not related to the financial distress prediction for the UK firms. Overall, our findings with respect to the ANRATE are in line with Agarwal and Taffler (2008). Hillegeist et al. (2004) find that the ANRATE is positively related to the financial distress prediction. This is because Hillegeist et al. (2004) do not make any adjustment to the test statistic derived from the logit regressions. In all of our models we find that there is no association between the GDP growth rate and the prediction of financial distress. Similar to the GDP growth rate, we document that the three-month UK treasury bill rate does not contribute to forecasting bankruptcy in all of our models. All the coefficients of the remaining variables for the five bankruptcy models are qualitatively the same as in Table 3.[9]

Similar to Campbell et al. (2008) we also exploit the time-series dynamics of the excess past stock returns (EXPR_AVG), the GDP growth rate (GDPRATE_AVG) and the three-month treasury bill rate (TB3M_AVG).[10] In particular, we apply geometrically declining weights on the lags of the three variables, which is expressed by the following series:

[9] The only difference compared to the results of Table 3 is that in this case REL_SIZE does not contribute to the prediction of financial distress in the SHUM-Z model.

[10] Campbell et al. (2008) add lagged information about two variables, i.e., profitability and excess past stock returns. However, it is infeasible to use lagged information about profitability for UK data as the UK accounting items for this ratio are available on an annual basis.

$$EXPR\_AVG = \frac{1-\phi}{1-\phi^{12}}(EXPR_{t-1} + \phi EXPR_{t-2} + ... + \phi^{11} EXPR_{t-12}) \tag{4}$$

$$TB3M\_AVG = \frac{1-\phi}{1-\phi^{12}}(TB3M_{t-1} + \phi TB3M_{t-2} + ... + \phi^{11} TB3M_{t-12}) \tag{5}$$

$$GDPRATE\_AVG = \frac{1-\phi^3}{1-\phi^{12}}(GDP_{t-1,t-3} + \phi^3 GDP_{t-4,t-6} + ... + \phi^9 GDP_{t-10,t-12}) \tag{6}$$

where the coefficient $\phi = 2^{-\frac{1}{3}}$. In line with Campbell et al. (2008) when the monthly lagged excess past stock returns are missing we replace them by its cross-sectional mean so as not to lose firm-year observations.

We compare the SHUM model presented in Table 5 with the SHUM-DYN model, which takes advantage of the lagged information about excess past stock returns (EXPR_AVG), GDP growth rate (GDPrate_AVG) and the three-month treasury bill rate (TB3M_AVG) . Table 6 presents the results of the SHUM-DYN model. Similar to Table 5, we find that the GDPrate_AVG and TB3M_AVG are not significant predictors of financial distress. We also observe that the magnitude of the coefficient of the EXPR_AVG is much larger than that of the EXPR in the SHUM model. The findings for the remaining variables in the SHUM-DYN model remain unaltered with respect to the SHUM model. Overall, accounting for the time-series dynamics of the three covariates in the SHUM-DYN model does not deliver further improvement in the explanatory power over the SHUM model.

5 Concluding remarks

This paper uses discrete hazard approach to explore whether the UK-based Taffler Z-score carries adequate information with respect to the prediction of corporate financial distress. Our results from this analysis document four important findings, providing insight in the distress forecast for the UK firms. First, with respect to the ZCOMP model we find that half of the accounting ratios on which Taffler Z-score is based are not related to forecasting corporate failure. Second, SHUM model contains significantly more information about the probability of financial distress than ZCOMP and ZSCORE model. Third, incorporating Z-score measure either in the SHUM model or in the SHUM_MV model shows that Z-score does not contribute to the prediction of financial distress for the UK firms. Fourth, out-of sample forecasts clearly demonstrate that SHUM model outperforms ZCOMP and ZSCORE model. Also, SHUM_MV has greater predictive ability than Z-score and ZSCORE model, which both use accounting-driven predictors. However, SHUM model outperforms SHUM_MV model. ZCOMP model has the least forecasting ability. Overall, our study suggests that Z-score is not a powerful predictor of corporate financial distress as it lacks statistical power when we also consider accounting and market-based variables.

