On The Prediction Of Financial Distress For Greek firms: Accounting or Market information?

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Abstract

We evaluate the impact of accounting and market-driven information on the prediction of bankruptcy for Greek firms using a discrete hazard model suggested by Shumway (2001). We show that a hazard model that incorporates three accounting ratio components of Z-score and three market-driven variables is the most appropriate model for the prediction of corporate financial distress in Greece. This model outperforms a univariate model that uses the expected default frequency (EDF) derived from the Merton distance to default model and a multivariate model that is exclusively based on accounting variables. Forecast accuracy tests confirm the main findings.

1 Introduction

Interest in the prediction of financial distress is widespread.[1] Since Beaver (1966) and Altman (1968) a significant body of research uses accounting ratios to predict corporate bankruptcy.[2] More recent studies take advantage of market information derived from the Merton (1974) structural model for pricing corporate debt to forecast bankruptcy; see for example Vassalou and Xing (2004), Duffie, Saita, and Wang (2007) and Bharath and Shumway (2008) and Agarwal and Taffler (2008).[3] Shumway (2001) applies a unique discrete hazard model to predict bankruptcy combining both accounting and market information. Shumway (2001) develops a hazard model that considers all the available observations for bankrupt and non-bankrupt firms addressing efficiently problems associated with biased parameter estimates and statistical inference. He shows that using the hazard model delivers efficient and consistent parameter estimates. In addition, he documents that when using a hazard model, half of the accounting ratios incorporated in Altman's (1968) and Zmijewski's (1984) accounting-based models are not statistically significant for predicting bankruptcy. Campbell, Hilscher, and Szilagyi (2008) use a similar model to explore how distress risk is priced in the equity market.

While there is extensive evidence on the performance of hazard models for developed countries, such as US and UK, we know little about the ability of hazard models to forecast corporate bankruptcy for developing markets. In this paper I assess the performance

[1]For the remainder of the paper, unless otherwise indicated, we use the terms bankruptcy and financial distress interchangeably.

[2]See, among many others, Ohlson (1980), Taffler (1983), Zmijewski (1984) Beaver, McNichols, and Rhie (1980) and Agarwal and Taffler (2007)

[3]I refer to models that measure the distance to default applying Merton's (1974) bond pricing model as Merton distance to default models, or Merton DD, models. The implied probability of default estimated from the Merton DD model is widely known as the expected default frequency (EDF).

of hazard models to predict financial distress for Greek firms using accounting and market information. To the best of my knowledge, there are no other studies that evaluate the performance of bankruptcy prediction models for Greek firms using the hazard approach of Shumway (2001). We compare the hazard models with a hazard model EDF derived from Merton DD model, providing insight into their ability to forecast corporate financial distress. The paper also makes a contribution to the literature by focusing on the performance of these models before and after the financial market turmoil in 2007.

The existing literature uses various methods to estimate the probability of financial distress. Altman (1968) uses discriminant analysis to estimate Z-scores, while Ohlson (1980) and Zmijewski (1984) use logit and probit models to predict the probability of financial distress . These multivariate statistical techniques have been applied to the prediction of financial distress for Greek firms; see, for example, Gloubos and Grammaticos (1988), Theodossiou and Papoulias (1988), Papoulias and Theodossiou (1992).However, some important methodological issues arise when using these models. Shumway (2001) shows that well-established bankruptcy prediction models, such as Altman's (1968) Z-score and Ohlson's (1980) conditional logit model are misspecified as they do not take into account all the available firm-year observations. This induces a bias on the estimated coefficients of the variables used to forecast bankruptcy, resulting to incorrect statistical inferences. Non-parametric statistical approaches have also been used to predict corporate financial distress. For example, artificial neural networks approach; e.g., Altman, Marco, and Varetto (1994), rough set approach; e.g., Dimitras, Slowinski, Sumaga, and Zopounidis (1999) multicriteria decision aid approach; e.g., Zopounidis and Dimitras (1998) and multi-group hierarchical discrimination approach; e.g., Doumpos, Kosmidou, Baourakis, and Zopounidis (2002).

The empirical design of the paper is based on a discrete hazard model in the spirit of Shumway (2001). First, I examine the ability of accounting information to predict financial distress. In particular, I focus on the individual accounting ratio components of the popular Z-score measure to explore whether and to what extent they are associated with the probability of financial distress. The accounting ratio components of Z-score are based on Altman's (Altman (1968)) and Taffler's model (Taffler (1983).[4] I then examine the ability of market information to predict bankruptcy for Greek firms. In particular, I test whether the EDF, derived from the Merton DD model, is related to the forecast of financial distress. Following Shumway (2001), I evaluate the performance of a hazard model that contains three market-based variables, i.e. market capitalization, past excess returns and stock return volatility.Finally, similar to Shumway (2001), I assess the performance of a hazard model that contains both accounting and market-driven variables with respect to financial distress forecast.

The results show that three accounting ratio components of Z-score, contribute significantly to the prediction of corporate financial distress in Greece. In particular, sales to total assets and profitability are negatively associated with the probability of financial distress whereas financial risk is positively related to the probability of financial distress. However, liquidity cannot explain the likelihood of bankruptcy. I document that EDF has a positive impact on the probability of financial distress using a univariate hazard model. When EDF is combined with accounting ratios in a multivariate hazard model, EDF is not related to bankruptcy prediction. Using a hazard model that exclusively is based on

[4]The use of retained earnings divided by total assets as an accounting ratio component of Altman's Z-score was infeasible due to lack of data for retained earnings.

market information I show that market size and excess past stock returns have a negative effect on the probability of bankruptcy and stock return volatility has a positive effect on the likelihood of Greek firms to go bankrupt. Incorporating accounting ratios with market information I show that while profitability financial risk, excess returns and stock return volatility enter with the expected signs, market size fails to remain a significant predictor of financial distress.

