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On the prediction of corporate financial distress in the light of the financial crisis: empirical evidence from Greek listed firms

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164

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ON THE PREDICTION OF CORPORATE FINANCIAL DISTRESS IN THE LIGHT OF THE FINANCIAL CRISIS: EMPIRICAL EVIDENCE FROM GREEK LISTED FIRMS

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Abstract

This paper evaluates the impact of accounting and market-driven information on the prediction of bankruptcy for Greek firms using the discrete hazard approach. The findings 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, a multivariate model that is exclusively based on accounting variables, a model that combines EDF and accounting variables and a multivariate model that uses only market-driven variables. In-sample forecast accuracy tests confirm the main results. The out-of-sample evidence also suggests that the model yields the highest predictive ability during financial crisis when using data prior to the financial crisis.

*Keywords***:** financial distress; financial forecasting; hazard model; expected default frequency

JEL Classification: G13, G17, G33, C41

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1 Introduction

Corporate financial distress prediction is a central issue in empirical finance. Since Beaver (1966) and Altman (1968) a significant body of research uses accounting ratios to predict corporate bankruptcy.[1] More recent studies are based on market information to measure distress risk. In particular,a firm's distance to default is estimated by applying Merton's (1974) structural model for pricing corporate debt. These models are widely known as Merton distance to default models (hereafter, Merton DD models).[2] Shumway (2001) applies a discrete hazard model to predict bankruptcy combining both accounting and market information. His model considers all the available observations for bankrupt and non-bankrupt firms addressing efficiently problems associated with biased parameter estimates and statistical inference observed in previous studies. Campbell, Hilscher and Szilagyi (2008) use the estimated probability of financial distress derived from a hazard model to explore how distress risk is priced in the equity market. Following Shumway (2001),Agarwal and Taffler (2008) apply discrete hazard analysis to compare accounting-based versus market-based models for UK firms.

The recent economic crisis of 2007 along with the ongoing Eurozone debt crisis highlight the importance of predicting accurately financial distress in the corporate sector, which is a crucial aspect of the economy. While there is extensive evidence on the performance of hazard models for large developed countries with Anglo-saxon financial systems, such as US and UK, we know little about the ability of hazard models to forecast corporate bankruptcy for smaller countries. In this paper we assess the performance of hazard models to predict financial distress for Greek firms using accounting and market information. The contribution of the study is twofold. First, to the best of our knowledge, there are no other studies that evaluate the performance of bankruptcy prediction models for Greek firms using the hazard approach of Shumway (2001). In particular, we use a large set of

[1] See, for example, Ohlson (1980), Taffler (1983) and Zmijewski (1984).

[2] For papers that use Merton DD models see for instance,Vassalou and Xing (2004), Duffie, Saita and Wang (2007) and Bharath and Shumway (2008) are among others.

accounting and market information to compare the performance of various hazard models that use either accounting ratios or market-driven variables and a combination of the two. This will shed light on what type of variables contribute most to the prediction of corporate financial distress in Greece. Second, the Greek market has increasingly attracted the attention of both academics and practitioners due to its sovereign debt crisis. During 2000s Greek external debt increased significantly mainly due to the large amount of government borrowing. The economic crisis of 2007-2008 drove up Greece's borrowing costs. Greece's credit default swap spreads (CDS) surpassed 900 basis points for 5-year CDS and closed at 760 basis points at the end of April 2010. In May 2010, the Greek government, European Union, European Central Bank, and the International Monetary Fund announced a major financial assistance package for Greece. This bailout was conditional on compliance with the implementation of austerity measures to restore the fiscal balance along with the implementation of far-reaching economic reforms. Ireland was next to require a bailout in November 2010, with Portugal following in May 2011. The global financial crisis along with the Eurozone debt crisis provide us with a unique opportunity to examine the forecast accuracy of bankruptcy prediction models for Greek firms during these two crucial economic events.

The empirical design of the paper is based on a discrete hazard model in the spirit of Shumway (2001). This enables us to evaluate the ability of accounting and market information to forecast corporate financial distress. In particular, we focus on a model that contains solely the accounting ratio components of the Z-score and a model that is based exclusively on the expected default frequency (EDF), which is derived from the Merton DD model. We proceed to explore the performance of a hazard model that contains three market-based variables, i.e., market capitalization, past excess returns and stock return volatility. Finally, we combine accounting with market-driven variables to predict corporate default.