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Appendix: Variable construction

This Appendix describes the construction of the variables used. All numbers or any other information in parentheses correspond to the Datastream code. LSPD in the parentheses indicates that the data are obtained from the LSPD. We lag all the variables for the purpose of the study.

$$\text{PROF} = \frac{\text{Profit before tax (384)}}{\text{Current liabilities (389)}}$$

$$\text{Total liabilities} = \text{Total assets (392)} - \text{Equity capital \& reserves (305)}$$

$$\text{WCAP} = \frac{\text{Current assets (376)}}{\text{Total liabilities}}$$

$$\text{FRISK} = \frac{\text{Current liabilities (389)}}{\text{Total assets}}$$

$$\text{Quick assets} = \text{Current assets} - \text{Total inventories (364)}$$

$$\text{LIQUID} = \frac{\text{Quick assets -current liabilities (389)}}{\frac{\text{Sales(104)- profit before tax - depreciation (696)}}{365}}$$

$$\text{Z-score} = 3.20 + 12.18 * \text{PROF} + 2.50 * \text{WCAP} - 10.68 * \text{FRISK} + 0.029 * \text{LIQUID}$$

$$\text{EBITDA\_TA} = \frac{\text{Earnings before interest, tax and depreciation (154+153+696)}}{\text{Total assets}}$$

$$\text{BLEV} = \frac{\text{Total debt (1301)}}{\text{Total debt+Total share capital \& reserves (307)}}$$

$$\text{REL\_SIZE} = \text{Log}\left(\frac{\text{Market value of equity (HMV)}}{\text{Market value of FTSE all share index}}\right)$$

$$\text{EXPR} = r_{i,t-1}\text{(LSPD)} - r_{FTSE\_allshare,t-1} \text{ (LSPD)}$$

σ = Sigma is the standard deviation of the residual of this regression : $r_{i,t-1} = \alpha + \beta r_{FTSE\_allshare,t-1}$

ANRATE = $\frac{\text{Number of corporate bankruptcies}}{\text{total number of firms}}$ in the previous year

GDPRATE = Annual growth rate of real GDP in constant 2002 prices

TB3M = three-month UK treasury bill rate

EXPR_AVG = a series of geometrically declining weights on lagged monthly EXPR, see Eq(4)

TB3M_AVG = a series of geometrically declining weights on lagged monthly TB3M, see Eq(5)

GDPRATE_AVG = a series of geometrically declining weights on lagged quarterly GDP, see Eq(6)

Table 1: Distribution of bankrupt and non-bankrupt firms (1980-2006)

This table shows the frequency and the percent of bankrupt firms and non-bankrupt firms by year.

	Bankrupt firms		Non-bankrupt firms	
Year	Frequency	Percent	Frequency	Percent
1980	0	0.00	786	2.63
1981	8	2.58	812	2.72
1982	7	2.26	840	2.81
1983	10	3.23	877	2.94
1984	7	2.26	928	3.11
1985	2	0.65	966	3.23
1986	1	0.32	975	3.26
1987	2	0.65	1,018	3.41
1988	1	0.32	1,052	3.52
1989	17	5.48	1,080	3.61
1990	15	4.84	1,065	3.56
1991	12	3.87	1,050	3.51
1992	3	0.97	1,035	3.46
1993	10	3.23	1,039	3.48
1994	4	1.29	1,095	3.66
1995	6	1.94	1,131	3.79
1996	13	4.19	1,226	4.10
1997	16	5.16	1,283	4.29
1998	18	5.81	1,275	4.27
1999	15	4.84	1,163	3.89
2000	30	9.68	1,162	3.89
2001	40	12.90	1,268	4.24
2002	21	6.77	1,282	4.29
2003	15	4.84	1,203	4.03
2004	19	6.13	1,274	4.26
2005	16	5.16	1,456	4.87
2006	21	6.77	1,538	5.15
Total	310	100.00	29,879	100.00

Table 2: Descriptive Statistics

The UK sample consists of 3,459 firms and 32,257 firm-year observations for the period 1980-2006. We identify 310 financially distressed firms with 2,378 firm-year observations and 3,149 non-financially distressed firms with 29,879 firm-year observations. The lagged independent variables are winsorized at the 1% in either tail of distribution apart from the relative size which is normally distributed. PROF is measured as profit before tax divided by current liabilities. WCAP is the ratio of current assets to total liabilities. FRISK is measured as current liabilities to total assets. LIQUID is defined as (quick assets minus current liabilities) divided by (sales minus profit before tax minus depreciation divided by 365). Z-score is calculated as 3.20 + 12.18*PROF + 2.50*WCAP -10.68*FRISK + 0.029*LIQUID. EBITDA_TA is the ratio of EBITDA to total assets. Book leverage is measured as the book value of debt divided by the book value of debt plus stockholders' equity. REL_SIZE is the natural logarithm of annual firm's market capitalization over the market capitalization of FTSE ALL SHARES index. EXPR is the firm's annual returns in the year t-1 minus the return on FTSE ALL SHARES index in the year t-1. σ is is obtained by regressing each stock's monthly returns in year t-1 on FTSE ALL SHARES index for the same period. σ is the standard deviation of the residual of this regression.

