PREDICTING FINANCIAL DISTRESS USING FINANCIAL AND NON-FINANCIAL VARIABLES

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Abstract

This study attempts to clarify whether using a hybrid model based on non-financial variables and financial variables is able to provide a more accurate company financial distress prediction model than using a model based on financial variables only. The relationship between the model test results and the De la Rey K-Score for the subject companies is tested, employing Cramer's V statistical test. A movement towards a Cramer's V value of one indicates a strengthening relationship, and a movement towards zero is an indication of a weakening relationship. Against this background, further empirical research is proposed to prove that a model combining financial variables with true non-financial variables provides a more accurate company distress prediction than a financial variable-only model. The limited evidence of a strengthening relationship found is insufficient to establish the superiority of the proposed model beyond reasonable doubt.

Keywords

Financial distress prediction, non-financial variables, financial distress continuum, neural networks

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1. INTRODUCTION

When companies fail, the consequences for stakeholders are far-reaching. Shareholders stand to lose most, because the value of their investment deteriorates significantly or is lost completely. Creditors may receive only partial repayment or nothing at all of the loans advanced to the company. Employees lose their jobs. The government collects less revenue in the form of company and employee taxes, and, to make matters worse, the government has to allocate additional social grants to support the unemployed, affecting the remaining taxpayers (Balcaen & Ooghe, 2004:2; Zhang, 2006:1; Muller, Steyn-Bruwer & Hamman, 2009:21).

To establish a company's financial health and make relevant decisions, stakeholders rely on officially published information, such as financial statements and press releases (Hol, 2007:76; Agarwal & Taffler, 2008:1542; Altman, Sabato & Wilson, 2008:2). In some instances, stakeholders use the information in a given financial distress prediction model to support the decision-making process.

Various financial distress prediction models, such as multivariate discriminant analysis, logistical regression analysis (logit), probit analysis, genetic algorithms and neural networks have evolved from the pioneering studies of Beaver (1966) and Altman (1968). Each of these financial distress prediction models is confident in predicting company distress with reasonable accuracy (Aziz & Dar, 2006:2). Most of these financial distress prediction models rely on historical financial and point-in-time information. However, continuously changing market dynamics that affect company performance could potentially have a detrimental effect on the validity of these models. It is therefore doubtful whether a model based purely on historical financial variables would be able to predict company financial distress with reasonable accuracy (Agarwal & Taffler, 2008:1542).

This objective of this study is to capture the dynamics of the external and internal environment to determine whether a hybrid model using a combination of financial and non-financial variables is able to predict company financial distress more accurately than a model based purely on financial variables.

The following key limitations to this study are identified:

- The study is exploratory, and is not intended to prove the correlation between dependent and independent variables empirically.
- Limited information is provided in some companies' director reports, which could affect the evaluation and test result negatively.
- The phased sampling approach may eliminate some eligible companies.
- The non-financial variables to be tested are of a qualitative nature. A Balanced Scorecard-type approach is applied to quantify the variable; however, this may be affected by a subjective interpretation of information presented in a given director's report.

Muller et al. (2009:22) express concern about the lack of consensus on the definition of financial distress and failure, as the terms are often used interchangeably. To address this concern, the study distinguishes between company financial failure and financial distress. For the purposes of this study, financial failure is defined as factual insolvency because a company's liabilities exceed its assets, and where liquidation is unavoidable. For financial distress, the definition in the Companies Act, No 71 of 2008 (South Africa, 2008), sections 128 (f) (i – ii) is used:

> '... in reference to a particular company at any particular time, [financial distress] means that –
>
> (i) It appears to be reasonably unlikely that the company will be able to pay all of its debts as they become due and payable within the immediate ensuing six months; or
>
> (ii) It appears to be reasonably likely that the company will become insolvent within the immediate ensuing six months.'

Cybinski (2001) was the first to acknowledge that a company's financial health can be positioned along on a continuum, and need not simply be classified as either 'failed' or 'non-failed'. It is rather a gradual transformation process from being successful to failed, or vice versa. The 'financial distress continuum' is illustrated in FIGURE 1.

