

UNIVERSITY OF WAIKATO

**Hamilton
New Zealand**

**The Role of Corporate Governance and Estimation Methods
in Predicting Bankruptcy**

Nawaf Almaskati, Ron Bird, Yue Lu and Danny Yeung

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Corresponding Author

Nawaf Almaskati (nawafmask@hotmail.com)

Ron Bird (ronbird@waikato.ac.nz)

Yue Lu (susanna.lu@waikato.ac.nz)

School of Accounting, Finance and Economics

University of Waikato

Private Bag 3105

Hamilton 3240

NEW ZEALAND

Danny Leung (danny.yeung-1@uts.edu.au)

University of Technology

Sydney

AUSTRALIA

Abstract

In a sample covering bankruptcies in public US firms in the period 2000 to 2015, we find that the addition of governance variables significantly improves the classification power and prediction accuracy of various bankruptcy prediction models. We also find that while adding governance variables improves the performance of bankruptcy prediction models, the additional explanatory power provided by adding the governance measures improves the further we are from bankruptcy, which implies that governance variables tend to provide earlier and more accurate warnings of the firm's bankruptcy potential. Our analysis of five commonly used statistical methods in the literature showed that regardless of the bankruptcy model used, hazard analysis provides the best classification and out-of-sample forecast accuracy among the parametric methods. Nevertheless, non-parametric methods such as neural networks or data envelopment analysis appear to provide better classification accuracy regardless of the model selected.

JEL Classification

D81; G10; G14; G30; G32

Key Words

corporate governance
bankruptcy studies
default prediction
non-parametric methods

1. Introduction

Over the last few decades, enquiries into the role of corporate governance practices in reducing agency issues as well as their effect on firm's performance have been a major research area for academics and practitioners (Daily *et al.* 2003, Shleifer and Vishny 1997). Corporate governance practices have also been a major concern for investors and regulators in recent times due to the detrimental effects that the failure of these mechanisms has on financial markets, economic activity and society as a whole. The importance of the role of governance stems from its influence on the decision-making process inside the firm as well as on the structure and operations of the board which in turn influences the process of selecting, monitoring and remunerating the firms' executives. Furthermore, the role of a firm's board of directors is not only limited to its monitoring function but also extends to advising the firm's management and undertaking strategic financing and investment decisions (*see* Daily *et al.* 2003, Shleifer and Vishny 1997, Walsh and Seward 1990).

On this basis, one can argue that a firm's probability of bankruptcy may at least be partially explained by its corporate governance characteristics through their influence on how the firm is operated and how the interests of the managers are aligned with those of the shareholders. This proposition has been the focus of several recent studies which found a significant role for corporate governance measures in improving the prediction and classifications powers of bankruptcy prediction models in several markets (*see* Daily and Dalton 1994, Darrat *et al.* 2016, Elloumi and Gueyie 2001, Fich and Slezak 2008, Liang *et al.* 2016). However, we are still far from having closure on the extent to which corporate governance variables improve the predictability of bankruptcy prediction models. Additionally, many of the recent studies on governance and bankruptcy suffer from several limitations, such as focusing on a particular family of bankruptcy models (for example, market-based or accounting-based), overlooking the impact of the estimation technique on the classification and/or prediction accuracy, lacking a meaningful and comprehensive analysis of the prediction performance and classification power of the different models tested.

This study re-examines the role of corporate governance variables in improving the predictability power of bankruptcy prediction models, while analyzing the classification powers yielded by the different estimation techniques. The study is among the first to comprehensively examine the nexus between bankruptcy, corporate governance, and estimation techniques. Majority of the prior studies have primarily focused on examining the added value from adding governance variables to a bankruptcy prediction model without considering the comparability across the different models or estimation techniques (for example, Daily and Dalton 1994, Darrat *et al.* 2016, Elloumi and Gueyie 2001, Fich and Slezak 2008, Wang and Deng 2006). Furthermore, recent studies by Chan *et al.* (2016) and Liang *et al.* (2016) cover a very limited set of bankruptcy models and estimation techniques which limits the comparability of the results significantly. We cover a more comprehensive set of models and estimation techniques. Also, using a larger sample and a longer timeframe to examine

different combinations of models and estimation techniques allows better comparison between both the predictive powers of these models and the classification ability of the different estimation methods. Overall, the study addresses several limitations observed in related previous studies, such as focusing on a very limited set of models and/or estimation methods, using limited datasets and/or governance variables, and overlooking potential statistical and endogeneity issues (see Schultz *et al.* 2017).

We find that the addition of governance variables significantly improves the classification power and prediction accuracy of the different bankruptcy prediction models covered in the study. We also find that while adding governance variables improves the performance of bankruptcy prediction models, the additional explanatory power provided by adding the governance measures improves the further we are from bankruptcy, which implies that governance variables tend to provide earlier and more accurate warnings of the firm's bankruptcy potential (Daily and Dalton 1994, Darrat *et al.* 2016). Lastly, our analysis of five of the most used estimation methods in the literature showed that regardless of the bankruptcy model used, hazard analysis provides the best classification and out-of-sample forecast accuracy among the parametric methods, the other methods being multiple discriminant analysis and regression analysis. Nevertheless, non-parametric methods such as neural networks and data envelopment analysis appear to provide better classification accuracy regardless of the model selected (Cielen *et al.* 2004, Desai *et al.* 1996, Malhotra and Malhotra 2003, Premachandra *et al.* 2009, Wilson and Sharda 1994, Zhang *et al.* 1999).

The remainder of this study is organized as follows. Section 2 provides a summary of relevant prior studies and outlines the main research questions. Section 3 describes the sample and methodology used. Section 4 presents the results of our analysis while section 5 concludes.

2. Literature Review and Research Questions

2.1. Literature Review

Among the first attempts to examine the governance-bankruptcy relationship was Daily and Dalton (1994) who reported the presence of a significant relationship between several corporate governance measures and bankruptcy five years before the actual filing. Specifically, the results showed that bankrupt firms had CEO-chairman duality, less independent boards, lower institutional ownership levels, and lower overall board quality. However, Daily and Dalton point out that the additional explanatory power provided by adding the governance measures disappears in favor of financial measures as we approach the year of bankruptcy, suggesting that as time nears the actual event financial conditions gain more explanatory power while governance becomes less significant in deciding the firm's fate. Moreover, Elloumi and Gueyie (2001) report that the number of independent board members seem to be inversely related to financial distress, suggesting that board independence improves firm's financial health (see also Parker *et al.* 2002). In another related study on a sample of Chinese firms, Wang and Deng (2006) found that the probability of financial distress is inversely related to blockholder (including state) ownership and board independence. However, they found no evidence that

managerial ownership, board size, or CEO-chairman duality affect the probability of financial distress. In contrast, using a sample of US firms, Fich and Slezak (2008) report that corporate governance characteristics, such as: smaller boards, high managerial ownership, and high board independence, reduce the probability of a distressed firm going into bankruptcy. Fich and Slezak suggest that such mechanisms provide effective monitoring and advising and thus help firms in financial distress avoid bankruptcy.

Several recent studies have examined the potential role of corporate governance mechanisms in improving the accuracy of bankruptcy prediction models. The premise behind these studies is that corporate governance practices can affect the probability of bankruptcy of a firm by affecting its operating performance, valuation, and its ability to attract more financing (Daily *et al.* 2003, Jensen 1993, Shleifer and Vishny 1997, Walsh and Seward 1990). For instance, Tsai (2013) found that the prediction power of a distress prediction model can be improved significantly by introducing corporate governance measures. Specifically, Tsai's results show that the inclusion of managerial ownership and pledge-ownership ratio of insiders in the basic Z-score model introduced by Altman (1968) reduces the classification error considerably. In contrast, the findings of Elshahat *et al.* (2015) confirm that the addition of a corporate governance index measure to Altman's original model does not improve the prediction power of the model when using a one-year prediction window. However, the results of this study do not rule out the role of governance measures in improving bankruptcy prediction models but may rather confirm the findings of earlier studies (for example, Daily and Dalton, 1994) that the relationship between governance and financial distress or bankruptcy fades as we get closer to the event.

