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On corporate financial distress prediction: What can we learn from private firms in a small open economy?

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ON CORPORATE FINANCIAL DISTRESS PREDICTION: WHAT CAN WE LEARN FROM PRIVATE FIRMS IN A SMALL OPEN ECONOMY?

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Abstract

We use a large panel dataset that includes nearly 31,000 Greek private firms to investigate which variables impact on the prediction of corporate financial distress. Based on a multi-period logit model that accounts for industry effects, we identify six firm-specific variables that best describe the probability of financial distress for Greek private firms. In particular, the results show that profitability, leverage, the ratio of retained earnings to total assets, the ability of a firm to export, liquidity and the ability of a firm to pay out dividends are strong predictors of financial distress. We also find that GDP growth and a dummy variable that considers the effect of the Greek debt crisis affect the probability of financial distress. In-sample and out-of-sample forecast tests show that the model that includes the six firm-specific variables , GDP growth and industry dummies exhibits the highest predictive ability. Finally, the predictive ability of the model remains high when we increase the forecast horizon.

Keywords: corporate financial distress; bankruptcy prediction; hazardmodel; financial statements

JEL Classification: G13; G17; G33; C41

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1 Introduction

Academic researchers and practitioners have developed various models to predict financial distress for listed firms using accounting and market information. Since the seminal work of Beaver (1966) and Altman (1968) several studies use mainly accounting ratios to predict corporate bankruptcy.[1] Vassalou and Xing (2004), Duffie, Saita and Wang (2007) and Bharath and Shumway (2008), among others, focus on Merton's (1974) structural market-based model for pricing corporate debt to derive the probability of corporate default. Shumway (2001) and Campbell, Hilscher and Szilagyi (2008) use a hazard model that incorporates both accounting and market information.

Despite the abundance of empirical evidence on the financial distress prediction for publicly traded firms, we know little about what determines the probability of bankruptcy for private firms. In addition, to the best of my knowledge there is no evidence on financial distress prediction for private firms in developing economies. This is possibly due to the lack of information on the date that a private firm enters financial distress. Focusing on private firms is important for the following three reasons. First, private firms are different from public ones. Private firms are more leveraged, invest more, face higher borrowing costs and have higher returns on assets and equity.[2]Due to these different characteristics, an accurate bankruptcy prediction model is essential for private firms as it will determine the supply of credit by banks and the cost of credit. Second, the role played by such companies in the US and European market is crucial. In particular, over 99% of firms in the United States and United Kingdom are privately owned and are responsible for more than half of the GDP of the US and the UK ,respectively. SMEs, a specific type of private firms, are the backbone of the economy in the Eurozone as they constitute about 98% of all Euro area firms and account for around three quarters of total employment and generate around 60% of gross value added in 2012.[3] Third, providing information on the probability of bankruptcy for private firms is quite challenging as these firms do not

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

[2]For a comparison between public and private firms, see Petersen and Rajan (1994),Brav (2009), Asker, Farre-Mensa and Ljungqvist (2012), Gao, Hartford and Li (2012) Michaely and Roberts (2012), Faccio, Marchica, McConnell and Mura (2012) and others.

[3]For more details, see, Wymenga, Spanikova, Barker Konings and Canton (2012).

trade shares on a stock exchange and hence there is lack of market data. As a result, the source of information we can use to predict bankruptcy is mainly derived from financial statements. Therefore, the evidence on the performance of bankruptcy forecast models for private firms will shed light on the ability of accounting ratios to predict bankruptcy.

In this paper we estimate the probability of corporate financial distress for a developing economy using a large database of Greek private companies from 2003 to 2011. In particular, we develop discrete duration models or, equivalently multi-period logit models to evaluate what type of variables are associated with the prediction of financial distress leading to the highest predictive performance. We provide strong evidence, that a model that contains six firm-specific variables and considers industry effects, explains best the likelihood that a private firm defaults. In particular, we find that profitability, leverage, the ratio of retained earnings to total assets, a dummy variable that captures export activity, liquidity, a dividend payer dummy variable and industry dummies are associated with the bankruptcy prediction of Greek private firms. We enhance the model by adding GDP growth and a a dummy variable that captures the financial crisis period. We find a negative effect of the two variables on the probability of financial distress. To evaluate the performance of the multiperiod logit models relative to each other, we use Vuong's (1989) test to compare the log-likelihood ratios of the discrete models. Vuong test confirms that the model that includes six firm-specific factors, along with the GDP growth, the crisis dummy variable and industry dummies, contains most information about the probability of bankruptcy for private firms. In-sample forecast tests also show that the model that contains the six firm-specific variables and the industry dummies exhibit the highest predictive ability. The predictive ability remains the same when adding the GDP growth and the crisis dummy variable. 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 financial crisis, i.e., from 2003-2008 and use the estimated coefficients to predict corporate bankruptcies during the global financial crisis, i.e., for the period 2009-2011. In line with the in-sample evidence, we show that the model that incorporates six firm-specific characteristics combined with GDP growth and three industry dummies provides the most accurate forecasts throughout the economic crisis. The performance of the model is similar when we do not use GDP growth as an additional predictor of financial distress. In-sample and out-of-sample tests show that the high predictive performance of the model is sustained when we augment the forecast horizon from one to two and three years, respectively. We also document that the results remain unaltered when we increase the forecast horizon from one year to two and three years. The six firm-specific characteristics, GDP growth, the crisis dummy variable and the industry dummies are strongly associated with the probability of financial distress, in line with the core findings. The predictive performance of the model remains high based on the in-sample and out-of-sample forecast accuracy tests.

We further perform some tests for robustness. We evaluate the impact of the variables of the best model over shorter time periods and specifically focus on pre and post financial crisis. We document that leverage is not a significant predictor of financial distress in the post-financial crisis period. The signs of the estimated coefficients of the remaining variables on the probability of bankruptcy before and after the crisis remain unaltered. We also find that there is variation on the predictors of bankruptcy across small and medium private firms. Finally we document that macroeconomic factors, i.e., the government bond spread, domestic credit to the private sector scaled by GDP and Greek public debt scaled by GDP are not associated with the prediction of financial distress for Greek private firms.