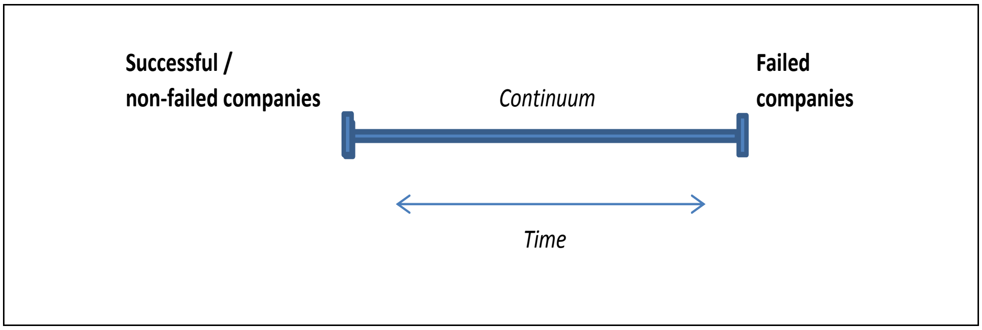

FIGURE 1: Financial distress continuum

Source: Adapted from Cybinski (2001:30)

In a financial distress prediction model, it is important to overcome the constraints of dichotomist classifications of companies as either failed or non-failed. A 'pseudo' time dimension can be added by including non-financial variables in pure financial distress prediction models (Cybinski, 2001:30).

This study is important to stakeholders and will benefit them because it combines non-financial variables with an existing South African-based financial distress prediction model. This hybrid model has the potential to enhance the ability of a particular stakeholder to identify financial distress timeously, and, where applicable, to take appropriate remedial action to avoid failure. If it is a viable model, investors can use the model to determine whether the potential financial distress is of a temporary or permanent nature and whether the company's share price would be affected. A temporary drop in the share price could be an opportunity to invest in the share in anticipation of a rise in the share price once the effect of remedial action has materialised. However, if a stakeholder determines that the financial distress is of a more permanent nature, the stakeholder can avoid investment in this particular company, or an existing shareholder may decide to divest from the company.

If the model works well, lenders can use it to determine whether to provide new funding or increase their funding to a company. Depending on the company's position on the distress continuum, the model should provide an indication of whether an existing loan should be restructured or not. At the negative end of the distress continuum, where failure is inevitable, a lender can maximise loan recovery by timeously exercising its legal rights.

In other instances, suppliers could use the hybrid model in negotiating payment terms with the company, depending on where the company is positioned on the continuum. Labour unions can use the hybrid model in their annual wage negotiations to fine-tune negotiations and make demands, which are more realistic in line with the company's financial results.

The Companies Act, No. 71 of 2008 (South Africa, 2008), in terms of chapter 6, section 129 (1)(a), allows for a company's board to resolve that the company should voluntarily initiate business rescue proceedings if there are reasonable grounds to believe that the company is financially distressed. Stakeholders may be able to determine at which point a company is in fact in financial distress, or where on the distress continuum it is positioned. This will prevent any 'affected person' from having the company placed under business rescue without reasonable grounds. In terms of clause 128(a) of chapter 6 of the new Companies Act, No 71 of 2008, an affected person, in relation to a company, refers to any 'shareholder or creditor of the company'; 'any registered trade union representing employees of the company'; and any employees who are 'not represented by a registered trade union', or such employees' representatives.

The remainder of this paper is organised as follows: section 2 reviews prior research findings relating to the development of company distress models based on financial and non-financial distress models; section 3 discusses the methodology applied to determine the relative predictive content of financial variables and non-financial variables; section 4 discusses the experimental results and, lastly, concluding remarks and proposals for future research are presented in section 5.

2. REVIEW OF PREVIOUS STUDIES

Based on an extensive literature review, Aziz and Dar (2006:18-33) have narrowed the multitude of financial distress prediction techniques down to three broad categories, namely classical statistical models, artificially intelligent expert system models, and theoretical models. The discussion below is based on these three categories.

2.1 Classical statistical models

2.1.1 Univariate analysis

Most statistical models originate from Beaver's (1966) univariate analysis, where individual ratios were examined. The results indicate that failing companies have limited cash flow and smaller amounts of liquid assets than healthy companies. Beaver was able to classify 78% of the sample companies accurately five years before failure. Although Beaver's study exhibited good failure prediction ability, its main constraint, according to Gudmundsson (2002:4), was that classification can be based on only one ratio at a time. The potential risk is that conflicting classifications may be made for a particular company by applying various ratios.

2.1.2 Multiple discriminant analysis

In an effort to address the question of the predictive accuracy of univariate analysis, Altman (1968) converted a univariate analysis to a multiple discriminant analysis (MDA). The MDA's strength lies in its ability to measure a company's financial attributes by analysing several ratios simultaneously, as well as the interaction between these ratios. Altman's MDA model (1968) is expressed in Equation (1) below:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.0999X_5 \quad \textbf{(1)}$$

where: Z = overall index

X_1 = working capital / total assets

X_2 = retained earnings / total assets

X_3 = earnings before interest and taxes / total assets

X_4 = market value of equity / book value of total debt

X_5 = sales / total assets

In this model, a company with a Z-Score higher than 2.99 falls into the non-failed category, while a company with a Z-Score below 1.81 is categorised as a failed company. The range between 1.81 and 2.99 is regarded as a grey area, because of its susceptibility to error classification. The midpoint of the interval is 2.675, which is chosen as the Z-Score that discriminates best between failed and non-failed companies.

