A Comparison of Corporate Bankruptcy Models in Australia: the Merton vs Accounting-based Models

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Abstract

Actuaries have long employed logistic type regression models in their analysis of renewal rates for property and casualty insurance products. This paper introduces an application of such methodology to the prediction of corporate bankruptcy. This is an example of a wider-field area of endeavour where actuaries have the potential to add real value. The results presented in the paper have implications for levels of risk-based capital to be held by insurers and other financial organizations. This paper examines how effectively the default likelihood indicator (DLI) estimated from the Merton model can predict corporate bankruptcy in Australia during 1990-2003. In addition, the performance of the Merton model and the three most popular bankruptcy models i.e. Altman (1968), Zmijewski (1984), and Shumway (2001) are also compared. Our findings suggest that the Merton model is the most informative model in explaining corporate bankruptcy, followed by the Shumway model. Among accounting and market-based variables in bankruptcy models, only two variables, namely the ratio of total liabilities to total assets (TL/TA) and the idiosyncratic standard deviation of stock returns (σ) are most significant in predicting corporate bankruptcy. Finally, the results from our comparative study of bankruptcy prediction models suggest developing a multivariable logistic regression model which includes both financial ratios and Merton's default likelihood indicator as predictors. We assess the predictive ability of this model by comparing 95% confidence intervals for the predicted probability of default for firms that default and firms that are not observed to default.

Keywords: Default risk, risk-based capital, financial reporting.

1. Introduction

Corporate bankruptcy has received much attention from academics and practitioners since the seminal work by Beaver (1966). Most previous studies have relied on financial data to quantify corporate bankruptcy, for example Altman (1968), Ohlson (1980), and Zmijewski (1984) to name just a few. Recently, Shumway (2001) employs market-driven variables as well as financial ratios in his study. However, only a few studies such as Bongini et al. (2002), and Hillegeist et al. (2004) employ the Merton model to predict corporate bankruptcy. It appears that only Gharghori et al. (2007) have used the Merton model to predict corporate bankruptcy in an Australian context.

Moreover, recent studies, like Vassalou and Xing (2004), indicate that the default probabilities estimated from the Merton model are superior to traditional accounting-based models in explaining the credit ratings of corporate firms.[1] Because the Merton model has been perceived as a forward-looking model, the model performance in predicting corporate bankruptcy is likely to be more favorable than traditional accounting-based models.[2]

This study proposes to examine how effectively the Merton model can explain corporate bankruptcy in Australia. Moreover, the study empirically compares the performance of the Merton model with the other three well-cited bankruptcy models. Specifically, sets of financial variables from Altman (1968), Zmijewski (1984), and Shumway (2001) as well as the default likelihood indicator (DLI) computed by the Merton model are used as explanatory variables in the study to quantify corporate failure. Using logistic regression analysis, the parameters of each

[1] Tanthanongsakkun and Treepongkaruna (2007) also report that the Merton based model is superior to the traditional accounting based model in an Australian context.
[2] In this paper, we use the following words interchangeably: financial distress, bankruptcy, default, insolvency and failure.

bankruptcy model are estimated. Our main findings indicate that the DLI computed from the Merton model has the most explanatory power in predicting corporate bankruptcy in Australia. In addition, the results tend to suggest that market-based variables are more useful than accounting variables in explaining the likelihood of corporate bankruptcy. The ratio of total liabilities to total assets is easily the most significant financial ratio in explaining bankruptcy in Australia.

Our modeling of Australian corporate bankruptcy suggests that the inclusion of financial ratios, market variables and the Merton model default likelihood indicator in a single multivariable logit model may yield a model with superior predictive ability. We develop such a model and test its predictive ability. We find that this model, allowing for the fact that is has significantly greater complexity, does not perform sufficiently better than the Merton model to warrant its use.

The remainder of this paper is organized as follows. Section 2 provides a review of related literature. Section 3 outlines methodology. Section 4 describes data and preliminary results. Section 5 discusses empirical results. Section 6 concludes.

2. A Review of Related Literature

We review the relevant literature in two parts. First we describe studies that have incorporated the Merton model in predicting corporate bankruptcy. Second, we review Australian studies of corporate bankruptcy.

A. The Merton Model and Corporate Bankruptcy

Bongini et al. (2002) empirically examine bank fragility in East Asian countries during the Asian financial crisis from 1996 to 1998. The study uses three sets of indicators in forecasting bank failure during this period. The three sets of indicators include changes in bank credit ratings, deposit insurance premiums, and balance sheet data. Changes in credit ratings have clear implications for bankruptcy prediction, see for example Lando and Skodeberg (2002). Insurance premiums are the rate per dollar of deposits that banks pay to a government agency insuring depositors in the case of bank insolvency. Generally banks with higher perceived risk of default will pay higher deposit insurance premiums. Their study employs the structural model of Merton (1977)[3], which is an extension of the celebrated Black and Scholes (1973) and Merton (1974) option pricing models, to estimate the deposit insurance premiums. The study also uses five financial variables derived from the balance sheet. These so called "CAMEL" ratios, which measure bank healthiness relate to capital adequacy, asset quality, management quality, earnings, and liquidity. After controlling for macroeconomic factors and bank size, they find that none of the three indicators has strong predictive power in forecasting bank failure.