To evaluate the performance of the models relative to each, I use Vuong's (1989) test to compare the log-likelihood ratios of the hazard models. I provide evidence that the combination of sales scaled by total assets, profitability and financial risk with market size, excess returns and stock return volatility best captures the variation in the actual probability of bankruptcy. Forecast accuracy tests also show that the model that uses three accounting ratios along with three market-based variables yields the highest predictive ability. Also, I show that a hazard model that contains only three market-driven variables and a multivariate model that uses the accounting ratios of Z-score perform better than a univariate model that contains EDF.

Further to the main findings of the paper, I segregate the sample period into pre-financial crisis period (2002-2006) and post-financial crisis period (2007-2010) to explore the performance of the hazard models across these two subperiods. I find that the impact of accounting ratios and market-based variables on the probability of financial distress for the two subperiods weakens. For the period 2002-2006, sales to total assets, profitability and excess returns are strongly associated with the prediction of bankruptcy. During the financial crisis (2007-2010) only financial risk has a significant impact on the probability of financial distress. Despite the smaller effect of accounting and market-variables on the likelihood of a Greek firm to go bankrupt pre and post crisis, the forecast accuracy test shows that the hazard model that combines accounting and market-driven variables exhibits the highest predictive ability.

The rest of the paper is organized as follows. Section 2 provides a methodological background on modeling the probability of financial distress using the discrete hazard approach. Section 3 describes the Greek dataset. Section 4 presents the main results from the various discrete hazard models and the respective forecast accuracy tests along with the results that correspond to pre and post-financial crisis.

2 Empirical Design

The empirical analysis of the study is based on a discrete hazard model introduced by Shumway (2001) and is of the following form:

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

where $h_i(t)$ represents the hazard of bankruptcy at time t for company i, conditional on survival to t; $\alpha(t)$ is the baseline hazard; β is a vector of coefficients and $\mathbf{x}_{it}$ a $k \times 1$ vector of observations on the ith covariate at time t. The innovative feature of this approach, as Shumway (2001) shows, is that the discrete-time hazard model can be estimated as a dynamic multi-period logit model where each period that a firm survives is included as a non-failing firm-year observation. Therefore, we estimate the probability of bankruptcy as

$$P_{t-1}(Y_{it} = 1) = \frac{1}{1+\exp\left(-\alpha - \beta'\mathbf{x}_{it-1}\right)} \tag{2}$$

where Y_{it} is a variable that equals one if firm i enters financial distress in year t, zero otherwise. β and $\mathbf{x}$ are as before. Notice that we use data dated $t-1$ in estimating the probability of bankruptcy. This is to ensure that we only use data that is actually available prior to the occurrence of bankruptcy.

Prior to Shumway (2001), several econometric techniques have been used to predict corporate financial distress. Altman (1968) employs multivariate discriminant analysis to determine Z-score, which ia a widely used measure for predicting bankruptcy for US firms; Taffler (1983) employs the same technique for UK firms. Altman, Haldeman, and P.Narayanan (1977) use quadratic discriminant analysis to identify firms in danger of going bankrupt. Ohlson (1980) estimates a conditional logit model to generate the probability that a firm will enter bankruptcy (known as the "O-score") while Zmijewski (1984) estimates a probit model. Lau (1987) uses a multinomial logit model that allows for more than two states of financial distress. Most of these estimation methods have been applied to the Greek context; see, for example, Gloubos and Grammaticos (1988), Theodossiou and Papoulias (1988), Papoulias and Theodossiou (1992). However, Shumway (2001) argues that these bankruptcy forecasting models are misspecified as they do not properly address the length of time that a healthy firm has survived. In particular, such models are static because they use only one firm-year observation for a non-failed firm. This induces a selection bias. Shumway (2001) documents that ignoring firm-year observations with respect to the length of time a healthy firm has survived produces biased and inconsistent estimates of the parameters of the model. Shumway (2001) shows that this caveat is properly addressed by using a discrete time hazard model. In the hazard model, the hazard rate is the probability of the firm going bankrupt at time t conditional upon having survived until time t. Therefore, the probability of bankruptcy changes through time.

The competitive advantage of the hazard approach is twofold. First, it allows researchers to take advantage of all the available firm-year observations. Second it enables the probability of bankruptcy to change over time as a function of a vector of explanatory variables that also change over time. While previous studies were merely based on accounting ratios, Shumway (2001) uses a combination of accounting and market information that vary over time to estimate the probability of financial distress following the hazard approach. I evaluate the contribution of accounting and market-driven variables to the prediction of corporate financial distress in Greece employing a discrete hazard model. The hazard model proposed by Shumway (2001) is estimated as a dynamic logit model using maximum likelihood estimation method.

3 Sample and Data

The sample consists of Greek firms that operate in Greece and are listed in the Athens Stock Exchange (ASE). We obtain the accounting data and the market data from Thomson Financial Datastream. We exclude financial firms and utilities from the sample. We exclude firm-year observations for which we do not have available data. The initial sample consists of 303 alive and dead Greek listed firms with 2,710 firm-year observations over the period 2002–2010. In particular, the sample includes 228 alive and 75 dead firms. The hazard approach requires the identification of bankrupt firms. I consider a firm to be dead when it is delisted from ASE. I gather this specific information from the Athens Stock Exchange and the Hellenic Capital Market Commission. I define a firm as bankrupt if a firm is delisted from the Athens Stock Exchange due to bankruptcy or if the firm is suspended according to the Hellenic Capital Market Commission. I identify 36 bankrupt firms whereas the remaining firms (39) were delisted from ASE for other reasons that are beyond the scope of the paper, such as mergers and acquisitions. The sample contains 303 Greek firms with 2,710 firm-year observations. There are 36 bankrupt firms with 324 firm-year observations and 267 non-bankrupt firms providing 2,386 firm-year observations. Table 1 provides detailed information on the definition of all variables used in the study.

