Asian Journal of Accounting and Governance **7**: 41–55 (2016) ISSN 2180-3838
(http://dx.doi.org/10.17576/AJAG-2016-07-04)

Comparing the Reliability of Accounting-Based and Market-based Prediction Models

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ABSTRACT

Recently developed financial distress prediction models adopt a market-based approach. It gained its popularity in the academic world due to its theoretical appeal. However, the comparison of market-based with traditional accounting-ratio-based models is limited in the literature. Therefore, this paper humbly attempts to add finding to the literature by comparing the accounting-based model with market-based model in order to present a comprehensive computational comparison of methodologies to fulfil the strategic information needs of investors and other stakeholders. Our accounting-based model employed multivariate discriminant analysis (MDA) and logistic regression analysis (LRA) and for market-based model, we adopted Merton technique. Our sample consists of one hundred and fifty eight public listed companies in Malaysia. Sixteen financial ratios with five-feature groups including activity ratio, cash flow ratio, solvency ratio, liquidity ratio and profitability ratio are selected as variables for our accounting-based model. For the market-based model, we generate the logarithm by adopting the information from the market such as stock price and interest rate. The result of one year prior to financial distress classification indicates that LRA has the highest accuracy compared to other methodologies and both the accounting-based models (LRA and MDA) outperformed market-based (Merton) model.

Keywords: Financial distress prediction; Logistic regression analysis; Merton model; Multivariate discriminant analysis; Receiver operating characteristics curve

Introduction

Financially distressed companies cause financial and economic losses to management, stockholder, employees, customers, and others, together with a substantial social and economic cost to the nation. It is important for all stakeholders to continuously assess the going concern of companies in order to avoid the companies from facing financial difficulties. The job security of employers and employees is not assured should their companies struggle financially. Stockholders' equity position and lenders' claim are also not guaranteed if companies are defaulting. Government, as a regulator in a competitive market, has concerns about the consequences of financial distress for companies, which will cause unrest to the society through unemployment and job insecurity (Mingo 2000). Therefore, a model predicting companies' failure would serve to reduce such losses by providing a pre-warning to these stakeholders. An early warning signal of probable failure will enable stakeholders to take preventive actions; and therefore, shorten the length of time of losses. In view of this, an accurate distress prediction model has become an important aspect in finance.

The incidences of important bankruptcy cases such as Enron and Worldcom have led to growing interest in corporate bankruptcy prediction models since 1960s. Numerous researchers have studied bankruptcy prediction over the past sixty years. We can trace the beginning of research on financial distress to Beaver (1966) when he used accounting ratio to assess the probability of default. Beaver uses univariate discriminant analysis in his study. It was followed by Altman in 1968 who has improved on the study through multivariate discriminant analysis (MDA) by optimizing the accounting ratio (Altman 1968). MDA has been a popular model since then mainly due to its simplicity and reported high accuracy (Ruhani & Woon 2003). Many other models have been introduced after that due to the importance of the subject matter in the corporate world. For example; artificial neural network (ANN) model, linear probability models, expert system and many others.

The high cost faced by financially distressed companies makes this problem a priority to stakeholders. Bankruptcy or financial distress condition is usually considered to apply to a company if it cannot pay its debts as they fall due, and it is the threat or occurrence of financial distress which is normally be originator of formal restructuring arrangements (Rees 1990). Financial distress could arise from any number of causes and there are numerous classifications of these. Table 1 presents one such listing.

During the 1960s and 1970s, many researchers employed the accounting-ratio based models in their studies. These ratios are typically built by adopting a large number of accounting ratios with the ratio weightings estimated on a sample of financially distressed and non-financially distressed companies. Accounting-based models are likely to be sample specific because the ratios and their weightings are derived from sample analysis. Mensah (1984) found that the distribution of accounting

TABLE 1. Possible causes of financial distress (Rees 1990)

Low and declining real profitability
Inappropriate diversification – into unfamiliar industries or not away from declining ones
Import penetration into the company's home markets
Deteriorating financial structures.
Difficulties controlling new or geographically dispersed operations.
Over-trading in relation to the capital base.
Inadequate financial control over contracts.
Inadequate control over working capital.
Failure to eliminate actual or potential loss-making activities.
Adverse changes in contractual arrangements.

ratios changes over time, and hence recommends that such models be redeveloped periodically (Mensah 1984). Therefore, instead of using the Altman's or Ohlson's models in our study, we redevelop the MDA and LRA models based on selected accounting ratios of the Malaysian public listed companies from year 2001 to year 2012 in order to improve the performance of the accounting-based model.

Researchers argue that the validity of the ratios generated from the financial statements on which these models are based upon casts doubt due to: (i) financial statements present past performance of a company and it is doubtful to present conclusive information to predict the future, (ii) conservatism and historical cost accounting means that the true asset values may be understated, (iii) management may manipulate the financial statements by reporting a good financial result that is in favour of the management, (iv) and lastly, Hillegeist, Keating, Cram and Lundstedt (2004) and Agarwal and Taffler (2008) claimed that since the accounting statements are prepared on a going-concern basis, they are less useful in predicting financial distress (Hillegeist, Keating et al. 2004; Agarwal and Taffler 2008).

Market-based models using the Black and Scholes (1973) and Merton (1974) contingent claims approach provide attractive option and several recent papers have been using this methodology to assess the likelihood of financial distress of companies such as studies by Bharath and Shumway (2004), Hillegeist et al. (2004), Vassalou and Xing (2004), Reisz and Perlich (2007) and Campbell, Hilscher and Szilagyi (2008) (Bharath and Shumway 2004; Hillegeist, Keating et al. 2004; Vassalou and Xing 2004; Reisz and Perlich 2007; Campbell, Hilscher et al. 2008). Market-based model counters most of the criticisms on accounting-ratio-based models whereby: (i) the market-based model provides a sound theoretical approach for distressed company, (ii) in efficient markets, stock prices will reflect all the information contains in the financial statements and will also reflect information which is not captured by financial statements, (iii) company accounting policies unable to influence market variables, (iv) future cash flow of company is reflected in the stock market price, and therefore it is a reliable variable to predict the future of the company, and (v) the market-based models is not time or sample dependent (Agarwal and Taffler 2008).

Merton model is a structural form model and employing the model in our study requires a number of assumptions. As Saunders and Allen (1998) explained, the fundamental theoretical Merton model requires the assumption of normality of stock returns (Saunders and Allen 1998). Besides that, the Merton model also does not differentiate the different categories of debt and assumes that company only has a single zero coupon loan. The Merton model also needs a measurement of asset value and asset volatility which are not directly available in the market. Therefore, the empirical evidence from the market-based model is always mixed and this is as per expectation due to the violation of the assumptions. Kealhofer (2003) and Oderda, Dacorogna and Jung (2003) found that market-based models out-performed credit ratings; and Hillegeist et al. (2004) explained that their market-based model carries more information about the probability of bankruptcy than the accounting-ratio based models (Kealhofer 2003; Oderda, Dacorogna et al. 2003; Hillegeist, Keating et al. 2004).