In contrast, the study by Hillegeist et al. (2004), which investigates the likelihood of corporate bankruptcy in the U.S. market, finds that the probability of default estimated from the Black-Scholes-Merton model provides significantly more information than those of the two accounting-based bankruptcy models, namely Altman (1968) and Ohlson (1980). Unlike previous bankruptcy studies that rely on forecasting accuracy test to examine model performance, the study employs relative information content tests to compare the out-of-sample performance of each bankruptcy model. By using a sample of 78,100 firm-year observations and 756 initial bankruptcies during 1980-2000, log likelihood ratio tests indicate that the default probability estimated from the structural model contains significantly more information in forecasting bankruptcy than any of the accounting-based bankruptcy models. Moreover, a comparison of each model Psuedo-R^2 shows that structural model outperforms the original Z-score and O-score models by 71 percent and 33 percent respectively.

[3] The insurance premiums can be viewed as a put option on the values of the bank's assets. If values of the bank's assets are below its liabilities, a bank will be taken over by a government agency.

B. Australian Studies of Corporate Bankruptcy

Castagna and Matolcsy (1980) are the first to examine corporate failure using Australian data. The sample consists of 21 insolvent companies which are matched to 21 surviving companies during 1963-1977. The study employs ten financial ratios suggested in previous studies, in particular Altman (1977), as explanatory variables. These ratios reflect measures of profitability, liquidity, coverage and leverage, and capitalization. By applying linear and quadratic discriminant analysis, the results of one year before failure show that the model can correctly predict ranging from 62-90 percent, and 95-100 percent for failed and non-failed companies respectively. This study also emphasizes the importance of a specified utility function when attempting to derive an optimal bankruptcy model. The relative importance of Type I errors, Type II errors and the overall error rate need to be specified.

Later studies by Izan (1984) and Lincoln (1984) also employ discriminant analysis to predict financial distress in Australia. Lincoln (1984) examines the insolvency of corporate companies in four major industries i.e. manufacturing, retailing, property and finance during 1969-1978. With a sample of 41 failed and 90 industry-matched, non-failed companies, many combinations of financial ratios are assessed. Moreover, he tests for industry effects by examining classification accuracy in six different sample construction strategies. These include a general model with firms from all four industries; two distinct models comprising of manufacturing-retailing companies, and property-finance companies; and separate models for all three industries[4]. Overall, the results show that the predictive accuracy of the models in manufacturing and retailing industries are high, but quite low for the property and finance industries. Unlike the previous studies that use traditional raw financial ratios, Izan (1984) suggests the use of industry relative financial ratios in quantifying the corporate failure. This is an attempt to reduce the impact of financial ratio differences across industries. By using a larger initial sample that consists of 53 failed and 50

[4] Because there are only four failed observations in the finance industry, the single-industry model for finance industry is not constructed.

non-failed firms during 1963-1979, the results suggest that the predictive accuracy using industry-relative variables is higher than that obtained using raw financial ratios. In addition, the results of one year before failure prediction shows that the model employing industry-relative variables can perfectly classify the failed firms in the out-of-sample test.

Yim and Mitchell (2002) perform a comparison of corporate failure models in Australia. By using the initial sample of 20 failed and 80 non-failed firms during 1995-1999, the study compares the predictive accuracy of three bankruptcy models: artificial neural network (ANN), logit model, and discriminant analysis. The results suggest that hybrid neural networks outperform all other models one and two years before failure.

3. Methodology

This paper adopts the multiple-period logit model to predict corporate bankruptcy. While multivariable discriminant analysis (MDA) has disadvantages[5], the coefficient estimates of the static single-period logit model are also biased and inconsistent. As noted by Shumway (2001) and Hillegeist et al. (2004), the sample selection bias of the static single-period logit model arises from the fact that bankrupt firms are non-randomly included in the sample with only one observation. By doing this, the data on healthy firms that eventually go bankrupt are ignored. Moreover, the model is unable to measure the time-varying changes of firm characteristics. Thus, the multiple-period logit model that allows the use of multiple firm-year observations for nonbankrupt firms is more favorable.