The results show that three accounting ratio components of the 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. We document that the EDF has a positive impact on the probability of financial distress using a univariate hazard model. When the EDF is combined with accounting ratios in a multivariate hazard model, the EDF is marginally related to bankruptcy prediction. Using a hazard model exclusively based on market information, we show that relative size and excess past stock returns have a negative effect on the probability of bankruptcy whereas stock return volatility has a positive effect. Incorporating accounting ratios with market-based variables we show that sales to total assets, profitability, financial risk, excess returns and stock return volatility retain the expected signs. However, relative size fails to remain a significant predictor of corporate financial distress.

To evaluate the performance of the models relative to each other, we use Vuong's (1989) test to compare the log-likelihood ratios of the hazard models. We provide evidence that the combination of sales scaled by total assets, profitability and financial risk with relative size, excess returns and stock return volatility best captures the variation in the actual probability of bankruptcy. We also document that stock return volatility has the largest impact on the prediction of financial distress. In-sample forecast test also shows that this model identifies the highest number of bankrupt firms and exhibits the highest predictive ability. Also, we provide evidence that a hazard model that contains only three market-driven variables and a multivariate model that uses the accounting ratios of the Z-score perform better than a univariate model that contains the EDF. To provide stronger evidence on the predictive ability of the hazard models we perform out-of-sample forecast tests. We estimate the models using data prior to the global financial crisis, i.e., from 2002-2006 and use the estimated coefficients to predict corporate bankruptcies during the global financial crisis, i.e., for the period 2007-2011. In line with the in-sample evidence, we show that the model that incorporates three accounting ratios with three market-driven variables classifies the largest number of bankrupt firms and provides the most accurate forecasts throughout the economic crisis.

Further to the main findings of the paper, we examine whether the behavior of accounting and market-based predictors of corporate financial distress varies across shorter time periods focusing on pre-financial crisis and post financial crisis. 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. This should not be surprising when forecasting corporate bankruptcy during financial crisis. As stated by Campbell et al. (2008, 2900), " it would not be useful to predict a heart attack by observing a person dropping to the floor clutching his chest". We also investigate the impact of the Greek adjustment programme signed in May 2010 on the forecasting ability of the hazard models. We document that the in-sample predictive ability of the best model has weakened since the implementation of the fiscal adjustment programme suggesting that the programme was associated with a structural break in economic behaviour. Finally, we examine whether macroeconomic factors are associated with the probability of financial distress for Greek firms. We provide evidence that there is no impact of government bond spreads, domestic credit scaled by GDP and GDP growth on the likelihood of corporate bankruptcy.

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. It also discusses the results from the robustness tests. Section 5 concludes.

2 Empirical design

Several econometric techniques have been used to predict corporate financial distress in previous studies. Altman (1968) employs multivariate discriminant analysis to determine the Z-score, which is a widely used measure for predicting bankruptcy for US firms; Taffler (1983) employs the same technique for UK firms. Altman, Haldeman and 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)and 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. As a result, the number of non-bankrupt firms is arbitrarily chosen. 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. He also 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.[3]

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

[3]Non-parametric statistical approaches have also been used to predict corporate financial distress. For example, artificial neural networks ; e.g., Altman, Marco and Varetto (1994), the rough set approach; e.g., Dimitras, Slowinski, Sumaga and Zopounidis (1999) the multicriteria decision aid approach; e.g., Zopounidis and Dimitras (1998) and the multi-group hierarchical discrimination approach; e.g., Doumpos, Kosmidou, Baourakis and Zopounidis (2002).

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 both vary over time to estimate the probability of financial distress following the hazard approach. We 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 is estimated as a dynamic logit model using maximum likelihood estimation method. The specific analysis in this study is based on a discrete hazard model 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.

3 Sample and data

The sample consists of Greek firms that operate in Greece and are listed on the Athens Stock Exchange (ASE). We obtain the accounting data and the market data from Thomson Reuters 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 active (227) and inactive (76) Greek listed firms with 2,710 firm-year observations over the period 2002–2010. The hazard approach requires the identification of bankrupt firms. We consider a firm to be dead when it is delisted from the ASE. We gather this specific information from the Athens Stock Exchange and the Hellenic Capital Market Commission. We define a firm as bankrupt if it is delisted from the Athens Stock Exchange due to bankruptcy or if the firm is forced to suspend its shares following a report of the Hellenic Capital Market Commission. We identify 37 bankrupt firms; the remaining firms (39) were delisted from ASE for other reasons that are beyond the scope of the paper, such as mergers and acquisitions. 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 the Z-score based on Altman (1968) and Taffler (1983). 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 (CL_TA) 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. We analyse how the EDF is derived from the Merton DD model in the Appendix. Note that the EDF has no meaning 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 the EDF into a "score", EDF-SCORE, using the inverse logistic function $EDF - Score = \ln(EDF/(1 - EDF))$ when performing logit regressions. We also use the three market-based variables that have been included in Shumway's (2001) model, i.e. relative size (REL_SIZE), which is defined as 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. We winsorize the independent variables at the 0.5th and 99.5th percentiles of the distribution to deal properly with outliers. Descriptive statistics for the core explanatory variables are reported in Table 2.