Schultz *et al.* (2017) confirm the presence of an association between corporate governance mechanisms and the probability of default which disappears after controlling for endogeneity, suggesting that prior findings in the literature may suffer from inadequate attention to endogeneity issues such as: unobserved heterogeneity, possible simultaneity, and reverse causality (see also Wintoki *et al.* 2012). Darrat *et al.* (2016), however, show that corporate governance variables retain their explanatory powers even after controlling for endogeneity. Furthermore, Darrat *et al.* report that board size and the proportion of insiders on the board are inversely related with the risk of bankruptcy in complex firms, suggesting that complex firms require larger boards with more insider expertise to survive. The results further suggest that the relationship between governance and risk of bankruptcy becomes more significant the further we are from the event. Additionally, Chan *et al.* (2016) provides further evidence that the addition of governance variables to well-known bankruptcy prediction models improves their forecasting powers considerably, and more so post the enactment of the Sarbanes-Oxley act in the United States (see also Liang *et al.* 2016, Manzaneque *et al.* 2016).

On balance, results from past studies suggest that the different governance mechanism are significantly related to the firm's health and performance and that adding them to bankruptcy prediction models is expected to significantly improve the prediction and

classification accuracy of such models. However, we are still far from having closure on the extent to which corporate governance impacts the probability of bankruptcy as well as on the role played by the different governance mechanism in the whole prediction process. Furthermore, past attempts have primarily focused on examining the effect from adding governance variables to a bankruptcy prediction model without considering the comparability across the different models or estimation techniques. Also, majority of these studies have overlooked concerns about endogeneity with their results which casts some doubts about earlier findings.

2.2. Research Questions

This study has two main interconnected objectives, which are: (1) to test whether governance mechanisms improve the forecasting power of some well-known bankruptcy models and to highlight the change in this forecasting power as we move away from the event and (2) to examine the classification and prediction accuracy of the different estimation methods. Earlier findings in the literature suggest the presence of a significant relationship between the quality of corporate governance and the probability of bankruptcy or financial distress (Daily and Dalton 1994, Elloumi and Gueyie 2001, Fich and Slezak 2008, Wang and Deng 2006). Furthermore, a relatively recent group of empirical studies has found that the addition of governance variables to some well-known bankruptcy prediction models improves their prediction powers considerably (Chan *et al.* 2016, Darrat *et al.* 2016, Liang *et al.* 2016, Tsai 2013). This is based on the premise that corporate governance mechanisms play a vital role in determining the firm's fate through influencing, directly and indirectly, the allocation and management of its resources on a daily basis. The firm's corporate governance framework influences and includes many aspects of how the firm is managed such as the characteristics of its board and its role in advising and monitoring the firm's executives as well as other internal control mechanisms that help align the interests of the managers' with those of the shareholders (Daily *et al.* 2003, Shleifer and Vishny, 1997). Based on this premise and prior findings in the literature, our first research question is:

1. *Does the addition of governance variables significantly improve the classification accuracy of bankruptcy prediction models?*

Additionally, the firm's corporate governance framework tends to influence its medium- to long-term decisions, while financial ratios are seen as the consequences of these decisions. Therefore, one would expect corporate governance attributes to provide an earlier warning of imminent financial distress or bankruptcy, when compared to financial ratios. Daily and Dalton (1994) point out that the additional explanatory power provided by adding the governance measures disappears in favor of financial measures as we approach the year of bankruptcy, suggesting that as time nears the actual event financial conditions gain more explanatory power while governance becomes less significant in deciding the firm's fate. This finding was also confirmed by Darrat *et al.* (2016), who found that the explanatory power of

the governance variables increases with the time to bankruptcy. On this basis, our next research question is:

2. *Does the additional explanatory power gained from adding corporate governance measures to the bankruptcy prediction models decline as we approach the year of bankruptcy?*

Moreover, prior studies have found that the prediction accuracy of bankruptcy prediction models depend largely on the estimation method used. For example, Mousavi *et al.* (2015) and Shumway (2001) found that models estimated using hazard modelling technique had better prediction accuracy compared to when discriminant analysis or regression analysis were used. Shumway (2001) argues that hazard models are far better for predicting bankruptcy because they account for changes in the firm's performance and characteristics over time¹. Furthermore, findings in the literature suggest that non-parametric methods like data envelopment analysis provide a better prediction accuracy in small samples, an important feature of bankruptcy research (Cielen *et al.* 2004, Premachandra *et al.* 2009, Sueyoshi and Goto 2009). Data envelopment analysis do not require the use of estimation samples which helps avoid issues with using deficient or biased samples of the true population. Additionally, evidence from the credit scoring literature suggests that neural networks consistently outperform traditional estimation methods such as discriminant analysis and regression analysis in identifying bad loans (Desai *et al.* 1996, Malhotra and Malhotra 2003, Piramuthu 1999, West 2000). This superior performance is attributed to the brain-like learning process in neural networks which involves estimating the output and re-adjusting the weights in a repeated process in order to minimize the difference between the outputs and the desired targets. The ability of such techniques to identify bad versus good loans with higher accuracy than other methods as well as the presence of some evidence from past studies on the superiority of neural networks in bankruptcy prediction (Wilson and Sharda 1994, Zhang *et al.* 1999), suggest potential benefits from applying these methods in the field of bankruptcy prediction. Thus, our final research question is:

3. *Does any estimation method show consistent superior prediction/classification accuracy than other methods?*

3. Data and Methodology

3.1. Sample Description

For the purpose of our study, we define bankruptcy as the event of going in liquidation or in reorganization (Chapters 7 and 11) even if the latter did not lead to bankruptcy. The sample of our study covers all events between January 2000 and December 2015 and consists of all firms

¹ While discriminant analysis and regressions estimations use the firm's last observation only to estimate the model, hazard models utilize more data points over the life of the firm and thus are more likely to provide more accurate and consistent estimates.

that were part of S&P500, S&P MID CAP 400 or S&P SMALL CAP 600, during the period studied².

Following prior studies and due to the special nature of such firms, we exclude all financial and insurance related firms from our sample³. We build our initial list of bankrupt firms manually using publicly available lists of delisted firms as well as several news items. Our final list of bankrupt firms is confirmed by examining form 8-K filings with the Securities and Exchange Commission (SEC). We extract all governance data (*Table 2*) for our study from BoardEx⁴. However, since some of the firms on our list of bankrupt firms do not have governance data in BoardEx, we rely on the firm's proxy statements (SEC filings - DEF 14A) to collect the missing data manually⁵. Finally, we use CRSP/COMPUSTAT database to source the necessary accounting and market data for all firms in our sample. Our final sample consists of a total of 1,650 firms (out of which 146 firms are bankrupt) with a total of 21,721 firm-year observations.

3.2. Methodology

We focus our efforts on examining the bankruptcy models (henceforth referred to as models) that got most attention in the literature, while also trying to ensure a balanced mix of both estimation methods and accounting- versus market-based models^{6,7}. The characteristics and structure of the models covered in our study are described in *Table 1*.

We follow the estimation process below to address our research questions:

Step 1: Estimate the original models using our sample and the original estimation methods (one year) and re-estimate all models after adding the governance variables (see *Table 2*). This

² We limit our study to this period only because of the unavailability of sufficient governance data for earlier periods.

³ These firms are excluded because the dynamics of their balance sheets are significantly different from industrial/service firms which makes the usual bankruptcy prediction models and ratios irrelevant for such firms.

⁴ For the United States, BoardEx covers all firms part of S&P500, S&P MID CAP 400 and S&P SMALL CAP 600, as well as some notable private firms. We only include publicly listed firms in our study.

⁵ These firms would normally fall under the scope of coverage of BoardEx, however, no governance data is available in BoardEx for any of these firms, which is why we resort to collecting the data manually to complete our sample. In some years, some non-bankrupt firms do not exist in BoardEx because of the limited coverage by BoardEx during that year, we exclude these firms from our analysis and utilize several matching techniques to avoid sample bias.

⁶ We use the number of citations and the statistical technique used as the main indicators for including a model in our study.

⁷ A consensus on whether market-based or accounting-based bankruptcy prediction models are more accurate does not seem to arise in the literature. As a matter of fact, the evidence in the literature suggests that a mixture of both measures might provide a better prediction accuracy than either alone (see Agarwal and Taffler 2008, Hillegeist *et al.* 2004, Mousavi *et al.* 2015).

allows us to measure the added-value from adding the governance variables to the original models, which is related to our first research question.