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 Existing bankruptcy prediction models and related literature

Several econometric techniques have been used to predict financial distress for publicly traded firms. Altman (1968) employs multiple discriminant analysis to determine a Z-score, which is a widely used measure for predicting bankruptcy. Altman, Haldeman and Narayanan (1977) use quadratic discriminant analysis to forecast bankruptcy. 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. According to Shumway (2001) these econometric specifications are misspecified as they do not properly address the length of time that a healthy firm has survived inducing a selection bias. He overcomes the caveat of the econometric techniques used in previous studies on financial distress prediction by employing a a discrete hazard approach, which is econometrically equivalent to a multiperiod logit model. This model has two main advantages. First, it allows researchers to take advantage of all the available firm-year observations. Second, it is a dynamic model in the sense that enables the probability of bankruptcy to change over time as a function of a vector of explanatory variables that also vary with time.

The empirical analysis of the 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 $t-1$ to estimate the probability of bankruptcy. This is to ensure that we only use data that is actually available prior to the occurrence of bankruptcy.

While there is wealth of empirical evidence on forecasting bankruptcy for listed firms, we know little about the prediction of financial distress for private firms. This relative paucity of academic research is to a great extent attributed to the lack of information on the date of financial distress for private firms and especially in a developing economy. Standard and Poor's makes the first attempt to examine the default of private firms. In particular, Falkenstein, Boral and Carty (2000) use a reduced-form approach to evaluate the credit risk of the US private firms. Cangemi, Servigny and Friedman (2003) examine the default risk of French private firms based on the maximum expected utility (MEU) approach, which is equivalent to regularized maximum likelihood estimation.[4] Altman and Sabbato (2007) develop a Z-score model for 2,000 small and medium sized enterprises (SMEs) in the US using a set of five accounting ratios. These ratios are earnings before interest, taxes, depreciation and amortization (EBITDA) divided by total assets, leverage, retained earnings scaled by total assets, cash to total assets and EBITDA to interest expenses. Dierkes, Erner, Langer and Norden (2013) show that business credit information improves the accuracy of default predictions for private firms.

3 Sample and Data

The sample consists of Greek private firms that operate in Greece obtained from the ICAP database. It contains publicly available information mainly derived from financial statements for nearly 60,000 Greek private firms. 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 33,867 Greek private firms with 230,532 firm-year observations over the period 2003–2011. We also lag the time-varying covariates so as to predict financial distress more efficiently. The final sample includes 30,934 firms leading to 188,364 firm-year observations. To forecast corporate financial distress we need to define which firms enter financial distress and when this occurs. ICAP database identifies the date of a firm's death and the type a of a private firm's death, such as bankruptcy, liquidation, resolution, mergers and acquisitions, inactivity etc. We consider a Greek private firm to be financially distressed if a) either it has been bankrupt or b) if it has been inactive

[4] Regularization is a technical method that effectively balances the tradeoff between consistency with the data and overfitting.

or liquidated or dissolved and concurrently its common equity is less than fifty percent of its share capital.[5] Based on these two criteria we classify 1772 bankrupt firms with 5,965 firm-year observations and 29,162 non-bankrupt firms providing 182,399 firm-year observations. Table 1 provides detailed information on the definition of all variables used in the study.

To deal with extreme observations, we winsorize the independent variables at the 1st and 99th percentiles of the distribution. Descriptive statistics of the full sample for the firm-specific variables are reported in Table 2. Looking at Table 2, we observe that the sales to total assets, profitability, debt ratio and the ratio of retained earnings to total assets are positively skewed for the Greek private firms. Also, on average, private firms have negative retained earnings. Focusing on the dummy variables, less than 25% of firms show export activity and half of the private firms are liquid and have the ability to pay out dividends. We also report the descriptive statistics for the sample of bankrupt and non-bankrupt firms in Table 3. As we expect, bankrupt firms on average are less profitable, more levered and they accumulate more losses in contrast to non-bankrupt firms. Also, bankrupt firms are less liquid and have much lower capacity to export and pay dividends than non-bankrupt firms.

4 Results

4.1 Predictive ability of discrete hazard models

We estimate the probability of financial distress for Greek private firms using a series of multi-period logit models. The results are presented in Panel A of Table 4. The column named BPM1 is a bankruptcy prediction model that incorporates three accounting ratios, i.e., profitability, leverage and retained earnings scaled by total assets. The results show that the three variables are strongly associated with the probability of financial distress for Greek private firms. In particular, profitability and retained earnings to total assets have a negative impact on the probability of financial distress whereas leverage has a positive

[5]According to the Greek law 2190/1920, a Greek private firm enters financial distress if its common equity is less than half of its share capital.

effect on the probability of financial distress. This model outlines the basic structure of the next bankruptcy prediction models that will be developed. BPM2 column presents the results from a model that apart from profitability,leverage and retained earnings to total assets, incorporates the ability of the private firm to export. We observe that the ability of a private firm to export plays a significant role in the prediction of financial distress. We provide evidence that the export dummy variable is negatively related to the probability of corporate default. The signs and the magnitude of the estimated coefficients of profitability, leverage and retained earnings to total assets are similar to those presented in BPM1 column. BPM3 column incorporates sales to total assets as an additional predictor of financial distress. We find that there is no impact of sales to total assets on the probability of financial distress. The impact of the remaining firm-specific variables is not altered. BPM4 column reveals the result from a multi-period logit model that augments the predictors of financial distress by including liquidity. Liquidity affects negatively the probability of financial distress for private firms. This is plausible as the more liquid a firm is the less likely to go bankrupt. Profitability, leverage, retained earnings and the export dummy variable enter with the expected signs in line with those of BPM3 column. BPM5 column reveals the results from a multi-period logit model that additionally incorporates the ability of a private firm to pay out dividends. We provide evidence that a private firm that pays dividends is less likely to go bankrupt. This is not surprising as dividends convey information about firms' future earnings and prospects. The inferences on the remaining five variables are qualitatively the same irrespective of the inclusion of the dividend payer dummy variable. We then enhance our model incorporating industry dummies to explore whether there are any industry effects on bankruptcy prediction. We document that three sectors of the Greek economy, namely, trade, manufacturing and services are positively associated with the probability of financial distress. Finally, we add to the empirical specification of the model the GDP growth and a crisis dummy variable that captures the effect of the Greek public debt crisis. As we expect GDP growth is negatively related to the probability of bankruptcy for private firms. In addition, we provide evidence that the crisis dummy variable has a negative effect on the probability of financial distress. This is likely to occur as more private firms enter financial distress in the period prior to the crisis, i.e., 2003-2008.