Contrary finding by other research such as Campbell et al. (2008) found that market-based models have little predicting supremacy after controlling for other variables. Reisz and Perlich (2007) found that Altman's (1968) z-score performed better at failure prediction over a 1-year period than their two newly developed KMV-type. However, their study indicated that market-based models performed better over longer horizons (3 to 10 years). Agarwal and Taffler (2008) found that there is little difference between accounting-based model and market-based model in terms of predictive accuracy. They also found that neither the market-based model nor the accounting-based model is a sufficient statistic for failure prediction and both carry unique information about company that faced financial distress.

This paper compares the reliability performance of the accounting-based model (LRA and MDA) against market-based model (Merton model) over a 12-year period from 2001 to 2012 using Receiver Operating Characteristic (ROC) curves. The main conclusions of this study for one year before the actual event of financial distress classification are: (i) while the LRA model is marginally more accurate compared to MDA, the difference is statistically not significant, (ii) accounting-based models are superior compared to the market based model. This is mainly due to the superior performance of the newly developed MDA and LRA models which are based on the up-to-date sample, (iii) the LRA model is significantly superior compared to Merton model, (iv) no conclusive evidence can be obtained from the study for period beyond one year before the actual event of distress classification.

The result from this research is expected to have significant implications for investors and other stakeholders in their decisions concerning the tools to be adopted in their research. For example, bankers can use the information from this study to identify the best financial predictor for default risk. Meanwhile for investors, they can allocate their funds efficiently by having the knowledge on distress predicting model. This study may also help regulators to implement an internal risk assessment method to identify distress risk.

In summary, this paper humbly attempts to apply MDA, LRA and Merton techniques to the public listed companies in Malaysia as our case study, and to present a comprehensive computational comparison of the classification performances of the techniques tested in order to fulfil the strategic information needs of investors and other stakeholders that have interest in the Malaysian public listed companies.

The following sections of the paper are organized as follows. Section 2 reviews the relevant literature relating to development of the financial distress prediction models; section 3 details out the methodologies to be employed to achieve the research objective of this paper; section 4 contains the comprehensive data analysis and empirical results; and lastly, section 5 discusses the results obtained from the previous section using reasonable justifications and past findings in the literature. References make up the end of this paper.

Literature Review

Accurate financial distress predictions are of great interest to academicians, practitioners, and policy makers. Policy makers use forecasting models to monitor the financial health of companies, banks, pension funds, and other institutions. Practitioners use financial distress prediction to price corporate debt. Academicians use financial distress prediction to test various assumptions like the hypothesis that bankruptcy risk is priced in stock returns. Given the broad interest in accurate forecasts, a superior forecasting methodology is priceless (Hillegeist, Keating et al. 2004). Statistical methods or accounting-based methods such as univariate discriminant analysis (UDA), multivariate discriminate analysis (MDA), quadratic discriminant analysis (QDA), multiple regression, logistic regression analysis (LRA), as well as probit and factor analysis (FA) have been applied in the research of financially distressed companies. Many researchers can be categorised under accounting-based method and that include Beaver (1966) who used univariate discriminant analysis in his study; and followed by Altman (1968) who utilised multivariate discriminant analysis to predict the failure of firms from different industries. Sinkey (1975) also adopted multivariate discriminant analysis to predict bank failure (Sinkey 1975). Altman (1977) developed another discriminant model to predict the failure of the Savings and Loan Associations for the period of 1966–1973 using 32 ratios as input variables. Lam and Moy (2002) combined several discriminant models, and performed simulation analysis to enhance the accuracy of classification results for classification problems in discriminant analysis (Lam and Moy 2002). Another multivariate statistical method that is used to predict bank failure is multiple regression analysis that was first used by Meyer and Pifer (1970) (Meyer and Pifer 1970). Martin (1977) and Ohlson (1980) utilised logistic regression to predict banks and companies' failure (Martin 1977; Ohlson 1980).

Khong, Low, Tee and Leng (2015) developed a financial prediction equation that is based on public listed companies in Malaysia. They employed LRA in their study and selected eleven financial ratios that were found to be useful in developing the financial distress prediction model. Sample for their research consisted of forty eight public listed companies in Malaysia from year 2010 to 2014. They found that the selected financial ratios are significant for corporate failure prediction in Malaysia with accuracy rate of eighty eight percent for the developed equation (Khong, Low et al. 2015).

The best well known market based approach to predict financial distress probability by relying on market information is the Merton (1974) model. It is an innovative forecasting model which has been widely applied in both practice and academic research (Byström 2003). Merton model assumes that company has certain amount of zero-coupon debt that will become mature at a future time T. If the value of the company assets is less than the promised debt repayment at time T, the equity holders will choose to default. The company equity is a European call option on the assets of the company with maturity T and a strike price equal to the face value of the debt. The Merton model can be used to estimate risk-neutral probability that a company will default and it also can be used to estimate credit spread on the debt (Merton 1974).

Bystrom (2003) has introduced a simple approximation to the Merton (1974) model and exhibits that the errors made by his simplification model are relatively small compared to those caused by other deficiencies of Merton's model. His model produced distance to default measures quite similar to the original Merton's model. He also managed to identify the drivers of default, which are equity (or asset) volatility and leverage ratio.

Ardiansyah and Qoyum (2010) have studied the impact of default on Islamic equity return by using Merton technique. The research is about the correlation between the size and the book to market value (BMV) ratio with the default probability. The default probability is obtained from Merton model and used as a proxy of dependent variable. The samples taken are public listed companies listed in Bursa Malaysia that have issued sukuks in year

2009 and classified as Shariah compliance. There are only forty-two companies that complied with the criteria mentioned. The regression analysis is done for three years on each company since 2007 until 2009. Therefore in total, the data are one hundred and six (42 companies × 3 years = 106) (Ardiansyah and Qoyum 2010). The research samples consist of only forty-two companies and these companies are not financially distressed. To assess companies that are healthy, it is very unlikely that the result will give any indication of financial distress. Most of the previous researches focused their attention on companies that have been classified as financially distressed to find early warning signal and variable that is significant to predict the condition of the companies.