Step 2: Re-estimate all models with different horizons to bankruptcy (two and three years). This allows us to answer our second research question regarding the potential variation in the explanatory power of governance variables in the time leading to bankruptcy.

Step 3: Re-estimate all models using Discriminant Analysis (DA), Logistic Regression (LR), Hazard Analysis (HA), Data Envelopment Analysis (DE)-additive model, and Neural Networks-Backpropagation Network (NN)⁸. This allows us to address our last research question regarding the prediction/classification accuracy of the different methods.

Step 4: Test the validity of our results after accounting for endogeneity.

As the main goals of this study are to both investigate the benefits gained from adding the governance variables and to test the accuracy of the different statistical estimation techniques (henceforth referred to as estimation methods or techniques) at the same time, we use a battery of tests to compare the prediction performance, the classification power, and the information content of our models.

Multiple Discriminant Analysis (MDA) and Regression Analysis

Both MDA and regression analysis have been used extensively in the bankruptcy prediction literature. Put simply, an MDA model is a linear combination of two or more independent variables that are used to differentiate between pre-defined groups. This differentiation is achieved through maximizing the between-group variance relative to the within-group variance in order to produce the discriminant score (also called the Z-score) which is then used to classify the different observations into different groups. The average of the Z-scores of the individual observations in each group are used to measure group means which are also called centroids. The statistical significance of the model is determined through measuring the distance between these different centroids. Furthermore, the optimal cutoff discriminating scores between the different groups are selected so that the risk of classification is minimized. MDA is well-suited for analyses with categorical dependent variables and metric independent variables.

Regression analysis is one of the most widely used statistical techniques across different disciplines and research streams including bankruptcy prediction. Much like MDA, it is a statistical technique that is used for estimating the relationship between a dependent variable and one or more independent variables. The form of the regression model and its coefficients help understand the relationship between the dependent variable and the independent variables

⁸ A full description of these techniques can be obtained from the literature (see Bharath and Shumway 2008, Kumar and Ravi 2007, Malhotra and Malhotra 2003, Mousavi *et al.* 2015, Premachandra *et al.* 2009).

by measuring average changes in the dependent variable due to changes in the independent ones. Logit analysis is the most frequently used method in the bankruptcy prediction field (Mousavi *et al.* 2015). Many researchers have favored regression analysis over MDA because regression models tend to work under less restrictive statistical properties than MDA (*see* Ohlson, 1980). Additionally, the score output from MDA has little explanation power in terms of closeness to the event as opposed to the more informative output from regression analysis. However, it is worth mentioning that MDA and logit estimations are closely linked under the normality assumption (McFadden 1976).

Hazard Analysis

A number of bankruptcy prediction studies have used hazard analysis to estimate their models rather than MDA or regression analysis. Shumway (2001) argues that hazard models are far better than MDA or regression analysis for predicting bankruptcy because they provide more consistent estimates. Cross-sectional models such as MDA and logit models, fail to take account of changes in the firm's performance or characteristics over time. Specifically, these models consider each firm-year as an independent observation rather than looking at related firm-years as a series of observations on the same firm. Furthermore, while MDA and logit estimations use the firm's last observation only to estimate the model, hazard models utilize more data points over the life of the firm and thus consider the full available history of each firm. Shumway equates hazard models to logit models where no data points were excluded. As a result, the use of more data points is expected to produce more consistent and efficient estimates which are not time-dependent⁹. Hazard models also allow explanatory variables to vary over time which makes it possible to capture any deterioration in the firm's financial health in the time leading to bankruptcy.

In hazard analysis, the survival and the hazard functions are the two most relevant functions needed to perform the analysis. While both are functions of time, the hazard function represents the probability of failure at time (t) having survived until or after that point in time, whereas the survival function represents the probability of survival beyond time (t). Shumway's discrete-time hazard model is the most frequently used hazard model in the field of bankruptcy prediction. Shumway's definition of both functions is as follows:

$$S(t, x; \theta) = 1 - \sum_{j < t} f(j, x; \theta) \quad \text{and} \quad H(t, x; \theta) = \frac{f(t, x; \theta)}{S(t, x; \theta)}$$

where $S(t, x; \theta)$ and $H(t, x; \theta)$ are the survival and hazard functions, respectively, and $f(t, x; \theta)$ is the probability mass function of failure. Also, t represents the time when the firm leaves the sample and θ is the vector of the function's parameters, while x is the vector of bankruptcy prediction variables. Bharath and Shumway (2008) among others, employ Cox proportional hazard models in estimating the probability of default. The Cox proportional model is a

⁹ For a more detailed discussion of the characteristics of such models, see Mousavi *et al.* (2015) and Shumway (2001).

semiparametric hazard regression model that allows testing for differences in survival times between two or more groups. The model assumes a nonlinear relationship between the hazard function and the predictors. In this model, the hazard function is assumed to be:

$$H(t) = \phi(t)[e^{(x(t)'\beta)}]$$

where $\phi(t)$ is the common baseline hazard rate and $e^{(x(t)'\beta)}$ allows variation in the expected time to bankruptcy across firms. In our study, we use the proportional hazard models to estimate our different models. We use the following formula to estimate the discrete-time hazard rate (or probability of default):

$$PD_t = \frac{e^{\phi(t) + \beta_t x_t}}{1 + e^{\phi(t) + \beta_t x_t}}$$

where β_t and X_t are the estimated coefficients and estimated variables, respectively.

Data Envelopment Analysis (DEA)

DEA is a nonparametric method mostly used in the field of operations research for estimating production frontiers and measuring production efficiency of decision-making units (DMUs)¹⁰. DEA functions focus on determining the most efficient DMU, whereas the normal regression analyses focus on the average DMU. DEA offers a nonparametric and distribution free approach to bankruptcy prediction modelling as opposed to the restrictions imposed by MDA and regression analysis (Premachandra *et al.* 2009). Furthermore, because no estimation samples are required under the DEA framework, potential issues with using deficient or biased samples of the true population to estimate the model can be avoided. Nevertheless, Premachandra *et al.* (2009) argue that DEA is inferior to the conventional models when it comes to the availability of statistical tests as well as bankruptcy prediction in varying time horizons. The results of DEA models are also sensitive to the selection of inputs and outputs.

Following Premachandra *et al.* (2009) and others, we use the additive DEA model introduced in Charnes *et al.* (1985) to estimate the probability of bankruptcy of firms in our sample. The additive model allows for negative values in the inputs/outputs which is an important feature in bankruptcy data. Additionally, the additive model circumvents issues observed in prior bankruptcy studies with regards to measuring the efficiency and slack scores for outputs and inputs separately (for example, Cielen *et al.* 2004). With regards to defining inputs and outputs, the guideline provided in Premachandra *et al.* (2009) is to use ratios that increase (decrease) with the probability of bankruptcy as outputs (inputs). The intuition behind this guideline is simple, because higher (lower) values of outputs (inputs) tend to result in a value of zero for the objective function of the additive model, which makes the firm more likely to appear on the bankruptcy frontier. Following Premachandra *et al.* (2009), any firm that has zero on all input and output slacks is classified as bankrupt and thus falls on the bankruptcy frontier. Due to limitations with regards to computing power, we use our full bankrupt sample

¹⁰ Stochastic Frontier Analysis is the parametric equivalent of DEA.

and match each bankrupt firm with ten non-bankrupt firms based on market value (+/- 20%) and the 3-digit Standard Industrial Classification (SIC).

Neural Networks

Neural networks models have long been used in the credit scoring literature and were hailed in many studies for their superiority over many conventional models (Desai *et al.* 1996, Malhotra and Malhotra 2003, Wilson and Sharda 1994, Zhang *et al.* 1999). The computational framework of neural networks is inspired by the neural networks of the human nervous system. It processes information by linking an enormous number of artificial nerves to simulate the capabilities of biological neural networks. Put simply, neural networks use a combination of concepts and algorithms to learn from examples, simulating the learning experience of a human being. The process of estimation or learning in neural networks involves estimating the output and re-adjusting the weights in a repeated process in order to minimize the difference between the outputs and the desired targets. Kumar and Ravi (2007) point out that although neural networks tend to perform well in different classification and forecasting tasks, the selection of the different parameters involved in the neural networks training and estimation process is not a simple task.