Altman (1968) concluded that if the discriminant model was used correctly and periodically, it would be able to predict company financial distress early enough to enable management to realise the extent of the distress in time and consider corrective action to avoid failure. However, Altman admitted that his study was subject to some limitations. He warned that the predictive ability of the discriminant model declines rapidly if a prediction horizon beyond one year is used – the MDA cannot discriminate distress as accurately with a horizon greater than two years prior to failure. By contrast, the univariate model displayed some predictive power as long as five years before the failure of companies.

In addition to the limitations in Altman's study indicated above, the following additional limitations are pointed out by Rees (1995:305-306):

- Altman's (1968) variables were chosen for their effect on the efficiency of the discriminant equation, rather than on the basis of any underlying theory, and they exhibit considerable sample dependence;
- The samples used were not random. They were matched for industry and size, which is a useful method of controlling these variables. However, this contravenes the basic assumptions of discriminant analysis, which requires random samples from independent populations;
- Former probabilities of failure and non-failure were assumed to be equal for failed and non-failed companies, and no allowance was made for different classification errors when assessing the performance of the model;
- The definition of a failed company is complex, and Altman used companies that had applied for liquidation. It was unclear whether a given company had undergone some capital restructuring or any other structuring prior to liquidation; and
- The variables incorporated in the equation were based on accounting values. These are therefore imperfect estimates of the underlying characteristic they purport to measure.

There were various subsequent attempts to improve on the Altman research (Thevnin, 2003:35). One such example is the study by Deakin (1972), who combined the univariate model and MDA into a new model. Deakin attempted to revert to the original ratios tested in Beaver's univariate model, and incorporated a random, rather than a matched, sample of healthy companies. The resulting discriminant equation outperformed the classificatory accuracy Altman had achieved and was able to discriminate effectively up to three years in advance of failure. Deakin's overall conclusion was that discriminant analysis could be used with a high degree of accuracy to predict company failure, but that some ratios contributed more than others in failure prediction. However, when tested against a validation sample, Rees (1995:307) identified some inconsistency, suggesting that there was considerable instability in the estimated model.

Libby (1975) modified Deakin's study to demonstrate that financial ratios could have better predictive values in conjunction with multivariate techniques. Libby's evaluation of the predictive power of financial ratios showed that it enabled a company's management to predictively evaluate company failures.

Blum (1974) noted that financial ratios provide relatively accurate company failure predictions, but concluded that the accuracy decreases if the forecast extends beyond two years. Blum also concluded that traditional financial ratios alone could provide accurate information when companies are susceptible to failure for a limited period. Thevnin (2003:37) questioned the accuracy of Blum's assessment of bankruptcy, because Blum's (1974) study lent itself to confusing and faulty interpretations. Firstly, liquidity is a normal trend to the point where being above average could lead one to construe a company as financially sound when it might not be. Furthermore, the liquidity ratios might not be as good in assessing companies that could be susceptible to failure because the emphasis tends to be very specifically on liquidity to such an extent that other warning signs may be left undetected.

De la Rey (1981) developed an MDA-based failure prediction model for the South African context. The objective was to distinguish between financially sound and failed companies by using the K-Score model. The model was developed by paying attention to various combinations of financial ratios. The K-Score model successfully scored 94.5% of the financially sound companies and 98.6% of the failed companies out of a sample of 138 failed and 255 financially sound companies. The average success rate was 96.6%.

2.1.3 Logit and probit analysis

Ohlson's (1980) research on MDA was extended by Harrison (2005), who employed logit and probit analysis. Logit analysis refers to logistic regression, which is a type of regression analysis for predicting the outcome of categorical dependent variables based on one or more predictor variables. Probit analysis refers to a specialised regression model of binomial response variables. The Harrison analysis surmounted constraints associated with MDA. One of the constraints was that certain statistical requirements were imposed on the distributional properties of the predictors. Secondly, the output of the application of the MDA model had limited intuitive interpretation. Lastly, there was a constraint related to the matching procedures used in the MDA. Using variables for predictors was better than using them for matching purposes.