The multiple-period logit model is a binary dependent variable model. The dependent variable, Y_i, takes the value 1 if firm i is bankrupt, and 0 otherwise:

[5] The use of MDA models in analyzing bond ratings also has been criticized about the problem of distributional assumptions on the independent variables e.g. Kaplan and Urwitz (1979) and the inability to screen out insignificant variables through tests of significance on explanatory variables.

$$Y_i = \begin{cases} 1 & \text{if firm } i \text{ is bankrupt} \\ 0 & \text{otherwise} \end{cases}. \quad (1)$$

To relate the dependent variable with observed explanatory variables, a linear relationship between an unobserved latent variable, Y_i^* and explanatory variables is defined as follows:

$$Y_i^* = \alpha + X_i^{'}\beta + \varepsilon_i, \quad (2)$$

where α is a constant term, X_i is the vector of explanatory variables, β is the vector of estimated parameters, and ε_i is the standardized logistic error term. Therefore, a default probability estimated from the model can be written as follows:

$$\text{Prob}(Y_i = 1 \mid X_i) = \frac{e^{\alpha + X_i^{'}\beta}}{1 + e^{\alpha + X_i^{'}\beta}}. \quad (3)$$

Although the multiple-period logit model that includes all firm-year observations eliminates the problem of sample selection bias, the inclusion of multiple observations from the same firm in the regression can violate an assumption of independence among all observations and therefore underestimates the standard errors of reported parameter estimates. As suggested by Altman and Rijken (2004), and Hillegeist et al. (2004), Z-statistics of coefficients are calculated using Huber-White standard errors[6]. The parameters α, and β are estimated using the maximum likelihood procedure.

4. The Data and Preliminary Results

A. Sample

Our sample contains companies listed on the Australian Stock Exchange (ASX) during 1990-2003. Bankruptcy data is collected from two sources: The website of *www.delisted.com.au* and *Delisted Companies (1900-2003)* by Financial Analysis Publications. These two sources provide

[6] See Rogers (1993) for more discussions of Huber-White standard errors.

information on delisting reasons and significant events. The study defines corporate bankruptcy in the strict legal sense. Therefore, firms are defined as bankrupt if they are in administration, receivership, or liquidation. To compute financial ratios, Aspect Fin Analysis and/or Aspect Dat Analysis are used to obtain the financial statements. All stock prices (total return index) and their market values are collected from Thomson Financial Datastream. Due to the incompatibility of accounting standards, the companies from the banking, insurance, and financial sectors are excluded. Firms with incomplete data are also deleted. In total, the final sample contains 6,530 firm-year observations including 93 bankruptcies from 1,144 firms during 1990-2003.

B. Variables

This study uses sets of financial variables from three well-cited bankruptcy models i.e. Altman (1968), Zmijewski (1984), and Shumway (2001) to predict the likelihood of corporate bankruptcy. In addition, the default likelihood indicator (DLI) estimated from the Merton model is proposed as a potential explanatory variable to quantify corporate bankruptcy.

Altman (1968), the Z-score model, measures the financial distress of industrial firms using five financial ratios, namely, working capital to total assets (WC/TA), retained earnings to total assets (RE/TA), earnings before interest and taxes to total assets (EBIT/TA), market value of equity to total liabilities (MV/TL), and sales to total assets (Sales/TA)[7]. Zmisjeski (1984) employs only three financial ratios as independent variables in his study to predict firm bankruptcy. The three financial variables are total liabilities to total assets (TL/TA), current assets to current liabilities (CA/CL), and net income to total assets (NI/TA). Unlike the previous two models, Shumway (2001) estimates corporate bankruptcy by using two financial ratios from Zmijewski (1984) i.e. total liabilities to total assets (TL/TA) and net income to total assets (NI/TA) as well as three market-driven variables: the relative firm size (Rel-Size), the past year excess returns (Ri-Rm), and the idiosyncratic standard deviation of stock returns (Sigma).

[7] The original paper employs multivariable discriminant analyis as the statistical approach to obtain the coefficients.

Unlike healthy firms, firms with financial difficulties are unlikely to release their financial statements on time. To ensure that the financial statements of all firms are observable at the time of variable calculation, we follow Shumway (2001) by assuming a six-month gap after a fiscal year-end. Therefore, market-driven variables and the DLI are also estimated at this point of time (six months after fiscal year-end). The relative firm size (Rel-Size) is measured by the natural logarithm of a firm's market capitalization to the total market capitalization of ASX. It should be noted that the estimates of Rel-Size are negative because they are the natural logarithm of small fractions. The past year stock performance (Ri-Rm) is the difference between the firm's return and the return achieved on the value-weighted ASX index in the previous year. Each firm's annual returns are computed by accumulating monthly returns. The idiosyncratic standard deviation of stock returns (Sigma) is the standard deviation of the residual from the regression of monthly individual stock returns on value-weighted market returns. The DLI is estimated using the method described in Vassalou and Xing (2004).

Specifically, we follow Vassalou and Xing (2004) by assuming that the market value of the firm's assets follows a geometric Brownian motion. Hence the firm's market value can be written in the form:

$$dV_A = \mu V_A dt + \sigma_A V_A dW, \tag{4}$$

where V_A is the market value of firm's assets, μ is the instantaneous drift rate of return on the firm's assets, σ_A is the instantaneous volatility of the returns on firm's assets, and W is a standard Wiener process.