As with many statistical techniques, there are different algorithms or estimation techniques for neural networks of which the backpropagation model is the most popular for classification and prediction problems (Kumar and Ravi 2007). Malhotra and Malhotra (2003) point out that the ability of the backpropagation model to identify patterns in large pools of data makes it a suitable technique for credit scoring and bankruptcy problems. A standard backpropagation model consists of three layers: the input layer, the hidden layer, and the output layer. The input layer processes the inputs, which usually correspond to the independent variables in a standard regression analysis, and provides the processed values to the hidden layer, which in turn processes the values further before sending them to the output layer. This process continues until the model is able to remember the output of most of the observations in the training sample. The technique takes its name from the process that takes place once the network does a mistake, because when this happens the algorithm starts at the last layer (the output) and backpropagates the error to the hidden layer. For the purposes of our study, we will use the backpropagation model with the independent variables as inputs and the bankruptcy indicator (1 or 0) as an output. As with other studies, we allow the number of hidden neurons to vary based on a trial and error approach while allowing up to 1,000 training cycles. We find that on average six neurons provide the most efficient results and hence use this setup throughout our study. As with DEA, due to limitations with regarding to computing power, every bankrupt firm will be matched with ten similar non-bankrupt firms based on market value (+/- 20%) and the 3-digit Standard Industrial Classification (SIC).

3.3. Governance Variables

We focus our analysis in this study on a number of governance variables related to board composition and structure. While the firm's governance framework extends well beyond the structure and composition of its board of directors, the board's monitoring and advising functions stand out as two of the most important mechanisms in which a firm's fate is determined (Darrat *et al.* 2016). The firm's board influences its performance through its role, directly and indirectly, in the allocation and management of its resources. First of all, a large number of studies have documented positive effects of board independence on firm value and operating performance due to reasons such as the role of independent directors in offering better and more autonomous advices compared to insider directors (Baysinger and Butler 1985, Boone *et al.* 2007, Raheja 2005, Rosenstein and Wyatt 1990, Weisbach 1988, Yermack 2006).

Secondly, findings in the literature on CEO-Chairman duality seem to be mixed. While some studies find that the separation costs are larger than the benefits gained (Baliga *et al.* 1996, Brickley *et al.* 1997), others argue that the duality weakens the board monitoring powers and reduces the likelihood of firing underperforming managers (Adams *et al.* 2005, Dey *et al.* 2011, Goyal and Park 2002).

Thirdly, many studies found a negative relationship between board size and firm value or performance (Eisenberg *et al.* 1998, Mak and Kusnadi 2005, Yermack 1996). This is supported by claims in the literature that larger boards tend to have poor communication issues and ineffective decision-making process (Lipton and Lorsch 1992, Jensen 1993). Other studies, however, found some support for the arguments that larger boards tend to take less extreme decisions and that they are beneficial for complex firms (Boone *et al.* 2007, Cheng 2008, Coles *et al.* 2008).

Fourthly, staggered boards have been found to be harmful to firm performance through contributing to managers' entrenchment and reducing the board's monitoring powers (Bebchuk and Cohen 2005, Cohen and Wang 2013, Faleye 2007, Faleye 2009). Fifthly, Yermack (2004) report that more than half of the overall incentives to external directors come from changes in the value of equity-related holdings (stocks and options), confirming the vital role of equity-related incentives in aligning the interests of board members with those of the shareholders. Sixth, Adams and Ferreira (2009) document a positive relationship between gender-diversity and the board's monitoring activities. The results show that female directors have less attendance problems and more active participation in the board's committees than their male counterparts. Lastly, several studies have documented a negative link between director busyness and firm value and performance based on the fact that boards with more busy members tend to be less effective at monitoring and advising the firm's management (Adams and Ferreira 2008, Ahn *et al.* 2010, Fich and Shivdasani 2006, Jiraporn *et al.* 2009). With regards to the bankruptcy literature, Daily and Dalton (1994) found that bankrupt firms had CEO-chairman duality, less independent boards, and lower overall board quality. Additionally, Elloumi and Gueyie (2001) found that board independence is inversely related with financial

distress. Also, Fich and Slezak (2008) show that smaller and more independent boards reduce the probability of a distressed firm going into bankruptcy (see also Liang *et al.* 2016, Manzaneeque *et al.* 2016).

The definition of the different governance variables covered in our study and their expected effect on the firm's probability of bankruptcy are included in Table 2.

3.4. Performance Comparison Metrics

Prediction Performance

To examine the prediction performance of the various models, we use a number of interrelated ratios as explained below.

Accuracy ratio (AR): is the proportion of cases correctly classified (bad or good), and is measured as follows:

$$\text{Accuracy ratio (AR)} = \frac{N_{GG} + N_{BB}}{\text{Total sample}}$$

where N_{GG} (N_{BB}) is the number of good (bad) cases classified as good (bad).

Sensitivity: is the proportion of bad cases correctly classified as bad, and is measured as follows:

$$\text{Sensitivity} = \frac{N_{BB}}{N_{BB} + N_{BG}}$$

where N_{BG} (N_{BB}) is the number of bad (bad) cases classified as good (bad).

Specificity: is the proportion of good cases correctly classified as good, and is measured as follows:

$$\text{Specificity} = \frac{N_{GG}}{N_{GG} + N_{GB}}$$

where N_{GG} (N_{GB}) is the number of good (good) cases classified as good (bad).

Type I and Type II errors: Type I error is the proportion of bad cases classified as good, while Type II error is the proportion of good cases classified as bad, and are measured as follows:

$$\text{Type I error} = 1 - \text{Sensitivity} \quad \text{and} \quad \text{Type II error} = 1 - \text{Specificity}$$

Misclassification costs: this is basically the sum of Type I and Type II errors and reflects the total costs associated with using the model to classify the different cases.

It can be argued that the ratio that conveys the most important piece of information from the perspective of the decision maker is Type I error. This is because the expected costs from classifying a bad case as good far exceed the costs from classifying a good case as bad. In other words, the losses to a bank from lending a bad firm (Type I error) are expected to be much

higher than the losses from refusing to lend to a good firm (Type II error). It is worth mentioning, however, that the costs to the society and the economy from Type II errors might be significant when good opportunities are systematically disregarded due to this error.

Classification Power

In line with prior studies in the field, we utilize the receiver operating characteristic (ROC) curve to compare the classification ability of each model in our study. ROC is a graphical representation of the levels of true positive rate (TPR) and false positive rate (FPR) as the discrimination threshold settings are varied. For the purposes of our study we plot FPR and TPR on the x-and y-axis of the ROC curve, respectively¹¹. The larger the area under the curve (AUC) the better the model's classification ability is. Furthermore, to compare the significance of the AUC of the different models, we use the Hanley and McNeil (1983) test which adjusts for the induced correlation due to the usage of the same sample in both models.

Information Content

As highlighted by Hillegeist *et al.* (2004) and Agarwal and Taffler (2008), a decision maker does not always face a dichotomous decision, thus he or she may use the output of the model to rate the firm's riskiness in order to decide on the interest to be charged or the collateral to be used, among other things. Therefore, rating models by their prediction performance only may not be the best approach to select which model to use. As a result, we use the Akaike information criterion (AIC) to compare the information content of the different models in our study. AIC measures the relative quality of a model compared to other models, through considering the tradeoff between the model's complexity and its goodness of fit. The reason behind our selection of the AIC measure instead of the various other measures used in prior studies, is our need to compare the quality of each model relative to all other models¹². It is worth mentioning that the AIC does not test the absolute quality of the model, so no inferences about the absolute fit of the model can be made using this measure. The smaller the value of the AIC measure the better the model in comparison to other models.

4. Results and Discussion

4.1. Univariate Analysis

Table 3 provides mean and median statistics for the governance variables and some of the financial variables included in our analysis based on the split between non-bankrupt and bankrupt firms. Out of the eleven governance variables included in the study, ten have significantly different mean and median statistics between the non-bankrupt and bankrupt firms. The statistics suggest that, compared to non-bankrupt firms, bankrupt firms tend to have: higher attrition, more male dominated boards, less independent boards, less cases of CEO-

¹¹ TPR and FPR are also calculated as sensitivity and (1-specificity), respectively (explained earlier).