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 (37) divided by the total number of firms (303). The minimum value of EDF is zero and the maximum 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

We 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 results show that SALES_TA and profitability are negatively related to the probability of bankruptcy whereas CL_TA 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 the 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, we 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 incorporated in the ACCR model with the EDF-score to forecast financial distress. The signs of the coefficients of sales to total assets, profitability, financial risk and the EDF-score remain unaltered. However, the predictive power of the EDF-sccore weakens compared to the EDF column.

The model in the MV column predicts the probability of financial distress using three market-driven variables, i.e., relative size, excess returns and stock return volatility. The results show that relative size and excess returns have a negative and significant impact on the probability of bankruptcy, whereas stock return volatility has a positive and significant effect on the probability of bankruptcy for Greek firms. This is consistent with US 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 three accounting ratios of the Z-score. Unlike ACCREDF column, there is strong evidence that both accounting and market information play an important role in the prediction of financial distress for Greek firms. We 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. However, there is no impact of relative size on the probability 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, we 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, accounting information alone 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. We also document that the 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; see, ACCREDF column. MVACCR model is better than MV model. Therefore market information alone cannot predict financial distress adequately. We also find that there is no difference between MV model and the ACCR model. Finally, we report that both the MV and the ACCR model outperform the univariate EDF model.

Table 4 shows the marginal effects of the explanatory variables on the probability of financial distress for each hazard model. In the ACCR model we observe that profitability has the largest impact on the probability of financial distress. Also the magnitude of the coefficient of financial risk is higher than that of sales to total assets. Liquidity has no impact on the probability of financial distress, in line with Table 3. In the EDF model, the EDF-score impacts on the probability of financial distress. However, the magnitude of the effect is low. In the ACCREDF model, the effect of the EDF-score on the probability of financial distress disappears when incorporating accounting ratios. In the MV model, the idiosyncratic stock return volatility captures most of the variation of the probability of financial distress. Also, firms' excess stock returns have higher predictive ability than the relative size. In our best model, MVACCR, profitability and relative size do not impact on the probability of financial distress. Stock return volatility contributes most to the prediction of bankruptcy.

To provide a better understanding of the predictive ability, firms are sorted into groups in descending order based on the probability of bankruptcy estimated by each of the hazard model described in Table 3. In particular, groups one to three contain firms that are more likely to go bankrupt. Group one consists of firms that exhibit the highest estimated probability of bankruptcy, while groups four to six contain those firms that are less likely to enter financial distress. Group 6 contains firms with the lowest predicted probability of bankruptcy. To investigate the predictive ability of a hazard model we define the percentage of bankrupt firms that are allocated to the various groups 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 (groups 1-3). Also, for each model, we show the percentage of bankrupt firms classified in firms with low probability of financial distress (groups 4-6). This represents the misclassification rate of each model. The ideal case would be all the bankrupt firms to be allocated in groups one to 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 5 presents the results.

At first glance we observe that each of the hazard model identifies a large number of bankrupt firms in groups 1-3, i.e., firms that are more likely to go bankrupt than less. Looking at Table 5 more thoroughly we observe that the ACCR model classifies more than 60% of the bankrupt firms (61.29%) in group 1 and 87.09 % in groups 1-3. As we move from group 4 to 6, which include firms with the lowest probability of financial distress derived from ACCR model (groups 4-6), one would anticipate a lower number of bankrupt firms to be identified. However, group four and six incorporate the same percentage of bankrupt firms, i.e., 3.23% of bankrupt firm. In total the ACCR model wrongly classifies 12.91% of bankrupt firms in Deciles 4-6. The EDF model exhibits the worst performance of all hazard models. It correctly places only 52% of firms that go bankrupt in groups 1 through 3 and has the highest misclassification rate. In particular, the EDF model classifies 48% of bankrupt firms in the groups with the lowest probability of financial distress; see, groups 4-6. ACCREDF model classifies the highest number of bankrupt firms (91.30%) in groups one to three. It also exhibits the lowest misclassification rate (8.70%); see, groups 4-6. However, it only identifies 23 bankrupt firms and fails to allocate the highest number of bankrupt firms in group 1 (60.87%). While the MV model predicts the highest number of bankrupt firms, i.e., 35 firms, it correctly predicts only 74.29% of those firms that actually go bankrupt as more likely than to go bankrupt; see, groups 1-3. Also, we would expect a higher number of firms to be identified in group 2 than in group 3. Instead, 8.57% of bankrupt firms are identified in group 2 whereas 11.43% of bankrupt firms are identified in Decile 3. Moreover, it has a high misclassification rate, 25.71%; see, groups 4-6. The MVACCR model, which combines accounting with market-driven variables yields the greatest predictive ability, identifying 31 bankrupt firms. It correctly classifies the highest number of bankrupt firms in group 1, i.e., 74.19% and 90.32% in groups 1-3. It also exhibits a very low misclassification rate, i.e., 9.68% in groups 4-6. Hence the probability of financial distress estimated by the MVACCR model allocates most effectively the number of bankrupt firms.