With respect to accounting information the analysis of the paper is focused on the accounting ratios of Z-score based on Altman (1968) and Taffler (1983) model. In particular, we use net sales divided by total assets (SALES_TA), profitability defined as earnings before interest, taxes, depreciation and amortization to total assets (EBITDA_TA), financial risk measured as current liabilities to total assets (FRISK) and liquidity defined as current assets minus current liabilities scaled by total assets (LIQUID) . To consider the role of market information in the bankruptcy prediction for Greek firms, we use the expected default frequency (EDF) estimated from the Merton DD Model. I also use the three market-based variables that have been included in the model of Shumway (2001), i.e. relative size (REL_SIZE), which expresses the equity market capitalization of the firm relative to total equity market capitalization, excess stock returns (EXRET) and idiosyncratic stock return volatility (SIGMA). Table 1 describes the variables in more detail. I winsorize the independent variables at the 0.5th and 99.5th percentiles of the distribution to deal properly with outliers. Descriptive statistics for the explanatory variables are provided in Table 2. Note that EDF cannot be meaningful in a logit model as it is expressed in the form of a probability, which is inconsistent with the assumptions of a logit model.

Therefore, based on Hillegeist, Keating, Cram, and Lundstedt (2004), in the next section we transform EDF into a "score", namely EDF-SCORE, using the inverse logistic function $EDF - Score = \ln(EDF/(1-EDF))$ when performing logit regressions.

According to Table 2, the distribution of SALE_TA is positively skewed while the distribution of EBITDA_TA is symmetrical. We also observe that the market-based variables, REL_SIZE, EXRET, SIGMA and EDF are the most volatile variables. The average expected default frequency (EDF) for our sample is 10%, which is close to the bankruptcy rate of our sample (12%). The bankruptcy rate is defined as bankrupt firms (36) divided by the total number of firms (303). The minimum value of EDF is 0.00 and the maximum value of EDF is 0.51. This is because the descriptive statistics in Table 2 are expressed to two decimal places. The average and the median of REL_SIZE is negative as it is defined as the logarithm of a generally small number; see, Table 1.

4 Results

4.1 Predictive ability of discrete hazard models

I estimate the probability of financial distress for Greek firms using a series of multi-period logit models each of which contains different information. The results are presented in Panel A of Table 3. The first column provides evidence on the ability of accounting information to predict financial distress. The column named ACCR is a model that incorporates accounting ratios that are used to calculate the widely known Z-score. The motivation is to explore which, if any, of the ratios that make up the Z-score individually contribute to the prediction of financial distress. The results show that sales scaled by total assets and profitability are negatively related to the probability of bankruptcy whereas financial risk is positively associated with the probability of bankruptcy. However, liquidity is not a significant predictor of bankruptcy. Overall, three out of four accounting ratio components of Z-SCORE are relevant to the forecast of financial distress. EDF presents the results from a univariate model that uses an equivalent measure of the expected default frequency (EDF-score), derived from a Merton DD model, as a predictor of financial distress. As expected, I find that there is a positive association between EDF-score and the probability of financial distress. The next column, ACCREDF, presents the results of a model that combines the accounting ratios of the first column with EDF-score to forecast financial distress. While the signs of the coefficients of sales to total assets, profitability and financial risk remain unaltered and in line with the findings presented in the first column EDF-score is no longer related to the prediction of financial distress.

The model in the MV column predicts the probability of financial distress using Shumway's three market-driven variables, i.e., relative size, excess returns and stock return volatility (SIGMA). The results show that relative size and excess returns have a negative and significant impact on the probability of bankruptcy, where as stock return volatility has a positive and significant effect on the probability of bankruptcy for Greek firms. This is consistent with prior evidence; see, Shumway (2001) and Campbell, Hilscher, and Szilagyi (2008). MVACCR column reports the results from a model that combines the three market-based predictors with the accounting ratios of Z-score. Unlike ACCREDF column, there is clear evidence that both accounting and market information play an important role in the prediction of financial distress for Greek firms. I show that sales to total assets, profitability and excess stock returns are negatively associated with the prediction of financial distress. Financial risk and SIGMA are positively associated with the prediction of financial distress.

Apart from the choice of variables that contribute to the prediction of financial distress, the evidence on which of the above models best captures the probability of financial distress for Greek firms is considerably appealing. This will lead to the most accurate bankruptcy prediction model. To this end, we follow Hillegeist, Keating, Cram, and Lundstedt (2004) and use the comparison test of Vuong (1989) model. Vuong (1989) develops a test for choosing between two models, i and j. Under the null hypothesis that there is no difference between the two models, the log of the ratio of the likelihood for model i to that for model j should be zero. If the difference is significantly positive, i is preferred to j and vice versa. Vuong (1989) derives a statistic that allows us to test this hypothesis. Under the null hypothesis that there is no difference between the competing models, the test statistic has a standard normal distribution. Panel B of Table 3 contains results of the Vuong test for the models shown in Panel A of Table 3. First, I investigate how the MVACCR model performs versus the ACCR model. The z-statistic derived from the Vuong test is positive and significant at 10% showing that the MVACCR outperforms ACCR model. Therefore, the accounting information is not sufficient to estimate an accurate probability of corporate financial distress. Instead, the combination of accounting and market information is needed to explain the probability of financial distress for Greek firms. I also document that MVACCR model yields a more efficient estimate of the probability of bankruptcy than the model that is exclusively based on expected default frequency (EDF). MVACCR model captures more effectively the probability of financial distress than a model that combines the accounting ratios with EDF (ACCREDF). MVACCR model is better than a model that is based only on market-based variables (MV model). Therefore market information alone cannot predict financial distress adequately. I also find that there is no difference between MV model and the ACCR model. Finally, I report that both the MV and the ACCR model outperform the univariate EDF model.