¹² Similar studies in the literature (for example, Agarwal and Taffler, 2008; Liang *et al.* 2016; Mousavi *et al.* 2015, among others) use the Log-likelihood statistic and the Pseudo-R² measure.

chairman duality, smaller boards, larger proportion of directors whose appointments predates that of the CEO, less experienced directors (external, internal and company), and lower presence of equity-based components in directors' compensation. This is in line with the previous findings in the literature and our predictions (see Table 2) about the expected relationship between governance structure and the probability of bankruptcy (Daily and Dalton 1994, Elloumi and Gueyie 2001, Fich and Slezak, 2008, Liang *et al.* 2016, Manzanque *et al.* 2016). We can also see significant differences in the financial variables between the two groups (bankrupt versus non-bankrupt) in line with our expectations and findings in prior studies regarding the financial health of a bankrupt firm one year before bankruptcy. More specifically, we can see from the different ratios that bankrupt firms have significantly lower earnings, working capital and market value as well as significantly higher liabilities.

4.2. Corporate Governance Structure and Bankruptcy Prediction

Panel A in Table 4 shows the results of re-estimating the original models using our sample and the original estimation methods. The results show that Altman (1968)'s original model as well as Zmijewski's (1984) provide the most accurate overall classification as measured by the accuracy ratio (proportion of correctly classified cases). However, the models of Shumway (2001), Bharath and Shumway (2008) and Premachandra *et al.* (2009), provide better accuracy with regards to classifying bankrupt firms (sensitivity > 75%). Additionally, the latter models have better classification power as shown by the higher area under the curve (AUC) measure. The accuracy rates of the out-of-sample forecasts of the different models are very close with an average accuracy ratio of 70%.

Next, when we add the eleven governance variables covered by our study (Table 2) to each of these models, we notice a general improvement, sometimes very significant, in the prediction and classification accuracy of these models. Panel B in Table 4 shows the results of re-estimating the original models from Panel A after adding the governance variables, while Panel C shows the differences between Panels A and B. First of all, all models now show better classification accuracy and improved classification power as measured by the accuracy ratio and the AUC, respectively. Using the Hanley and McNeil (1983) test, we find that the AUC results of all models are significantly different from the baseline or the random predictor (AUC = 0.5). Specifically, the models of Shumway (2001) and Bharath and Shumway (2008) show the biggest improvement from including the governance variables by classifying 18% and 22% more cases correctly, respectively.

These two models in addition to Premachandra *et al.* (2009) also provide a more accurate classification of the bankrupt companies with an average increase in the classification accuracy of 6% in comparison to the original models without governance variables. Additionally, all models are now able to predict bankruptcy in firms outside the sample with better accuracy, with an increase of between 4% and 14% in the accuracy of out-of-sample forecasts after the inclusion of the governance variables. With regards to the information content of the different

models, we notice that the models with governance variables have lower AIC values which suggests that these models are more informative and of a better quality than the original ones.

Overall, this suggests that the addition of governance variables to the different bankruptcy prediction models leads to a significant improvement in their classification power and prediction accuracy. The most noticeable improvement is found in models utilizing hazard analysis, which might be related to the fact that unlike cross-sectional models such as MDA and logit models, hazard analysis takes account of changes in the firm's performance or characteristics over time. Specifically, hazard analysis looks at related firm-years as a series of observations on the same firm and thus is able to incorporate changes in the firm's governance structure and as a result produce more consistent and efficient predictions (Shumway 2001). Both error I (classifying a bad case as good) and error II (classifying a good case as bad) are lower under hazard analysis, confirming the superiority of these models in reducing the potential economic impacts from erroneously classifying a firm that is about to be bankrupt as a healthy one and vice versa. Our findings on the effect of including governance factors in bankruptcy prediction models are largely in line with findings of several recent empirical studies who covered a limited set of models and techniques (Chan *et al.* 2016, Darrat *et al.* 2016, Liang *et al.* 2016, Tsai 2013).

However, as highlighted in the discussion leading to our second research question, previous findings in the literature also suggest that the additional explanatory power provided by adding the governance measures increases with the time to bankruptcy (Daily and Dalton, 1994, Darrat *et al.* 2016). Therefore, we re-estimate the models including the governance variables with two and three years to bankruptcy. Panels A and B in Table 5 present the differences in the performance of the different prediction models before and after adding the governance variables (After minus Before), two- and three-years before bankruptcy, respectively. Compared to the results shown in Panel C in Table 4, the current results show improved accuracy in the overall classification and out-of-sample forecast as well as higher classification power as measured by the accuracy ratios and the AUC, respectively. Additionally, the different models are either able to provide the same level of classification accuracy or better when it comes to classifying bankrupt companies, with clear dominance for models utilizing DEA and hazard analysis. In a set of unreported results, we compare the performance of the original models without the governance variables and notice a general deterioration in the forecasting and classification ability as we increase the time to bankruptcy. Overall, these findings suggest that while adding governance variables improves the performance of bankruptcy prediction models, the additional explanatory power provided by adding the governance measures improves with time to bankruptcy. This effect is however not applicable to models without governance variables, which implies that governance variables tend to provide earlier and more accurate warnings of the firm's bankruptcy potential.

4.3. The Role of the Different Estimation Techniques in Bankruptcy Prediction

Table 6 shows the results of re-estimating the bankruptcy models including the governance variables using different estimation techniques. Due to limitations with regards to computing power as well as potential sample bias from over representing bankrupt firms, we use our full bankrupt sample and match each bankrupt firm with 10 non-bankrupt firms based on market value (+/- 20%) and the 3-digit Standard Industrial Classification (SIC) code^{13,14,15}. With regards to the parametric models: Discriminant Analysis (DA), Logistic Regression (LR), and Hazard Analysis (HA), the results suggest that regardless of the bankruptcy model selected, HA provides the best classification performance as well as the highest average of out-of-sample forecast accuracy, which confirms prior findings in the literature (Shumway, 2001). Models estimated using HA are also able to more accurately identify bankrupt firms as shown by the lower Type I error (the proportion of bankrupt firms classified as non-bankrupt). The higher AUC values for HA estimates also indicate higher classification powers compared to DA or LR estimates. This is further confirmed by the results of the Hanley and McNeil (1983) difference test (unreported).

However, the superior results from the non-parametric methods: Data Envelopment Analysis (DE)-additive model and Neural Networks-Backpropagation Network (NN), suggest that such methods tend to provide more accurate classifications both overall and for bankrupt firms irrespective of the bankruptcy prediction model used. The unreported results of the Hanley and McNeil (1983) test confirm that DE and NN estimations provide significantly higher AUC results. This is in line with prior findings in the literature which claim superiority of Neural Networks (Desai *et al.* 1996, Malhotra and Malhotra 2003, Wilson and Sharda 1994, Zhang *et al.* 1999) and Data Envelopment Analysis (Cielen *et al.* 2004, Premachandra *et al.* 2009) over the standard methods in classifying different cases and identifying patterns in data. Though the computing power and resources needed to estimate bankruptcy prediction models using Neural Networks or Data Envelopment Analysis restrict the wider application of such methods in the field, this is in addition to the challenges faced with the selection of the different parameters involved in the estimation process (Kumar and Ravi 2007, Premachandra *et al.* 2009).

Overall, hazard analysis provides the best classification and out-of-sample forecast accuracy among the most widely used parametric methods in bankruptcy prediction.

¹³ The accuracy ratios will be different due to the higher representation in table 6 of the bankrupt firms (as a proportion) as opposed to Table 4 which uses the full sample of healthy firms.

¹⁴ The matching is done through selecting ten non-bankrupt firms with the same SIC code that are closest in terms of market value during the year of observation to the bankrupt firm. 76 percent of the bankrupt firms in our sample are matched with non-bankrupt firms that are within 10-15 market value.

¹⁵ Our overall conclusions remain essentially the same when we match each bankrupt firm to one non-bankrupt firm only, or match firms based on propensity scores, or when we run a sample with the same proportion of bankrupt to non-bankrupt firms as observed in reality.

Nevertheless, non-parametric methods such as Neural Networks or Data Envelopment Analysis appear to provide better classification accuracy regardless of the model selected. They also have lower Error I rates (classifying a bad case as good), which suggests that these estimation methods are better at reducing the potential economic impacts of bankruptcy.

4.4. Corporate Governance, Bankruptcy and Endogeneity Concerns

While the findings of some studies suggest that the relationship between corporate governance and the probability of default disappears after accounting for endogeneity (e.g. Schultz *et al.* 2017), others have documented the persistence of such relationships after addressing the endogeneity concerns (for example, Darrat *et al.* 2016). Following Wintoki *et al.* (2012) and others, we use the dynamic-panel GMM (generalized methods of moments) estimator introduced by Arellano and Bover (1995) and Blundell and Bond (1998) and follow a three steps estimation process. First of all, the regression model is modified to include the first lagged probability of default in addition to the other explanatory variables¹⁶.