As the market equity of a firm can be viewed as a call option on the firm's assets with strike price equal to its book value of the liabilities, at maturity, the value of equity will be equal to the difference between the market value of the firm's assets and the book value of the firm's liabilities. According to Black and Scholes (1973), the market value of equity can be written as:

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2), \tag{5}$$

$$d_1 = \frac{\ln(V_A / X) + (r + 0.5\sigma_A^2)T}{\sigma_A \sqrt{T}} \tag{5a}$$

$$d_2 = d_1 - \sigma_A \sqrt{T} \tag{2b}$$

where V_E is the market value of equity, X is the book value of liabilities, r is the risk-free rate, T is time to maturity, and $N(.)$ is the cumulative standard normal distribution function.

To estimate the volatility of firm's assets (σ_A), an iterative procedure is employed. At the end of each month, using the past 12 months of daily equity returns, the volatility of equity returns (σ_E) is estimated and used as an initial value of the volatility of returns on firm assets (σ_A). Therefore, for each day in the past 12 month period, the market value of the firm's assets (V_A) can be computed from equation (5). The standard deviation of returns on firm assets (σ_A) is then re-estimated and used for the new iteration. The procedure is repeated until the values of the volatility of returns on firm assets (σ_A) from two consecutive iterations converge. By keeping the estimation window equal to 12 months, the estimation of the volatility of return on firm assets (σ_A) is repeated at the end of every month. The estimates of monthly volatility of the firm's assets and market value of the firm's assets can be obtained.

From the assumption of the distribution function of firm's assets, the drift term (μ) can be obtained by calculating the mean of the changes of the natural logarithm of firm's assets. Equation (4) together with Ito's lemma imply that the change in the natural logarithm of the firm's assets between time t and T is normally distributed. Specifically,

$$\ln(V_{A,t+T}) - \ln(V_{A,t}) \sim N\left[(\mu - 0.5\sigma_A^2)T, \sigma_A \sqrt{T}\right]. \tag{6}$$

Hence, the expected value and standard deviation of the natural logarithm of firm's assets at time T is:

$$\ln(V_{A,t+T}) \sim N\left[\ln(V_{A,t}) + (\mu - 0.5\sigma_A^2)T, \sigma_A \sqrt{T}\right]. \tag{7}$$

The default probability is the probability that the value of firm's assets is less than firm's liabilities and hence can be written as follows:

$$P_{def,t} = \text{Prob}\left(\ln(V_{A,t}) - \ln(X_t) + (\mu - 0.5\sigma_A^2)T + \sigma_A \sqrt{T}\varepsilon_{t+T} \leq 0\right) \tag{8}$$

$$P_{def,t} = \text{Prob}\left(-\frac{\ln(V_{A,t} / X_t) + (\mu - 0.5\sigma_A^2)T}{\sigma_A \sqrt{T}} \geq \varepsilon_{t+T}\right). \tag{9}$$

Following Vassalou and Xing (2004), we define the distance to default (DD)[8]as follows:

$$DD_t = \frac{\ln(V_{A,t} / X_t) + (\mu - 0.5\sigma_A^2)T}{\sigma_A \sqrt{T}}. \tag{10}$$

Finally, theoretical probability of default can be written as:

$$P_{def,t} = N(-DD_t) = N\left(-\frac{\ln(V_{A,t} / X_t) + (\mu - 0.5\sigma_A^2)T}{\sigma_A \sqrt{T}}\right). \tag{11}$$

Structural models have gained increasing acceptance not only in academic but also in commercial areas. In 1995, the KMV Corporation[9] has launched a default prediction model (the Credit Monitor Model) that produces and updates default predictions for most companies that are listed on stock markets. The KMV model is conceptually the same as the Merton (1974) model. Given the market value of assets and debt obligation, and a calculated volatility of asset returns (σ_A), the default probability or expected default frequency (EDF™) can be calculated for each corporate firm. Because KMV has obtained a large database containing the default incidents, the estimate of the EDF is based on the empirical distribution of defaults.

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[8] The distance to default which is defined by Vasaalou and Xing (2004) differs from the one used in KMV as follows: DD=(Market Value of Firm's Assets-Default Point)/(Market Value of Firm's Assets x Asset Volatility).

[9] KMV Corporation has been merged with Moody's Investor and has become Moody's KMV.

Vassalou and Xing (2004) note that the probability of default calculated from equation (11) is the theoretical probability of default. The default probability, the so called the Expected Default Frequency (EDF™), estimated by KMV is the true default probability because KMV has obtained a large database containing the default incidents which can be used to estimate the empirical distribution of defaults. Hence, the probability of default calculated by equation (11) will be called the default likelihood indicator instead (DLI)[10]. As can be seen from (11), the DLI of a firm has a positive nonlinear relation with the default probability computed from the KMV model. Moreover, the time to maturity is set at 1 year.