In-sample forecast tests can be driven from over-fitting of the data. Therefore a more realistic test to evaluate the performance of a forecasting model is its out-of-sample predictive ability. To provide a deeper analysis of the predictive ability of the hazard models we perform out-of-sample forecast tests. We re-estimate the hazard models described in Table 3 using data from 2002-2006, i.e., the period prior to the global financial crisis. We use the estimated coefficients of the variables for each model to predict corporate bankruptcies throughout the financial crisis, i.e., for the period 2007-2011. The results are shown in Table 6. We observe that our best model, when judged on in-sample forecasting, MVACCR, exhibits the best out-of-sample performance. It classifies the highest number of Greek bankrupt firms during the financial crisis within the groups 1-3 , i.e., 92.31%. It also yields the lowest misclassification rate 7.69%. The ACCR and ACCREDF models have the same out-of-sample performance, which is considerably lower than that of the MVACCR model. In particular, both models allocate 84,62% of bankrupt firms in the groups with the highest probability of financial distress (groups 1-3) and misclassify 15.38% of bankrupt firms in groups 4-6. MV model identifies 73.33% in groups 1-3 and allocates inappropriately 26.67% of bankrupt firms in groups 4-6. Finally, in-line with the in-sample evidence, the EDF models has the worst out-of-sample predictive ability.

Taken together the results in Tables 3, 4, 5 and 6 we provide insights into forecasting the probability of financial distress for Greek firms. We show that the MVACCR model, i.e., a model that includes three accounting ratios and three market-driven variables best describes the probability of bankruptcy. However, the findings strongly suggest that the choice of accounting and market information matters when evaluating a financial distress prediction model. We provide evidence that a model that uses the EDF using 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 nor market-driven variables (market capitalization, excess past stock returns and stock return volatility) alone are sufficient to predict corporate bankruptcy in Greece.

4.2 Robustness Tests

To explore the predictive accuracy of the hazard models over shorter time horizons, we split the sample into two subperiods, i.e., 2002-2006 and 2007-2010. The two subperiods are not randomly chosen. We explore the performance of the discrete hazard models before the global financial crisis (2002-2006) and during the global financial crisis (2007-2010). Panel A of Table 7 presents the results for the multi-period logit models for the period 2002-2006. The 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, the EDF column documents a positive relation between the EDF-score and the probability of financial distress. However, when the EDF is combined with the accounting ratios, it cannot explain a firm's probability of going 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. Negative values for the liquidity ratio imply that current liabilities are greater than current assets revealing that firms lack liquidity. This increases a firm's likelihood of going bankrupt. With respect to the 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. The results from the MVACCR model shows that only two accounting ratios and one market-based variable are significant predictors of financial distress prior to the global financial crisis. In particular, sales to total assets, profitability and excess past stock returns play a significant role in the financial distress prediction for the period 2002-2006.

Panel B of Table 7 presents the results for the multi-period logit models for the financial crisis period, i.e., 2007-2010. Based on the ACCR model we show that there is clearly a positive a association between financial risk and probability of financial distress.

However, there is no impact of the remaining accounting ratios on the probability of corporate bankruptcy during the financial crisis. The EDF-score is positively related to the probability of bankruptcy; see, the EDF column. With respect to the ACCREDF model, we document that neither the accounting ratios nor the EDF are significant predictors of corporate bankruptcy. The MV column shows that only relative size is negatively associated with the likelihood of financial distress throughout the 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. Overall, we observe that market-driven information is unable to forecast bankruptcy for Greek firms during the crisis as this type of information is forward-looking. Therefore, firms'equity value has already deteriorated within the financial crisis.

