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Malaysian Companies Distress Prediction: DEA and Multinomial Logit Model

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ABSTRACT

Past studies have employed different models incorporating corporate governance and market prices variables to predict financial distress. However, the models ignore the quality and efficiency of management in running the organization. Previous studies indicate these two variables as the main factors for corporate failure. It is evident that effective resources allocations and efficient control of operations are prerequisite of the success of companies. This paper proposes a financial failure prediction model using efficiency as a predictor variable along with traditional corporate governance and financial variables. The model employs input-oriented data envelopment analysis (DEA) with variable return to scale (VRS) assumption to evaluate the company input/output efficiency. The study use data of 68 financially distressed companies in Bursa Malaysia to verify the efficacy of efficiency as a predictor. We find that management efficiency has a significant explanatory power in predicting the likelihood of delisting of distressed companies in Malaysia. In particular, we find that more efficient companies are less likely to fail.

Keywords: Distressed Companies, financial ratios, corporate governance, DEA, Multinomial logit model, Malaysia.

INTRODUCTION

Traditional distress prediction models employ a variety of predictive methodologies and models including multivariate discriminant analysis, probit and logit models, survival analysis and neural networks. Traditionally, these methodologies use financial ratios, corporate governance variables and market prices as predictors to predict distress prior to its happening. Lately, the quality of management and the ability of a company and its management to operate the institution efficiently have been recognized as cited as the leading reasons for failure. The quality of management is often cited as the leading reasons for failure. Some studies on company performance and company failure cite management quality as the most important factor to long-run survival. For a company to continue to survive, its management must understand, manage, and control the increased risks inherent in today's financial and external environment. This means that companies must effectively allocate resources and efficiently control its operations.

There are various credit models which have been used in financial distress prediction. For example, there are traditional statistical methods Altman's (1968) Multiple Discriminant Analysis (MDA), Ohlson's (1980) Logistic Regression (LR), and nonparametric statistical models, K-Nearest Neighbour (Henley and Hand 1997), Classification Trees (Davis et al. 1992). In recent years, along with the rapid development of computing techniques, some intelligent models like Neural Networks (NN) (Desai et al. 1996), Support Vector Machines (SVMs) (Gestel et al. 2003) and Generic Algorithm (GA), and Genetic Programming (GP) (Ong et al. 2005). More recently, because of the dynamic feature and incorporation of time varying covariates, survival models are preferred in the latest research (Shumway 2001). In all credit risk prediction models, variable selection is always a fundamental issue in the modeling because it has significant impact on the prediction accuracy of models. Financial ratios which are the quotient of two items in financial statements are the most popular ones tried in the past. It is believed that a company's financial statement appropriately report its characteristics, information and financial conditions.

Beaver (1966) was the first one who introduced financial ratios into bankruptcy prediction. Following him, Altman (1968) and Ohlson (1980) in their classic models all use financial ratios and

achieved great success. Even until now, financial ratios are still the key source where we can distinguish the good and bad one from. However the sensitivity of ratios selection is still a problem attaching to them. Later on, Merton (1974) digs information from the market prices and its volatility (option or share prices) by option pricing models and the distance to default is given by his model which is intuitive to tell how far away to default or how healthy a company is. Corporate governance measures are another group of information which can help prediction in analysis and they can roughly be classified into four kinds of measures: board composition, ownership structure, management compensation and director's characteristics. Some paper by Campbell et al. (2008), Ashbaugh-Skaife et al. (2006), and Lee and Yeh (2004) has tried corporate governance measures and found they are helpful in prediction. Since the emphasis on macroeconomic factors by BASEL II, macroeconomic variables receive more attention which can be found in research paper Duffie et al. (2007), Carling et al. (2007) and Bonfim (2009). This is evidence that the macroeconomic conditions change the survival risk for corporations. From the literature reviewed, it can be found that financial ratios are still dominating the variable selection, however it is widely recognized that a main cause of financial failure is its poor management (Gestel et al. 2006) and the management performance can be measured by its efficiency which is the output over input according to the normal definition.

To sum, not only literature sees various prediction distress models findings regarding the determinants of failures are also mixed. Traditional distress prediction models employ financial ratios, corporate governance variables and market prices to predict distress prior to its happening. Corporate governance has long been recognized as one of key factors associated with financial distress (Johnson et al. 2000), e.g. ownership concentration and poor corporate governance (Rajan and Zingales 1998). McKinsey (2002) further improved corporate governance has become one of the tools and over 78 percent of corporations and institutional investors are willing to pay a premium for a well-organized company.

In Malaysia, financial distress is often associated with the PN17 status of companies. In pursuant to Paragraph 8.14C(2) of the Bursa Malaysia Listing Requirements, companies that do not meet any or all of the conditions specified under the provision of Practice Note No. 17/2005 Listing Requirements are classified as PN17 and these companies considered to have financial problems. These financially distressed companies fall within the definition of PN17 mainly because of failing to meet minimum capital or equity requirement (i.e., not less than 25% of the paid up capital). The success of implementing the PN17 provision largely depends on the ability of board of directors to carry out its responsibilities in recovering the company financial difficulties. Past studies provide supports for significant positive relationships between effectiveness of board of directors and company performance (Coles et al. 2001; Mohd-Mohid et al. 2004). An unsatisfactory performance of company is the result of ineffective board of directors (Ho and Williams 2003).

The increasing numbers of corporate bankruptcies in the 1990s have reemphasized the need for research in the area of identifying early warning indicators of corporate distress. The traditional methodologies used for this purpose have a number of known problems and shortcomings associated with them and there is a continuing need to explore other methods of analyzing financial data. The multidimensional nature of corporate performance makes it a very attractive application area for Data Envelopment Analysis (DEA). The strength of this technique lies in its ability to handle multiple inputs and outputs without making judgments on their relative importance, the fact that it does not require the specification of a functional form for input-output correspondence, and that it gives a single measure of performance which takes into account the multiple dimensions of corporate activity. The findings in Paradi et al. (2001) have validated the DEA approach for predicting bankruptcy as it compared favorably with, and in most cases outperformed, the existing discriminate analysis based "Z-score" approach. The fact is to calculate the efficiency of a corporation is not easy given a single company's information. In Operational Research, the efficiency can be optimized by the ratio of weighted output over weighted input in DEA and DEA is the tool to compute relative efficiencies compared to the best practice in the sample. This tool makes it possible to use efficiencies in distress prediction modeling and this paper is going to employ technical efficiency calculated from VRS assumption and input oriented approach in DEA as one of the distress predictors in multinomial logit model.