Loeffler and Posch (2011) have applied Merton model with some modifications (Löeffler and Posch 2011). Their model follows similar assumption made by Merton (1974) whereby they assumed that company's liabilities consist of just one zero-coupon bond with notional value *"L"* maturing in *"T"*, and there is no payment until *T*. Whenever the value of the assets is below the value of the liabilities at time *T*, the company's default probability is obtained. Another similar assumption adopted by Loeffler and Posch is that the logarithm of the asset value is normally distributed or follows a log-normal distribution. The difference between Merton model and Loeffler and Posch model is that in Merton model, interest rates and liabilities are constant; whereas in Loeffler and Posch model, they use time-varying interest rates and liabilities which are closer to market valuation. Loeffler and Posch also use iterative procedure which means daily data (such as market value of the equity, risk free rate and Bursa Malaysia FTSE index) are utilized in their model. Meanwhile in Merton model, he only uses a constant data. Therefore, by using Loeffler and Posch model, we can select any date within the year to find the probability of default without waiting for the maturity date of *T* like the Merton model. We have employed this model in our research to represent market-based model.

Data and Methodology

Practice Notes 4 and 17

The companies selected in this study were listed under Practice Note 4/2001 (PN4) or 17/2005 (PN17). Alifiah, Salamudin and Ahmad (2011) informed that PN4 was introduced on 15 February 2001 to overcome some weaknesses in Section 176. PN4 provides a comprehensive plan for listed companies that cannot justify continued trading and listing on the exchange. It requires companies listed under PN4 to make sufficient disclosure and ensure that those companies take action to overcome their unsatisfactory condition such as by restructuring their debts and assets. PN4 was also unable to meet its objective because some companies that had been released from PN4, after restructuring and solving their financial problems, were found to be back in financial difficulties after several months. Therefore, PN17 was introduced on 3rd January 2005 by amending the requirements of PN4. Bursa Malaysia made those amendments in order to improve and increase the qualities of companies that are listed on the exchange. The amendments were also aimed to accelerate the time taken by troubled companies to improve their financial condition and expedite their restructuring plan. The amendments were also expected to enhance the capital market and securities industry in Malaysia. PN17 was amended again on 5 May 2006 by Bursa Malaysia to further improve the reliability and trustworthiness of listed companies on the exchange. Among other objectives of the amendments are to further strengthen the quality of listed companies, improve investor protection mechanism and enhance investor confidence. The amendment of the PN17 has made the companies under the PN17 listing facing more stringent rules and regulation from Bursa Malaysia. Those companies which have been listed under PN17 have to submit a restructuring plan to Securities Commission (SC) within a period of eight months. Those companies also have to implement their restructuring plans within the timeframe predetermined by the SC. The Amended PN17 also requires that all restructuring plans undertaken by the PN17 companies to fall within Section 32 of the Securities Commission Act 1993, which means those companies require the SC's approval to procure (Alifiah, Salamudin et al. 2011).

Data

Below are the selected variables for LRA and MDA models:

Activity ratio

1. Quick asset turnover: Sales/(cash + receivables) = QAT
2. Current asset turnover: Sales/current assets = CAT
3. Asset turnover: Sales/total assets = AT
4. Days sales in receivable: Receivables/(sales/365) = DSR
5. Sales to fixed assets: Sales/fixed assets = ST/FA

Cash flow ratio

1. EBIT to total asset ratio: EBIT/total assets = EBIT/TA
2. Cash flow to assets: Earnings before interest, taxes, depreciation and amortization (EBITDA)/total assets = C/TA
3. Cash flow to total debt: EBITDA/total liabilities = CT/TL

Solvency ratio

1. Debt to assets: Total liabilities/total assets = TLT/TA
2. Debt to equity: Total liabilities/(total assets - total liabilities) = D/TE
3. Book value of equity to total liabilities: Book value of equity / total liabilities = BVE/TL
4. Market value of equity to total liabilities: Market value of equity / total liabilities = MVE/TL

Liquidity ratio
1. Current ratio: Current assets/current liabilities = CR
2. Net liquid asset ratio: Working capital/total asset = WC/TA

Profitability ratio
1. Return on equity: Net income/(total assets - total liabilities) = ROE
2. Retained earnings to total assets ratio: Retained Earnings/ Total Assets = RE/TA

Meanwhile for Merton model, the selected variables are as below:
1. Daily share prices for all companies in the respective period
2. Total number of outstanding shares for all companies in the respective period
3. Daily FTSE Bursa Malaysia index for the respective period
4. Companies' liabilities (obtained from companies financial statements) in the respective period
5. Daily risk free rate in the respective period

The financially distressed companies have been identified from Bursa Malaysia website for the period of January 2001 until December 2012. There were seventy-nine financially distressed companies that we managed to obtain complete financial information from DataStream. The list is matched against non-distressed companies of the same industry and asset size. Selected companies must have a complete set of financial data for a period of five years prior to the event year to be included in the sample.

The selected financially distressed companies are matched against the non-financially distressed companies in terms of assets size, same industry and same financial reporting year. The matching criteria mentioned are needed to ensure the distress prediction model produces the lowest amount of bias result (Karbhari and Muhamad Sori 2004; Chin 2005). The selected matching criteria will also enhance the credibility and reliability of the analysis. If the matching criteria are not observed, it will generate a model whereby the matched samples will consist of mostly big companies (or mostly small companies) which will lead to biased prediction result (Beaver 1966; Altman 1968; Platt and Platt 1990; Nam and Taehong 2000).

METHODOLOGY

MERTON MODEL

One of the most popular approaches to default probability estimation using market information is the Merton (1974) approach. Black and Scholes (1973) have developed option pricing methodology and Merton (1974) applied it to valuation for companies (Black and Scholes 1973; Merton 1974). Merton model defines a company as defaulted when the company's value fall below its debts. It explicitly models a company's market value, market value volatility and liability structure over time using contingent claims analysis (Byström 2003). Lin, Ansell and Andreeva (2007) informed that the algorithm of equity value in relation to probability of default is the key expression of Merton type models (Lin, Ansell et al. 2007). Merton also assessed the risk of default for any particular company based on the company's capital structure. In the Merton model, the company's equity can be seen as a European call option on the company's assets with a strike price equal to the book value of the company's liabilities. Shareholders are considered as residual claimants with limited liability which is similar to option pricing methodology. This limited liability gives the shareholders the right, but not the obligation to pay off the debt holders and to take over the remaining assets of the company (Crosbie and Bohn 2002). For example, the shareholders only exercise their option on the assets if the market value of the company's assets is greater than the book value of liability at maturity date and assuming that all liabilities are due on the same date. Whenever the company's market value of assets is greater than the book value of liability at maturity date, shareholders pay off the debt-holders and the company continues to exist. However, if book value of liabilities is greater than company's market value of asset, shareholders will choose to let the option expires implying that the equity value of the company is zero. This will cause the company assets to be transferred to the debt holders. Therefore, in the Merton methodology, the market value of the company's equity to the shareholders at the date of maturity of debt is defined as follows:

$$V_E = \max[V_A - X, 0] \tag{1}$$

TABLE 2. Breakdown of Companies by Industry

Industry	Number of financially distressed companies	Number of non-financially distressed companies	Total
Industrial product	34	34	68
Trading and services	20	20	40
Consumer product	1	1	2
Construction	20	20	40
Plantation	2	2	4
Hotel	2	2	4
Total	79	79	158

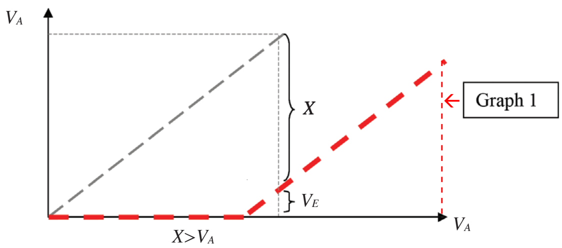
where V_E is the market value of the company's equity, V_A is the market value of total assets and X is the book value of liabilities.