Apart from the choice of variables that contribute to the prediction of financial distress, it would be intriguing to compare the six bankruptcy prediction models models to investigate which model incorporates most information about the probability of financial distress. 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 4 contains results of the Vuong test for the models shown in Panel A of Table 4. We show that the six firm-specific variables combined with the GDP growth, the crisis dummy variable and the industry dummies predict bankruptcy most accurately for the Greek private firms. Comparing the seventh model with each of the five models, we observe that the z-statistic is positive and significant in all cases.

Going deeper into the predictive ability of the multi-period logit models, firms are sorted into groups in descending order based on the probability of bankruptcy estimated by each of the hazard model described in Table 4. In particular, deciles 1-5 contain firms that are more likely to enter financial distress. Decile 1 consists of firms that exhibit the highest estimated probability of bankruptcy, while deciles five to ten contain those firms that are less likely to enter financial distress. Decile 10 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 (deciles 1-5). Also, for each model, we show the percentage of bankrupt firms classified in firms with low probability of financial distress (deciles 6-10). 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 hazard model identifies a large number of bankrupt firms in deciles 1-5, i.e., firms that are more likely to go bankrupt than less. Looking at the Table 5 more thoroughly we observe that the BPM1, BPM2 and BPM3 models classify the number of bankrupt firms in decile 1 (54.12%). However, the BPM1 model has greater predictive ability than that of BPM2 and BPM3 models as it allocates more bankrupt firms in deciles 1-5; 85.84% versus 85.05% and 85%, respectively. Alternatively, looking at deciles 6-10, BPM1 has lower misclassification rate than BPM2 and BPM3. Moving on to the next models we document that the BPM4 model has higher predictive ability than the BPM1. While it identifies a lower number of bankrupt firms in decile 1 (53.89%), it identifies a higher number of bankrupt firms in deciles 1-5, i.e., 86.06%. The inclusion of the dividend payout dummy variable further improves the performance of the BPM5 model. It yields a lower misclassification rate (11.39%) than that of BPM4 model. Finally, accounting for industry effects the BPM6 model exhibits the highest predictive ability classifying the largest number of bankrupt firms in decile 1 and groups 1-5 (55.08% and 90.80%, correspondingly). In effect, it has the lowest misclassification rate of the five models, 9.20%. Therefore, the BPM6 model suggests that apart from the firm-specific factors we need to take into account industry effects to predict financial distress for private firms more accurately. We also observe that the predictive ability of the model is the same when using two more predictors of financial distress, that is, GDP growth and the crisis dummy variable; see, BPM7 column.

In-sample forecast tests may induce a bias on the results due to 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 offer robust evidence on the predictive ability of the hazard models, we perform out-of-sample forecast tests. We re-estimate the hazard models described in Table 4 using data from 2002-2008, i.e., a period prior to the Greek 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 2009-2011. The results are shown in Table 6. We observe that the BPM7 exhibits the best out-of-sample performance.[6] It classifies the highest number of Greek bankrupt firms during the Greek financial crisis within the deciles 1-5 , i.e., 88.83%. As a result it yields the lowest misclassification rate 11.17%. BPM6 model has similar out-of-sample predictive ability. It classifies 88.59% of bankrupt firms in deciles 1-5 and its misclassification rate is 11.41%. We also observe that the model that includes six firm-specific factors outperforms the remaining four models as it documents a higher percentage of financially distress firms during the crisis in deciles 1-5 than that of the BPM1, BPM2, BPM3 and BPM4 models.

We then explore how efficiently BPM6 and BPM7 predict bankruptcy for Greek private firms when we increase the forecast horizon from one to two and three years. To do so we lag our independent variables two and three years, respectively except the dummy variables. The results are presented in Table 7. We provide strong evidence that the signs and the magnitudes of the estimated coefficients of the variables are very similar to those documented in Table 4. Profitability, retained earnings to total assets, export dummy variable and dividend payout dummy variable are negatively related to the probability of financial distress whereas leverage, and the industry dummies are positively related to the probability of financial distress. The coefficients of the GDP growth and the crisis dummy variable retain their signs. We also observe that the magnitude of the estimated coefficient of the dividend payout dummy variable is higher when the forecast horizon is two and three years rather than one year. This means that the impact of the ability of a firm to payout dividends on the probability of financial distress is much stronger when we predict bankruptcy in the long run.

We also investigate the predictive ability of the model when we augment the forecast horizon of the BPM6 model. We perform in and out-of-sample forecast accuracy tests for the two and three-year forecast horizons. The interesting finding is that when we augment the forecast horizon from one to two and three years the misclassification rate of the model is relatively lower. Based on the in-sample results presented in Table 5 and Table 8 the misclassification rate is 9.20% when the horizon is one and decreases to 8.97% and 8.82% in the case of two and three-year horizons. It merits attention that more bankrupt firms are identified for the two-year forecast horizon instead of the three-year

[6]Note that for the out-of-sample tests, the crisis dummy variable is omitted from the BPM7 model due to the out-of-sample period.

horizon. This is plausible as we use more data when the forecast horizon is smaller. The in-sample evidence is in line with the out-of sample evidence reported in Panel B of Table 8. Taken together Tables 6 and 8 we point out that the misclassification rate of the best model decreases from 11.41% to 10.03% and 10.14% for one, two and three-year horizon, respectively. The better performance of the model when we increase the horizon from one to two and three years is most possibly attributed to the stronger predictive ability of the dividend payout dummy variable. We additionally find that more bankrupt firms are classified in the decile with the highest probability of financial distress during the crisis when using a two-year horizon instead of a three-year horizon. The in-sample and out-of-sample misclassification rate of the model is quite similar either we use a two-year or a three-year horizon. With respect to BPM7 model we notice that its predictive ability deteriorates relative to the BPM6 model when increasing the forecast horizon from one to two and three years. Looking at the in-sample results, we notice that the misclassification rate of the BPM7 model in a two-year horizon is 9.04% which is higher than that of the BPM6 model. Based on the out-of-sample results the misclassification rate of the BPM7 model is 10.60% for a two-year horizon and 10.81% for a three-year horizon.