The goal of this work is to validate the hypothesis that DEA can be used as a tool for predicting future corporate distress. Production models based on the DEA methodology are developed and used to predict the financial viability of firms based on their historical financial data. Accordingly, the objectives of this article are in two folds. The first objective is to generate efficiency score using DEA input-oriented approach with VRS. The second objective is to determine the effectiveness of efficiency score along with corporate governance and financial variables for predicting company distress in Malaysia. The reminder of this paper is organized as follows. The next section provides a brief overview of approaches and variables used in the literature for predicting business failures.

Section 3 explains how we propose to construct the firm efficiency measures and outlines the specification of the bankruptcy model. Section 4 describes the data and discusses the relative importance of financial and non-financial factors used in the empirical analysis of default prediction. The last section concludes the paper.

LITERATURE REVIEW

The board of directors plays a key role in the company corporate governance. The board would conscientiously develop the monitoring and controlling mechanisms to ensure the effectiveness of the company decision making process and financial management (Mohd-Mohid et al. 2004). The failure of big companies to continue their business is often associated with weak controlling and monitoring mechanism over the strategic decision making process of the board of directors (Mohd-Mohid et al. 2004). Previous studies identify characteristics of board of directors including leadership structure, financial literacy, multiple directorships, activeness, and equity ownership that relate to the company performance. However, the studies do not examine how these characteristics relate to the improvement of the financial distress by using the longitudinal data approach.

There are two types of leadership structures often referred in literature, either as a joint leadership or a separate leadership structure. Although there are two opposing views on the optimal leadership structure of a company, a number agrees that the management of a company is more effective if positions of CEO and chairman are held by separate individuals (Fama and Jensen 1983). Previous studies show that companies would assign separate individuals to hold the positions of CEO and chairman in order for them to perform their functions effectively. Controls of the top management actions by two separate individuals would be better and more effective because it helps overall monitoring and reduction in agency costs (Pi and Timme 1993). However, Donaldson and Davis (1991) and Brickley et al. (1997) give contradicting arguments against separate leadership. They argue a joint leadership structure results in a more clear and transparent communication between the management and board of directors.

Financial literacy of board of directors has been identified as one of the most significant factors that increase the credibility of company financial performance from the perspectives of the customers, banks, and government bodies (Nik Hasyudeen 2003). A financially literate board of directors is able to give guidance to the company in obtaining sources of capital effectively to help overcome financial problems (Lee et al. 1999). Another corporate governance variable which has been considered to have an impact on company performance is multiple directorships. Multiple directorships refer to the number of directorship appointments in different companies held by members of the board. Previous studies on the effect of multiple directorships on the company performance produce mixed results. One school of thought believes that board members need to be focused in order to monitor the company more effectively (Core and Larcker 1998). Others believe that the number of director position held by an individual reflects his or her competency and capability to provide an effective role of directors (Mace 1986). A board member who holds a number of director positions would benefit from his or her broad experience and exposures, hence, is more capable in carrying out the duties effectively (Mohd-Mohid et al. 2004).

Another relevant corporate governance variable is the activeness of board of directors which is reflected in the number of board meetings in a year. Boards of directors that meet actively are expected to be able to design strategic action plans for the company and to suggest improvements for current unsatisfactory operating performance in order to achieve better future achievements (Vafeas 1999). Another characteristic of effective board of directors is equity ownership of board members. Managerial ownership reduces agency costs resulting from a reduction in the gap between owners and the management (Jensen and Meckling 1976). Members of board of directors who own shares in the company establish a controlling mechanism for the company to achieve a better financial and market performance (Coles et al. 2001). When a director is also the owner of the company, he or she has a better access to information and a direct influence on decisions to affect his/her own wealth which ensures an increase in the company overall economic value.

In the 1990s, data envelopment analysis was introduced in credit risk evaluation as in Troutt et al. (1996). He provides an idea of how to apply DEA in credit application system. The efficient frontier in DEA could be used to develop an acceptance boundary and any case lies on or above the efficient frontier can be accepted in the DEA sense. Then Simak (1999) in his thesis compared the average DEA efficiency between bankrupt and non-bankrupt firms. Generally, the average efficiency in bankrupt group is less than that in non-bankrupt group and there is a trend that when approaching the time of bankruptcy, the efficiency is getting smaller. His pioneering work is of great meaning but the

application is very limited, it requires further analysis of relative efficiencies. Recently, Premachandra et al. (2009) use the additive DEA model to compare with Logistic Regression (LR). Their conclusion is that under sampling conditions, the DEA is superior because LR is unable to obtain a good estimated equation. But in within-sample evaluations, LR appears to be superior to DEA.

It is widely recognized that a main cause of financial failure is poor management. And the efficiency of a corporation is quite informative for its operation and financial health. So many researchers have done experiments to incorporate efficiency as a predictor in other models. Xu and Wang (2009) put the efficiency obtained through DEA in SVMs, LR and MDA. Yeh et al. (2010) also use the efficiency score in DEA in the integrated Rough Set Theory (RST) with SVM. Their results validate their hypothesis that efficiency as a predictor will to some degree increase the prediction power. However, they both utilize the relative efficiency directly in other algorithms. It is acceptable when making in-sample prediction but if they want to predict the failure probability of a case out of the sample, there may be some troubles that any new case entering the DEA will affect the overall programming, optimal weights may change and efficient frontier may move. Therefore DEA model should be run again. If the sample size is large enough, as long as the new observation falls in the productivity probability set, its relative efficiency still can be measured by fixed efficient frontier. The situation is not true at most time because normally we cannot get a large sample in a single industrial sector.