Secondly, we take the first-difference of the variables to account for any unobserved heterogeneity. Lastly, we use the dynamic panel GMM estimator to estimate the final model while using the lagged values of the explanatory variables as instruments. Hoechle *et al.* (2012) point out that using the lagged variables as instruments for the current values of the same variables accounts for possible simultaneity and reverse causality. This setup allows us to treat all explanatory variables as endogenous ones while adding the years' dummy variables as the only exogenous variables. Following Darrat *et al.* (2016) we also believe that the results from our lagged bankruptcy models (two and three years to bankruptcy) provide another test for endogeneity.

Table 7 presents the results of two different regressions with the probability of default estimated using discrete-time hazard rate (SHW model) and logistic regression (OHL model), respectively, as the dependent variable. In addition to including the different governance variables as independent variables, we also include control variables that were found in previous studies to be related to the probability of default (Bhojraj and Sengupta 2003, Klock *et al.* 2005, Schultz *et al.* 2017). The results from both estimations show that even after controlling for unobserved heterogeneity, possible simultaneity, and reverse causality, corporate governance variables have a significant role in predicting bankruptcy. Specifically, five of the eleven governance variables included in the GMM estimations are significant. Furthermore, using the Hansen test of over-identification, we fail to reject the null hypothesis that the instruments employed in our models are valid confirming the validity of our results. At large, this confirms the presence of a statistically significant relationship between corporate governance and the probability of default even after controlling for different forms of

¹⁶ Probability of default is estimated using the discrete-time hazard rate and logistic regression analysis as explained earlier.

endogeneity concerns that have been highlighted in the literature (Wintoki *et al.* 2012, Schultz *et al.* 2017).

5. Concluding Remarks

This study re-examines the role of corporate governance variables in improving the predictability power of bankruptcy prediction models, while analyzing the classification powers yielded by the different estimation techniques. The study is among the first to comprehensively examine the nexus between bankruptcy, corporate governance, and estimation techniques. The study also addresses several limitations observed in previous studies, such as: focusing on a very limited set of bankruptcy models and/or estimation methods, using a fairly limited dataset or governance variables, and overlooking potential statistical and endogeneity issues.

We find that the addition of governance variables to various bankruptcy prediction models significantly improves their classification power and prediction accuracy. The most noticeable improvement is found in models utilizing hazard analysis, which might be related to the fact that hazard analysis takes account of changes in the firm's performance or characteristics over time and thus is able to incorporate changes in the firm's governance structure and as a result produce more consistent and efficient predictions (Shumway 2001).

We also find that while adding governance variables improves the performance of bankruptcy prediction models, the additional explanatory power provided by adding the governance measures improves the further we are from bankruptcy, which implies that governance variables tend to provide earlier and more accurate warnings of the firm's bankruptcy potential (Daily and Dalton 1994, Darrat *et al.* 2016). Lastly, our analysis of five of the most used estimation methods in the literature showed that regardless of the bankruptcy model used, hazard analysis provides the best classification and out-of-sample forecast accuracy among the parametric methods. Nevertheless, non-parametric methods such as Neural Networks or Data Envelopment Analysis appear to provide better classification accuracy regardless of the model selected (Cielen *et al.* 2004, Desai *et al.* 1996, Malhotra and Malhotra, 2003, Premachandra *et al.* 2009, Wilson and Sharda 1994, Zhang *et al.* 1999). The study also employed the dynamic panel GMM estimator to address any endogeneity concerns with regards to the relationship between bankruptcy prediction and corporate governance and found no support for such concerns.

While we do not attempt to examine the process through which corporate governance influences the probability of bankruptcy, prior evidence from the literature suggests that corporate governance impacts the firm's operating performance and its risk-taking behavior and hence its probability of default through mitigating and limiting agency issues (Bhagat and Bolton 2008, Bhojraj and Sengupta 2003). The results of this study contribute to the debate on the best estimation methods and the role of governance characteristics in improving the

bankruptcy prediction process. The results also inform future decision-making process with regards to improving corporate governance practices and increasing investor protection. Future research can focus on examining a wider set of governance factors across different geographies which will improve our understanding of the contribution of the different governance factors in each geography.

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Table 1: Description of Previous Models in the Literature

| Study (in chronological order) | Accounting or Market Based? | Shorthand Reference | Estimation Technique | Variables |
|--------------------------------------|--------------------------------|------------------------|------------------------------------|---|
| Altman (1968) | Accounting | ALT | Discriminant Analysis | <p><i>WCTA</i> = Working capital / total assets. <i>RETA</i> = Retained earnings / total assets. <i>EBITTA</i> = Earnings before interest and taxes / total assets. <i>METD</i> = Market value of equity / total debt. <i>STA</i> = Sales / total assets.</p> |
| Ohlson (1980) | Accounting | OHL | Regression Analysis (Logit) | <p><i>TLTA</i> = Total liabilities / total assets. <i>WCTA</i> = Working capital / total assets. <i>CLCA</i> = Current liabilities / current assets. <i>OENEG</i> = 1 if total liabilities exceed total assets, 0 otherwise. <i>NITA</i> = Net income/total assets. <i>FUTL</i> = Funds from operations (operating income minus depreciation) / total liabilities. <i>INTWO</i> = 1 if net income has been negative for the last 2 years, 0 otherwise. <i>CHIN</i> = $(NI_t - NI_{t-1}) / (NI_t + NI_{t-1})$, NI_t is the net income for the latest period. <i>Ohlsonsize</i> = $\log(\text{Total assets} / \text{GNP price-level index})$</p> |
| Zmijewski (1984) | Accounting | ZMJ | Regression Analysis (Probit) | <p><i>NITA</i> = Net income / total assets. <i>TLTA</i> = Total liabilities / total assets. <i>CACL</i> = Current assets / current liabilities</p> |
| Shumway (2001) | Mix | SHW | Hazard Analysis | <p><i>NITA</i> = Net income / total assets. <i>TLTA</i> = Total liabilities / total assets. <i>RelativeSize</i> = $\log(\text{the number of outstanding shares multiplied by year-end share price divided by total market value})$. <i>LagExReturn</i> = Cumulative annual return in year $t - 1$ minus the value-weighted index return in year $t - 1$. <i>LagSigma</i> = Standard deviation of residuals derived from regressing monthly stock return on market return in year $t - 1$.</p> |

| | | | | |
|------------------------------------|-------------------|-----|--------------------------------------|--|
| Bharath and Shumway (2008) | Market | BSH | Hazard Analysis | <p>V_A = Market value of assets, estimated as $F + V_E$. V_E = Market value of equity. μ = Continuously compounded expected return on assets Estimated using the 1-year Treasury constant maturity rate. δ = Continuous dividend rate estimated as total dividends / V_A. F = Face value of debt maturing at time T, proxied by total liabilities. σ = Volatility of stock returns. Annualized percent standard deviation of returns and is estimated from the prior year stock return data for each month. T = Time to debt maturity, considered as 1 year</p> |
| Premachandra <i>et al.</i> (2009) | Mostly Accounting | PRM | Data Envelopment Analysis (additive) | <p><u>Outputs:</u> $TDTA$ = Total debt / total assets. $CLTA$ = Current liabilities / total assets <u>Inputs:</u> $CFTA$ = cash flow / total assets. $NITA$ = net income / total assets. $WCTA$ = working capital / total assets. $CATA$ = current assets / total assets, $EBITTA$ = earnings before interest and taxes / total assets. $EBIE$ = earnings before interest and taxes / interest. $MVCE$ = market value of equity / book value of common equity</p> |
| Almamy <i>et al.</i> (2016) ALM | Accounting | ALM | Discriminant Analysis | <p>$WCTA$ = Working capital / total assets. $RETA$ = Retained earnings / total assets. $EBITTA$ = Earnings before interest and taxes / total assets. $METD$ = Market value of equity / total debt. STA = Sales / total assets. $CFOTL$ = Cash flow from operations / total liabilities</p> |