Table 1 reports summary statistics for the potential explanatory variables used in the study. It should be noted that there are a number of extreme values among the observations of raw financial ratios, especially MV/TL and CA/CL. To ensure that statistical results are not heavily influenced by the outliers, we follow the Shumway (2001) treatment of outliers. Any observation higher than the ninety-ninth percentile of each variable is set to that value. Similarly, observations lower than the first percentile of each independent variable are truncated in the same manner.

C. Preliminary Results

Panels A and B of Table 1 report the summary statistics of all independent variable observations for both non-default and default firms, respectively. In general, the findings are in line with our expectation. That is, there are different characteristics of explanatory variables between non-default and default groups. A comparison of the means and medians for the two groups suggest that firms in the default group are more likely to have higher DLI, smaller firm size, higher volatility of equity returns, and lower excess returns than firms in the non-default group. In

[10] It is interesting to note that the DLI's formula is very similar to that of the risk–neutral default probability which is equal to $N(-d_2)$. The risk–neutral default probability can be obtained by substituting the drift term (μ) with a risk-free rate (r) in equation (11).

addition, nonbankrupt firms tend to have higher liquidity, lower debt leverage, higher profitability, and higher capital than bankrupt firms. Moreover, the equality of mean tests of all independent variables confirm that the mean differences between two groups for all independent variables are statistically different from zero except for MV/TL and CA/CL. It is surprising that the mean and median of Sales/TA in the default group are higher than those of the non-default group. In addition, the equality of means test also shows that the mean difference between the two groups of Sales/TA is statistically different from zero. The result may arise from the fact that firms which are close to bankruptcy have inadequate liquidity, and therefore have to service their debt by selling their assets. This would cause a rapid drop of firms' total assets at the fiscal year-end balance sheet and a consequent increase in firm revenue.

In the case of MV/TL and CA/CL ratios, it is not surprising that the differences between the means of MV/TL and CA/CL are not statistically significant although there are rather large differences between the means. Specifically, the means of MV/TL, and CA/CL equal to 27.6754 and 7.0702 for the non-default group whereas their means are 1.6681 and 1.6945 for the default group. This can be explained by very high variations of the two financial ratios in Panel A of table 1: their standard deviations are high at 179.6985 and 26.7137 respectively. Moreover, the average of MV/TL for the bankrupt group at 1.6681 should be interpreted with caution. If the market value of equity is higher than total liabilities (MV/TL>1), a firm is less likely to be bankrupt. As can be seen Table 1, the mean and the median of MV/TL ratio are quite significantly different. Therefore, the high average of MV/TL ratio is influenced by some extreme value observations. These outliers can have their market equity 45 times as high as the total liabilities. These observations with high MV/TL ratios are verified in the bankrupt sample. The findings show that market equities of some default firms are relatively much higher than their liabilities at the time of ratio calculation and then subsequently plunge before bankruptcy announcements.

It is also interesting to note that there are some very high DLI observations for non-default observations in Panel A of table 1: its maximum reaches the ceiling at 100 percent. After investigating these high DLI observations, the study finds that most high-default-risk firms are eventually taken over, or are in business restructuring, debt restructuring and/or recapitalization processes. This could be evidence that the DLI, estimated by the Merton model, is a good indicator in predicting the financial distress of firms.

Tables 2a and 2b present the correlation matrices of all explanatory variables in the non-default and default groups, respectively. In general, correlations between the variables in both groups are not significantly different. It is found that the DLI is highly correlated with Sigma. Because Sigma positively relates to the volatility of asset returns[11], the positive correlation between the two variables can be explained by the formula of default probability estimated from the Merton model. In addition, DLI is positively correlated with total liabilities to total assets (TL/TA). The explanation for this positive correlation is logically obvious because liabilities are a key input to the Merton model. However, the magnitudes of the correlations in both the non-default and default groups are rather different. It seems that TL/TA ratio in the non-default group is less correlated with DLI. This may arise from the fact that firms in the non-default group have much lower leverage than those in the default group. When leverage is low at a certain level, marginal changes in debt levels hardly affect DLI estimates and therefore lead to the low correlation between DLI and TL/TA. In addition, it seems that there are some high correlations between financial ratios i.e. WC/TA-CA/CL, RE/TA-NI/TA, and EBIT/TA-NI/TA. Specifically, the correlations between these variable are about 0.52-0.82 and 0.74-0.83 for nonbankrupt and bankrupt firms respectively. The high correlations are due to the interrelation between the variables. Moreover, it seems that the correlations between these financial ratios for bankrupt firms are higher than those of nonbankrupt firms.

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[11] As discussed in Merton (1974), it can be shown that the standard deviation of equity returns (σ_E) is positively related to the volatility of asset returns (σ_A) as follows: $\sigma_E = \sigma_A V_A N(d_1)/V_E$.