He's (2002:49) study reported on logit analysis, which was an improvement on the prediction reliability and accuracy of the MDA model. Three reasons for the superiority of logit analysis over MDA were highlighted. Firstly, the logit model is more robust and reliable, since it does not require the normality assumption for ratio variables, which is a basic assumption under MDA. Secondly, instead of a numerical composite score for the dependent variable in MDA, the dependent variable in logit falls within the zero or one distribution. Lastly, it was pointed out that the coefficient of individual variables in a discriminant function is not meaningful in the MDA model and it is impossible to identify the significance of an explanatory variable in the model, whereas the coefficient of individual variables in a logit model is interpretable and the significance of a variable can be tested statistically.

Koh (1991) used probit analysis based on six financial ratios to compare the predictions of assessments of auditors on the going concern status of sample companies. Koh (1991) concluded that this model was an effective prediction model that outperformed auditors' going concern assessments. The probit model was, however, limited by the use of only six financial ratios, which laid it open to the risk of misclassification costs.

2.2 Artificial intelligent expert system models

2.2.1 Recursive partitioning analysis

Recursive partitioning analysis (RPA) is a non-parametric procedure that estimates a classification rule as a sequence of binary partitions of independent variables. At each set this technique splits a subset of the sample into two groups by selecting and partitioning the independent variable that most improves the homogeneity of category assignments applied to the two resulting groups (Harrison, 2005:44). According to Harrison (2005), RPA has attributes that make it similar to both the univariate approach to classification and multivariate procedures. While both RPA and MDA techniques lead to accurate classification results on a data set of failed and healthy companies, RPA was usually superior to MDA. The RPA models performed better than the MDA models in terms of actual cross-validated bootstrapped results. However, Harrison (2005:46) admitted that RPA did not exhibit the same continuous scoring system qualities that MDA displayed.

Steyn-Bruwer and Hamman (2006) used the RPA model to classify financially distressed companies in South Africa. They concluded that the prediction accuracies in their study were not what they expected, because of two phenomena. Firstly, the complete population of industrial companies was modelled; hence the researchers attributed their average results to a 'grey area' in contrast to the extreme input data used in other studies. Secondly, they argued that most of the previous research did not use a hold-out sample, and therefore did not report validation results.

2.2.2 Neural networks

One major disadvantage of the statistical approaches is that the required assumptions are fairly restrictive, since the Gaussian or normal distribution has to be assumed. Such an assumption may not be applicable to real-world problems (Shah & Murtaza, 2000:80).

Shah and Murtaza (2000) were of the opinion that by using a neural network (NN) approach such an assumption could be avoided, since the application of NN models does not require Gaussian distribution assumptions. In addition, NN systems are much faster than conventional statistical approaches, require less storage, are more robust to noise or missing data, and can be generalised. The conceptual basis of a NN model is rooted in attempts to simulate the neural construction of the human brain (Gudmundsson 2002:5). Muller et al. (2009:24) describe an NN as a complex learned algorithm where inputs are mapped to outputs using layers and neurons. Muller et al (2009) further indicated that parameters (coefficients and weights) were trained for the duration of historical data based on known inputs and outputs. Each of the layers consisted of many neurons connected to other neurons in the network. A second dataset was used with these predetermined parameters, obtained from training the network, to obtain the relevant output. These outputs were then statistically compared with actual outputs to determine whether there was any correlation between the simulated and actual results.

Cybinski (2001:31-32) and Aziz and Dar (2006:21) claimed that most studies in the area of NNs involve some comparison with a published univariate or MDA model and may be automated offspring of the statistical approach, albeit more sophisticated. Cybinski (2001) indicated that NN models reported superior results in all instances, and that NN models are simpler to apply, more robust, more flexible and more responsive to change than regression models. However, one constraint that Cybinski does acknowledge is that, although NN technology has aided researchers with the classification problem in failure prediction studies, it has failed to provide an explanation of the process. Furthermore, the most important constraint is the 'black box' nature of NN models, which allows a limited understanding or knowledge of how a particular problem is resolved.

2.3 Theoretical models

According to Aziz and Dar (2006:21), theoretical models are often developed by employing an appropriate available statistical technique rather than by building directly on theoretical principles. Unlike the statistical and artificial intelligence expert system models, which focus on the symptoms of company failure, theoretical models attempt to determine the causes of failure. Some of these models are the Balance Sheet Decomposition Measurement Theory, Gambler's Ruin Theory, the Cash Management Theory, and the Credit Risk Theories.