The debt of the company can be seen as a default-risk-free loan less a put option sold to equity holders by debt holders, which is similar to the put-call parity (Brealey and Meyers 2000). Then, the value to the debt holders at maturity T may be expressed as:

$$X_T = X - \max\,[X - V_A, 0] \tag{2}$$

This means that the equity holders own assets and borrow debt with a put option. This put option allows them to sell off the company's assets for the borrowed amount. From the debt holders' point of view, they have written a put option to the equity holders and take possibility of default risk. Since the equity holders have put option in hand, they will definitely choose to exercise the put option (or let the call option to expire) whenever the market value of the company's asset is below the book value of liability and caused the company to default. The option on the company's assets can be illustrated graphically as follows:

Basic Option Relationship



V_E : market value of the company's equity
V_A : market value of total assets
X : book value of liabilities

Since the behaviour of the asset value is described by the same flow process as in the model by Black and Scholes (1973), the current stock price is subject to the boundary condition above and can be found analytically by means of the Black-Scholes formula:

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2)$$

$$d_1 = \frac{\ln\left(\frac{V_A}{X}\right) + \left(r + \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}},$$

$$d_2 = d_1 - \sigma_A\sqrt{T} = \frac{ln(\frac{V_A}{X}) + (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}, \tag{3}$$

V_E is the market value of the company's equity, V_A is the market value of total assets, X is the book value of liabilities maturing at time T, τ is the risk-free rate, σ_A is the volatility of the asset value, $N(.)$ is the cumulative density function of the standard normal distribution, and $Xe^{-\tau T}$ represents the present value of the promised debt payment.

Merton's model estimates today's risk neutral probability that the value of the company will be greater than the face value of its debt at time T. Therefore, the risk-neutral probability of default is computed as:

$$PD = 1 - N(d_2) \tag{4}$$

The risk-neutral probability of default depends on the five option variables which influence d_2. The risk of default will be lower, implying that d_2 is higher when:

1. High (natural logarithm of) current value V_A.
2. The (natural logarithm of) face value of debt at maturity X is low or when the company's leverage X/V_A is low and, therefore $\ln(V_A/X)$ is high.
3. Low volatility of the company's return σ_A.
4. Shorter average maturity of debt.
5. High risk-free interest rate.

Merton's model is a simple and vibrant technique which builds a general theoretical framework for valuing contingent claims. It produces forecasting probabilities of financial distress on the company's volatility, debt structure, current asset value, leverage, and the market risk-free interest rate. However, some of the assumptions made by Merton are not congruent with reality. The capital structure of company is more complex in reality. Company may combine many classes of debt with different maturity date. Besides that, in the Merton model, the bond is assumed as a zero-coupon bond while in reality many of the corporate bonds have a coupon. Merton model also assumes that default can happen only once when the debt is mature at time T. In reality, default can happen during the life of the bond. Assumption has also been made on asset volatility and the risk-free rate as constant variable; and this is not in line with reality.

These limitations have led to further research and improvements on the Merton methodology from the theoretical and practical points in order to ensure the model is closer to reality. Among the improvements made are models by Black and Cox (1976), Geske (1977), Longstaff and Schwarz (1995), Leland and Toft (1996), Collin-Dufresne and Goldstein (2001). Black and Cox (1976) improved the Merton model by relaxing the assumptions of default before maturity. It allows default to happen every time the asset value reaches a pre-determined lower boundary (Black and Cox 1976). Meanwhile Geske (1977) improvises the Merton model by allowing for coupon and more complex debt arrangements. Geske model permits company to have multiple options to default on different types of debt. Therefore, an option on a stock can be seen as a compound option (Geske 1977). The Leland and Toft's (1996) model assumes that a company continuously issues bonds with fixed maturity and continuous coupon. Their model also has an endogenous default boundary (Leland and Toft 1996). Meanwhile for Longstaff and Schwarz

(1995) model, it allows stochastic interest rates. Finally, Collin-Dufresne and Goldstein (2001) extend the model of Longstaff and Schwarz by allowing changes in leverage ratios because in practice the companies usually adjust their outstanding debt levels corresponding to changes in company value (Collin-Dufresne and Goldstein 2001). One most successful methodology to the application of the Merton function is a model developed by Kealhofer and Vasicek (1995). This is a patented model of Moody's-KMV or also known as KMV. Many practitioners use this commercial version of KMV model in assessing distressed companies.

MULTIVARIATE DISCRIMINANT ANALYSIS (MDA) MODEL

The first methodology which is accounting-based model that we will use is the multivariate discriminant analysis (MDA). According to Altman, MDA is a statistical method used to classify an observation into one of several priori groupings depending upon the observation's individual characteristics. MDA is primarily used to classify and/or make predictions of problems whereby the dependent variable is in qualitative form, such as day or night, success or failure. To build MDA model, the first step that needs to be taken is to establish unambiguous group classifications whereby the number of groups can be two or more. After that, data are collected for the objects in the group. From the MDA result, a linear combination of characteristics which "best" discriminates between the groups can be obtained. MDA determines a set of discriminant coefficient for a particular object such as a company. A basis for classification into one of the mutually exclusive groupings exists whenever these coefficients are applied to the actual ratio. The MDA technique has the advantage of considering an entire profile of characteristics common to the relevant companies, and also the interaction of these properties. In contrast, a univariate study can only consider the measurements used for group assignments one at a time. MDA is also able to reduce the analyst's space dimensionality, i.e. from the number of different independent variables to G – 1 dimension(s), where G equals the number of original a priori groups. This research paper concerned with two groups, i.e. non-financially distressed companies and financially distressed companies. Therefore, the MDA analysis is transformed into its simplest form, which is one dimension. The discriminant function of the form $Z = V_1X_1 + V_2X_2 + \ldots + Vn\ Xn$ transforms individual variable values into a single discriminant score or Z value which is then used to classify the object where

$V_1, V_2 \ldots Vn$ = Discriminant coefficients
$X_1, X_2 \ldots Xn$ = Independent variables

The MDA computes the discriminant coefficients, Vj, while the independent variables Xj are the actual values where

$j = 1, 2, \ldots n$

The primary advantage of MDA in dealing with classification problems is the potential of analysing the entire variable profile of the object simultaneously rather than sequentially examining its individual characteristics. Combination of ratios can be analysed together by using MDA in order to remove possible uncertainties and misclassifications observed in univariate studies. The analysis is conducted using SPSS version 20.