To make DEA's efficiency transferrable and easy to be calculated, Emel et al. (2003) proposed a credit scoring system which consists of seven steps. In its last but most important step, they don't use relative efficiencies in univariate comparison or in other models as a potential predictor, but instead, they go to validate the inputs and outputs variables by a regression or discriminant model or judgmental analyses. As it is known that DEA does not provide statistic test for input and output variables, the significance level of them are unsure when using DEA. Now a statistical validation step makes up this limitation. Min and Lee (2008) developed the approach of Emel et al. (2003). Similarly, they fitted the DEA scores by over 1000 cases in the sample and found that the DEA score can indeed be linearly approximated by DA with five financial ratios which are ensured by statistical tests. It can be used to give credit score of applicants without recalculate the DEA programming. At last, according the Good/Bad distribution, the DEA score could be adjusted to cope with the real situation by the relevant cut-off point. Unlike many applications of DEA measuring relative efficiency to the best practice, Paradi et al. (2004) introduced a reverse concept: the worst practice DEA. Where normal DEA selects potentially distressed firms by measuring how inefficient they are being good, worst practice DEA picks out distressed firms based on how efficient they are at being bad. This requires indicators of poor performance on the output side and result in placing the distressed firms on the 'efficient' frontier. This approach ideally suit credit risk evaluation problem where it is the worst performing firms needed to be clearly identified. The same idea can be found in the paper of Premachandra et al. (2009).

DEA, when being applied in credit risk evaluation, has several advantages. Firstly, it gives a single measure of performance, which can take into account all dimensions of corporate activity, by simultaneously handling multiple inputs and outputs in different units of measurement without making judgements on their relative importance (Paradi et al. 2004). Second, it does not require an a priori specification of a functional form for the input and output's relationship (Paradi et al. 2001). Besides them, DEA has additional features of non-parametric, distribution-free, no assumption on covariance (Premachandra et al. 2009), which are all superior to statistical discriminant analysis (DA) methods. Li et a. (2009) used DEA to generate corporate performance measures namely technical efficiency, sacle efficiency and return to scale and incorporated these measures into logistic regression. Their findings show that the predictive power is improved by this corporate performance information.

METHODOLOGY

Data Envelopment Analysis

As improving productivity is naturally preferred in any organization, the measurement of efficiency becomes a key issue in it. However performance is a general concept that cannot be numerically measured easily. Farrell (1957) was the first people who successfully constructed an index of efficiency by a group of weighted inputs over outputs. He tried an empirical experiment on four inputs and one output. Twenty years later, building on Farrell's work, Charnes et al. (1978) extended the relative efficiency theory to multi-input and multi-output production units, which is a more realistic and powerful methodology named Data Envelopment Analysis (DEA). DEA is a nonstochastic and nonparametric fractional programming approach. It is a powerful optimizing tool for performance

evaluation which measures the relative efficiencies of peer Decision Making Units (DMUs) in multiple input and multiple output settings. In a DEA framework, performance is evaluated with respect to an efficient frontier which is formed by a group of efficient DMUs. In traditional DEA, there are input-oriented and output-oriented models where input-oriented one aims to minimize inputs when satisfying at least the given output levels while output-oriented tries to maximize output when giving a certain level of inputs. The idea of it is to find out the ones yielding best practice within a set of comparable Decision Making Units (DMUs) and they can form an efficient frontier whereby relative efficiencies of all other DMUs can be measured by the distance to the efficient frontier. Based on the assumptions of constant returns to scale (CRS) and non-negative variables, they create CCR (Charnes et al. 1978) model in the original paper. Banker et al. (1984) then followed the earlier work of Charnes et al. (1978), formulated a BCC model by dealing with variable returns to scale (VRS). They use an additional constraint to control the convexity of the efficient frontier. It is an effective way to model variable returns to scale problem.

Suppose we have a set of n DMUs, which produce multiple outputs y_j (j = 1, 2,...,n), by utilizing multiple inputs x_j (j =1, 2,...,n). During a production process, it is expected that minimum inputs be used and maximum output be produced. There are two types of Production Possibility Set (PPS) depending on assumptions of either constrant return to scale (CRS) or Variable Return to scale (VRS). When the relative change in output is the same compared to the relative change in input, it is called CRS. If the proportional increase in output is larger than the proportional increase in input, it is increasing returns to scale and if the proportional increase in output is smaller than the proportional increase in input, it is decreasing returns to scale. Increasing and decreasing returns to scale both are variable returns to scale (VRS) (cooper et al. 1999). The CCR model (Charnes et al. 1978) is a typical CRS DEA model, and the BCC model (Banker et al. 1984) is a typical VRS DEA model. When a DMU_0 is evaluated by the CCR model, we have

$$\text{Min } \theta \quad \text{subject to} \quad \sum_{j=1}^{n} \gamma_j x_j \leq \theta x_0$$

$$\sum_{j=1}^{n} \gamma_j y_j \leq y_0$$

$$\gamma_j \geq 0, \text{ j} = 1, 2, \ldots, \text{n}$$

When a DMU_0 is evaluated by the BCC model, we have an extra constraint for γ that is $\sum_j^n \gamma_j = 1$. The optimal value θ is the pure technical efficiency of DMU_0 which signifies the extent to which the inputs need to be reduced to bring DMU_0 onto the best practice frontier without worsening output under VRS.

Stiglitz (1972) emphasizes that there is association between returns to scale assumptions and the probability of bankruptcy at any given debt-equity ratio. Even it is easy to understand that in reality, the true returns to scale is either increasing or decreasing, it is surprisingly to see most applications of DEA in corporate failure prediction have an assumption of CRS. So their model to generate relative efficiency is basic CCR model. The examples are Xu and Wang (2009), Yeh et al. (2010). The paper of Psillaki et al. (2010) is one of the few cases which use VRS assumption to evaluate credit risk. They use BCC model with only one output and two inputs.