2.4 The evolution of non-financial models

Although there is no generally accepted listing of non-financial variables that can be used in forecasting company distress, a limited number of studies have identified a unique set of non-financial variables. Keasey and Watson (1987:338) and Lussier (1995:8) have identified a number of non-financial variables, for example, financial control, industry experience, management experience, staffing, product/service timing, economic timing and marketing skills, age of the company, and any changes over the past three years in the number of directors, non-executive directors, shareholders and auditors.

Shumway (2001:51) and He (2002) have used financial ratios and market-driven variables to develop financial distress prediction models. Both Shumway (2001) and He (2002) concluded that the combined financial and market variables exhibit remarkable discriminatory power in differentiating between failed and non-failed or healthy companies several years prior to failure.

Lussier (1995) developed and tested a non-financial model. The company success versus failure prediction model reliably outperformed the random classification of a group of companies as failed or healthy more than 99% of the time. Lussier's model accurately predicted the success or failure of a specific company 70% of the time.

Finally, Zhang (2006) found that the failure prediction model augmented with macro-economic variables displayed greater parameter stability within sample prediction performance.

3. METHODOLOGY AND RESEARCH DESIGN

3.1 Background

The research design, including the methodology and variable selection, is described in this section. The INET BFA database, the pre-eminent South African provider of stock market, fundamental research data and news to the financial sector and the corporate market at large, is used to identify the sample for an eleven-year observation period, from January 2000 through December 2010. Standardised financial statements are used to calculate the financial variables and the director's reports are used to obtain the non-financial variables.

The financial ratios used in Scenario 1 and 3 consist of six ratios, covering various aspects of company performance, such as profitability, liquidity and gearing.

- Scenario 1 uses a model based on financial variables only;
- Scenario 2 uses a model based on non-financial variables only; and
- Scenario 3 uses a model based on a combination of financial and non-financial variables.

Scenario 1, which uses only financial ratios, is designed to serve as a benchmark to which to compare the results obtained in Scenarios 2 and 3. In the study, Scenario 3 incorporates both financial and non-financial information and is designed to test whether the two information sets working in conjunction with each other are able to produce superior results to those obtained from either of the individual information sets.

The financial ratios applied in Scenarios 1 and 3 are based on De la Rey's (1981) K-Score model as represented by Equation (2):

$$K = -0.01662a + 0.0111b + 0.0529c + 0.086d + 0.0174e + 0.01071f - 0.068881 \qquad \textbf{(2)}$$

where: K = overall index

a = (total outside financing / total assets) x (100 / 1)

b = (income before interest and tax) / average total assets) x (100 / 1)

c = total current assets and listed investments / total current liabilities

d = (income after tax / average total assets) x (100 / 1)

e = (net cash flow / average total assets) x (100 / 1)

f = (stock / inflation adjusted total assets) x (100 / 1)

The function of –0.068881 at the end of the model is included to return the point of separation between failed and financially sound companies to zero.

The zone of ignorance stretches from –0.19 to +0.2. A score below –0.19 is a certain indication of failure, unless positive corrective steps are taken, while a score above +0.2 is relatively safe.

The non-financial variables to be applied in this study are based on variables proposed by Jenster and Hussey (2001) to examine a company's strategic capability, which refers to a company's ability and means to be pro-active and to take action. The premise that underpins using non-financial variables to determine a company's strategic capability is that an effective strategy formulation and execution is interdependent with the company achieving its financial objectives (Grant, 1996:29).

The five broad non-financial variables applied are set out below:

- vulnerability – the internal and external risks to which a company is exposed (externally, the company can be exposed to sovereign risk, such as over-reliance on a country with political instability; internally, the company may rely on a single debtor);
- flexibility – the ability of a company to adapt to changes in market conditions, which includes the ability to redeploy resources to meet changes in the external environment (including plant and equipment, organisational software such as structure, systems of decision-making, breadth of job design and attitudes);
- effectiveness – the ability of a company's management to operate the business close to maximum efficiency, in terms of its distribution channels, product and service innovation as well as external communication;
- resources – the factors of economic activity which fall within the company's control; there are three subcategories: tangible capital (physical and financial), intangible capital (technology, reputation, culture) and human capital (specialised skills and knowledge, communicative and interactive abilities, and motivation); and
- capabilities – an all-encompassing term for all the competencies, knowledge and skills a company can apply in a situation.

Each of these five non-financial variables is expanded to include one or two simple and generic questions to appraise a company's strategic capability and the potential effect thereof on the company's financial results.

Each question is assessed on a scale from zero to five. A score of either zero or one is regarded as low or negative. A score of either two or three is neutral and scores of either four or five are regarded as high or positive. Each column from zero to five is added to reflect a sub-total value per column. All the sub-total columns are added to provide one single value per financial year for a subject company.