LOGISTIC REGRESSION ANALYSIS (LRA) MODEL

The other prediction model which is accounting-based that we will use in this research is logistic regression analysis or known as LRA. LRA is used to classify or make forecasting in situation where a dependent variable appears in qualitative forms; for example boy or girl and successful or unsuccessful. The LRA forecasting model of financial distress is measured by a maximum likelihood estimator. It is an alternative parametric approach to multivariate discriminant analysis (MDA) that has been popularly used for distress prediction in academic and business worlds. MDA's limitation such as multivariate normality and equality in dispersion matrices among groups can be overcome by LRA model. LRA provides the likelihood of occurrence of an outcome described by dichotomous (or polytomous) dependent variables using coefficients of the independent variables. The developed LRA model has the form of the cumulative logistic probability function. Its result has a value that can be understood as the conditional probability of failure; whereby the MDA's z-score result only has discriminant value that is a bit difficult to be deduced.

In the LRA model, coefficients are often estimated by the maximum likelihood method instead of the least squares method because of the non-linearity of the model. The value of the probability P(Z) is always between 0 and 1 instead of resulting in a group membership like the MDA model. The LRA model produces the likelihood of a group membership since its value changes between 0 and 1. If Z approaches minus infinite, P(Z) approaches zero, and if it approaches plus infinite, P(Z) approaches the value of 1. When the value of Z is 0, the probability of failure P(Z) is 0.5, which is commonly used as critical value in classifying the group membership. If misclassification costs for both error types are used when defining the critical value, it is often lower than 0.5 (misclassification costs for the Type I error are usually estimated to be higher than those of the Type II error). Based on the probability, a company is classified as financially distressed or non-financially distressed using a cut-off probability. Maximum likelihood estimation procedures are employed to determine the parameters (Laitinen and Kankaanpaa 1999).

In this study, the dependent variable is coded as one if the companies are financially distressed and coded as zero if the companies are non-distressed. The LRA model estimated that there is an underlying response variable Z, defined by the regression relationship. This model is employed from Ohlson (1980) and Gujerati (1995).

$$Z_1 = \beta\, x_1 + \mu_1 \qquad (5)$$

Where:
Z_1 = non-distressed if $Y_1, > 0$
Z_1 = distressed, otherwise
x_1 = financial ratios of company
μ_1 = error term
Z_1 ranges from $-\alpha\ to + \alpha$

The probability and likelihood function for the non-distressed can be defined as follows:

$$Pi = E\,(Y = 2|x_1) = \frac{1}{1+e^{-(\beta x_1 + \mu_1)}} \qquad (6)$$

Pi ranges between 0 and 1.

For ease of exposition, normally it is written as

$$Pi = \frac{1}{1+e^{-z_1}}$$

Where $Z_1 = \beta\, x_1 + \mu_1$

Equation (6) signifies what is known as the (cumulative) logistic distribution function. In order to apply the forecasting function, the weights of the financial ratios are estimated in equation (5) using the financial ratios of the selected companies. If Pi represents the probability of non-distressed which is given in equation (6), then $(1 – Pi)$ would be the probability of distressed. Hence,

$$1 - Pi = \frac{1}{1+e^{Z_1}} \qquad (7)$$

Optimal β (weight) can be assessed where the likelihood value is maximized. The probability of distressed is obtained by substituting β into the cumulative probability function. The company is classified as financially distressed if the calculated probability from the LRA model is more than 0.5, otherwise it will be classified as non-distressed (Gujarati 1995). Negative coefficients of ratios in the LRA model specify that these ratios are negatively correlated with the probability of financial distress whereby it decreases the risk of financial distress. For ratio with positive coefficient, it has a positive effect on the probability of financial distress whereby it increases the risk of financial distress. It is necessary to find major explanatory financial ratios that can discriminate between the two groups in order to get reliable results from LRA analysis (Nam and Taehong 2000).

RECEIVER OPERATING CHARACTERISTIC CURVE

Sobehart, Keenan and Stein (2000) explained that the Receiver Operating Characteristics (ROC) curve is broadly used in the arena of medicine to analyse the efficiency of various treatments and diagnostic methods. It is also a popular technique for assessing various rating methodologies (Sobehart, Keenan et al. 2000). They also provided in-depth clarification of how to use the ROC curve to certify internal credit rating models. Their main conclusion is that the area under the curve is an indicator of the quality of the model. Engelmann, Hayden and Tasche (2003) showed that the accuracy ratio is just a linear transformation of the area under the ROC curve (Engelmann, Hayden et al. 2003), i.e.:

Accuracy ratio = 2*(Area under ROC curve – 0.50)

Hanley and McNeil (1982) found Wilcoxon statistic to be an unbiased estimator; and therefore, the area under the ROC curve is estimated using the said statistic. Faraggi and Reiser (2002) compared the estimates of area under the curve using four different techniques and conclude that Wilcoxon statistic is often close to the best as estimator (Faraggi and Reiser 2002). Using the statistic also allows easy assessment of various rating models. Hanley and McNeil (1982) showed that the standard error of area under the ROC curve is given by:

$$se(A) = \sqrt{\frac{A(1-A)+(n_F-1)(Q1-A^2)+(n_{NF}-1)(Q2-A^2)}{n_F n_{NF}}} \qquad (8)$$

where:
A = area under the ROC curve,
n_F = number of financially distressed companies in the sample,
n_{NF} = number of non-financially distressed companies in the sample,
Q1 = A / (2-A), and
Q2 = $2A^2$ / (1+A)

and the test statistic is:

$$Z = \frac{A}{se(A)} \qquad (9)$$

where z is a standard normal variate. Hanley and McNeil (1983) compared the area under the curve for two different models through the following test statistic:

$$Z = \frac{A_1 - A_2}{\sqrt{(se(A_1))^2 + (se(A_2))^2 - 2.r.se(A_1).se(A_2)}} \qquad (10)$$

where z is the standard normal variate and r represents the correlation induced between the two areas under the curve due to application of the two models on the same sample. r is estimated using the following approach (Hanley and McNeil 1983):

1. Calculate the rank correlation between the scores on the two models for failed companies,
2. Calculate the rank correlation between the scores on the two models for non-failed companies,

3. Average the two rank correlations obtained,
4. Average the area under the curve for the two models, and
5. Find the value of *r* from table I of Hanley and McNeil (1983) (Hanley and McNeil 1983; Agarwal and Taffler 2008).