The points of this research are first, using Variable Return to Scale (VRS) assumption in modeling rather than Constant Return to Scale (CRS) which is not true in reality, and second, under the assumption of VRS, three additional variables would be introduced to prediction models. There are Technical Efficiency Score (CRS efficiency), Pure Technical Efficiency Score (VRS efficiency), Scale Efficiency Score and Return to Scale Estimation. Scale efficiency is the potential productivity gain from achieving optimal size of a firm. Pure Technical Efficiency is the potential productivity which can be achieved by optimization of inputs and outputs, from the technical point of view. Based on the definition of Charnes et al. (1978), they have a relationship as, Scale Efficiency = CRS efficiency / VRS efficiency.

Multinomial Logit Model

The study fits multinomial logit regression model which is appropriate when qualitative categorical response variables i.e. status of distressed company cannot be ordered in a meaningful way and having more than 2 categories. Multinomial logistic models are generalization of logistic models for binary responses and fitting the generalized logistic model requires simultaneously satisfying the J-1 equations that specify the model. One category is chosen as the “comparison category”, and the each slope

coefficient represents the change in log odds of being in the dependent variable category *relative to* the comparison category (for a one-unit change in the right-hand side variable). When explanatory variables contain only individual distressed company characteristics, the multinomial logit model is defined as:

$$P(y_i = j) = P_{ij} = \frac{\exp\,(x_i'\beta_j)}{\sum_{k=0}^{j} \exp\,(x_i'\beta_k)} \quad \text{for j = 0, ..., J}$$

where y_i is a random variable that indicates the status made, x_i is a vector of characteristics specific to the *i*th individual company, and β_j is a vector of coefficients specific to the *j*th alternative. This equation defines a given log odds of being at any particular level j as compared to being in the reference class and this relationship is allowed to be different across the covariates. The benefit of using multinomial logistic model is that it models the odds of each category relative to a baseline category as a function of covariates, and it can test the equality of coefficients even if confounders are different unlike in the case of pair-wise logistics where testing equality of coefficients requires assumptions about confounder effects. The ratio of the status probabilities for alternatives j and l, or the odds ratio of alternatives j and l, is

$$\frac{P_{ij}}{P_{il}} = \frac{\exp(x_i'\beta_j)/\sum_{k=0}^{J} \exp\,(x_i'\beta_k)}{\exp(x_i'\beta_l)/\sum_{k=0}^{J} \exp\,(x_i'\beta_k)} = exp\left[x_i'(\beta_j - \beta_l)\right]$$

In this study J = 3 hence we are modeling the log odds and odds of: 0 (delisted) versus 1 (remain as PN17) and 2 (relisted) versus 0 (delisted).

DATA SOURCE AND VARIABLE SELECTION

A pooled data approach of a period from 2005 to mid-2011 is used to evaluate the effectiveness of board of directors in safeguarding companies from financial difficulties. The year 2005 is selected following the implementation of Practice Note 17 (PN17) in 2005 which is the final year of reporting the company performance and its financial position before being classified as PN17. All companies that are identified as PN17 during the period under study (i.e. 2005 to 2011) are included in the sample. In this study, characteristics of board of directors and financial variables are identified at the time the companies become PN17. The level of recovery of success of PN17 companies is classified into three categories. The first category consists of PN17 companies that are being re-listed at any time during the period which are considered to be successful in overcoming their financial difficulties. Second category consists of companies that remain as PN17 until end of 2009. Third category comprises PN17 companies that are being de-listed from Bursa Malaysia during the period which are considered to be unsuccessful in solving their financial problems. There are about 68 financially distressed companies in a period from 2005 to Mid-2011 which comprise of 47 delisted, 9 remain as PN17, and 12 relisted companies.

For the DEA, informative input and output variables should be selected to enter the model. As Kao and Liu (2004) state, 'Selecting proper inputs and outputs is probably the most important task in successfully applying DEA to measure the relative efficiency of the DMUs since they deter mine the context for comparison'. But so far, there is no certain rule or the best way to be followed in selecting inputs and outputs. Consequently, different DEA users may select different combinations of inputs and outputs, which is a shortcoming of DEA (Premachandra et al. 2009). First of all, DEA requires a careful identification of inputs and outputs that is meaningful within the framework of the competitive environment of the sample to be compared (Oral and Yolalan, 1990). Usually, DEA provides better contrast with respect to the relative efficiency of the sample units when the number of units selected for comparison is significantly larger than the sum of the number of inputs and outputs considered (Parkan, 1987). This is normally true in recent research. And the number of input variables is chosen to be larger than or equal to the number of output variables (Yeh, 1996). Generally, the input variables for a corporation are capital, liability, human resources, technology, real property etc. and the output variables are commonly profit and sales. For example, in Psillaki et al. (2010) paper, they used one output (value-added) and two inputs, capital stock and number of full time equivalent employees to generate a firm's efficiency measure relative to best practice in each industry. It is not clear what value-added is and it is hard to calculate it. The same thing happened in Yeh et al. (2010) paper, they selected R&D expense, R&D designers and the number of patents and trademarks as input variables and the output variable included gross profit and market share.

Rather than physical or monetary items used as the input and output sets, to eliminate scale or size and unit effects in the values, more popularly, financial ratios are used instead. In Min and Lee (2008), three input ratios to be minimized are financial expenses to sales, current liabilities ratio and total borrowings and bond payable to total assets and three output ratios to be maximized are capital adequacy ratio, current ratio and interest coverage ratio. But as the authors stated in their paper, the rule to select final financial ratios entering the DEA is the loan officers and credit department officers' expert knowledge and 'the literature survey, and the authors' best judgement'. Cielen et al. (2004) setup an instruction that financial ratios with a positive correlation are defined as input factors while those with a negative correlation are defined as output factors. Premachandra et al. (2009) proposed another similar but not exact rule for variable selection. It is that the smaller (inferior) values in the financial ratios, which could possibly cause financial distress, are considered to be input variables whereas the larger (superior) values in those ratios, which could cause financial distress, are considered as output variables.