Table 1: Summary Statistics

The table reports the sample statistics of independent variables used in predicting the bankruptcies of firms. The final sample consists of 6,530 firm-year observations from 1,144 firms including 93 bankrupt firms during 1990-2003. In Panel A, the summary statistics of non-default sample are presented. The summary statistics of default firm sample are reported in Panel B. All explanatory variables are the default likelihood indicator (DLI), relative size (Rel-Size), idiosyncratic standard deviation of returns (Sigma), past year performance (Ri-Rm), and eight financial ratios: working capital to total assets (WC/TA), retained earnings to total assets (RE/TA), earnings before interest and taxes to total assets (EBIT/TA), market value of equity to total liabilities (MV/TL), sales to total assets (Sales/TA), total liabilities to total assets (TL/TA), current assets to current liabilities (CA/CL) and net income to total assets (NI/TA). *, ** indicate that the difference between the means of non-default and default groups is statistically significant from zero at 1%, and 5% respectively.

	DLI	Rel-Size	Sigma	Ri-Rm	WC/TA	RE/TA	EBIT/TA	MV/TL	Sales/TA	TL/TA	CA/CL	NI/TA
Panel A: Non-Default												
Mean	0.1270	-9.4483	0.1598	-0.1076	0.1688	-1.1516	-0.0852	27.6754	0.8059	0.3725	7.0722	-0.1724
Meadian	0.0042	-9.8823	0.1327	-0.0732	0.1280	-0.1752	0.0090	2.9872	0.4946	0.3697	1.6755	-0.0060
Max	1.0000	-1.7108	3.3506	6.8685	0.9987	0.8562	0.7895	12,066.32	37.2298	9.4371	969.8502	2.3220
Min	0.0000	-14.8562	0.0144	-5.3057	-7.7719	-97.0913	-17.4858	0.0050	0.0000	0.0007	0.0025	-52.8355
Standard Deviation	0.2329	2.1926	0.1252	0.6930	0.2975	3.3478	0.4286	179.6985	1.2019	0.3317	26.7137	0.8730
Skewness	2.0970	0.7409	5.5394	0.0959	-3.7440	-12.0262	-13.9254	48.5764	10.4559	7.2327	16.4849	-36.2052
Kurtosis	6.5298	3.1223	93.8248	8.2487	92.0586	260.2972	454.1728	3,146.7280	250.0147	157.8613	435.6268	2,074.4810
Panel B: Default												
Mean	0.6514*	-10.2760*	0.2415*	-0.8827*	-0.2122*	-2.0216**	-0.2563*	1.6681	1.3110*	1.0910*	1.6945	-0.6904*
Meadian	0.7548	-10.3812	0.2154	-0.8279	0.0111	-0.4737	-0.0540	0.2716	0.5568	0.6642	1.0238	-0.1706
Max	1.0000	-4.9935	0.7648	2.0314	0.8932	1.0913	0.5508	45.1590	28.1556	22.2485	12.4081	0.1032
Min	0.0000	-13.8110	0.0153	-3.0420	-21.4122	-59.7004	-3.7125	0.0071	0.0000	0.0592	0.0310	-22.7168
Standard Deviation	0.3547	1.7257	0.1442	0.8199	2.2533	6.6323	0.6601	5.8276	3.1176	2.4580	2.0698	2.4671
Skewness	-0.7394	0.4450	1.0930	0.1605	-9.0938	-7.3786	-3.7609	5.7140	7.1210	7.4025	2.9242	-7.8950
Kurtosis	2.0470	3.1637	4.2203	3.9843	86.1041	63.2412	18.1112	38.3690	60.7110	61.7200	13.4090	70.0063

Table 2a: Correlation Matrix of Nonbankrupt Firms

The table presents the correlation matrix of truncated explanatory variables by using 6,437 firm-year observations of non-default firms during 1990-2003. All explanatory variables are the default likelihood indicator (DLI), relative size (Rel-Size), idiosyncratic standard deviation of returns (Sigma), past year performance (Ri-Rm), and eight financial ratios: working capital to total assets (WC/TA), retained earnings to total assets (RE/TA), earnings before interest and taxes to total assets (EBIT/TA), market value of equity to total liabilities (MV/TL), sales to total assets (Sales/TA), total liabilities to total assets (TL/TA), current assets to current liabilities (CA/CL) and net income to total assets (NI/TA).