Empirical Findings and Interpretation

SUMMARY STATISTICS

Table 3 presents the summary statistics for probability of financial distress classification generated by each of our three models (MDA, LRA and Merton). The table indicates that the average probability of financial distress for companies that subsequently classified as financially distressed is significantly higher than companies that are not classified as distressed for all the models considered. The result from one year prior to actual event of distress classification indicates that the mean probability of financially distressed companies is within the range of 67% to 75% for accounting-based models. Meanwhile, the market-based model mean for financially distressed companies is only 19%. The results are consistent for all the five years under investigation, whereby the accounting-based models have higher mean compared to market-based model. Agarwal and Taffler (2008) reported in their study that one year prior to default the mean probability of failed companies for accounting-based model is 88%; and for market-based model the mean is between 8% and 16% (Agarwal and Taffler 2008). Bharath and Shumway (2004) reported an overall mean of 10.95% for KMV model in predicting distress probability which is lower than our Merton model mean of 12%. However, poor calibration of mean between mean of financially distressed and non-financially distressed among the models is not relevant in our tests of predictive ability or information content as it does not essentially signify that these models will not carry information about the true probability of distress in cross-section.

Table 4 below presents the correlations between the probability estimates generated by various models. All of the models have positive correlation with one another through all the period under study. The highest correlation one year before the financial distress classification event is between MDA and LRA (0.859) with both models are accounting-based model. The results are consistent for all the five years period under study; whereby the correlation between the accounting-based models is higher than the market-based model. The significantly high correlation between the two accounting-based model estimates indicates that using similar variables to generate the models will not produce material impact on probability estimates even though two different methodologies are used. The results here are similar to those of Bharath and Shumway (2004) and Agarwal and Taffler (2008) who find high correlations among the various specifications they use. The lowest correlation is between accounting-based model (MDA) and market-based model (Merton) at only 0.458, indicating that the two modelling approaches are carrying information incremental to each other. The results are consistent for all years under investigation except for year four prior to distress classification event. The market-based and accounting based financial distress probability estimates are positively correlated with each other, but the moderate magnitudes of the correlations suggest that each

TABLE 3. Summary Statistic

Occurrence	Model	Mean Probability of Default			t-statistic for difference
		All	Default	Non-default	
One year prior to financial distress event	MDA	50%	67%	34%	10.260
	LRA	50%	75%	25%	13.264
	Merton	12%	19%	4%	8.117
Two year prior to financial distress event	MDA	50%	61%	40%	7.546
	LRA	50%	65%	35%	8.232
	Merton	10%	15%	5%	4.620
Three year prior to financial distress event	MDA	50%	55%	45%	4.960
	LRA	50%	62%	38%	7.015
	Merton	8%	10%	5%	3.690
Four year prior to financial distress event	MDA	49%	58%	39%	7.076
	LRA	50%	63%	37%	7.903
	Merton	7%	10%	3%	5.437
Five year prior to financial distress event	MDA	50%	60%	39%	6.633
	LRA	50%	62%	38%	6.891
	Merton	5%	8%	2%	4.167

TABLE 4. Pearson Correlation Matrix

Occurrence	Model	p(MDA)	p(LRA)	p(Merton)
One year prior to financial distress event	p(MDA)	1	0.859**	0.458**
	p(LRA)	0.859**	1	0.552**
	p(Merton)	0.458**	0.552**	1
Two year prior to financial distress event	p(MDA)	1	0.883**	0.377**
	p(LRA)	0.883**	1	0.404**
	p(Merton)	0.377**	0.404**	1
Three year prior to financial distress event	p(MDA)	1	.726**	.322**
	p(LRA)	.726**	1	.436**
	p(Merton)	.322**	.436**	1
Four year prior to financial distress event	p(MDA)	1	0.940**	0.439**
	p(LRA)	0.940**	1	0.415**
	p(Merton)	0.439**	0.415**	1
Five year prior to financial distress event	p(MDA)	1	0.965**	0.281**
	p(LRA)	0.965**	1	0.282**
	p(Merton)	0.281**	0.282**	1

**. Correlation is significant at the 0.01 level (2-tailed)

financial distress probability estimate may be reflecting different information about the probability of financial distress. The result is consistent for all the five-year period under investigation.

TEST OF PREDICTIVE ABILITY

Figure 1 below presents the ROC curves for the market-based model (Merton) and the accounting-based models (MDA and LRA). From Figure 1, it clearly indicates two things: (i) there is only small difference between MDA and Merton model (ii) the accounting-based models especially the LRA has a slightly larger area under the ROC curve than the market-based model, indicating marginal LRA superiority. Figure 2 to 5 show that no clear conclusion can be drawn from the ROC curve beyond the period of one year under study because all the lines of the curve that represent the models do not indicate difference from each other.

Summary statistics for all the models along with random variables such as asset value, asset volatility, distance to default, return on equity (ROE), working capital to total assets (WCTA), retained earnings to total assets (RETA), earnings before interest and tax to total assets (EBITTA), book value of equity to total liabilities (BVETL) and market value of equity to total liabilities (MVETL) are presented in Table 5 below. It