The final score per financial year for a subject company is divided by the maximum value of 70 (five points times 14 line-items) to provide a weighted, four-decimal fraction value that could be compared to the Scenario 1 scores. A score below 0.3750 is regarded as indicative of a financially distressed company. A score between 0.3750 and 0.7500 is perceived as neutral. Where the score is higher than 0.7500, the company is perceived as successful.

3.2 Availability of data

Financial information on private companies is not readily and publically available, so the study relies on publically available information. Data are obtained from the INET BFA, JSE-listed company database.

A total of 95 companies are identified as suitable subjects for this study. These are extracted from a population of 416 companies and trade securities listed on the JSE Main Board, the

Alternative Exchange (AltX), the Development Capital Market (DCM) and the Venture Capital Market (VCM) on 6 April 2010.

A phased approach is applied to eliminate traded securities and companies that are not regarded as suitable subjects for the purposes of this study. Firstly, all listed traded securities, for example, debt instruments, preference shares and other trade instruments and suspended shares are eliminated. Secondly, all mining and mining-related companies, financial companies and financial service providers (banks, long- and short-term insurance companies), as well as property companies, are excluded from the sample. The reason for this criterion is due to the differences in accounting systems and financial reporting formats, which may materially be different from those in the sample sectors. Thirdly, any companies not listed on the JSE are eliminated – the primary listing has to be on the JSE. Fourthly, only companies listed for more than 11 years, or listed prior to 2010, are retained. Lastly, all companies which changed their financial year-end within the 11-year observation period are eliminated. The final sample is limited to industrial sector companies, services sector companies, and wholesale and retail sector companies.

A director's report usually includes an overview of the past financial year, as well as a discussion of future prospects. The director's report, among other officially published press statements, is assumed to be the most authoritative medium of communication by the company to existing and prospective stakeholders. The director's report for each company is obtained in line with the financial statement data sourcing process. In some instances, the interim report will be used to fill in missing data where the director's report was not published, or is unavailable for a particular financial year.

3.3 Statistical analysis

Most of the prior research on company failure used discriminant analysis, but, according to Keasey and Watson (1987:345), this is inappropriate. One of the assumptions underlying the efficient use of discriminant analysis is that the variables are multivariate normal in their distribution, which is clearly a condition which is not fulfilled by the use of non-financial data. The form of the non-financial variables suggests the use of logit as the ideal estimation procedure.

In the Keasey and Watson (1987:352) study, if the dependent variable was continuous, the analysis could proceed via the usual regression route. However, if the dependent variable was dichotomous (0 or 1), a linear regression model had the undesirable property of heteroscedasticity. An obvious means of correcting heteroscedasticity proposed by Keasey and Watson (1987:352) is to apply weighted least-squares estimation. However, the difficulty with weighted least-squares is that there is no guarantee that the predicted value of the dependent variable will fall into an interval between zero and one. In respect of company financial distress prediction, this amounts to the possibility of a company having a negative probability of failure.

The above difficulties with linear regression suggest the solution of transforming the original model in such a manner that for all independent variables, prediction would fall in the interval between zero and one. When the main concern in the prediction of financial distress is to achieve a predicted probability of financial distress, given a set of attributes, it makes sense, according to Keasey and Watson (1987:352), to use probability as the basis for transformation. This requirement and that of monotonicity suggest that a cumulative probability function would provide a suitable transformation. Keasey and Watson (1987) claim that any non-linear estimation technique should provide the required parameter estimates. Thus, if a model contains dichotomous dependent and independent variables, a cumulative probability model such as probit or logit, coupled with maximum likelihood estimation, seems to be the obvious solution.

However, for the purposes of this study, it is reasoned that a logit or probit procedure evaluating questions of either 'yes' (1) or 'no' (0) might be too limiting. The evaluation procedure is therefore expanded on a scale from zero to five to capture a more sensitive response. Keasey and Watson's (1987) approach, as initially envisaged, is therefore not appropriate for this study. Instead, Cramer's V statistic is applied to accommodate multiple variables, irrespective of whether they are placed in rows or columns. The argument for Cramer's V was published by Cramer (1946). It is a chi-square-based measure of nominal association resulting in a value between zero and one (inclusive, regardless of table size).

Cramer's V is calculated by dividing the chi-squared root by the sample size and the length of the minimum dimension (*k* is the smaller of the number of rows *r* or columns *c*).

The chi-square is an indication of the significance of the relationship between variables, but fails to indicate how significant and important the relationship is. Cramer's V is a post-test to provide this additional information. Cramer's V varies between zero and one. A Cramer's V value close to zero indicates little association between variables, and a Cramer's V value close to one indicates a strong relationship. A Cramer's V value of one is an indication of perfect association between variables.