To provide a better understanding on the predictive ability , I sort firms into six deciles in descending order based on the probability of bankruptcy estimated by each of the hazard model described in Table 3. In particular, Deciles one to three contain firms that are more likely to go bankrupt. Decile one consists of firms that exhibit the highest estimated probability of bankruptcy, while Deciles four to six contain those firms that are less likely to enter financial distress. Decile 6 contains firms with the lowest predicted probability of bankruptcy. To investigate the predictive ability of a hazard model I define the percentage of bankrupt firms that are allocated to the various deciles by the estimated probability of financial distress derived from each model. This can be thought of as a means by which we can assess the ability of the models to correctly classify those firms that went bankrupt as likely to go bankrupt. In particular, for each model, we report the percentage of bankrupt firms classified in firms with high probability of financial distress (deciles 1-3). Also, for each model, we show the percentage of bankrupt firms classified in firms with low probability of financial distress (deciles 4-6). This represents the misclassification rate of each model. The ideal case would be all the bankrupt firms to be allocated in Deciles one till three implying that the model does not suffer from misclassification. However, this is very rare. Therefore, the main objective is to minimize the classification error when assessing a bankruptcy forecast model. Table 4 presents the results.

At first glance we observe that each of the hazard model identifies a large number of bankrupt firms in Deciles 1-3, i.e., firms that are more likely to go bankrupt than less. Looking at the Table 4 more thoroughly we observe that the ACCR model classifies more than 60% of the bankrupt firms (63.32%) in Decile 1 and 89.98 % in Deciles 1-3. As we move from Decile 4 to 6, which include firms with the lowest probability of financial distress derived from ACCR model (Deciles 4-6), one would anticipate a lower number of bankrupt firms to be identified. However, Decile four, five and six incorporate the same percentage of bankrupt firms, i.e., 3.34% of bankrupt firm. In total ACCR model wrongly classifies 10.04% of bankrupt firms in Deciles 4-6, which is not a negligible misclassification rate. EDF model exhibits the worst performance of all hazard models. It correctly places 64% of firms that go bankrupt in Deciles 1 through 3 and has the highest misclassification rate. In particular, EDF model classifies 46% of bankrupt firms in the deciles with the lowest probability of financial distress. It is striking that 24% of the bankrupt firms are allocated in the last decile, i.e, the decile with the lowest probability of bankruptcy. ACCREDF model classifies the highest number of bankrupt firms (95.45%) in Deciles one two and three. It also exhibits the lowest misclassification rate (4.55%); see, Deciles 4-6. However, it only identifies 22 bankrupt firms. The model that includes only market-driven variables, described in the column headed MV of Table 3, correctly predicts that 82.36% of those firms that actually go bankrupt as more likely than not to go bankrupt; see, Deciles 1-3. However, we would expect a higher number of firms to be identified in Decile 2 than in Decile 3. Instead, only 5.88% of bankrupt firms are identified in Decile 2 whereas 17.65% of bankrupt firms are identified in Decile 3. Also, it has a high misclassification rate, 17.64%; see, Deciles 4-6. The MVACCR model, which combines accounting with market-driven variables yields the greatest predictive ability, identifying

30 bankrupt firms. It correctly classifies the highest number of bankrupt firms in Decile 1, i.e., 76.66% and 93.33% in Deciles 1-3.It also exhibits a low misclassification rate, i.e., 6.67% in Deciles 4-6. Hence the probability of financial distress estimated by MVACCR model allocates most effectively the number of bankrupt firms.

Taken together the results in Tables 3 and 4, I provide insights into forecasting the probability of financial distress for Greek firms. We show that MVACCR model, i.e., a model that includes three accounting ratios and three market-driven variables best describes the probability of bankruptcy. Therefore we can forecast financial distress more accurately by combining accounting and equity market-driven variables. However, the findings strongly suggest that the choice of accounting and market information matters when evaluating a financial distress prediction model. I provide evidence that a model that uses EDF estimated by the Merton DD model has considerably lower predictive ability than a model that uses three market-based variables suggested by Shumway (2001). The results also show that neither accounting ratios (net sales scaled by total assets, profitability and financial risk) alone or market-driven variables (market capitalization, excess past stock returns and stock return volatility) alone are sufficient enough to predict corporate bankruptcy in Greece.

Table 5 shows the time-series variation of the average probability of financial distress for Greek firms derived from the MVACCR model. We observe that the year 2003 exhibits the lowest average probability of financial distress (0.72%). There is a considerable increase in the probability of financial distress across 2004-2005, which amounts to 2.33% in 2005. The average probability of financial distress slightly decreases in 2006. Despite the burst of the global financial crisis in 2007-2008, Greek economy has not initially been affected. In particular, there is a decrease in the probability of corporate bankruptcy in Greece at that period (1.10% and 1.16%, respectively). Since 2008 the credit crunch has a significant effect on the estimated probability of financial distress. Looking at Table 5, the probability of financial distress increases to 1.48% in 2009 and augmented more than 0.85% in 2010 reaching the maximum, i.e., 2.76%. Table 6 presents the variation of the average probability of financial distress across industries Personal goods, media, food producers, health care equipment, construction-materials, software-computer services, pharmaceuticals-biotechnology, general retailers and beverages are the sectors that exhibit the highest estimated probability of financial distress. The average probability of financial distress of each of these sectors is more than 1.50%. Oil- Gas producers, mobile telecommunications, leisure goods, electronic-electrical equipment, mining, software services, industrial transportation and industrial engineering are the sectors that are less likely to go bankrupt. The time-series variation of industries with the highest average probability of financial distress is presented in Table 7. The probability of bankruptcy for the personal goods sector considerably increased from 0.89% in 2003 to 4.89% and 5.55% in 2005 and 2006, respectively. There is an increase in the probability of bankruptcy for the media industry for the period 2004 to 2006 and in particular from 1.37% to 2.86% The effect of the global financial crisis on the sector of media is strong. The probability of financial distress for this specific industry amounts to 2.57% in 2009 and jumps to 6.23% in 2010. There is more than 142% increase in its probability of financial distress in one year. The food producers sector exhibits high probabilities of default in 2004-2006 period. Due to the credit crunch effect, the probability of bankruptcy of this industry highly increases from 2.24% in 2009 to 5.00% in 2010. The probability of financial distress of health care equipment industry augments highly between 2004-2006 and specifically from 1.83% to 4.73%. Construction-materials industry exhibits high probability of financial distress for the periods 2004-2005 and 2008-2010. Software-Computer services is affected by the debt crisis as its probability of financial distress reaches the optimum of 3.76% in 2009. The probability of bankruptcy pharmaceuticals-biotechnology industry significantly increases over the 2004-2006 period rocketing to 7.45% in 2006. The highest increase in the probability of bankruptcy for the General retailers industry occurs in 2010. In particular, it increases from 0.35% in 2009 to 6.55% in 2010.