4.2 Robustness Tests

To explore how the predictive ability of the variables in the BPM6 and BPM7 models vary across shorter time horizons, we split the sample into two subperiods, i.e., 2003-2008 and 2009-2011.[7] The period 2003-2008 reflects the pre-financial crisis in Greece whereas the period 2009-2011 reflects the post-financial crisis in Greece. Table 9 presents the results. With respect to the pre-financial crisis period,the coefficients of the variables enter the same sign and retain similar magnitudes with those documented in Table 4 for the entire sample period. In the next column we report the results of the multi-period logit model during the crisis. We observe that leverage cannot predict financial distress for private firms during the crisis. It is also noticeable that the predictive power of the the export dummy variable and liquidity increases during the crisis. The impact of the remaining variables on

[7]Note that the crisis dummy variable is omitted from the BPM7 model due to the pre and post-crisis periods.

the probability of financial distress is the same as in the pre-financial crisis period. With respect to the BPM7 model the inference on the variables remains the same, consistent with the BPM6 model. Also, the GDP growth is negatively related to the probability of financial distress in both periods.

Our sample mainly consists of small and medium-sized (SMEs) firms. Therefore, we proceed to estimate the probability of financial distress for small and medium private Greek firms based on the proposed discrete hazard model. Following the recommendation of European Commission (2003), we define the size of a firm based on the number of employees. A small firm is considered a firm with less than fifty employees whereas a medium firm is a firm with fifty to 249 employees. The sample contains 26,534 small firms with 163,851 firm-year observations and 2,460 firms with 17,315 firm-year observations. Table 10 reports the results for the BPM6 AND BPM7 model. The impact of the variables on the probability of financial distress for small firms remain unaltered except the export dummy variable. There is no association between the ability of a small firm to export and the probability of financial distress. This is a rational finding as it is difficult for small firms to export. Moving on to medium firms, profitability, leverage, retained earnings to total assets, export dummy variable, liquidity and dividend payout dummy variable and industry dummies enter the expected signs. The results also reveal that the predictive power of profitability and leverage increases for medium firms compared to small firms. On the other hand, the predictive power of liquidity and dividend payout variable is stronger for small firms than medium firms. This is more likely attributed to the fact that there is lack of access to external financing for small firms. We document that the negative effect of the GDP growth and the crisis dummy variable sustains for small and medium firms.

We augment the BPM6 model to examine whether there are some other macroeconomic effects on the probability of financial distress for private firms. In particular, we incorporate three macroeconomic variables, i.e., the term spread defined as the difference between a 10-year Greek government bond yield minus a 10-year German government bond yield, the domestic credit to the private sector scaled by GDP and the government debt scaled by GDP. Table 11 presents the results. We find that term spread is positively related to the probability of financial distress, as expected. When then term spread increases, it is more likely that a firm will go bankrupt because its cost of financing increases. However, the effect is marginally significant at 10%. We document that there is no impact of the domestic credit to the private sector and the GDP growth rate on the probability of bankruptcy for private firms. The estimated coefficients of the remaining variables have the expected signs retaining similar magnitudes. We proceed to test whether this model with the macroeconomic factors adds any incremental information on the estimation of probability of bankruptcy compared to the BPM6 model. Therefore, we perform the Vuong test and the result is documented in Panel B of Table 11. We find that the inclusion of the three macroeconomic factors offers no further contribution to the prediction of financial distress for private firms.

5 Concluding remarks

This paper estimates the probability of financial distress for private firms in a developing economy based on the discrete hazard approach . In particular, we use a large dataset of Greek private firms from 2003-2011. The results show that six firm-specific factors are strongly associated with the probability of financial distress for private firms. Profitability, retained earnings to total assets, liquidity, a dummy variable that captures the ability of a firm to export and a dummy variable that reflects the ability of a firm to pay out dividends are negatively associated with the probability of bankruptcy whereas leverage is positively related to the probability of bankruptcy. The findings of the study strongly recommend to account for industry effects when forecasting financial distress for private firms. We show that the probability of bankruptcy increases in the trade, manufacturing and services sectors. We also provide evidence that the GDP growth and a crisis dummy variable have a negative impact on the probability of financial distress. The model that incorporates the six firm-specific factors and considers industry effects exhibits the highest predictive ability based on in-sample accuracy tests. When we add the GDP growth and the crisis dummy variable, the model has slightly better out-of-sample-predictive ability. The model retains its predictive power when we increase the forecast horizon from one to two and three years. In addition to this, the effect of the dividend payout dummy variable on the probability of financial distress is stronger in magnitude when we enlarge the forecast horizon. We then perform some robustness tests. We re-estimate the probability of financial distress focusing on the pre-Greek crisis period and we find that the effect of the variables is in line with the core results. However, performing the multi-period logit model in the post Greek crisis period, leverage cannot predict bankruptcy for private firms. We also show that the impact of the variables do vary across small and medium firms. Finally, we document that do not contribute on the financial distress prediction for private firms.