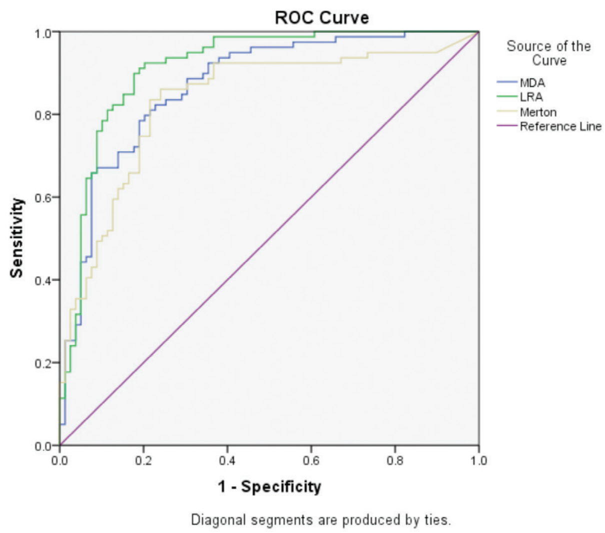


FIGURE 1. ROC Curves One Year before Actual Event of Distress Classification

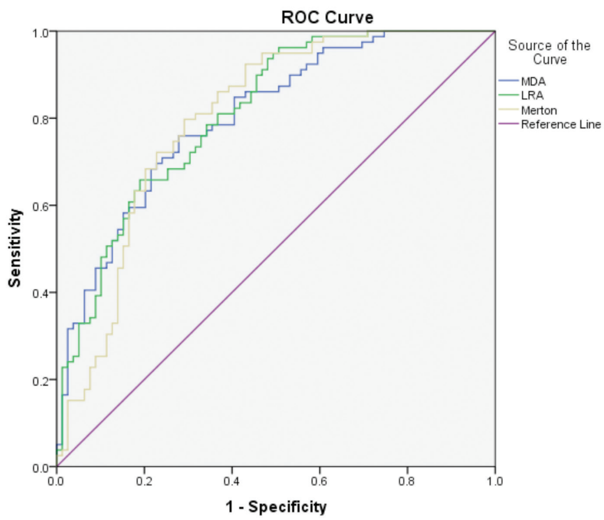


FIGURE 2. ROC Curves Two Year before Actual Event of Distress Classification

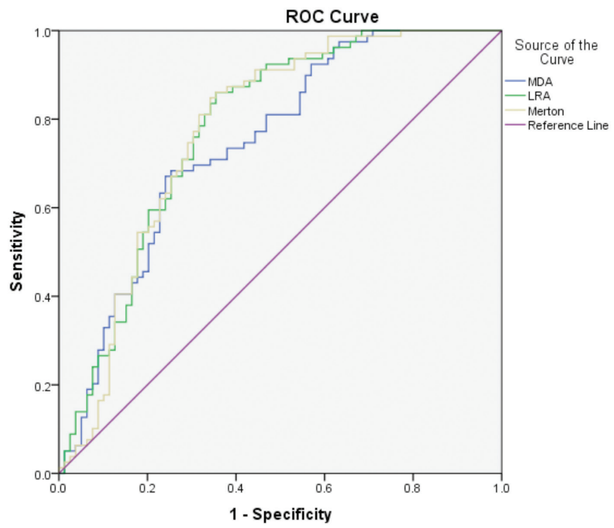


FIGURE 3. ROC Curves Three Year before Actual Event of Distress Classification

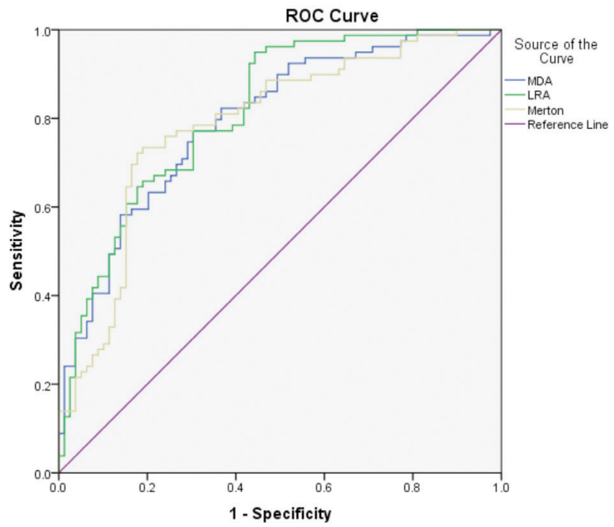


FIGURE 4. ROC Curves Four Year before Actual Event of Distress Classification

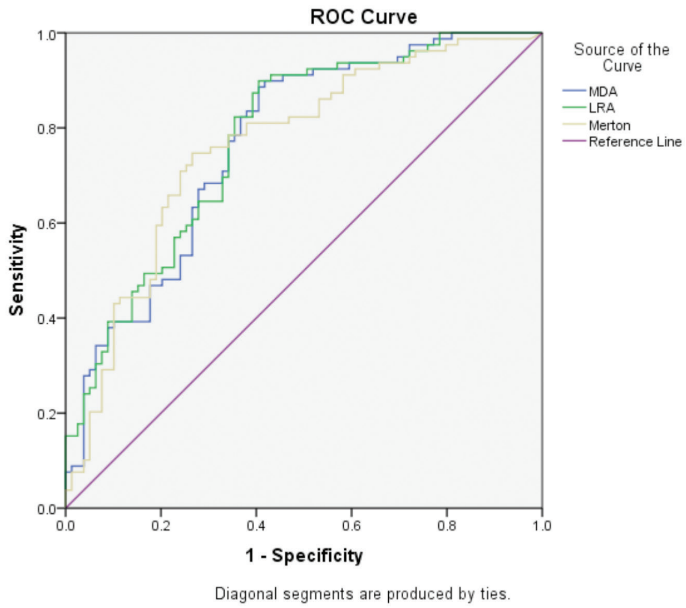


FIGURE 5. ROC Curves Five Year before Actual Event of Distress Classification

shows that each of the models does a better job at predicting financial distress than the simple variables. Among the three models, LRA has the highest accuracy for all the five years under investigation. Both the accounting-based models performed better than the market-based model in all periods under investigation except for year three before the actual event of financial distress classification. All the three models (LRA, MDA and Merton) performed better than the random variables through the five year period under investigation. The areas under the curves reported in the table below indicate a favourable result compared with those reported by Agarwal and Taffler (2008).

To test whether the LRA model is significantly better than the market-based model (Merton) and the other accounting-based model (MDA), the area under the ROC curve for the LRA model is again compared against Merton and MDA model using equation (10). The LRA model significantly outperforms the Merton model (with z = 2.2). Meanwhile, there is no significant difference between the performances of the LRA against MDA (with z = -1.68). Result for MDA against Merton model as indicates by Table 6 (with z = 0.9) also shows that there is no significant difference between MDA and Merton model. For the period of second to fifth year before the actual event of distress classification, we find no significant difference from all the three models.

CONCLUSION

Our study aims to compare the reliability of the accounting-based models with market-based model by evaluating the