Variable	Mean	Median	Std.dev	Min	Max
PROF	-0.01	0.19	1.04	-6.57	1.28
WCAP	1.46	1.09	1.73	0.09	13.37
FRISK	0.39	0.38	0.19	0.03	1.07
LIQUID	0.11	-0.02	0.79	-1.38	5.65
Z-score	3.01	3.40	8.63	-18.42	18.42
EBITDA_TA	0.08	0.12	0.22	-1.20	0.42
Book Leverage	0.26	0.23	0.25	0.00	1.44
REL_SIZE	-2.77	-2.94	2.07	-13.22	4.82
EXPR	0.02	0.00	0.49	-1.25	1.80
Sigma	0.11	0.09	0.08	0.02	0.49

Table 3: Discrete multi-period logit models

The dependent variable is an indicator variable that equals zero if the firm is not financially distressed. If the firm is financially distressed, then the dependent variable equals one only for its last firm-year observation. The independent variables are lagged to ensure that the data are observable prior to the event of financial distress. ZCOMP model is a discrete hazard model that incorporates the accounting-based components of Taffler Z-score. ZSCORE model is a univariate hazard model that uses only Z-score to predict bankruptcy. SHUM model is a discrete hazard model based on the accounting and market-based predictors used in Shumway (2001). SHUM-Z model includes Taffler Z-score. SHUM_MV model is the hazard model based on the market-based predictors used in Shumway (2001). SHUM_MV-Z model incorporates Taffler Z-score. PROF is measured as profit before tax divided by current liabilities. WCAP is the ratio of current assets to total liabilities. FRISK is measured as current liabilities to total assets. LIQUID is defined as (quick assets minus current liabilities) divided by (sales minus profit before tax minus depreciation divided by 365). Z-score is calculated as 3.20 + 12.18*PROF + 2.50*WCAP -10.68*FRISK + 0.029*LIQUID. EBITDA_TA is the ratio of EBITDA to total assets. Book leverage is measured as the book value of debt divided by the book value of debt plus stockholders' equity. REL_SIZE is the natural logarithm of annual firm's market capitalization over the market capitalization of FTSE ALL SHARES index. EXPR is the firm's annual returns in the year t-1 minus the return on FTSE ALL SHARES index in the year t-1. σ is obtained by regressing each stock's monthly returns in year t-1 on FTSE ALL SHARES index for the same period. σ is the standard deviation of the residual of this regression.

	ZCOMP	ZSCORE	SHUM	SHUM-Z	SHUM_MV	SHUM_MV-Z
Constant	-5.6872***	-4.7329 ***	-6.4965***	-6.5547***	-6.3067***	-6.2375***
PROF	-0.3355**					
WCAP	-0.0206					
FRISK	2.1191**					
LIQUID	0.0003					
Z-score		-0.0795***		-0.0305		-0.0305
EBITDA_TA			-0.1210	-0.4021		
BLEV			1.1238 **	0.7553		
REL_SIZE			-0.2035*	-0.2203*	-0.2144*	-0.2065
EXPR			-0.8569 **	-0.7952**	-0.9856***	-0.7802**
σ			5.1454 **	5.2495 **	5.9369***	5.1522**
Pseudo-R^2	0.04	0.05	0.10	0.11	0.09	0.11
Number of observations	22,785	22,785	27,796	21964	28,503	21,982

***,** and * denote significance at the 1, 5 and 10 percent level respectively.

Table 4: Forecast accuracy of UK firms

This table presents an out-of-sample accuracy of four financial distress prediction models. ZCOMP model is a discrete hazard model that incorporates the accounting-based components of Taffler Z-score. ZSCORE model is a univariate hazard model that uses only Z-score to predict bankruptcy. SHUM model is a discrete hazard model based on the accounting and market-based predictors used in Shumway (2001). SHUM_MV model predicts financial distress including only the market-driven variables, i.e., REL_SIZE, EXPR and σ. Parameter estimates calculated with 1981-1990 data are combined with annual data between 1991-2006 to forecast corporate failures that occurred in 1991-2006. We rank the probabilities of financial distress for UK firms into deciles. Deciles 1-5 are the deciles with the highest probability of financial distress, whereas Deciles 6-10 are the deciles with the lowest probability of financial distress. The table shows how much of the percentage (%) of the actual distressed firms is explained by the probability rankings.

Decile	ZCOMP	ZSCORE	SHUM	SHUM_MV
1	28.85	27.86	36.72	35.58
2	17.91	20.90	20.29	17.79
3	10.94	17.91	15.46	15.38
4	8.46	7.46	9.66	9.13
5	6.97	5.97	6.75	6.25
6-10	26.87	19.90	11.11	15.87
Corporate failures	201	201	207	208