Xu and Wang (2009) did a Chinese case study in their paper. Their variable selection goes back to the original definition of efficiency. They use total assets, total liability and costs of sales as the inputs and output is the income of sales. Considering the structure of my research, since financial ratios are going to be used with other models such as LR and it is better to not employ them again to avoid the homogeneity in variables. Therefore as financial reports are the best data source, some physical quantities such as total assets and number of employees in them will be picked as input as outputs. Based on the general rule, variables are chosen from capital, liability, human resources. They are total cost, total assets, total liabilities, share capital, number of employees as 5 inputs, and total sales, total profit, cash accrued as 3 outputs.

Our DEA model uses one output (total sales) and two inputs, total assets and total liability, to generate a firm's efficiency measure relative to best practice in each distressed company. We apply the DEA model with VRS assumption and input-oriented approach. The DEA scale efficiency scores that we obtain are used along with corporate governance variables and financial variables as predictors in multinomial logit model to determine the probability of firms to survive or fail. Our main proposition is that company efficiency is an important indicator of business failure.

For multinomial logit model, the explanatory variables incorporate both the corporate governance and financial ratios variables. Previous studies have found evidence on the effects of several corporate governance variables such as leadership structure (CEO), financial literacy (EXPERT), multiple directorships (MULTIDIR), board activeness (ACTIVE), equity ownership (MANOWN) as discussed in the section 2. Variable leadership structure refers to either joint leadership or separate leadership. Joint leadership exists when the posts of chief executive officer and chairman are held by the same individual. Separate leadership, on the other hand, exists when both positions are held by two separate individuals. In this study, joint leadership is coded 1 and separate leadership is coded 0. This measurement approach is also used by Judge et al. (2003). Variable financial literacy of board of directors is determined based on the members' knowledge of accounting and finance as well as the working experience in both areas. Prior studies in Malaysia use the Malaysian Institute of Accountants (MIA) membership as the proxy of financial literacy (e.g. Ruzaidah and Takiah 2004; Nor Haizah et al. 2006; Mohd-Mohid *et al.* 2004). It is argued that MIA membership does not provide an accurate basis of financial literacy because it does not take into consideration the formal higher education and experience in the related areas (Collier 1993).

In this study, the financial literacy considers two components, knowledge and experience, in accounting and finance. Scores for accounting and financial knowledge of board members are calculated in the following manner: a score 3 is assigned for directors who are members of MIA, score 2 for directors with experience in financial sector, and score 1 for directors who are not members of MIA but with education in accounting and finance. The score for experience is based on the years of experience in the area of accounting and finance as follows: score 4 for experience of >30 years, score 3 for >20 years and ≤30 years, score 2 for >10 years and ≤20 years and score 1 for ≤10 years. Thus, the financial literacy of board of directors is determined based on the ratio between the financial literacy score of board members and the possible maximum score to be attained by all board members. The financial literacy ratio for each company is calculated based on the following formula:

$$\frac{\text{(Score of accounting \& finance knowledge + Score of experience)}}{\text{Maximum score}}$$

Variable multiple directorships of board members is measured by the average number of directorship positions of board members in other companies. It is determined by dividing the total number outside directorship positions of all board members by the number of board members. This

method of measuring multiple directorships is used by Song and Windram (2000), and Ruzaidah and Takiah (2004). Meanwhile, variable board activeness represents the total number of board meeting for the year measures the activeness of board of directors. This approach is used in previous studies to determine the activeness of board of directors (Ruzaidah and Takiah 2004; Mohd-Mohid et al. 2004). Variable equity ownership of board of directors is determined by the number of company share owned directly and indirectly by the board members. The share equity held by board members through subsidiary or nominee companies are not included. In this study, equity ownership is the percentage of the total shares owned by board members divided by total shares issued by the company. This method is consistent with that used by Joh (2003) and Mohd-Mohid et al. (2004).

This article includes four control variables, three representing financial ratio and one representing audit quality. Financial ratios have long been widely used in explaining the possibility of corporate financial distress such as Beaver (1966), Altman (1968), Bongini, Ferri and Hahm (2000), Routledge and Gadenne (2000), Catanach & Perry (2001), and Rommer (2005). The three financial variables are company performance which is represented by return on assets (ROA), logarithm on total assets (SIZE) (Coles et al. 2001; Mohd-Mohid et al. 2004) and ratio of debt to total assets (LEVERAGE) (Mueller & Becker III 1997). Quality of audit is measured based on size of audit firms (DeAngelo 1981; Becker et al. 1998). The dummy variable, the BIG4, which represents high quality audit services is coded 1 and the non-BIG4 which represents low quality audit services is coded 0. Table 1 shows the details and definitions of the covariates used in the DEA and Multinomial logit model.

RESULTS

Table 2 depicts descriptive statistics on variables used in the study corresponding to status of distress. We use DEAP program introduced by Coelli (1996) to run the DEA model. Table 3 summarizes the distribution and frequency for various efficiency measures. In general, under, the mean of overall technical efficiency is 0.303. This means that, on average, a company can produce output with 69.7% less input. Under CRS, only 4 companies (5.8%) are efficient and 49 companies with efficiency less than 0.50. This means that those inefficient companies can produce outputs with more than 50% less inputs. When assumption VRS is applied, efficiency scores are much higher with an overall average of 0.424 and more efficient companies are found. The study finds that most distressed companies operate at increasing return to scale (73.5%). This finding is associated with small and medium scale enterprises (SME).

For multinomial logit model, the overall test of relationship among the independent variables and groups defined by the dependent is based on reduction in the likelihood values for a model which does not contain any independent variables and the model that contains the independent variables. This difference in likelihood follows a chi-square distribution and is referred to as the model chi-square. The significant test for the final model chi-square (after the independent variables have been added) is the statistical evidence of the presence of a relationship between the dependent variable and the combination of the independent variables. The chi-square test result shows evidence of the presence of a relationship between the dependent variable and the combination of the independent variables at 1% significant level ($0.001 < 0.01$).