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Table 1: Definition of Firm-Specific 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
RET_TA	Retained earning/Total Assets
LIQUID	Dummy variable that equals one if (Current assets − current liabilities)/Total assets is greater than zero; otherwise it equals zero
EXPORT	Dummy variable if a firm exports
DIVPAY	Dummy variable if a firm pays out dividends

Note: This table defines the variables used in the study. The accounting data and other firm-specific variables are obtained from the ICAP database.

Table 2: Descriptive Statistics: Full Sample

Variable	Mean	Median	Std.dev	Min	Max
SALES_TA	0.95	0.72	0.96	0.00	5.31
EBITDA_TA	0.06	0.05	0.14	-0.52	0.56
BLEV	0.30	0.17	0.33	0.00	1.22
RET_TA	-0.14	0.00	0.47	-3.38	0.38
LIQUID	0.51	1.00	0.50	0.00	1.00
EXPORT	0.23	0.00	0.42	0.00	1.00
DIVPAY	0.49	0.00	0.50	0.00	0.00

Note:This table presents the mean, median, standard deviation, minimum and maximum values for the variables based on the entire sample of private firms. SALES_TA is the ratio of net sales to total assets. EBITDA_TA is measured as profit before tax divided by current liabilities; BLEV is measured as total debt to total assets. RET_TA is the ratio of retained earnings to total assets. LIQUID is a dummy variable derived from current assets minus current liabilities divided by total assets. If this ratios is greater than zero, it takes the value 1, zero otherwise. EXPORT is a dummy variable obtained from ICAP that takes the value one if the firm exports, zero otherwise. DIVPAY is a dummy variable which equals to one if a firm pays out dividends, zero otherwise.

Table 3: Descriptive Statistics for Non-Bankrupt and Bankrupt firms

Panel A: Non-bankrupt Firms					
Variable	Mean	Median	Std.dev	Min	Max
SALES_TA	0.95	0.72	0.95	0.00	5.31
EBITDA_TA	0.06	0.05	0.13	-0.52	0.56
BLEV	0.29	0.18	0.32	0.00	1.22
RET_TA	-0.12	0.00	0.42	-3.38	0.38
LIQUID	0.51	1.00	0.50	0.00	1.00
EXPORT	0.23	0.00	0.42	0.00	1.00
DIVPAY	0.50	0.00	0.50	0.00	0.00
Panel B: Bankrupt Firms					
Variable	Mean	Median	Std.dev	Min	Max
SALES_TA	0.89	0.56	1.13	0.00	5.31
EBITDA_TA	- 0.04	0.00	0.20	-0.52	0.56
BLEV	0.31	0.00	0.40	0.00	1.22
RET_TA	-0.76	-0.28	1.05	-3.38	0.38
LIQUID	0.35	0.00	0.48	0.00	1.00
EXPORT	0.15	0.00	0.35	0.00	1.00
DIVPAY	0.14	0.00	0.35	0.00	0.00

Note:This table presents the mean, median, standard deviation, minimum and maximum values for the variables based on the sample of non-bankrupt and bankrupt firms, respectively. SALES_TA is the ratio of net sales to total assets. EBITDA_TA is measured as profit before tax divided by current liabilities. BLEV is measured as total debt to total assets. RET_TA is the ratio of retained earnings to total assets. LIQUID is a dummy variable derived from current assets minus current liabilities divided by total assets. If this ratio is greater than zero, it takes the value 1, zero otherwise. EXPORT is a dummy variable obtained from ICAP that takes the value one if the firm exports, zero otherwise. DIVPAY is a dummy variable which equals to one if a firm pays out dividends, zero otherwise.

Table 4: Results For Hazard Models Predicting the Probability of Financial Distress

Panel A: Bankruptcy Prediction Models For Greek Private Firms							
	BPM1	BPM2	BPM3	BPM4	BPM5	BM6	BPM7
Constant	-5.1534^{***}	-5.0768^{***}	-5.0741^{***}	-4.8469^{***}	-4.4771^{***}	-5.5993^{***}	-4.4483^{***}
	(-132.78)	(-127.87)	(-114.89)	(-99.65)	(-90.39)	(-54.65)	(-32.88)
EBITDA_TA	-1.9701^{***}	-1.9177^{***}	-1.9176^{***}	-1.8328^{***}	-1.4924^{***}	-1.5078^{***}	-1.3190^{***}
	(-13.04)	(-12.78)	(-12.77)	(-12.20)	(-9.85)	(-10.05)	(-8.80)
BLEV	0.5408^{***}	0.5973^{***}	0.5975^{***}	0.4522^{***}	0.4493^{***}	0.3940^{**}	0.3853^{***}
	(8.20)	(9.09)	(9.09)	(6.59)	(6.67)	(5.79)	(5.65)
RET_TA	-0.8774^{***}	-0.8613^{***}	-0.8614^{***}	-0.8352^{***}	-0.7390^{***}	-0.7636^{***}	-0.7363^{***}
	(-32.65)	(-32.07)	(-32.07)	(-30.85)	(-27.67)	(-28.42)	(-27.44)
EXPORT		-0.4996^{***}	-0.4994^{***}	-0.5166^{***}	-0.3563^{***}	-0.6366^{***}	-0.6213^{***}
		(-6.68)	(-6.67)	(-6.90)	(-4.74)	(-8.10)	(-7.90)
SALES_TA			-0.0032				
			(-0.14)				
LIQUID				-0.4107^{***}	-0.3844^{***}	-0.3197^{**}	-0.2988^{***}
				(-7.56)	(-7.09)	(-5.83)	(-5.44)
DIVPAY					-1.4263^{***}	-1.4378^{***}	-1.5584^{***}
					(-18.18)	(-16.22)	(-19.73)
IND_DUM1						1.2579^{***}	1.3051^{***}
						(11.42)	(11.83)
IND_DUM2						1.3612^{***}	1.4341^{***}
						(13.02)	(13.70)
IND_DUM3						0.9804^{***}	1.0190^{***}
						(9.37)	(9.73)
GDP GROWTH							-0.21288^{***}
							(-10.64)
POSTCRISIS							-2.0164^{***}
							(-12.63)
Log Likelihood	-8911.35	-8886.54	-8886.53	-8857.23	-8640.10	-8591.53	-8420.18
Wald statistic	2241.84^{***}	2291.45^{***}	2291.47^{***}	2350.06^{***}	2784.34^{***}	2881.46^{***}	3224.16^{***}
Number of observations	188,364	188,364	188,364	188,364	188,364	188,364	