Table 5: Logit regressions of firm-specific and macroeconomic variables

The dependent variable is an indicator variable that equals zero if the firm is not financially distressed. If the firm is financially distressed, then the dependent variable equals one only for its last firm-year observation. The independent variables are lagged to ensure that the data are observable prior to the event of financial distress. ZCOMP model is a discrete hazard model that incorporates the accounting-based components of Taffler Z-score. ZSCORE model is a univariate hazard model that uses only Z-score to predict bankruptcy. SHUM model is a discrete hazard model based on the accounting and market-based predictors used in Shumway (2001). SHUM-Z model includes Taffler Z-score. SHUM_MV model is the hazard model based on the market-based predictors used in Shumway (2001). SHUM_MV-Z model incorporates Taffler Z-score. ANRATE is the ratio of the number of bankruptcies to the total number of firms over the previous year. GDPRATE is the annual real UK GDP growth rate. TB3M is the annual UK 3-month treasury bill rate. PROF is measured as profit before tax divided by current liabilities. WCAP is the ratio of current assets to total liabilities. FRISK is measured as current liabilities to total assets. LIQUID is defined as (quick assets minus current liabilities) divided by (sales minus profit before tax minus depreciation divided by 365). Z-score is calculated as 3.20 + 12.18*PROF + 2.50*WCAP -10.68*FRISK + 0.029*LIQUID. EBITDA_TA is the ratio of EBITDA to total assets. Book leverage is measured as the book value of debt divided by the book value of debt plus stockholders' equity. REL_SIZE is the natural logarithm of annual firm's market capitalization over the market capitalization of FTSE ALL SHARES index. EXPR is the firm's annual returns in the year t-1 minus the return on FTSE ALL SHARES index in the year t-1. σ is obtained by regressing each stock's monthly returns in year t-1 on FTSE ALL SHARES index for the same period. σ is the standard deviation of the residual of this regression.

	ZCOMP	SHUM	SHUM-Z	SHUM_MV	SHUM_MV-Z
Constant	-6.2707***	-7.1900 ***	-7.1613***	-6.7980***	-6.8079***
ANRATE	0.4645*	0.3021	0.2854	0.2242	0.2042
GDPRATE	0.1394	0.0762	0.1849	0.0446	0.1909
TB3M	0.0045	0.0587	0.0540	0.0445	0.0717
PROF	-0.2584*				
WCAP	0.0023				
FRISK	2.1217**				
LIQUID	0.0001				
Z-score			-0.0311		-0.0312
EBITDA_TA		-0.0697	0.5020		
BLEV		1.2144 **	0.9137		
REL_SIZE		-0.1947*	-0.1935	-0.2086*	-0.1899
EXPR		-0.8218 **	-0.8050**	-0.9487***	-0.7709**
σ		4.9218 **	5.1351 **	5.6894***	4.9170**
Pseudo-R^2	0.06	0.11	0.13	0.09	0.12
Number of observations	22,785	27,796	21964	28,503	21,982

***,** and * denote significance at the 1, 5 and 10 percent level respectively.

Table 6: Adjusting for the time-series dynamics of the covariates

The dependent variable is an indicator variable that equals zero if the firm is not financially distressed. If the firm is financially distressed, then the dependent variable equals one only for its last firm-year observation. SHUM model is a discrete hazard model based on the accounting and market-based predictors used in Shumway (2001). SHUM-DYN model exploits some of the time-series dynamics of the explanatory variables. ANRATE is the ratio of the number of bankruptcies to the total number of firms over the previous year. GDPRATE is the annual real UK GDP growth rate. TB3M is the annual UK 3-month treasury bill rate. GDPRATE_AVG is the annual real UK GDP growth rate applying geometrically declining weights on the lags of nominal GDP on quarterly basis. TB3M_AVG is computed by applying geometrically declining weights on the lags of TB3M on a monthly basis. EBITDA_TA is the ratio of EBITDA to total assets. Book leverage is measured as the book value of debt divided by the book value of debt plus stockholders' equity. REL_SIZE is the natural logarithm of annual firm's market capitalization over the market capitalization of FTSE ALL SHARES index. EXPR is the firm's annual returns in the year t-1 minus the return on FTSE ALL SHARES index in the year t-1. EXPR_AVG is computed by applying geometrically declining weights on the lags of EXPR on a monthly basis. σ is obtained by regressing each stock's monthly returns in year t-1 on FTSE ALL SHARES index for the same period. σ is the standard deviation of the residual of this regression.

	SHUM	SHUM-DYN
Constant	-7.1900 ***	-7.5387***
ANRATE	0.3021	0.3247
GDPRATE	0.0762	
GDPRATE_AVG		0.0936
TB3M	0.0587	
TB3M_AVG		0.0859
EBITDA_TA	-0.0697	-0.2404
BLEV	1.2144 **	1.5226***
REL_SIZE	-0.1947*	-0.2644**
EXPR	-0.8218 **	
EXPR_AVG		-7.4312**
σ	4.9218 **	3.3317 **
Pseudo-R^2	0.11	0.11
Number of observations	27,796	26844

***,** and * denote significance at the 1, 5 and 10 percent level respectively.