4. SUMMARY OF RESULTS

4.1 Model based on financial variables

The analysis of financial variables, as indicated earlier, is based on the De la Rey K-Score model. In TABLE 1 below, the number of observations in a particular calendar year, less than -0.19, more than +0.2 and between -0.19 and +0.20 is expressed as a percentage of the total number of observations, respectively.

In TABLE 1, a K-Score larger than +0.2 represents the majority (average 66%) of the sample companies, indicating that there is a relationship in the movement of the K-Score and the GDP. However, no relationship is observable between a K-Score below -0.19 (19% of the sample companies) and the GDP. Over time, the movement in the K-Score above +0.2 represents a mirror image of the movement in the K-Score below -0.19.

The remaining 15% of the sample companies falls within the neutral or indecision zone, between -0.19 and +0.20, indicating a stronger relationship with the movement in the GDP than with the +0.20 K-Score over the observation period.

TABLE 1: Number of observations less than –0.19, more than +0.2 and between –0.19 and +0.20 as a percentage of the total observations and gross domestic product (year-on-year change)

Interval & GDP	*OBSERVATION PERIOD (YEARS)*										
	2000	*2001*	*2002*	*2003*	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*
< -0.19	15.4	25.8	12.6	20.0	18.9	14.7	21.1	16.8	20.0	24.2	22.5
> +0.2	59.6	62.4	70.5	61.1	70.5	73.7	66.3	71.6	66.3	63.2	60.0
-0.19 <> +0.20	25.0	11.8	16.8	18.9	10.5	11.6	12.6	11.6	13.7	12.6	17.5
GDP	4.2	2.7	3.7	2.9	4.6	5.3	5.6	5.5	3.7	-1.8	2.8

Source: Authors' calculations

4.2 Model based on non-financial variables

A schedule comprising 14 questions, divided into five groups, is used to evaluate the directors' reports of the sample companies. Based on a subjective evaluation of the reports, a score between zero and five is assigned to each question – zero is a low score, and five represented a high score. Each sample company is assessed against a potential maximum score of 70 points (14 questions multiplied by five points).

For the purposes of the analysis below, the total scores attained by a sample company in a particular year is weighted against the potential maximum score of 70 points. A separation is performed in order to demonstrate the level of success or distress of a sample company. The test results are divided into three equal sub-sectors. A potentially financially distressed company scores below 0.375. A successful company achieves a score higher than 0.750. A score between 0.375 and 0.750 represents an ignorance or neutral zone.

TABLE 2: Results of Cramer's V test for Questions aa1 to ee2 and GDP (year-on-year change)

Ques & GDP	OBSERVATION PERIOD (YEARS)										
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
aa1	0.2349	0.1425	0.1880	0.0735	0.2073	0.1484	0.1647	0.1962	0.2713	0.3364	0.0000
aa2	0.2769	0.1021	0.1124	0.1493	0.1608	0.1722	0.1568	0.1910	0.2228	0.2374	0.2519
bb1	0.0544	0.1110	0.0660	0.0573	0.1187	0.1681	0.2198	0.1841	0.1391	0.1796	0.1870
bb2	0.2416	0.1202	0.2135	0.0553	0.1497	0.1607	0.2636	0.2851	0.1487	0.1777	0.2471
cc1	0.2054	0.1486	0.1655	0.1263	0.1264	0.1085	0.2072	0.1796	0.1351	0.2262	0.1850
cc2	0.3165	0.2388	0.0727	0.1220	0.1726	0.2413	0.2283	0.1683	0.1845	0.1923	0.2825
dd1	0.2302	0.1328	0.2274	0.0755	0.1579	0.2015	0.1848	0.1848	0.0495	0.1251	0.1284
dd2	0.1446	0.1592	0.1000	0.1235	0.0703	0.1317	0.1352	0.1623	0.1356	0.1105	0.2924
dd3	0.2627	0.1015	0.1169	0.2037	0.0786	0.1022	0.1797	0.1504	0.1448	0.1594	0.1377
dd4	0.2741	0.0901	0.1523	0.0963	0.1172	0.1450	0.1543	0.1494	0.0990	0.1290	0.2256
dd5	0.2627	0.1236	0.1320	0.2313	0.1208	0.1226	0.1450	0.1506	0.1705	0.1845	0.1377
dd6	0.1465	0.1350	0.1559	0.2344	0.0897	0.1082	0.2015	0.1253	0.1550	0.1080	0.1284
ee1	0.2461	0.2030	0.1830	0.2288	0.1131	0.2611	0.2351	0.2525	0.1703	0.1856	0.1846
ee2	0.0471	0.1929	0.1295	0.1326	0.0789	0.1529	0.2731	0.2026	0.2053	0.2180	0.3616
GDP	4.2	2.7	3.7	2.9	4.6	5.3	5.6	5.5	3.7	-1.8	2.8