We proceed to investigate the predictive ability of the hazard models since the adoption of the adjustment programme for Greece in May 2010. Therefore, we perform in-sample forecast accuracy tests extending the sample period one year ahead i.e., from 2002-2011. Table 8 demonstrates the results. We note that the predictive ability of the MVACCR model weakens compared to that of Table 5. In particular, the MVACCR model predicts 59.38% of bankrupt firms in the first group and 87.51% in groups 1-3. The misclassification rate is higher (12.49%) than that reported in Table 5 (9.68%). The in-sample forecast accuracy of the ACCR and ACCREDF models is similar to Table 4. While the MV model classifies a higher number of bankrupt firms (77.15%) in groups 1-3 than that of Table 5, it identifies a very low percentage of bankrupt firms in the second group, only 2.86%. In line with Table 5, the EDF model has the lowest predictive ability.

We augment the MVACCR model to account for the baseline hazard rate and some macroeconomic factors. I use the bankruptcy rate (BR) in the previous year as a proxy for the baseline hazard rate. Column MVACCR-BR of Table 9 presents the results of a model that incorporates the variables used in the MVACCR model along with the bankruptcy rate. We provide evidence that the bankruptcy rate is not related to the probability of financial distress. The remaining variables enter with the expected signs with the exception of profitability and relative size, which do not contribute to the prediction of corporate financial distress. We also explore whether macroeconomic factors impact on the probability of financial distress. In particular, we examine whether term spread defined as the difference between a 10-year Greek government bond yield minus a 10-year German government bond yield, domestic credit to the private sector scaled by GDP and GDP growth affect the likelihood of a firm going bankrupt apart from the variables used in the MVACCR model. The MVACCR-MACRO column of Table 9 shows that none of the three macroeconomic factors are related to the probability of financial distress for Greek firms. The inferences on the effect of the remaining variables on corporate bankruptcy prediction are the same as those documented in the MVACCR column of Table 3. Vuong test confirms the results showing that neither the bankruptcy rate nor the three macroeconomic factors add incremental information to the MVACCR model.

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. The results show that a 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. The analysis of marginal effects reveals that among these variables, stock return volatility impacts most on the firm's probability of going bankrupt. With respect to market information, a model that contains market capitalization, excess returns and stock return volatility explains better the probability of corporate bankruptcy than a model that includes the EDF. When combining the EDF with accounting ratios, the contribution of EDF to the prediction of bankruptcy is marginal. Evidence is inconclusive on whether accounting ratios contain more significant information about the prediction of financial distress than market-based variables. Overall, we suggest that both are necessary to forecast bankruptcy. However, the choice of variables matters as it can improve the forecasting ability of the model.

We conduct forecast accuracy tests to investigate in depth the predictive ability of the hazard models. In-sample evidence is in line with our core findings. The model that combines the three accounting ratios with three market-based variables exhibits the highest predictive ability. We also perform out-of-sample tests that enables us to provide insights into the forecasting ability of the hazard models during the global financial crisis with data prior to the financial crisis. Out-of-sample results confirm that the model with the best in-sample predictive ability also allocates the highest percentage of bankrupt firms within the financial crisis. This clearly shows that the proposed model provides early warning signals of the upcoming financial crisis.

We perform some robustness tests. We evaluate the impact of the accounting and market information on bankruptcy prediction for Greek firms over shorter time periods, specifically the pre and post financial crisis periods. We provide evidence that sales to total assets, profitability and excess returns are associated with the probability of financial distress for the period prior to the financial crisis. However, only financial risk predicts corporate financial distress in the post-financial crisis period. We also document that the misclassification rate of the best model has increased since the adoption of the adjustment programme. Finally, we document that macroeconomic factors, i.e., government bond spreads, domestic credit to the private sector scaled by GDP and GDP growth do not play significant role in the prediction of financial distress for Greek firms.

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Appendix A: Merton's distance to default (DD) model

Merton (1974) develops a contingent claims model in which equity is viewed as a call option on the value of the firm's assets with strike price equal to the face value of debt. The value of the equity is described by the following equation:

$$E = VN(d_1) - e^{-r_f T} DN(d_2) \tag{A.1}$$

where E is the market value of the firms equity, V is the value of the firm, D is the face value of the firms debt, r_f is the instantaneous risk-free rate, $N()$ is the cumulative standard normal distribution function, d_1 is given as

$$d_1 = \frac{\ln\left(\frac{V}{D}\right) + (r + 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}} \tag{A.2}$$