While multinomial logistic regression does compute correlation measures to estimate the strength of the relationship (pseudo R^2 measures, such as Nagelkerke's R^2, these correlations measures do not really tell us much about the accuracy or errors associated with the model. A more useful measure to assess the utility of a multinomial logistic regression model is classification accuracy which compares predicted group membership based on the logistic model to the actual, known group membership, which is the value for the dependent variable. Results of the study shows that the model is also useful since the classification accuracy rate is 80.9% which is greater than the proportional by chance accuracy criteria of 65.73% (= 1.25 x 55.58) is satisfied. The model passes the 25% improvement benchmark over the rate of accuracy achievable by chance alone.

For a multinomial logit regression model the interpretation for an independent variable focuses on its ability to distinguish between pairs of groups and the contribution which it makes to changing the odds of being in one dependent variable group rather than the other. The interpretation of an independent variable's role in differentiating dependent variable groups is the same as we used in binary logistic regression. The difference in multinomial logistic regression is that we can have multiple interpretations for an independent variable in relation to different pairs of groups.

Table 4 presents the results of the multinomial logit model. It provides the log odds ratios, odds ratios and percentage changes from the multinomial logit model. Odds ratios values above one

indicate that higher values of the explanatory variable increase the predicted probability of being relisted compared to being delisted. Values less than one indicate the opposite. The first three columns compare status 2 (relisted) with status 0 (delisted) and the results show the likelihood of the companies to be relisted rather than delisted. The results show that the relisting of PN17 has positive significant relationships with the activeness of board of directors (ACTIVE), return on assets (ROA) and scale efficiency (SEFF). These three variables play statistically significant roles in differentiating the category 0 (delisted) from the category 2 (relisted). For example, active boards of directors are more likely to bring PN17 companies back to be relisted on Bursa Malaysia. For one additional number of meeting the board of director held in a year, the odds of being relisted increased by 81.8% (1.818 -1 = 0.818). More frequent board meetings would increase the possibility of PN17 being relisted rather than being delisted. Results support hypothesis that suggests a significant positive relationship between activeness of board directors and relisting of distress companies. Variables ROA and SEFF also contribute positively and significantly on the likelihood of the companies to be relisted rather than being delisted. For one percentage point increase in ROA, the odds of being relisted increased by 10.6%. The results imply that companies with large ROA are more likely to be relisted than smaller ones.

For categories delisted versus relisted, the most important finding of the study is the ability of variable efficiency (SEFF) in predicting corporate failure. In particular, we find that more efficient companies are less likely to fail. Results show that efficient companies are more likely to bring the distressed companies back to be relisted. The relationships between the relisting status and financial literacy (EXPERT), managerial ownership (MANOWN) as well as ratio of debt to total assets (LEVERAGE) are negative and significant but in the opposite directions. Results suggest that companies with boards of directors that are financially literate (EXPERT) and high ownership concentration are less likely to be successfully relisted. For example, for one percentage point increase in MANOWN, the odds of being relisted decreased by 10.6%. Regarding MANOWN, this finding is in contrast to what is expected since most previous studies suggest negative relationship between ownership concentration and financial distress. However, La Porta et al. (1999) argue that ownership concentration decreases firm value because it leads to “tunnel” action by large shareholders who invade minor shareholders’ interests, while having more outside shareholders prevents it from happening. Other variables such as board structure (CEODUAL), multiple directory (MULTIDIR), audit quality (BIG4) and firm size (FIRMSIZE) are insignificant and unable to distinguish status 0 (delisted) of the dependent variable from status 2 (relisted) of the dependent variable. For one percentage point increase in managerial ownership, the odds of being relisted decreased by 10.6%.

Columns 5 and 6 in Table 4 report the log odds ratios and odds ratios comparing category being delisted with category remain as PN17. There are five variables namely equity ownership (MANOWN), size of company (FIRMSIZE), audit quality (BIG4), leverage (LEV) and efficiency (SEFF) which play statistically significant roles in differentiating the category 0 (delisted) group from the category 1 (remain as PN17) group. The results show the likelihood of the companies to remain as PN17 rather than being delisted. Similarly, the results show that the likelihood of companies to remain as PN17 has significant and positive relationships with ROA and SEFF but ACTIVE is no longer significant. The activeness of board of directors may not help PN17 overcome financial problems. However, for these two categories, delisted and remain as PN17, the negative relationships between MANOWN and LEVERAGE as found previously in categories delisted and relisted have changed to positive and these findings are more in lines with previous studies. The likelihood of companies to remain as PN17 is shown to have significant and positive relationships with these two predictors. These results suggest that companies with boards of directors that are financially literate (EXPERT) and high ownership concentration (MANOWN) are less likely to be delisted and more likely to remain as PN17. For one percentage increase in LEVERAGE, the likelihood to remain as PN17 increased by 10.6% rather than being delisted. In Malaysia, Mohamed et al. (2001) emphasized the importance of leverage ratio as a predictor of failure.