Table 2: Description of the Corporate Governance Variables

| Variable | Definition | Type | Expected sign* |
|-------------------------------------|--|-----------|----------------|
| Attrition Ratio (ATTR) | The number of directors that have left a role as a proportion of average number of directors | Fraction | + |
| Gender (GEND) | The proportion of male directors on the board | Fraction | + |
| Board Independence (INDP) | The proportion of total board members who are considered independent | Fraction | - |
| CEO-Chairman Duality (DUAL) | 1 if the chairman is a current or ex-CEO, 0 otherwise | Indicator | - |
| Board Size (BSIZ) | Natural log of the number of board members in a year | Number | - |
| Directors Predating CEO (DCEO) | The proportion of board members whose tenure predates the CEO's appointment | Fraction | - |
| Director External Experience (DEEP) | The average number of years that a director sits on the boards of other companies | Number | - |
| Director Internal Experience (DIEP) | The average number of years that a director sits on the board of the company | Number | - |
| Director Company Experience (DCEP) | The average number of years that a director works in the company | Number | - |
| Director busyness (BUSY) | 1 if the majority of outside directors hold three directorships or more, 0 otherwise | Indicator | + |
| Directors compensation (DCOM) | 1 if the compensation of directors includes equity-based component, 0 otherwise | Indicator | - |

* A positive (negative) sign means that higher values of this variable are expected to increase (decrease) the probability of bankruptcy.

Table 3: Descriptive Statistics of the Governance Variables

This table presents the mean and median values of the governance variables (refer to *Table 2* for details) and some of the main financial variables of non-bankrupt and bankrupt firms one-year before bankruptcy. The test for the equality of means uses Welch's t-test, while the test for the equality of medians uses Wilcoxon's rank-sum test. The p-values are reported in the parentheses.

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

| | Non-Bankrupt Firms | | Bankrupt Firms | | Difference | |
|---|--------------------|--------|----------------|--------|----------------------|----------------------|
| | Mean | Median | Mean | Median | Mean | Median |
| Attrition Ratio (ATTR) | 0.026 | 0.000 | 0.042 | 0.000 | -0.015** (0.011) | 0.000** (0.012) |
| Gender (GEND) | 0.887 | 0.889 | 0.927 | 1.000 | -0.040*** (0.000) | -0.111*** (0.000) |
| Board Independence (INDP) | 0.826 | 0.857 | 0.800 | 0.833 | 0.027*** (0.010) | 0.024*** (0.000) |
| CEO-Chairman Duality (DUAL) | 0.527 | 1.000 | 0.438 | 0.000 | 0.089** (0.034) | 1.000** (0.033) |
| Board Size (BSIZ) | 0.961 | 0.954 | 0.855 | 0.845 | 0.106*** (0.000) | 0.109*** (0.000) |
| Directors Predating CEO (DCEO) | 0.275 | 0.200 | 0.315 | 0.218 | -0.040* (0.098) | -0.018* (0.058) |
| Director External Experience (DEEP) | 3.746 | 3.600 | 2.619 | 2.279 | 1.127*** (0.000) | 1.321*** (0.000) |
| Director Internal Experience (DIEP) | 8.546 | 8.169 | 5.539 | 4.811 | 3.007*** (0.000) | 3.358*** (0.000) |
| Director Company Experience (DCEP) | 9.587 | 9.200 | 6.221 | 5.114 | 3.366*** (0.000) | 4.086*** (0.000) |
| Director busyness (BUSY) | 0.572 | 1.000 | 0.507 | 1.000 | 0.066 (0.117) | 0.000 (0.110) |
| Directors compensation (DCOM) | 0.275 | 0.000 | 0.178 | 0.000 | 0.097*** (0.003) | 0.000*** (0.009) |
| Earnings before interest and taxes/total assets | 0.080 | 0.080 | -0.323 | -0.054 | 0.403*** (0.000) | 0.134*** (0.000) |
| Working capital / total assets | 0.173 | 0.124 | -0.084 | -0.000 | 0.257*** (0.000) | 0.124*** (0.000) |
| Retained earnings / total assets | 0.086 | 0.189 | -0.330 | -0.342 | 0.416*** (0.000) | 0.531*** (0.000) |
| Net income / total assets | 0.033 | 0.043 | -0.261 | -0.217 | 0.294*** (0.005) | 0.260*** (0.000) |
| Total liabilities / total assets | 0.563 | 0.558 | 0.975 | 0.914 | -0.413*** (0.000) | -0.356*** (0.000) |
| Market value of equity / total debt | 1.869 | 1.766 | 1.108 | 0.560 | 0.760*** (0.000) | 1.206*** (0.000) |
| Current assets / current liabilities | 1.983 | 1.570 | 1.153 | 0.866 | 0.831*** (0.000) | 0.703*** (0.000) |

Table 4: The Performance of the Different Prediction Models Before and After Adding the Governance Variables

Panels A and B present the performance of the different prediction models (see *Table 1*) before and after adding the governance variables, respectively (one year before bankruptcy). Each model was estimated using the original estimation method. Panel C presents the differences in the performance of the different prediction models before and after adding the governance variables (*After minus Before*). Out-of-sample forecast accuracy is a ratio that measures the portion of cases correctly classified using the results from running the models on the first eight years (in-sample) to forecast the classification of the firms in the last eight years (out-of-sample). The Hanley and McNeil (1983) test (Z-value) is used to compare the significance of the AUC of the different models before and after adding the governance variables.

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

| Panel A: Performance of the Different Prediction Models Before Adding the Governance Variables | | | | | | | |
|---|--------------|--------------|--------------|--------------|--------------|-------------|--------------|
| | ALT | OHL | ZMJ | SHW | BSH | PRM | ALM |
| Prediction & Classification | | | | | | | |
| Accuracy Ratio | 0.87 | 0.76 | 0.87 | 0.79 | 0.72 | 0.81 | 0.87 |
| Specifity (Sensitivity) | 0.87 (0.44) | 0.76 (0.47) | 0.87 (0.48) | 0.79 (0.75) | 0.72 (0.80) | 0.81 (0.79) | 0.87 (0.44) |
| Type II Error (Type I Error) | 0.13 (0.56) | 0.23 (0.52) | 0.13 (0.52) | 0.21 (0.25) | 0.27 (0.19) | 0.19 (0.21) | 0.13 (0.56) |
| Misclassification Cost | 0.13 | 0.24 | 0.13 | 0.21 | 0.28 | 0.19 | 0.13 |
| Area Under the Curve - AUC | 0.71 | 0.91 | 0.90 | 0.89 | 0.90 | 0.86 | 0.71 |
| Out-of-sample Forecast Accuracy | 0.75 | 0.65 | 0.78 | 0.69 | 0.65 | 0.72 | 0.75 |
| Information Content | | | | | | | |
| Akaike Information Criterion - AIC | | 1225.943 | 1484.312 | 1587.549 | 1764.693 | | |
| Non-Bankrupt (Bankrupt) firm-years | 21,575 (146) | 21,575 (146) | 21,575 (146) | 21,575 (146) | 21,575 (146) | 1,460 (146) | 21,575 (146) |
| Panel B: Performance of the Different Prediction Models After Adding the Governance Variables | | | | | | | |
| | ALT | OHL | ZMJ | SHW | BSH | PRM | ALM |
| Prediction & Classification | | | | | | | |
| Accuracy Ratio | 0.89 | 0.78 | 0.88 | 0.97 | 0.94 | 0.83 | 0.89 |
| Specifity (Sensitivity) | 0.89 (0.53) | 0.78 (0.52) | 0.88 (0.55) | 0.97 (0.81) | 0.94 (0.86) | 0.83 (0.82) | 0.89 (0.53) |
| Type II Error (Type I Error) | 0.11 (0.47) | 0.22 (0.48) | 0.12 (0.45) | 0.03 (0.19) | 0.06 (0.14) | 0.19 (0.35) | 0.11 (0.47) |
| Misclassification Cost | 0.11 | 0.22 | 0.12 | 0.03 | 0.06 | 0.17 | 0.11 |
| Area Under the Curve - AUC | 0.75 | 0.93 | 0.92 | 0.94 | 0.92 | 0.90 | 0.75 |
| Out-of-sample Forecast Accuracy | 0.79 | 0.69 | 0.82 | 0.86 | 0.79 | 0.75 | 0.79 |
| Information Content | | | | | | | |
| Akaike Information Criterion - AIC | | 1205.345 | 1429.592 | 1541.342 | 1738.817 | | |