TABLE 5. Area under the Curve (AUC) and Accuracy Ratio (AR) -

One year prior to actual event of distress classification			
	AUC	SE	AR
MDA	0.870	0.028	0.740
LRA	0.914	0.024	0.828
Merton	0.833	0.034	0.666
Asset Value	0.454	0.046	-0.093
Asset Volatility	0.255	0.040	-0.489
Distance to Default	0.170	0.034	-0.661
ROE	0.234	0.042	-0.531
WCTA	0.153	0.032	-0.694
RETA	0.154	0.032	-0.691
EBITTA	0.157	0.032	-0.686
BVETL	0.173	0.032	-0.654
MVETL	0.099	0.025	-0.801
Two year prior to actual event of distress classification			
	AUC	SE	AR
MDA	0.803	0.034	0.606
LRA	0.810	0.034	0.619
Merton	0.801	0.036	0.602
Asset Value	0.494	0.046	-0.012
Asset Volatility	0.277	0.042	-0.447
Distance to Default	0.199	0.036	-0.602
ROE	0.217	0.038	-0.565
WCTA	0.263	0.039	-0.474
RETA	0.249	0.040	-0.503
EBITTA	0.266	0.040	-0.469
BVETL	0.214	0.036	-0.571
MVETL	0.151	0.031	-0.698
Three Year prior to actual event of distress classification			
	AUC	SE	AR
MDA	0.746	0.039	0.491
LRA	0.779	0.038	0.557
Merton	0.775	0.039	0.549
Asset Value	0.503	0.046	0.007
Asset Volatility	0.254	0.040	-0.492
Distance to Default	0.225	0.039	-0.549
ROE	0.246	0.039	-0.507
WCTA	0.280	0.041	-0.439
RETA	0.299	0.042	-0.403
EBITTA	0.263	0.040	-0.474
BVETL	0.243	0.039	-0.515
MVETL	0.170	0.032	-0.660
Four year prior to actual event of distress classification			
	AUC	SE	AR
MDA	0.795	0.035	0.589
LRA	0.814	0.033	0.628
Merton	0.787	0.037	0.574
Asset Value	0.524	0.046	0.048
Asset Volatility	0.301	0.042	-0.397
Distance to Default	0.213	0.037	-0.574
ROE	0.247	0.038	-0.507
WCTA	0.332	0.043	-0.336
RETA	0.302	0.043	-0.397
EBITTA	0.264	0.039	-0.473
BVETL	0.242	0.039	-0.516
MVETL	0.170	0.033	-0.659
Five year prior to actual event of distress classification			
	AUC	SE	AR
MDA	0.769	0.037	0.538
LRA	0.776	0.037	0.553
Merton	0.763	0.038	0.525
Asset Value	0.530	0.046	0.061
Asset Volatility	0.316	0.042	-0.367
Distance to Default	0.237	0.038	-0.526
ROE	0.280	0.041	-0.440
WCTA	0.370	0.045	-0.259
RETA	0.356	0.045	-0.289
EBITTA	0.301	0.041	-0.399
BVETL	0.282	0.041	-0.436
MVETL	0.228	0.037	-0.545

TABLE 6. Variables to test for significance of difference between area under the ROC Curve

Occurrence		Rank Correlation between probability estimate for: Distress	Rank Correlation between probability estimate for: Non-distress	Average Correlation	Average Area Under the Curve	Corre-sponding r	Critical ratio z
One year prior to financial distress event	p(MDA) vs p(LRA)	0.506	0.681	0.594	0.892	0.51	-1.6823
	p(MDA) vs p(Merton)	-0.032	0.486	0.227	0.852	0.18	0.9254
	p(LRA) vs p(Merton)	0.032	0.544	0.288	0.874	0.22	2.2097
Two year prior to financial distress event	p(MDA) vs p(LRA)	0.578	0.752	0.665	0.806	0.6	-0.2166
	p(MDA) vs p(Merton)	0.152	0.459	0.306	0.802	0.26	0.0488
	p(LRA) vs p(Merton)	0.139	0.545	0.342	0.805	0.3	0.2101
Three year prior to financial distress event	p(MDA) vs p(LRA)	0.505	0.604	0.555	0.762	0.5	-0.8612
	p(MDA) vs p(Merton)	0.017	0.471	0.244	0.760	0.21	-0.5947
	p(LRA) vs p(Merton)	0.067	0.652	0.360	0.777	0.32	0.0904
Four year prior to financial distress event	p(MDA) vs p(LRA)	0.814	0.744	0.779	0.804	0.74	-0.7816
	p(MDA) vs p(Merton)	0.272	0.430	0.351	0.791	0.3	0.1764
	p(LRA) vs p(Merton)	0.253	0.446	0.350	0.801	0.31	0.6498
Five year prior to financial distress event	p(MDA) vs p(LRA)	0.919	0.871	0.895	0.773	0.85	-0.3710
	p(MDA) vs p(Merton)	0.127	0.454	0.290	0.766	0.25	0.1311
	p(LRA) vs p(Merton)	0.103	0.417	0.260	0.770	0.23	0.2923

financial distress probability through the ROC curve. To obtain the financial distress probability for accounting-based models, we employed MDA and LRA. For market-based model, we adopted the modified Merton model. Our study applied to the models a sample of one hundred and fifty eight Malaysian public listed companies from six different business sectors. The empirical results of year one, two, four and five before the actual event of financial distress classification indicate that both the accounting-based models (MDA and LRA) performed better compared to market-based model. However, only LRA model in year one was found to have significant different performance compared to Merton model. Test on the accuracy ratio also indicated that LRA achieves the highest accuracy in all years under investigation. This study also found no conclusive evidence in comparing the accuracy of the three models beyond one year before the actual event of financial distress classification. This is mainly due to the sign of financial deteriorating of the companies is yet to be reflected in the variables of our models beyond the period of one year before financial distress event.

Our finding is contradictory to the findings by Hillegeist et al. (2004) and Gharghori, Chan and Faff (2006) who found market-based model is superior than accounting-based model (Hillegeist, Keating et al. 2004; Gharghori, Chan et al. 2006). This is mainly due to the accounting-based models used by them (Altman's 1968 model and Ohlson's 1980 model) are outdated and contain many weaknesses as addressed in the literature. Our accounting-based models were generated by using the up-to-date methodology and the result is consistent with Reisz and Perlich (2007) and Agarwal and Taffler (2008) who found accounting-based model to be superior than market-based model (Reisz and Perlich 2007; Agarwal and Taffler 2008).

While market-based models are theoretically attractive, their inferior empirical performance should not be shocking. Hillegeist et al. (2004) recommended two essential problems with Merton's (1974) contingent claims approach: (i) mis-specification due to the restrictive assumptions of the model (for example, single class of zero coupon debt, all liabilities mature in one-year, bankruptcy is costless, there is no safety covenants, default triggered only at maturity), and (ii) quantifying errors (mainly because assets value and assets volatility cannot be obtained directly from the market).

Although the accounting-ratio based methodology is criticized for its lack of theoretical foundation, it has few things in its favour: (i) financial distress or corporate bankruptcy is generally not an instant incident. Company that reported a good profit with strong balance sheet seldom files for bankruptcy because of sudden change in the economic environment. Normally, bankruptcy is the accumulation of few years of bad financial performance and, therefore, will be reflected by the company's financial statements. (ii) The accounting system and accounting standards adopted by the company will ensure that window dressing or change in accounting policies will have minimal impact on the measurement of company financial statements. (iii) Lastly, loan contracts are commonly based on accounting numbers and this information is generally reflected in accounting-ratio based models. Caouette, Altman and Narayanan (1998) concluded that a conceptual model that does not perform has no advantage over a statistical model that does (Caouette, Altman et al. 1998).

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