Our result that higher managerial ownership is associated with less likelihood to delisted is consistent with the argument of previous studies (Joh 2003, Coles et al. 2001, Tosi et al. 2003). The finding on LEVERAGE is also consistent with that of Rosenstein & Wyatt (1990), Lee et al. (1999) and Cheo et al (2003) who find that appointment of new directors who has expertise in accounting and finance significantly increases the financial achievement of companies. Variable FIRMSIZE now contribute significantly in differentiating these two categories. However, a significant positive sign for FIRMSIZE suggests that companies with a higher proportion of net income to total assets are more likely to experience financial distress and to be delisted than smaller ones. Even though this unexpected sign contradicts those appering in Beaver (1966), Ohlson (1980), and Ward & Foster (1997) and to be delisted than smaller ones but it is consistent with Elkhal (2002) and Chancharat et al. (2008). In the

Malaysia context this finding regarding positive impact of FIRMSIZE is consistent with Nuradiana Hiau et al. (2009). A possible explanation of this positive impact of FIRMSIZE phenomenon given by Chancharat et al. (2008) is that the companies could have had unsustainable growth rate in their total assets. A large company might have inflexible management and have problems monitoring managers and employees; consequently, the company may have inefficient communication and then face financial difficulties (Rommer 2004). The results also show that the delisting of PN17 has a significant negative relationship with audit quality of a company (BIG4). Companies with high audit qualities (BIG4) are 1063% more likely to remain as PN17 rather than being delisted compared with their counterparts. An additional variable that was found to be significant in this model is efficiency. The positive relationship between efficiency and the likelihood of remaining as PN17 suggest that efficient companies are less likely to be delisted. For one percentage point increase in efficiency score (SEFF), the odds of being delisted decreased by 3.5%. In other words, more efficient companies are less likely to be delisted.

Results of the multinomial logit regression analysis in Table 4 are able to explain the association between certain characteristics of board of directors and financial variables and the listing status of PN17 in different situations. Firstly, in identifying between companies being relisted on Bursa Malaysia or delisted (situation 1) from Bursa Malaysia and secondly to remain as PN17 or delisted (situation 2) from Bursa Malaysia. In those situations, three characteristics that play a significant influence are financial literacy, activeness and managerial ownership of board of directors. However, effects of each variable differ depending on the listing situation. Among these three governance characteristics only managerial ownership appeared to be significant in both situations but in opposite directions. In first situation (delisted versus relisted) the direction is negative but positive in the second situation (remains as PN17 versus delisted). The study finds that in the first situation, the higher managerial ownership is associated with less likelihood to be successfully relisted than being delisted but in the second situation. In this situation, the critical role demonstrated in managerial ownership is inconsistent with previous studies such as Joh (2003) and Coles et al. (2001) and Tosi et al. (2003) agree that corporate governance crisis can be addressed by bringing in shareholders or stakeholders with direct interest to be in the board. Accordingly, in this situation, the finding of this study contradicts with the alignment affect of agency theory which suggests the higher the managerial ownership the more aligned is the interest between managers and shareholders (Jensen & Mackling 1983). However, La Porta et al. (1999) argue that ownership concentration decreases firm value because it leads to "tunnel" action by large shareholders who invade minor shareholders' interest, while having more outside shareholders prevents it from happening. There is a possibility that this theory only apply for those companies operating normally, not for those with financial distress. On one hand, distressed companies' major shareholders improve supervision, with the aim of eliminating distress as soon as possible but on the other hand, high ownership balancing degree will lead lower decision efficiency because of quarreling among directors. In second situation, the finding on the positive significant relationship between MANOWN and the likelihood of companies to remains as PN17 rather than being delisted is in line with the agency theory.

In the situation where PN17 companies are on the verge of being relisted or delisted, the active involvement of board of directors through frequent meeting would provide opportunities for companies in the preparation of regularization plan as required by the Securities Commission for approval before the companies may be assessed for relisting. Results are consistent with Vafeas (1999) who finds that the company achievement increase significantly with increase in the number of board meeting.

The finding on financial literacy contradicts with Lee et al. (1999) and Cheo et al. (2003) who find that the appointment of new directors who has expertise in accounting and finance significantly increases the financial achievement of companies. However, in second situation (remain as PN17 versus being delisted) variable financial literacy is insignificant and this finding is consistent with that of Mohd-Mohid et al. (2004) suggesting that there is no significant difference in the financial literacy between members of directors of companies with financial difficulties and those with no financial difficulties. The result is consistent with the argument that financial literacy among board members is merely to fulfill the legal requirement of the Code of Corporate Governance (Mohd-Mohid et al. 2004). The financial literacy of board members does not seem to contribute towards offering solutions to financial distress.

Results in Table 4 also show that companies with high quality audits are more likely to remain as PN17 rather than being delisted. This implies that high quality audit may help PN17 companies overcome financial problems. The relationship between variable ROA and the likelihood of being relisted is positive in situation 1 but is insignificant in situation 2. This suggests higher rate on assets is associated with more likelihood to be successfully relisted than being delisted. However, in situation 2

there is no significant difference on the contribution of ROA on the likelihood of being delisted or remain as PN17. The only variable that appears as a consistent indicator of financially distressed companies is efficiency which has a positive and significant in both situations. This finding suggests that more efficient companies are less likely to fail. Even though the increases in percentage changes in the odds due to one percentage point increases in efficiency are quite small but they contribute significantly towards the likelihood of being relisted or remain as PN17 companies.

CONCLUSIONS AND POLICY IMPLICATIONS

This study presented DEA as an alternative tool for failure prediction due to its ability to handle multiple inputs and outputs, the absence of requiring the specification of a functional form, and the lack of need for assumptions of variable distributions. The goal of this work was to validate DEA as a competent technique to predict corporate failure and to examine the benefits that can be obtained from its use. The study employed 68 financially distressed companies that were identified as PN17 during a period of 2005-Mid 2011. The distressed companies were categorized as relisted, delisted and remain as PN17. The efficiency score were generated from input oriented DEA with VRS and then incorporated along with traditional corporate governance and financial variables in multinomial logit model to predict company failure. There were two situations corresponding to the three categories of distressed companies, relisted versus delisted (situation 1) and delisted versus remain as PN17 (situation 2). Eight variables were found to be important predictors of distressed companies however effects of each variable differ depending on the listing situation. For example, the relationships between variables ACTIVE and ROA with the likelihood of being relisted rather than being delisted were positive but in the situation delisted versus remain as PN17 both were insignificant. Similarly, the variables LEVERAGE were significant in both situations but in opposite signs. Variable audit quality (BIG4) only helped distressed companies to remain as PN17 rather than being delisted (situation 2) but it did not contribute much in helping distressed companies to be successfully relisted. The study found that the only variable that appeared to be consistent and significant in both situations is efficiency. The positive coefficients for efficiencies in both situations show that the more efficient the companies are, the lower the probability of defaulting among financially distressed companies.