4.2 Estimation of probability of financial distress across different horizons

To explore the predictive accuracy of the hazard models in different time periods I split the sample into two subperiods, i.e., 2002-2006 and 2007-2010. The two subperiods are not randomly chosen. I explore the performance of the discrete hazard models before the global financial crisis (2002-2006) and after the global financial crisis (2007-2010). Panel A of Table 8 presents the results for the multi-period logit models for the period 2002-2006. ACCR column shows that sales to total assets and profitability are negatively associated with the probability of financial distress whereas financial risk is positively associated with the probability of financial distress at 10%.As with Table 3 EDF column documents a positive relation between the EDF-score and the probability of financial distress. However, when EDF is combined with the accounting ratios EDF cannot explain the firm's probability to go bankrupt. The sign of sales to total assets and financial risk remain negative and positive, respectively. Unlike the core findings, liquidity has a positive impact on the probability of financial distress. This is possibly attributed to the high percentage of observations with negative values of liquidity, i.e., 46%, for the period 2002-2006. With respect to MV model, excess past stock returns have a negative and significant impact on the probability of default. However, market capitalization and stock return volatility cannot explain the probability of financial distress for 2002-2006. MVACCR model documents that only sales to total assets, profitability and excess past stock returns play a significant role in the financial distress prediction prior to the global financial crisis.

Panel B of Table 8 presents the results for the multi-period logit models for the financial crisis period, i.e., 2007-2010. According to ACCR model I document that apart from the negative impact of sales to total assets on the probability of financial distress, there is clearly a positive a association between financial risk and probability of financial distress. EDF-score is positively related to the probability of bankruptcy; see, EDF column. The results from ACCREDF model show that only profitability is marginally significant predictor of corporate bankruptcy. With respect to the MV model market capitalization and excess stock returns are negatively associated with the likelihood of financial distress during the period of financial crisis. Finally, when combining accounting ratios with market-driven variables, only financial risk can explain the probability of financial distress for Greek firms for the period 2007-2010.

Similar to Table 4, I explore the predictive ability of the hazard models for the two subperiods, i.e., 2002-2006 and 2007-2010. I sort the sample into six deciles based on the rankings of probability of financial distress. Deciles 1-3 contain firms that are more likely to go bankrupt and Deciles 4-6 include firms that are less likely to enter financial distress. Panel A of Table 9 presents the results for the 2002-2006 subperiod. ACCR model classifies 66.66% of bankrupt firms in the first Decile and 77.77% in Deciles 1-3. However, the misclassification rate is very high as 22.23% of firms are allocated in Deciles 4-6, which are included firms with the lowest probability of financial distress. EDF model exhibits the worst performance as it identifies only 45.46% of bankrupt firms in Deciles 1-3 and has the highest misclassification rate (54.54%); see, Deciles 4-6. ACCREDF model has the highest classification rate, as it incorporates all the bankrupt firms in Deciles 1 and 2. However, the model identifies only ten bankrupt firms. MV model classifies 80% of the bankrupt firms in the first three deciles. However, the entire misclassification rate 20% is allocated in the last decile, Decile 6. The MVACCR model is the best model in terms of its predictive ability. Given the availability of data it identifies 18 bankrupt firms for the period 2002-2006. It yields a very high classification rate, close to 90%, in Deciles 1-3.

Panel B of Table 9 documents the results for the subperiod 2007-2010. We observe that the predictive ability of the hazard model has improved during the financial crisis in contrast with the predictive ability of the models in 2002-2006 period. ACCR model has a high classification rate in Deciles 1-3 and in particular 91.67%. The misclassification rate is also very low, 8,33% incorporated in Decile 4. EDF model has the worst performance as it classifies the lowest number of bankrupt firms in the deciles with the highest probability of financial distress; see, Deciles 1-3. ACCREDF model exhibits the same classification rate with ACCR model.However, ACCREDF model misclassifies 8.33% of the bankrupt firms in Decile 5. Further to these models, MV model yields a high classification rate (85.72%). MVACCR model has the best predictive ability as it classifies 100% of bankrupt firms in Deciles 1-3 and hence there is no misclassification rate.

5 Concluding remarks

This paper evaluates the contribution of accounting and market information to the prediction of financial distress for Greek firms using the discrete hazard approach following Shumway (2001). In particular, I investigate whether and to what extent the accounting ratio components of Z-score can forecast bankruptcy for Greek firms. I explore the effect of EDF estimated from the Merton model on the likelihood of bankruptcy. I also test the predictive ability of a model that combines the accounting ratios with EDF. I also assess the ability of three market-based variables, i.e., market size, excess returns and sigma to predict financial distress. Finally, I examine the ability of three accounting ratios and three market-driven variables to forecast bankruptcy more accurately.

The results show that the model that combines sales to total assets profitability and financial risk with market capitalization, excess returns and stock return volatility best depicts the probability of financial distress for Greek firms. With respect to market information, the predictive ability of a model that contains market capitalization, excess returns and stock return volatility is clearly higher than of a model that includes EDF. Evidence is inconclusive on whether accounting ratios contain more significant information about the prediction of financial distress than market-based variables. Forecast accuracy tests are in line with the main findings. I also compare the performance of the hazard models across two different time horizons and specifically pre and post financial crisis. I document that he impact of accounting and market variables on the probability of financial distress weakens for the two subperiods. However, in line with the main findings, the model that combines accounting ratios with market-based variables exhibits the highest forecast accuracy.