Non-Default Firms	DLI	Rel-Size	Sigma	Ri-Rm	WC/TA	RE/TA	EBIT/TA	MV/TL	Sales/TA	TL/TA	CA/CL	NI/TA
DLI	1.0000	-0.4666	0.5044	-0.3054	-0.2001	-0.2045	-0.2433	-0.1380	-0.0034	0.2280	-0.1023	-0.1849
Rel-Size	-0.4666	1.0000	-0.1505	0.0395	-0.0991	0.0907	0.1060	-0.0518	0.0090	0.1097	-0.0559	0.0449
Sigma	0.5044	-0.5291	1.0000	-0.0553	0.0520	-0.3941	-0.4122	0.2204	-0.2359	-0.2023	0.1553	-0.1811
Ri-Rm	-0.3054	0.2661	-0.0553	1.0000	0.0330	0.0435	0.1962	0.1934	0.0619	0.0231	0.0117	0.1359
WC/TA	-0.2001	-0.1473	0.0520	0.0330	1.0000	-0.0425	-0.1125	0.3321	-0.0828	-0.4785	0.5194	0.0934
RE/TA	-0.2045	0.3779	-0.3941	0.0435	-0.0425	1.0000	0.6154	-0.1915	0.1727	0.1188	-0.0944	0.4139
EBIT/TA	-0.2433	0.4295	-0.4122	0.1962	-0.1125	0.6154	1.0000	-0.1717	0.2318	0.1773	-0.0977	0.4218
MV/TL	-0.1380	-0.0997	0.2204	0.1934	0.3321	-0.1915	-0.1717	1.0000	-0.2426	-0.4290	0.6248	-0.0739
Sales/TA	-0.0034	0.1615	-0.2359	0.0619	-0.0828	0.1727	0.2318	-0.2426	1.0000	0.4899	-0.2166	0.0717
TL/TA	0.2280	0.2720	-0.2023	0.0231	-0.4785	0.1188	0.1773	-0.4290	0.4899	1.0000	-0.4003	-0.1206
CA/CL	-0.1023	-0.1852	0.1553	0.0117	0.5194	-0.0944	-0.0977	0.6248	-0.2166	-0.4003	1.0000	-0.0329
NI/TA	-0.2709	0.3640	-0.3687	0.2234	-0.0308	0.5991	0.8172	-0.0986	0.1507	0.0719	-0.0351	1.0000

Table 2b: Correlation Matrix of Bankrupt Firms

The table presents the correlation matrix of truncated explanatory variables by using 93 observations of default firms during 1990-2003. All explanatory variables are the default likelihood indicator (DLI), relative size (Rel-Size), idiosyncratic standard deviation of returns (Sigma), past year performance (Ri-Rm), and eight financial ratios: working capital to total assets (WC/TA), retained earnings to total assets (RE/TA), earnings before interest and taxes to total assets (EBIT/TA), market value of equity to total liabilities (MV/TL), sales to total assets (Sales/TA), total liabilities to total assets (TL/TA), current assets to current liabilities (CA/CL) and net income to total assets (NI/TA).

Default Firms	DLI	Rel-Size	Sigma	Ri-Rm	WC/TA	RE/TA	EBIT/TA	MV/TL	Sales/TA	TL/TA	CA/CL	NI/TA
DLI	1.0000	-0.4794	0.5603	-0.2428	-0.1841	-0.2125	-0.2143	-0.4220	0.1420	0.5234	-0.1263	-0.3021
Rel-Size	-0.4794	1.0000	-0.2484	0.0523	0.1156	0.0926	0.1275	0.1510	-0.0588	-0.1292	0.0666	0.1557
Sigma	0.5603	-0.5078	1.0000	-0.2422	-0.1877	-0.3097	-0.4270	-0.1534	0.0856	0.3867	-0.1087	-0.4937
Ri-Rm	-0.2428	0.2530	-0.2422	1.0000	0.0432	-0.0566	0.2450	0.1245	0.0477	0.0157	0.0580	0.1918
WC/TA	-0.1841	0.3070	-0.1877	0.0432	1.0000	0.2396	0.2191	0.2611	-0.1393	-0.5138	0.8208	0.2515
RE/TA	-0.2125	0.3414	-0.3097	-0.0566	0.2396	1.0000	0.5061	-0.0536	0.0044	-0.4398	0.0861	0.7446
EBIT/TA	-0.2143	0.3628	-0.4270	0.2450	0.2191	0.5061	1.0000	-0.0751	-0.0631	-0.3172	0.1482	0.8308
MV/TL	-0.4220	0.1680	-0.1534	0.1245	0.2611	-0.0536	-0.0751	1.0000	-0.1354	-0.3750	0.3069	0.0337
Sales/TA	0.1420	-0.1377	0.0856	0.0477	-0.1393	0.0044	-0.0631	-0.1354	1.0000	0.2701	-0.1740	-0.0392
TL/TA	0.5234	-0.2644	0.3867	0.0157	-0.5138	-0.4398	-0.3172	-0.3750	0.2701	1.0000	-0.4869	-0.4082
CA/CL	-0.1263	0.2413	-0.1087	0.0580	0.8208	0.0861	0.1482	0.3069	-0.1740	-0.4869	1.0000	0.1781
NI/TA	-0.3021	0.4448	-0.4937	0.1918	0.2515	0.7446	0.8308	0.0337	-0.0392	-0.4082	0.1781	1.0000