More accurate distressed companies failure-prediction model, such as DEA, developed in this study, have several key implications for policy makers. First, more accurate models allow distressed companies regulators to deploy their examination resources more efficiently. An effective early-warning model will detect and classify the weakest financially distressed companies. Second, the models developed can be used by regulators to gain a better understanding of the reasons for company failure. Our second models, multinomial models, show that management quality has the great impact on company failure; companies receiving the highest DEA efficiency scores are much more likely to survive than companies which have relatively low scores. The model identifies seven additional variables that are significant in differentiating between failures (being delisted) and survivors (remain as PN17 or being relisted): LEVERAGE, ROA, ACTIVE, BIG4, EXPERT, MANOWN, and FIRMSIZE. If regulators have better understanding of why companies fail, they will be better able to offer companies especially remain as PN17companies suggestions on how to become more stable and to overcome financial problems. In addition, managers will be alerted to threatening conditions so that action can be taken before serious problems arise.

Results suggest that the management of PN17 needs to focus on the efficiency of utilization of their resources in implementing the restructuring plan submitted to Security Commission (SC). PN17 companies may need to develop a mechanism to measure the optimal use of resources to achieve the targeted goal.

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TABLE 1: The variables used in the study

Variable	Code	Definition
IN DEA ANALYSIS		
OUTPUT: Total Sales	TS	Total sales of a company
INPUT: Total Liability	TL	Total liability of a company
Total Assets	TA	Total assets
IN MULTINOMIAL ANALYSIS		
Leadership Structure	CEO	Joint leadership is coded 1; separate leadership is coded 0.
Financial Literacy	EXPERT	(Score of accounting & finance knowledge + Score of experience)/ maximum score (%)
Multiple Directorships	MULTIDIR	Average number of directorship positions of board members in other companies.
leverage	LEVERAGE	debt to total asset ratio
Company Size	SIZE	Natural logarithm of the total asset
Equity Ownership	MANOWN	Number of company share owned directly and indirectly by the board members (%).
Activeness	ACTIVE	The total number of board meeting for the year
Performance	ROA	Return on Assets (%)
Audit Quality	BIG4	High quality audit services is coded 1; low quality is coded 0
Scale efficiency	SEFF	In percentage

TABLE 2: Descriptive statistics

	DELISTED (n = 47)			REMAIN AS PN17 (n = 9)			RELISTED (n = 12)		
Variable	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
CEO	0.38	0.00	1.00	0.22	0.00	1.00	0.25	0.00	1.00
EXPERT	32.12	0.00	67.86	37.16	19.05	76.19	28.03	11.43	73.81
MULTIDIR	0.93	0.00	3.80	0.82	0.00	3.00	1.16	0.00	3.17
ACTIVE	5.32	2.00	16.00	6.22	4.00	16.00	7.17	4	11
MANOWN	16.73	0.00	59.33	26.33	0.00	54.30	10.95	0.00	34.64
BIG4	0.45	0.00	1.00	0.33	0.00	1.00	0.50	0.00	1.00
LEVERAGE	2.91	-21.59	47.15	5.44	-1.16	15.07	2.92	-15.87	29.07
SIZE	18.81	13.99	21.96	18.46	17.30	19.70	18.87	17.12	21.89
ROA	-60.43	-547.04	23.60	-.41.70	-301.72	5.23	-7.92	-45.88	36.07
SEFF	66.09	2.8	100.00	83.87	56.00	100.00	70.92	9.80	100.00

TABLE 3: Distribution and frequency for various efficiency measures

	TE (CRS)	TE (VRS)	SE
Efficiency Range	Frequency (%)	Frequency (%)	Frequency (%)
= 1	4 (5.8)	9 (13.2)	4 (5.8)
< 1	64 (94.1)	59 (86.8)	64 (94.1)
0.90 – 0.99	1 (1.4)	2 (2.9)	17 (25.0)
0.80 – 0.89	2 (2.9)	1 (1.4)	12 (17.6)
0.70 – 0.79	1 (1.4)	3 (4.4)	8 (11.8)
0.60 – 0.69	2 (2.9)	2 (2.9)	6 (8.8)
0.50 – 0.59	4 (5.8)	8 (11.8)	3 (4.4)
0.40 – 0.49	5 (7.3)	6 (8.8)	6 (8.8)
< 0.50	49 (72.1)	37 (54.4)	12 (17.6)
Total	68 (100)	68 (100)	68 (100)

Note: TE represents technical efficiency, SE represents scale efficiency, CRS and VRS indicate constant and variable return to scales, respectively.

TABLE 4: Results of multinomial Logistic regression on company distress status category

	Delisted vs. Relisted			Delisted vs. Remain as PN17		
	Ln (Odds Ratio)	Odds Ratio	% change	Ln (Odds Ratio)	Odds Ratio	% change
Constant	3.309			8.034		
CEODUAL	0.875	2.393	139.3	1.362	3.905	290.5
EXPERT	-0.094*	0.910	-9.0	0.049	1.050	5.0
MULTIDIR	-0.004	0.996	-0.4	-0.133	0.875	-12.5
ACTIVE	0.598*	1.818	81.8	0.107	1.112	11.2
MANOWN	-0.112*	0.894	-10.6	0.079*	1.083	8.3
BIG4	-0.836	0.434	-56.6	2.454*	11.630	1063.0
LEVERAGE	-0.129**	0.879	-12.1	0.101**	1.106	10.6
FIRMSIZE	-0.206	0.814	-18.6	-1.013*	0.363	-63.7
ROA	0.101*	1.106	10.6	0.008	1.008	0.8
SEFF	0.021**	1.021	2.1	0.034**	1.035	3.5

Notes: Reference category is delisted.
*and ** indicate significance at 5% and 10% level.