Overall, this paper provides useful insights on the prediction of corporate bankruptcy for Greek firms, which is of major concern to both academics and practitioners. I find that a model that incorporates three accounting ratios and three market-based variables leads to the most powerful prediction of corporate bankruptcy. I also show that the hazard model based on market capitalization, excess returns and sigma provides considerably better information on the probability of a Greek firm to go bankrupt than a hazard model that is exclusively based on EDF. Finally, we show that accounting information is not superior or inferior to market information with respect to the prediction of financial distress. In line with Shumway (2001), this study strongly recommends the use of both accounting and market-driven variables to forecast bankruptcy for Greek firms more accurately.

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Table 1: Definition of Variables
This table defines the variables used in the study. The accounting and market data is from Thomson Finanancial Datastream. Numbers in parentheses correspond to the Datastream code.

Variable Name	Variable definition
SALES_TA	$\frac{\text{Net Sales (101)}}{\text{Total assets}}$
EBITDA_TA	$\frac{\text{Earnings before interest, tax and depreciation (154+153+696)}}{\text{Total assets}}$
Total liabilities	Total assets (392) – Equity capital & reserves (305)
CA_TL	$\frac{\text{Current assets (376)}}{\text{Total liabilities}}$
CL_TA	$\frac{\text{Current liabilities (389)}}{\text{Total assets}}$
LIQUID	$\frac{\text{Quick assets} - \text{current liabilities (389)}}{\text{Total assets}}$
EDF	Expected default frequency derived from a Merton DD model
REL_SIZE	$\ln\left(\frac{\text{Market value of equity}}{\text{Market value of the FTSE/ASE-20 index}}\right)$
$r_{i,t}$	stock return for firm i at time t ()
$r_{ASE20,t}$	return on the ASE20 at time t
EXRET	$r_{i,t-1} - r_{FTSE/ASE-20,t-1}$ (LSPD)
SIGMA	standard deviation of $\varepsilon_{i,t}$ in the regression : $r_{i,t} = \alpha + \beta r_{FTSE/ASE-20,t} + \varepsilon_{i,t}$

Table 2: Summary Statistics

This table presents descriptive statistics for the variables used in this study. The initial sample consists of 303 firms for the period 2002-2010. We identify 36 financially distressed firms and 267 non-financially distressed firms. The variables are winsorized at the 0.5% fractile in either tail of distribution. PROF is measured as profit before tax divided by current liabilities; CA_TL is the ratio of current assets to total liabilities; FRISK is measured as current liabilities to total assets; LIQUID is defined as quick assets divided by current liabilities. EDF is the expected default frequency derived from a Merton DD model. EBITDA_TA is the ratio of EBITDA to total assets. REL_SIZE is the natural logarithm of the firm's annual market capitalization relative to the market capitalization of the FTSE/ASE-20 index. EXRET is the firm's annual returns in excess of the return on the FTSE/ASE-20 index. SIGMA is idiosyncratic return volatility. It is estimated as the standard deviation of the residuals from a regression of each stock's monthly return on the monthly return on the FTSE/ASE-20 index.

Variable	Mean	Median	Std.dev	Min	Max
SALES_TA	0.80	0.66	0.64	0.02	5.35
EBITDA_TA	0.08	0.08	0.10	-0.50	0.48
CL_TA	0.39	0.36	0.20	0.03	1.18
LIQUID	0.15	0.16	0.22	-0.70	0.75
EDF	0.01	0.00	0.03	0.00	0.51
REL_SIZE	-6.82	-6.94	1.54	-9.98	-1.95
EXRET	-0.05	-0.06	0.49	-1.42	1.56
SIGMA	0.10	0.09	0.07	0.00	0.44

Table 3: Results For Hazard Models Predicting the Probability of Financial Distress

This table contains results derived from the hazard 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. Panel A contains parameter estimates and test of their significance for each hazard model. The column headed ACCR contains results for a model that uses the accounting ratios of Z-score. The EDF column presents the results from a univariate model that uses EDF derived from a Merton DD model. EDF is converted to a Score labeled as EDF-score. The ACCREDF column shows the results from a model that combines the accounting ratios of Z-score with EDF. The MV column contains results from a hazard model that uses market-based variables (REL_SIZE, EXRET and SIGMA) to predict financial distress.The MVACCR column contains results from a hazard model that combines market-based variables with EBITDA_TA, LIQUID and FRISK. The row labeled Wald Statistic contains the Wald test testing the hypothesis that the coefficients are jointly zero. It is distributed as $\chi^2(k)$, where k is the number of parameters (excluding the constant.) We scale the Wald-Chi Square statistic by the average number of observations per firm. Figures in parentheses are scaled Wald statistics testing the hypothesis that the individual coefficient is zero. These have a $\chi^2(1)$ distribution. Panel B contains the results from Vuong tests for model comparison. Under the null hypothesis that there is no difference between the two models, the log of the ratio of the likelihood for model i to that for model j should be zero. If the difference is significantly positive, i is preferred to j and vice versa. $***$, $**$ and $*$ denote significance at the 1, 5 and 10 percent levels respectively.