and

$$d_2 = d_1 - \sigma_V \sqrt{T} \tag{A.3}$$

In the Merton DD model, the value of the firms equity is observed, while the value of the underlying asset (the total value of the firm) is not directly observable. Thus, while V must be inferred, E is easily observed by multiplying the firms shares outstanding by its current stock price. Similarly, the volatility of equity, σ_E, can be estimated but the volatility of the underlying firm, σ_V, must be inferred. σ_E is the annualized standard deviation of the residuals from regressions of of monthly stock returns on the returns on the FTSE/ASE-20 index. We define the face value of debt as $(0.5 \times \text{short-term debt}) + \text{long-term debt}$. We measure the risk-free rate r_f as the three-month Greek Treasury bill rate. Apart from (A.1) the Merton DD model uses a second equation, often referred to as the optimal hedge equation, that relates σ_E to σ_V:

$$\sigma_E = \left(\frac{V}{E}\right) N(d_1)\sigma_V \tag{A.4}$$

We estimate V and σ_V by simultaneously solving (A.1) and (A.4). The starting values are determined by setting $V = E + D$ and σ_V=$\sigma_V E/(E+D)$. Once we obtain the estimated values of V and σ_V we can calculate the distance to default (DD) as

$$DD = \frac{\ln\left(\frac{V}{D}\right) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}} \tag{A.5}$$

The corresponding implied probability of default, referred to as the expected default frequency (EDF), is:

$$EDF = N\left(-\left(\frac{\ln\left(\frac{V}{F}\right) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}\right)\right) \tag{A.6}$$

where μ is the average equity premium . The average equity premium in Greece for the period 2002–2011 is 0.06.

Table 1: Definition of Variables

Variable	Definition
SALES_TA	Net Sales/Total assets
EBITDA_TA	Earnings before interest, tax and depreciation/Total assets
CL_TA	Current liabilities/Total assets
LIQUID	(Current assets $-$ current liabilities)/Total assets
EDF	Expected default frequency derived from the Merton DD model
REL_SIZE	log(Market value of equity/Market value of the FTSE/ASE-20 index)
$r_{i,t}$	stock return for firm i at time t
$r_{FTSE/ASE-20,t}$	return on the index that consists of the top 20 firms at time t
EXRET	$r_{i,t-1}$ - $r_{FTSE/ASE-20,t-1}$
SIGMA	standard deviation of the residual derived from the regression of $r_{i,t}$ on $r_{FTSE/ASE-20,t}$

Note: This table defines the variables used in the study. The accounting and market data is from Thomson Finanancial Datastream.

Table 2: Descriptive statistics

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

Note:This table presents the mean, median, standard deviation, minimum and maximum values for the variables used in this study. SALES_TA is the ratio of net sales to total assets. EBITDA_TA is measured as profit before tax divided by current liabilities; CL_TA is measured as current liabilities to total assets; LIQUID is defined as current assets minus current liabilities divided by total assets. 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.

Table 3: Results for hazard models predicting the probability of financial distress

Panel A: Bankruptcy Prediction Models For Greek Firms					
	ACCR	EDF	ACCREDF	MV	MVACCR
Constant	-3.9659^{***}	-2.4024^{***}	-3.1015^{***}	-7.5591^{***}	-4.7393^{***}
	(-6.63)	(-5.14)	(-3.60)	(-6.87)	(-3.68)
SALES_TA	-2.5493^{***}		-2.8938^{***}		-2.2547^{***}
	(-3.51)		(-3.41)		(-3.12)
EBITDA_TA	-4.3972^{***}		-5.4241^{***}		-2.5727^{*}
	(-2.87)		(-3.41)		(-1.65)
CL_TA	3.2740^{***}		3.0790^{**}		2.2291^{***}
	(2.94)		(2.53)		(2.67)
LIQUID	1.1258		1.8316		
	(1.06)		(1.52)		
EDF-Score		0.2002^{***}	0.1140^{*}		
		(3.70)	(1.81)		
REL_SIZE				-0.3538^{**}	-0.0180
				(-2.43)	(-0.11)
EXRET				-1.4704^{**}	-1.1037^{***}
				(-4.34)	(-2.92)
SIGMA				6.0779^{**}	6.1798^{**}
				(2.39)	(2.22)
Log Likelihood	-132.63	-129.16	-103.62	-159.87	-127.46
Wald statistic	51.70^{***}	12.11^{***}	54.60^{***}	29.40^{***}	58.92^{***}

Panel B: Vuong Tests	
Model *i* versus Model *j*	*z* statistic
MVACCR versus ACCR	1.80^{*}
MVACCR versus EDF	3.18^{***}
MVACCR versus ACCREDF	1.72^{*}
MVACCR versus MV	2.06^{**}
ACCR versus MV	0.89
MV versus EDF	2.27^{**}
ACCR versus EDF	2.33^{**}

Note: 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 that combines SALES_TA, EBITDA_TA, CL_TA with REL_SIZE, EXRET and SIGMA. The value of z-statistics is reported in the parentheses. 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). 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.