Source: Authors' calculations based on multiplier analysis

Of the total number of observations, 22.5% reflect a value less than 0.375 – these are financially distressed companies. Of the total number of observations, 6.7% reflect a value higher than 0.750 – these are successful companies. The balance or 72.9% of the total number of observations indicate a value between 0.375 and 0.750 – this is a neutral response.

4.3 Model based on a combination of financial and non-financial variables

4.3.1 Cramer's V results

Cramer's V test is applied to determine the correlation between the K-Score result and the multiple test score results. Because the chi-square does not indicate the significance of the association between the financial and non-financial variables, the Cramer's V test is used to overcome this constraint.

The question schedule for non-financial variables is divided into five broad groups – vulnerability, flexibility, effectiveness, resources and capabilities. The Cramer's V results for each group and question are set out below.

- Vulnerability

  Question 1: (aa1) Does the company operate in politically and economically stable countries?

  Question 2: (aa2) How well does the company manage operational risk?

- Flexibility

  Question 3: (bb1) Are plant and equipment or services adaptable to changes in consumer demand?

  Question 4: (bb2) Is key management structured in line with the company's core functions?

- Effectiveness

  Question 5: (cc1) Are cost drivers clearly identifiable?

  Question 6: (cc2) Does the company differentiate itself through a unique product or service offering?

- Resources

  Question 7: (dd1) Was the company successful during the year in raising additional debt and/or equity funding?

  Question 8: (dd2) Does the company have easy access to raw material and other supply resources?

  Question 9: (dd3) Does the company rely on complex technology?

  Question 10: (dd4) How well does the company manage reputational risk?

  Question 11: (dd5) Is the company reliant on highly specialised skills?

  Question 12: (dd6) Is the company transparent in its external communications?

- Capabilities

  Question 13: (ee1) Does the company reflect the ability to acquire new capabilities?

  Question 14: (ee2) Is the company a market leader?

The above questions are categorised into three broad groups:

- questions where Cramer's V indicate a strengthening in the relationship between the K-Score and the non-financial variable – movement towards one;
- questions where Cramer's V indicate a neutral relationship between the K-Score and non-financial variable – stable or no movement over time; and
- questions where Cramer's V indicate a weakening relationship between the K-Score and the non-financial variable – movement closer to zero over time.

Six questions (aa1, aa2, bb1, bb2 and dd2), 42.9%, out of the 14 questions indicate a strengthening in the relationship between the K-Score and the non-financial variable over the observation period. Three questions (cc1, cc2 and dd4), 21.49%, out of the 14 questions indicate a neutral relationship between the K-Score and the non-financial variable over the observation period. Five questions (dd1, dd3, dd5, dd6 and ee1), or 35.7%, out of the 14 questions indicate a weakening relationship between the K-Score and the non-financial variable over the observation period.

An overall view of the results indicates a marginal weighting in favour of using non-financial variables in combination with financial variables in enhancing the prediction accuracy of company financial distress. The results indicate a marginal weighting in favour of adopting the use of non-financial variables in combination with financial variables to enhance the prediction accuracy of company financial distress, but because only 42.9% of the questions indicate a strengthening relationship between the De la Rey K-Score and the non-financial variable, the results are not strong enough to claim that the objective has been achieved convincingly.

5. RECOMMENDATIONS FOR FURTHER RESEARCH

The field of company financial distress and the prediction models based on financial and non-financial variables present significant scope for further research. Research on the effect of non-financial variables on a financial distress prediction model is still in its infancy.

The challenge is therefore to identify applicable non-financial variables that could contribute to and could be employed to develop a hybrid distress prediction model. The director's report was used as a primary source of input information. Such reports consist of an overview of the past financial year's performance and an interpretation of the external and internal environment in the company's future strategy. The director's ability to interpret the information translates into the company's strategic capability and ultimately its financial performance.

Although the study did not provide the compelling result expected, the outcome nevertheless indicates that there is merit in combining non-financial variables with an existing company financial distress model. In view of this finding, further comprehensive empirical research is required to overcome some or all of the limitations of the current study in order to demonstrate convincingly that combining financial and non-financial variables enhances the accuracy of a company financial distress model.

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