Panel A: Bankruptcy Prediction Models For Greek Firms

	ACCR	EDF	ACCREDF	MV	MVACCR
Constant	-3.9942^{***}	-2.5259^{***}	-3.3042^{***}	-8.0585^{***}	-5.2022^{***}
	(-6.55)	(-5.21)	(-3.69)	(-6.94)	(-3.84)
SALES_TA	-2.6356^{***}		-3.0753^{***}		-2.2996^{***}
	(-3.54)		(-3.49)		(-3.09)
EBITDA_TA	-4.6458^{***}		-5.8068^{***}		-2.6251^{*}
	(-3.01)		(-3.63)		(-1.68)
CL_TA	3.3295^{***}		3.2217^{***}		2.1774^{***}
	(2.95)		(2.59)		(2.59)
LIQUID	1.2170		1.9687		
	(1.12)		(1.60)		
EDF-Score		0.1897^{***}	0.0965		
		(3.42)	(1.48)		
REL_SIZE				-0.4145^{***}	-0.0778
				(-2.74)	(-0.46)
EXRET				-1.6009^{***}	-1.2409^{***}
				(-4.61)	(-3.21)
SIGMA				5.8063^{**}	6.0460^{**}
				(2.21)	(2.11)
Log Likelihood	-127.69	-125.85	-98.67	-153.97	-121.89
Wald statistic	53.33^{***}	10.31^{***}	56.00^{***}	33.21^{***}	61.91^{***}

Panel B: Vuong Tests

Model i versus Model j	z statistic
MVACCR versus ACCR	1.80^{*}
MVACCR versus EDF	4.13^{***}
MVACCR versus ACCREDF	2.53^{**}
MVACCR versus MV	2.01^{**}
ACCR versus MV	0.76
MV versus EDF	3.53^{***}
ACCR versus EDF	3.05^{***}

Table 4: Forecast Accuracy Tests
This table examines the forecast accuracy of five hazard models we estimate. Firms are sorted in six deciles based on their estimated probability of financial distress. Decile 1 contains those firms with the highest probability while decile 6 contains those with the lowest. We then calculate the percentage (to two decimal places) of firms that subsequently went bankrupt the models place in to each decile. The column headed ACCR contains results for a model that uses the accounting ratios of Z-score. The EDF column presents the results from a univariate model that uses EDF derived from a Merton DD model. EDF is converted to a Score labeled as EDF-score. The ACCREDF column shows the results from a model that combines the accounting ratios of Z-score with EDF. The MV column contains results from a hazard model that uses market-based variables (REL_SIZE, EXRET and SIGMA) to predict financial distress.The MVACCR column contains results from a hazard model that combines market-based variables with EBITDA_TA, LIQUID and FRISK.

Decile	ACCCR	EDF	ACCREDF	MV	MVACCR
1	63.32	44.00	68.18	58.83	76.66
2	13.33	8.00	22.72	5.88	10.00
3	13.33	12.00	4.55	17.65	6.67
4	3.34	6.00	4.55	5.88	0.00
5	3.34	6.00	0.00	8.82	6.67
6	3.34	24.00	0.00	2.94	0.00
No. of Bankrupt Firms	30	25	22	34	30

Table 5: Time-Series Variation of the Probability of Financial Distress
This table presents the time-series variation of the probability of financial distress derived from the best bankruptcy forecast model, i.e., MVACCR model. This model combines REL_SIZE, EXRET and SIGMA with EBITDA_TA, LIQUID and FRISK.

Year	PROBFD (%)
2003	0.72
2004	1.47
2005	2.33
2006	2.21
2007	1.10
2008	1.16
2009	1.48
2010	2.76

Table 6: Variation of the Probability of Financial Distress across Industries
This table presents the variation of the probability of financial distress derived from MVACCR model across Greek industries. This model combines REL_SIZE, EXRET and SIGMA with EBITDA_TA, LIQUID and FRISK.

Industries	PROBFD (%)
Beverages	1.51
Chemicals	1.16
Construction and Materials	1.98
Electronic and Electrical Equipment	0.34
Fixed Line Telecommunications	0.96
Food Producers	2.17
Food and Drug Retailers	0.07
General Industrials	0.92
General Retailers	1.61
Health Care Equipment and Services	2.10
Household Goods and Home Construction	1.13
Industrial Engineering	0.73
Industrial Metals and Mining	1.01
Industrial Transportation	0.71
Leisure Goods	0.29
Media	2.26
Mining	0.28
Mobile Telecommunications	0.12
Oil and Gas Producers	0.02
Personal Goods	2.76
Pharmaceuticals and Biotechnology	1.70
Software and Computer Services	1.91
Support Services	0.69
Technology Hardware and Equipment	0.92
Tobacco	0.58
Travel and Leisure	1.39

Table 7: Time-series variation across industries with the highest PROBFD

This table presents the time-series variation of the probability of financial distress derived from MVACCR model across Greek industries that are most likely to go bankrupt.. This model combines REL_SIZE, EXRET and SIGMA with EBITDA_TA, LIQUID and FRISK. The probability of financial distress is expressed as a percentage.

	2003	2004	2005	2006	2007	2008	2009	2010
Personal Goods	0.89	1.95	4.89	5.55	1.67	1.42	2.16	2.93
Media	0.71	1.37	1.79	2.86	1.95	1.28	2.57	6.23
Food producers	0.73	2.85	2.02	1.96	0.93	1.70	2.24	5.01
Health care equipment	1.09	1.83	2.25	4.73	1.56	1.73	1.30	1.70
Construction and Materials	0.91	1.15	3.73	2.17	1.99	1.58	2.11	2.47
Software and Computer Services	0.77	2.55	2.06	1.88	1.00	0.61	3.76	2.51
Pharmaceuticals and Biotechnology	0.68	0.55	2.06	7.45	0.34	0.57	0.46	1.47
General Retailers	0.82	1.74	2.08	0.91	0.33	0.24	0.35	6.55
Beverages	0.65	1.02	2.54	2.30	1.13	1.42	1.42	1.62