Table 4: Marginal effects on the probability of financial distress

	Marginal Effects				
	ACCR	EDF	ACCREDF	MV	MVACCR
SALES_TA	-0.0182^{***}		-0.0148^{***}		-0.0150^{***}
	(-4.32)		(-3.68)		(-3.50)
EBITDA_TA	-0.0313^{**}		-0.0266^{***}		-0.0171
	(-2.28)		(-2.33)		(-1.43)
CL_TA	0.0233^{***}		0.0151^{**}		0.0148^{**}
	(2.64)		(2.14)		(2.31)
LIQUID	0.0080		0.0090		
	(1.07)		(1.50)		
EDF-Score		0.0024^{***}	0.0006^{*}		
		(3.97)	(1.65)		
REL_SIZE				-0.0042^{***}	-0.0001
				(-2.66)	(-0.11)
EXRET				-0.0176^{**}	-0.0073^{***}
				(-4.38)	(-2.63)
SIGMA				0.0729^{**}	0.0411^{**}
				(2.32)	(2.02)

Note: This table shows the marginal effects of the variables on the probability of financial distress for each hazard model. The column headed ACCCR presents the marginal effect of the accounting ratios of Z-score. The EDF column quantifies the marginal impact of EDF derived from a Merton DD model. EDF is converted to a Score labeled as EDF-score. The ACCREDF column shows the marginal effect of the accounting ratios of Z-score and EDF. The MV column shows the marginal effect of REL_SIZE, EXRET and SIGM) on the probability of financial distress.The MVACCR column shows the marginal effect of SALES_TA, EBITDA_TA, CL_TA with REL_SIZE, EXRET and SIGMA.

Table 5: In-sample forecast accuracy tests

Group	ACCCR	EDF	ACCREDF	MV	MVACCR
1	61.29	44.00	60.87	54.29	74.19
2	12.90	4.00	26.08	8.57	9.68
3	12.90	4.00	4.35	11.43	6.45
4	3.23	12.00	8.70	11.43	0.00
5	6.45	24.00	0.00	8.57	9.68
6	3.23	12.00	0.00	5.71	0.00
No. of Bankrupt Firms	31	25	23	35	31

Note: This table examines the forecast accuracy of five hazard models we estimate. Firms are sorted in groups based on their estimated probability of financial distress. Group 1 contains those firms with the highest probability while Group 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 group. The column headed ACCCR 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 SALES_TA, EBITDA_TA, CL_TA with REL_SIZE, EXRET and SIGMA.

Table 6: Out-of-sample forecast accuracy tests: Predictive ability of hazard models during financial crisis

Group	ACCCR	EDF	ACCREDF	MV	MVACCR
1	53.85	20.00	38.46	26.67	38.46
2	7.69	20.00	23.08	33.33	30.77
3	23.08	13.33	23.08	13.33	23.08
4	7.69	0.00	15.38	20.00	0.00
5	7.69	0.00	0.00	0.00	7.69
6	0.00	46.67	0.00	6.67	0.00
No. of Bankrupt Firms	13	15	13	15	13

Note: This table examines the out-of-sample forecast accuracy of six of the hazard models we estimate. The models are estimated using data over the period 2002–2006. These parameter estimates are then used to calculate the probability of financial distress over the period 2007–2011.This table examines the forecast accuracy of five hazard models we estimate. Firms are sorted in groups based on their estimated probability of financial distress. Group 1 contains those firms with the highest probability while Group 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 group. 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 SALES_TA, EBITDA_TA, CL_TA with REL_SIZE, EXRET and SIGMA.