Panel B: Vuong Tests	
Model i versus Model j	z statistic
BPM7 versus BPM6	7.23^{***}
BPM7 versus BPM5	11.46^{***}
BPM7 versus BPM4	15.73^{***}
BPM7 versus BPM3	16.16^{***}
BPM7 versus BPM2	16.17^{***}
BPM7 versus BPM1	16.53^{***}

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 accounting ratios 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. BPM1 column contains results for a model that uses three accounting ratios, i.e., profitability, leverage and retained earnings divided by total assets. BPM2 column shows the results from a model that incorporates an export dummy variable along with the three accounting ratios. BPM3 column contains results from a hazard model that additionally includes the ratio of net sales to total assets. BPM4 column contains results from a hazard model that combines that combines the variables used in the BPM3 model with liquidity dummy variable. BPM5 column contains results from a hazard model that also considers the impact of ability of a firm to pay out dividends on the probability of financial distress. BPM6 column presents results from a hazard model that additionally accounts for industry effects. BPM7 column reports the results from a hazard model that also incorporates GDP growth and a post crisis dummy variable. The dummy variable takes the value 1 if the years refer to the Greek post-crisis period, i.e, 2009-2011, otherwise it takes the value zero. 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 5: In-sample Forecast Accuracy Tests

Decile	BPM1	BPM2	BPM3	BPM4	BPM5	BPM6	BPM7
1	54.12	54.12	54.12	53.89	53.95	55.08	55.08
2	15.07	13.71	13.65	13.43	14.90	15.63	15.52
3	7.79	7.39	7.33	7.73	8.75	8.07	8.18
4	4.63	5.64	5.89	6.04	5.93	6.83	6.88
5	4.23	4.18	4.01	4.97	5.08	5.19	5.14
6-10	14.16	14.95	15.00	13.94	11.39	9.20	9.20
No. of Bankrupt Firms	1772	1772	1772	1772	1772	1772	1772

Note: This table examines the forecast accuracy of five hazard models we estimate. Firms are sorted in deciles based on their estimated probability of financial distress. Decile 1 contains those firms with the highest probability while Deciles 6-10 contains those with the lowest. The BPM1 column contains results for a model that uses three accounting ratios, i.e., profitability, leverage and retained earnings divided by total assets. The BPM2 column shows the results from a model that incorporates an export dummy variable along with the three accounting ratios. The BPM3 column contains results from a hazard model that additionally includes the ratio of net sales to total assets. The BPM4 column contains results from a hazard model that combines that combines the variables used in the BPM3 model with liquidity dummy variable. The BPM5 column contains results from a hazard model that also considers the impact of ability of a firm to pay out dividends on the probability of financial distress. The BPM6 column presents results from a hazard model that additionally accounts for industry effects. The BPM7 column reports the results from a hazard model that also incorporates GDP growth and a post crisis dummy variable. The dummy variable takes the value 1 for the Greek post-crisis period, i.e, 2009-2011, otherwise it takes the value zero.

Table 6: Out-of-sample Forecast Accuracy Tests: Predictive ability of hazard models during financial crisis

Decile	BPM1	BPM2	BPM3	BPM4	BPM5	BPM6	BPM7
1	56.82	56.07	56.07	57.07	57.57	57.08	56.82
2	14.14	13.40	13.90	13.15	12.65	13.40	13.90
3	7.44	7.94	7.20	6.70	5.96	7.69	7.44
4	4.47	4.23	4.47	5.71	6.20	6.20	6.20
5	4.71	4.71	5.46	4.96	5.46	4.22	4.47
6-10	12.42	13.65	12.90	12.41	12.16	11.41	11.17
No. of Bankrupt Firms	403	403	403	403	403	403	403

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 2002–2008. These parameter estimates are then used to calculate the probability of financial distress over the period 2009–2011.This table examines the forecast accuracy of five hazard models we estimate. Firms are sorted in deciles based on their estimated probability of financial distress. Decile 1 contains those firms with the highest probability while Deciles 6-10 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 group. The BPM1 column contains results for a model that uses three accounting ratios, i.e., profitability, leverage and retained earnings divided by total assets. The BPM2 column shows the results from a model that incorporates an export dummy variable along with the three accounting ratios. The BPM3 column contains results from a hazard model that additionally includes the ratio of net sales to total assets. The BPM4 column contains results from a hazard model that combines that combines the variables used in the BPM3 model with liquidity dummy variable. The BPM5 column contains results from a hazard model that also considers the impact of ability of a firm to pay out dividends on the probability of financial distress. The BPM6 column presents results from a hazard model that additionally accounts for industry effects. BPM7 column reports the results from a hazard model that also incorporates GDP growth. The post crisis dummy variable is omitted from the BPM7 model for the out-of-sample test.