Table 8: Bankruptcy Forecast Prediction Models pre and post crisis

Panel A presents the results from the hazard models for the period before the crisis, i.e., 2002-2006. Panel B reports the results from the hazard models for the period after the crisis, i.e., 2007-2010. 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. Panel A contains parameter estimates and test of their significance for each hazard model. The column headed ACCR contains results for a model that uses the accounting ratios of Z-score. The EDF column presents the results from a univariate model that uses EDF derived from a Merton DD model. EDF is converted to a Score labeled as EDF-score. The ACCREDF column shows the results from a model that combines the accounting ratios of Z-score with EDF. The MV column contains results from a hazard model that uses market-based variables (REL_SIZE, EXRET and SIGMA) to predict financial distress.The MVACCR column contains results from a hazard model that combines market-based variables with EBITDA_TA, LIQUID and FRISK. The row labeled Wald Statistic contains the Wald test testing the hypothesis that the coefficients are jointly zero. It is distributed as $\chi^2(k)$, where k is the number of parameters (excluding the constant.) We scale the Wald-Chi Square statistic by the average number of observations per firm. Figures in parentheses are scaled Wald statistics testing the hypothesis that the individual coefficient is zero. These have a $\chi^2(1)$ distribution. Panel B contains the results from Vuong tests for model comparison. Under the null hypothesis that there is no difference between the two models, the log of the ratio of the likelihood for model i to that for model j should be zero. If the difference is significantly positive, i is preferred to j and vice versa. $***$, $**$ and $*$ denote significance at the 1, 5 and 10 percent levels respectively.

Panel A: Bankruptcy Prediction Models:2002-2006					
	ACCR	EDF	ACCREDF	MV	MVACCR
Constant	-2.9783^{***}	-2.5306^{***}	-2.6035^{*}	-5.9698^{***}	-2.4754
	(-4.01)	(-3.03)	(-1.84)	(-4.36)	(-1.51)
SALES_TA	-3.3767^{***}		-6.2160^{***}		-3.0603^{***}
	(-3.03)		(-3.32)		(-2.71)
EBITDA_TA	-7.0421^{***}		-8.5584^{***}		-4.3925^{*}
	(-3.33)		(-3.30)		(-1.88)
CL_TA	2.5013^{*}		4.3497^{**}		1.2526
	(1.70)		(2.22)		(0.99)
LIQUID	1.8192		4.0623^{**}		-0.0115^{**}
	(1.41)		(2.45)		(-2.45)
EDF-Score		0.1875^{***}	0.0973		
		(3.42)	(0.93)		
REL_SIZE				-0.0998	0.1597
				(-0.49)	(0.69)
EXRET				-1.9703^{***}	-1.5568^{***}
				(-4.16)	(-3.06)
SIGMA				5.6557	3.9777
				(1.44)	(0.89)
Log Likelihood	-74.02	-56.96	-40.69	-87.04	-69.75
Wald statistic	31.67^{***}	3.70^{***}	36.17^{***}	21.84^{***}	38.44^{***}

Panel B:Bankruptcy Prediction Models:2007-2010					
	ACCR	EDF	ACCEDF	MV	MVACCR
Constant	-5.4217^{***}	-2.5175^{***}	-3.6220^{***}	-12.3085^{***}	-10.4616^{***}
	(-5.04)	(-4.19)	(-2.96)	(-4.73)	(-3.40)
SALES_TA	-1.5864^{*}		-1.4301		-1.3257
	(-1.77)		(-3.32)		(-1.59)
EBITDA_TA	-1.9393		-3.6341^{*}		-1.3982
	(-0.85)		(-1.76)		(-0.59)
CL_TA	4.2115^{**}		2.3858		3.7223^{***}
	(2.26)		(1.35)		(2.78)
LIQUID	-0.5884		-0.6210		-0.0140^{**}
	(-0.32)		(-0.35)		(-1.97)
EDF-Score		0.1923^{***}	0.1112		
		(2.62)	(1.25)		
REL_SIZE				-0.9367^{***}	-0.5548
				(-3.07)	(-1.60)
EXRET				-1.1833^{*}	-0.5925
				(-1.79)	(-0.73)
SIGMA				4.7658	4.7798
				(1.30)	(1.05)
Log Likelihood	-48.12	-68.88	-52.47	-63.23	-45.76
Wald statistic	31.87^{***}	6.37^{**}	30.76^{***}	18.18^{***}	35.36^{***}

Table 9: Forecast Accuracy Test of the hazard models: pre and post crisis

Panel A presents the results from a forecast accuracy test of the five hazard models for the period before the crisis, i.e., 2002-2006. Panel B reports the results from a forecast accuracy test of the five hazard models for the period after the crisis, i.e., 2007-2010. Firms are sorted in six deciles based on their estimated probability of financial distress. Decile 1 contains those firms with the highest probability while decile 10 contains those with the lowest. We then calculate the percentage (to two decimal places) of firms that subsequently went bankrupt the models place in to each decile. The column headed ACCR contains results for a model that uses the accounting ratios of Z-score. The EDF column presents the results from a univariate model that uses EDF derived from a Merton DD model. EDF is converted to a Score labeled as EDF-score. The ACCREDF column shows the results from a model that combines the accounting ratios of Z-score with EDF. The MV column contains results from a hazard model that uses market-based variables (REL_SIZE, EXRET and SIGMA) to predict financial distress.The MVACCR column contains results from a hazard model that combines market-based variables with EBITDA_TA, LIQUID and FRISK.

Panel A:2002-2006

Decile	ACCCR	EDF	ACCREDF	MV	MVACCR
1	66.66	45.46	80.00	55.00	66.66
2	11.11	0.00	20.00	20.00	16.67
3	0.00	0.00	0.00	5.00	5.56
4	11.11	27.27	0.00	0.00	0.00
5	5.56	9.09	0.00	0.00	5.56
6	5.56	18.18	0.00	20.00	5.56
No. of Bankrupt Firms	18	11	10	20	18

Panel B:2007-2010

Decile	ACCCR	EDF	ACCREDF	MV	MVACCR
1	66.67	42.86	66.67	57.15	75.00
2	16.67	14.28	16.67	21.43	8.33
3	8.33	0.00	8.33	7.14	16.67
4	8.33	7.14	0.00	14.28	0.00
5	0.00	7.14	8.33	0.00	0.00
6	0.00	28.58	0.00	0.00	0.00
No. of Bankrupt Firms	12	14	12	14	12