Table 7: Bankruptcy forecast prediction models pre and post crisis

Panel A: Bankruptcy Prediction Models:2002-2006					
	ACCR	EDF	ACCREDF	MV	MVACCR
Constant	-2.9784^{***}	-2.5306^{***}	-2.6035^{*}	-5.9698^{***}	-2.4754
	(-4.01)	(-3.03)	(-1.84)	(-4.36)	(-1.51)
SALES_TA	-3.3761^{***}		-6.2160^{***}		-3.0603^{***}
	(-3.03)		(-3.32)		(-2.71)
EBITDA_TA	-7.0422^{***}		-8.5584^{***}		-4.3925^{*}
	(-3.33)		(-3.30)		(-1.88)
CL_TA	2.5010^{*}		4.3497^{**}		1.2526
	(1.70)		(2.22)		(0.99)
LIQUID	1.8191		4.0623^{**}		
	(1.41)		(2.45)		
EDF-Score		0.1875^{**}	0.0973		
		(2.11)	(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:2007-2011					
	ACCR	EDF	ACCEDF	MV	MVACCR
Constant	-5.5917^{***}	-2.6137^{***}	-3.7499^{***}	-10.1074^{***}	-7.9888^{***}
	(-5.45)	(-4.62)	(-3.27)	(-4.70)	(-3.31)
SALES_TA	-1.3888		-1.1948		-1.2230
	(-1.59)		(-1.42)		(-1.48)
EBITDA_TA	-0.6899		-2.0031		-0.2118
	(-0.29)		(-0.93)		(-0.08)
CL_TA	4.0357^{**}		2.2930		3.8289^{***}
	(2.26)		(1.35)		(2.94)
LIQUID	-0.4849		-0.6644		
	(-0.28)		(-0.39)		
EDF-Score		0.2006^{***}	0.1213		
		(2.83)	(1.47)		
REL_SIZE				-0.6662^{***}	-0.2530
				(-2.56)	(-0.89)
EXRET				-0.8920	-0.2513
				(-1.49)	(-0.34)
SIGMA				4.4189	3.2310
				(1.29)	(0.80)
Log Likelihood	-57.41	-75.51	-61.66	-73.24	-56.30
Wald statistic	27.16^{***}	7.54^{***}	26.53^{***}	12.60^{***}	28.22^{***}

Note: Panel A presents the results from the hazard models for the period prior to the financial crisis, i.e., 2002-2006. Panel B reports the results from the hazard models for the period during 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. 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 SALES_TA, EBITDA_TA, CL_TA with REL_SIZE, EXRET and SIGMA. The value of z-statistics is reported in parentheses. 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).

Table 8: In-sample forecast accuracy tests for the period 2002-2011

Group	ACCCR	EDF	ACCREDF	MV	MVACCR
1	61.29	42.30	65.21	60.00	59.38
2	12.90	11.54	21.74	2.86	18.75
3	12.90	0.00	4.35	14.29	9.38
4	6.45	11.54	8.70	8.57	3.12
5	3.23	11.54	0.00	8.57	3.12
6	3.23	23.08	0.00	5.71	6.25
No. of Bankrupt Firms	31	25	23	35	32

Note: This table examines the forecast accuracy of five hazard models since the implementation of the Greek fiscal adjustment programme. Therefore we augment the sample period by one year. Firms are sorted in groups based on their estimated probability of financial distress. Group 1 contains those firms with the highest probability while Group 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 group. The column headed ACCCR 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 SALES_TA, EBITDA_TA, CL_TA with REL_SIZE, EXRET and SIGMA.

Table 9: Accounting for the previous year's bankruptcy rate and macroeconomic factors in the MVACCR model

Panel A: Augmenting MVACCR With Other Predictors

	MVACCR-BR	MVACCR-MACRO
Constant	-4.7797^{***}	-4.4611^{*}
	(-3.69)	(-1.66)
SALES_TA	-2.2324^{***}	-2.2460^{***}
	(-3.08)	(-3.14)
EBITDA_TA	-2.3019	-2.6968^{*}
	(-1.45)	(-1.74)
CL_TA	2.1692^{***}	2.5134^{***}
	(2.58)	(2.90)
REL_SIZE	-0.0442	-0.0591
	(-0.27)	(-0.32)
EXRET	-1.2750^{***}	-1.0219^{**}
	(-2.91)	(-2.33)
SIGMA	6.5128^{**}	5.2853^{*}
	(2.31)	(1.76)
BR	-0.1649	
	(-0.80)	
TB_SPREAD		0.5507
		(0.98)
DOM_CREDIT		-0.0185
		(-0.64)
GDP_RATE		0.2080
		(1.55)
Log Likelihood	-127.13	-119.97
Wald statistic	59.58^{***}	59.55^{***}

Panel B: Vuong Tests

Model i versus Model j	z statistic
MVACCR versus MVACCR-BR	-0.74
MVACCR versus MVACCR-MACRO	-1.51

Note: This table contains the results of augmenting our preferred model, MVACCR, with time-series 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. Panel A contains these results. The column entitled MVACCR-BR contains results from including the previous year's actual bankruptcy rate as an additional explanatory variable. The MVACCR-MACRO column contains results from including the term premium, the Greek aggregate domestic credit to the private sector scaled by the GDP growth rate, and the GDP growth as explanatory variables. The value of z-statistics is reported in the parentheses. The row labeled Wald Statistic contains the Wald test testing the hypothesis that all of the coefficients (exclduing the constant) are jointly zero. It is distributed as $\chi^2(k)$, where k is the number of parameters (excluding the constant). 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.

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