Table 7: Extension of Forecast Horizon

	BPM6 Model		BPM7 Model	
	2-year Forecast Horizon	3-year Forecast Horizon	2-year Forecast Horizon	3-year Forecast Horizon
Constant	-5.5773^{***}	-5.7892^{***}	-5.2694^{***}	-4.4803^{***}
	(-48.27)	(-41.20)	(-37.36)	(-26.76)
EBITDA_TA	-1.1602^{***}	-0.8264^{***}	-1.0829^{***}	-0.8095^{***}
	(-6.51)	(-3.85)	(-6.09)	(-3.80)
BLEV	0.3820^{***}	0.3322^{***}	0.4052^{***}	0.3629^{***}
	(4.96)	(3.53)	(5.25)	(3.83)
RET_TA	-0.6717^{***}	-0.7067^{***}	-0.6913^{***}	-0.7191^{***}
	(-21.07)	(-18.43)	(-21.72)	(-18.64)
EXPORT	-0.5510^{***}	-0.5437^{***}	-0.5491^{***}	-0.5541^{***}
	(-6.59)	(-5.62)	(-6.57)	(-5.72)
LIQUID	-0.2515^{***}	-0.2661^{**}	-0.2291^{***}	-0.2482^{***}
	(-4.17)	(-3.70)	(-3.78)	(-3.44)
DIVPAY	-1.8327^{***}	-1.9265^{***}	-1.8221^{***}	-1.9262^{***}
	(-18.94)	(-15.71)	(-18.83)	(-15.71)
IND_DUM1	1.4043^{***}	1.6095^{***}	1.3989^{***}	1.6066^{***}
	(11.35)	(10.85)	(11.30)	(10.82)
IND_DUM2	1.5032^{***}	1.5033^{***}	1.4906^{***}	1.4977^{***}
	(12.72)	(10.41)	(12.61)	(10.36)
IND_DUM3	1.1600^{***}	1.2251^{***}	1.1544^{***}	1.2229^{***}
	(9.86)	(8.56)	(9.81)	(8.54)
GDP GROWTH			-0.0307^{*}	-0.2382^{***}
			(-1.87)	(-11.64)
POSTCRISIS			-0.7312^{***}	-1.1450^{***}
			(-7.33)	(-13.32)
Log Likelihood	-7043.97	-5098.33	-6994.41	-4975.36
Wald statistic	2080.04^{***}	1372.72^{***}	2179.16^{***}	1618.64^{***}
Number of observations	157,807	128,582	157,807	128,582

Note: This table presents the results from the best hazard model increasing the forecast horizon from one to two and three years, respectively. 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 accounting ratios are lagged to ensure that the data are observable prior to the event of financial distress. BPM6 model uses six firm-specific factors, i.e., profitability, leverage, retained earnings to total assets,an export dummy variable, a liquidity dummy variable and a dividend pay out dummy variable along with three industry dummies. BPM7 model also incorporates GDP growth and a post crisis dummy variable. The dummy variable takes the value 1 if the years refer to the Greek post-crisis period, i.e, 2009-2011, otherwise it takes the value zero. 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

	BPM6 Model		BPM7 Model	
Decile	2-year Horizon	3-year Horizon	2-year Horizon	3-year Horizon
1	47.95	44.42	47.60	44.63
2	19.07	18.66	19.14	18.56
3	10.24	11.26	10.59	11.05
4	8.05	8.32	7.84	8.32
5	5.72	8.52	5.79	8.62
6-10	8.97	8.82	9.04	8.82
No. of Bankrupt Firms	1416	986	1416	986

	BPM6 Model		BPM7 Model	
Decile	2-year Horizon	3-year Horizon	2-year Horizon	3-year Horizon
1	53.30	48.65	56.45	55.07
2	17.19	15.88	14.90	15.54
3	7.45	12.50	8.31	7.76
4	8.88	6.08	6.02	5.41
5	3.15	6.76	3.72	5.41
6-10	10.03	10.14	10.60	10.81
No. of Bankrupt Firms	349	296	349	296

Note: Panel A presents the in-sample forecast results from the best hazard model when the forecast horizon is two and three years, respectively. BPM6 model uses six firm-specific factors, i.e., profitability, leverage, retained earnings to total assets,an export dummy variable, a liquidity dummy variable and a dividend pay out dummy variable along with three industry dummies. BPM7 model also incorporates GDP growth and a post crisis dummy variable. Firms are sorted in deciles based on their estimated probability of financial distress. Decile 1 contains those firms with the highest probability while Deciles 6-10 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 group. Panel B presents the out-of-sample performance of the hazard models when the forecast horizon is two and three years, respectively. The post crisis dummy variable is omitted from the BPM7 model for the out-of-sample test. The models are estimated using data over the period 2002–2008. These parameter estimates are then used to calculate the probability of financial distress over the period 2009–2011.Firms are sorted in deciles based on their estimated probability of financial distress. Decile 1 contains those firms with the highest probability while Deciles 6-10 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 group.

Table 9: Bankruptcy Forecast Prediction Models pre and post crisis

	BPM6 Model		BPM7 Model	
	Pre-crisis	Post-crisis	Pre-crisis	Post-crisis
Constant	-5.4066^{***}	-6.0798^{***}	-4.4828^{***}	-6.6472^{***}
	(-47.08)	(-26.23)	(-27.30)	(-26.28)
EBITDA_TA	-1.4335^{***}	-1.0391^{**}	-1.3958^{***}	-1.0440^{***}
	(-8.31)	(-3.40)	(-8.14)	(-3.38)
BLEV	0.5051^{***}	-0.0095	0.4845^{***}	0.0407
	(6.53)	(0.06)	(6.26)	(0.28)
RET_TA	-0.7420^{***}	-0.8358^{***}	-0.7298^{***}	-0.7649^{***}
	(-23.90)	(-95.07)	(-23.43)	(-14.35)
EXPORT	-0.5755^{***}	-0.8333^{***}	-0.5621^{***}	-0.8229^{***}
	(-6.54)	(-4.78)	(-6.38)	(-4.71)
LIQUID	-0.2460^{***}	-0.4505^{**}	-0.2450^{***}	-0.4650^{***}
	(-3.92)	(-3.97)	(-3.90)	(-4.09)
DIVPAY	-1.5618^{***}	-1.8918^{***}	-1.6435^{***}	-1.2821^{***}
	(-16.78)	(-6.09)	(-17.65)	(-8.51)
IND_DUM1	1.1824^{***}	1.6080^{***}	1.1931^{***}	1.7014^{***}
	(9.56)	(6.53)	(9.65)	(6.90)
IND_DUM2	1.3914^{***}	1.3541^{***}	1.4085^{***}	1.5120^{***}
	(11.98)	(5.63)	(12.12)	(6.25)
IND_DUM3	0.9016^{***}	1.3102^{***}	0.9106^{***}	1.4007^{***}
	(7.70)	(5.55)	(7.78)	(5.93)
GDP GROWTH			-0.1994^{***}	-0.2300^{***}
			(-7.46)	(-7.54)
Log Likelihood	-6465.40	-2032.93	-6413.43	-1993.11
Wald statistic	2227.86^{***}	768.32^{***}	2331.80^{***})	847.95^{***})
Number of observations	128,487	59,877	128,487	59,877