Panel C: Differences in the Performance of the Different Prediction Models Before and After Adding the Governance Variables (After minus Before)

| | ALT | OHL | ZMJ | SHW | BSH | PRM | ALM |
|--|---------------|---------------|---------------|---------------|---------------|---------------|---------------|
| Prediction & Classification | | | | | | | |
| Accuracy Ratio | +0.02 | +0.02 | +0.01 | +0.18 | +0.22 | +0.02 | +0.02 |
| Specifity (Sensitivity) | +0.02 (+0.09) | +0.02 (+0.05) | +0.01 (+0.07) | +0.18 (+0.06) | +0.22 (+0.06) | +0.02 (+0.03) | +0.02 (+0.09) |
| Type II Error (Type I Error) | -0.02 (-0.09) | -0.01 (-0.05) | -0.01 (-0.07) | -0.18 (-0.06) | -0.22 (-0.06) | -0.02 (-0.03) | -0.02 (-0.09) |
| Misclassification Cost | -0.02 | -0.02 | -0.01 | -0.18 | -0.22 | -0.02 | -0.02 |
| Area Under the Curve - AUC | +0.04 | +0.02 | +0.02 | +0.05 | +0.02 | +0.04 | +0.04 |
| Out-of-sample Forecast Accuracy | +0.04 | +0.04 | +0.05 | +0.17 | +0.14 | +0.03 | +0.04 |
| Information Content | | | | | | | |
| Akaike Information Criterion - AIC | | -20.598 | -54.720 | -46.207 | -25.876 | | |
| Hanley and McNeil (1983) Test | -1.659* | -2.253** | -2.031** | -5.220*** | -2.031** | -2.666*** | -1.659* |

**Table 5: The Performance of the Different Prediction Models including Governance Variables
Two- and Three-years Before Bankruptcy**

Panels A and B present the differences in the performance of the different prediction models before and after adding the governance variables (*After minus Before*), two- and three-years before bankruptcy, respectively. Estimations were done using the full sample. Each model was estimated using the original estimation method. Out-of-sample forecast accuracy is a ratio that measures the portion of cases correctly classified using the results from running the models on the first eight years (in-sample) to forecast the classification of the firms in the last eight years (out-of-sample). The Hanley and McNeil (1983) test (Z-value) is used to compare the significance of the AUC of the different models before and after adding the governance variables.

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

| Panel A | | | | | | | |
|---|---------------|---------------|---------------|---------------|---------------|---------------|---------------|
| Differences in the Performance of the Different Prediction Models Before and After Adding the Governance Variables Two Years Before Bankruptcy | | | | | | | |
| | ALT | OHL | ZMJ | SHW | BSH | PRM | ALM |
| Prediction & Classification | | | | | | | |
| Accuracy Ratio | +0.10 | +0.02 | +0.01 | +0.19 | +0.23 | +0.00 | +0.10 |
| Specificity (Sensitivity) | +0.10 (+0.17) | +0.02 (+0.08) | +0.01 (+0.07) | +0.19 (+0.06) | +0.23 (+0.06) | +0.00 (0.09) | +0.10 (+0.17) |
| Type II Error (Type I Error) | -0.10 (-0.17) | -0.02 (-0.08) | -0.01 (-0.07) | -0.19 (-0.06) | -0.23 (-0.06) | -0.00 (0.09) | -0.10 (-0.17) |
| Misclassification Cost | -0.10 | -0.02 | -0.01 | -0.19 | -0.23 | -0.03 | -0.10 |
| Area Under the Curve - AUC | +0.07 | +0.03 | +0.03 | +0.06 | +0.02 | +0.05 | +0.07 |
| Out-of-sample Forecast Accuracy | +0.05 | +0.06 | +0.02 | +0.21 | +0.15 | +0.11 | +0.05 |
| Hanley and McNeil (1983) Test | -3.022*** | -3.553*** | -3.186*** | -6.501*** | -2.031** | -4.055*** | -3.022*** |
| Panel B | | | | | | | |
| Differences in the Performance of the Different Prediction Models Before and After Adding the Governance Variables Three Years Before Bankruptcy | | | | | | | |
| | ALT | OHL | ZMJ | SHW | BSH | PRM | ALM |
| Prediction & Classification | | | | | | | |
| Accuracy Ratio | +0.11 | +0.07 | +0.03 | +0.23 | +0.24 | +0.05 | +0.11 |
| Specificity (Sensitivity) | +0.11 (+0.20) | +0.07 (+0.16) | +0.03 (+0.09) | +0.23 (+0.09) | +0.24 (+0.10) | +0.05 (+0.10) | +0.11 (+0.20) |
| Type II Error (Type I Error) | -0.11 (-0.20) | -0.07 (-0.16) | -0.03 (-0.09) | -0.23 (-0.09) | -0.24 (-0.10) | -0.05 (-0.10) | -0.11 (-0.20) |
| Misclassification Cost | -0.11 | -0.07 | -0.03 | -0.23 | -0.24 | -0.05 | -0.11 |
| Area Under the Curve - AUC | +0.10 | +0.04 | +0.04 | +0.08 | +0.07 | +0.06 | +0.10 |
| Out-of-sample Forecast Accuracy | +0.09 | +0.08 | +0.06 | +0.24 | +0.19 | +0.15 | +0.08 |
| Hanley and McNeil (1983) Test | -4.506*** | -4.973*** | -4.439*** | -5.434*** | -4.506*** | -4.958*** | -4.506*** |

Table 7: Test for Endogeneity using Dynamic Panel GMM Models

This table presents the results of two different regressions with the probability of default estimated using discrete-time hazard rate and logistic regression, respectively, as the dependent variable. The regression includes first lagged probability of default in addition to the different governance variables and several control variables as independent variables (refer to *Table 2* for definitions). Details of the Dynamic Panel GMM procedure can be found in the text. Arellano-Bond test is a test for first and second-order autocorrelation in the first-differenced errors with the null hypothesis of zero autocorrelation (*p-value* is reported). Hansen test of over-identification tests the null hypothesis that all instruments are valid (*p-value* is reported). The different control variables are defined as follows: CAPX is the firm's capital expenditure scaled by sales; AGE and SIZE are the natural log of the firm's age in years and its book value of assets, respectively; LEVG is the ratio of the firm's total debt to total assets. The t-statistics are reported in the parentheses.

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

| | Probability of Default (SHW: Discrete-Time Hazard Rate) | Probability of Default (OHL: Logistic Regression) |
|-------------------------------------|--|--|
| Intercept | -5.377*** (-17.560) | -3.335*** (-15.290) |
| Lagged dependent variable (One Lag) | 0.734*** (5.060) | 0.564*** (10.740) |
| Attrition Ratio (ATTR) | 0.028 (0.240) | 0.274 (0.540) |
| Gender (GEND) | 0.259 (0.550) | 0.002 (0.370) |
| Board Independence (INDP) | -0.525*** (-2.780) | -0.660** (-1.980) |
| CEO-Chairman Duality (DUAL) | 0.505 (1.350) | 0.645 (1.110) |
| Board Size (BSIZ) | -3.106* (-1.690) | -4.011** (-2.330) |
| Directors Predating CEO (DCEO) | 0.168* (1.720) | 0.031* (1.810) |
| Director External Experience (DEEP) | 0.490 (1.650) | 0.160 (1.670) |
| Director Internal Experience (DIEP) | -0.179** (2.500) | -0.193** (-2.590) |
| Director Company Experience (DCEP) | -0.123 (1.640) | -0.117 (-0.890) |
| Director busyness (BUSY) | 0.115 (0.860) | 0.342 (0.670) |
| Directors compensation (DCOM) | -0.748* (1.880) | -0.777** (-2.440) |
| CAPX | -0.200 (-0.610) | -0.198 (-1.010) |
| AGE | 0.316* (1.940) | 0.643* (1.650) |
| LEVG | 10.313*** (2.340) | 18.184*** (3.620) |
| SIZE | -1.403*** (-4.510) | -1.083*** (-8.810) |
| Arellano-Bond first order test | 0.210 | 0.322 |
| Arellano-Bond second order test | 0.197 | 0.465 |
| Hansen Test of over-identification | 0.434 | 0.280 |
| Non-Bankrupt (bankrupt) firm years | 21,575 (146) | 21,575 (146) |