Note: The first column presents the results from the best hazard model for the period prior to the financial crisis, i.e., 2002-2008. The next column reports the results from the best hazard model for the period during the crisis, i.e., 2009-2011. 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 accounting ratios are lagged to ensure that the data are observable prior to the event of financial distress. BPM6 model uses six firm-specific factors, i.e., profitability, leverage, retained earnings to total assets,an export dummy variable, a liquidity dummy variable and a dividend pay out dummy variable along with three industry dummies. BPM7 model also incorporates GDP growth. The value of z-statistics is reported in parentheses.

Table 10: Bankruptcy Prediction for SMEs

	BPM6 Model		BPM7 Model	
	Small Firms	Medium Firms	Small Firms	Medium Firms
Constant	-5.9996^{***}	-7.0660^{***}	-4.4827^{***}	-5.0805^{***}
	(-43.36)	(-9.52)	(-23.94)	(-5.90)
EBITDA_TA	-0.9542^{***}	-1.7604^{**}	-0.9041^{***}	-1.7165^{**}
	(-4.58)	(-2.15)	(-4.41)	(-2.13)
BLEV	0.4273^{***}	1.3810^{***}	0.4394^{***}	1.4809^{***}
	(4.72)	(4.47)	(4.83)	(4.71)
RET_TA	-0.7173^{***}	-0.6969^{***}	-0.7356^{***}	-0.7355^{***}
	(-19.23)	(-4.47)	(-19.62)	(-4.63)
EXPORT	-0.1115	-0.9691^{***}	-0.1050	-0.9510^{***}
	(-1.18)	(-5.60)	(-1.11)	(-3.29)
LIQUID	-0.4465^{***}	-0.3202	-0.4213^{***}	-0.2891
	(-5.96)	(-1.17)	(-5.60)	(-1.05)
DIVPAY	-1.5727^{***}	-1.0142^{***}	-1.5506^{***}	-0.9798^{***}
	(-15.37)	(-3.58)	(-15.12)	(-3.44)
IND_DUM1	1.1990^{***}	2.1539^{***}	1.1904^{***}	2.1563^{***}
	(7.91)	(2.88)	(7.85)	(2.88)
IND_DUM2	1.4429^{***}	1.7377^{**}	1.4263^{***}	1.7337^{**}
	(10.17)	(2.30)	(10.04)	(2.29)
IND_DUM3	1.1502^{***}	1.7217^{**}	1.1303^{***}	1.7175^{**}
	(8.13)	(2.34)	(7.98)	(2.33)
POST CRISIS			-3.1653^{***}	-4.0756^{***}
			(-12.96)	(-4.62)
GDP GROWTH			-0.2994^{***}	-0.4300^{***}
			(-10.23)	(-4.11)
Log Likelihood	-5180.22	-453.30	-5059.86	-439.10
Wald statistic	1463.35^{***}	134.85^{***}	1704.08^{***}	163.23^{***}
Number of observations	163,851	17,315	163,851	17,315

Note: This table presents the results from the best hazard model focusing on small and medium firms. 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 accounting ratios are lagged to ensure that the data are observable prior to the event of financial distress. BPM6 model uses six firm-specific factors, i.e., profitability, leverage, retained earnings to total assets,an export dummy variable, a liquidity dummy variable and a dividend pay out dummy variable along with three industry dummies. BPM7 model also incorporates GDP growth and a post crisis dummy variable. The dummy variable takes the value 1 if the years refer to the Greek post-crisis period, i.e, 2009-2011, otherwise it takes the value zero. The value of z-statistics is reported in parentheses.

Table 11: Forecasting financial distress with other macroeconomic variables

Panel A: Augmenting BPM6 With Other Macro Predictors		
	BPM6	BPM6-MACRO
Constant	-5.5993^{***}	-3.0646^{***}
	(-54.65)	(-3.05)
EBITDA_TA	-1.8328^{***}	-1.3628^{***}
	(-10.05)	(-9.01)
BLEV	0.3940^{***}	0.3886^{***}
	(5.79)	(5.71)
RET_TA	-0.7636^{***}	-0.7305^{***}
	(-28.42)	(-27.28)
EXPORT	-0.6366^{***}	-0.6256^{***}
	(-8.10)	(-7.96)
LIQUID	-0.3197^{***}	-0.3063^{***}
	(-5.83)	(-5.59)
DIVPAY	-1.4378^{***}	-1.5673^{*}
	(-16.22)	(-19.86)
IND_DUM1	1.2579^{***}	1.3066^{***}
	(11.42)	(11.86)
IND_DUM2	1.3612^{***}	1.4384^{***}
	(13.02)	(13.75)
IND_DUM3	0.9804^{***}	1.0274
	(9.37)	(9.82)
TBSPREAD		0.0526^{*}
		(1.83)
DOM_CREDIT		-0.0048
		(-1.60)
GOVDEBT		-0.0101
		(-1.61)
Log Likelihood	-8591.53	-8507.25
Wald statistic	2881.46^{***}	3050.04^{***}
Number of observations	188,364	188,364

Panel B: Vuong Tests	
Model i versus Model j	z statistic
BPM6 versus BPM6-MACRO	-1.20

Note: This table contains the results of augmenting our preferred model 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 accounting ratios are lagged to ensure that the data are observable prior to the event of financial distress. Panel A contains these results. The column entitled BPM6 contains the results without accounting for macroeconomic variables, as shown in Table 4. The BPM6-MACRO column contains results from a hazard model that additionally includes the term premium, the Greek aggregate domestic credit to the private sector scaled by the GDP growth rate, and the government debt scaled by GDP growth rate 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 (excluding 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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