5. Empirical Results

To examine whether each independent variable can explain corporate bankruptcy, the study first presents the results from univariate logit regression using the individual explanatory variables shown in Table 3. Using sets of explanatory variables, the parameter estimates from the multivariable logit regression of each bankruptcy model are reported in Table 4. Moreover, statistical tests for a goodness of fit and model selection criteria are shown. Table 5 reports the results of forecasting accuracy for both bankrupt and nonbankrupt observations using various measures. Finally, Table 6 shows the ability of the various models fit to distinguish default firms from non-default firms by consideration of 95% confidence intervals for the predicted probability of default.

A. Univariate Tests

Table 3 reports the results of the univariate logit regression on each explanatory variable.[22] Using a sample of 6,530 firm-year observations, including 93 bankruptcies, a 0-1 dummy variable is regressed on each independent variable. The second and third columns present the estimated constant term and its Z-statistic. The estimated coefficient of each explanatory variable and its Z-statistic are shown in the fourth and fifth columns. In addition, the estimates of the Bayesian Information Criteria (BIC), and a measure of the goodness-of-fit (Psuedo-R^2) for each variable are reported in the two rightmost columns respectively.

In general, the study finds that all independent variables are statistically significant except RE/TA and MV/TL. In addition, the signs of all coefficients are in line with expectation except Sales/TA. The coefficient of Sales/TA turns out to be unexpectedly positive and statistically significant. This result can be explained using the previous discussion of Table 1. Moreover, the results show that the ratio of TL/TA is the most significant variable among all independent variables and the magnitude of its coefficient is also rather high. Specifically the coefficient of

12 Because DLI is the only variable used in the Merton model, its result will not be shown in this section.

TL/TA and its Z-statistic are equal to 4.0458 and 11.34 respectively. Furthermore, the results from the model selection criteria based on BIC and the goodness-of-fit model measured by Pseudo-R^2 indicate that TL/TA ratio is the most powerful variable in explaining firm bankruptcy. In addition, the two market-driven variables i.e. the excess returns (Ri-Rm) and the idiosyncratic standard deviation of equity returns (Sigma) are subsequently the most significant variables. Their Z-statistics are equal to –10.62 and 7.75 respectively. Moreover, BIC and the Psuedo-R^2 values of Ri-Rm and Sigma suggest that these two variables are highly significant in explaining firm financial distress. Default firms are more likely to have high Sigma and low excess returns (Ri-Rm). It is also interesting to note that the coefficient of Sigma has the highest magnitude among all independent variables. The marginal changes in Sigma can significantly increase default probabilities of firms.

Table 3: The Univariate Logit Regression of Explanatory Variables

The table reports the univariate logit model of explanatory variables in explaining the firm bankruptcies. Using sample of 6,530 firm-year observations including 93 firm bankruptcies during 1990-2003, a 0-1 dummy variable is regressed with individual explanatory variables. BIC is the Bayesian information Criteria. *, ** indicate that the coefficient is statistically significant at 1%, and 5% respectively. The Z-statistics is calculated from Huber-White standard errors.

Explanatory Variables	Constant	Z-Statistics	Coefficients	Z-Statistics	BIC	Psuedo-R^2
WC/TA	-3.9845	-37.21	-2.4704*	-3.78	0.1474	0.0310
RE/TA	-4.3242	-36.92	-0.0697	-1.94	0.1516	0.0031
EBIT/TA	-4.3581	-38.62	-0.9423*	-4.28	0.1502	0.0123
MV/TL	-3.4018	-10.15	-0.2553	-1.35	0.1406	0.0766
Sales/TA	-4.4420	-30.00	0.2324**	2.21	0.1513	0.0052
TL/TA	-6.3445	-24.15	4.0458*	11.34	0.1329	0.1282
CA/CL	-3.7472	-22.01	-0.1985*	-2.51	0.1477	0.0290
NI/TA	-4.4396	-38.53	-0.7983*	-6.40	0.1487	0.0226
Rel-Size	-6.2606	-11.20	-0.2048*	-3.82	0.1499	0.0147
Sigma	-5.2262	-27.96	5.1239*	7.75	0.1456	0.0432
Ri-Rm	-4.9220	-31.55	-1.4827*	-10.62	0.1358	0.1091

B. The Parameter Estimates of Bankruptcy Models

The results of parameter estimates for each bankruptcy model are presented in Table 4. The second to fourth columns labeled Altman, Zmijewski, and Shumway indicate that accounting and financial variables from Altman (1968), Zmijewski (1984), and Shumway (2001) are employed as independent variables to predict firm bankruptcy. In the same fashion, the fifth column labeled Merton represents the model that uses the default likelihood indicator (DLI) estimated from the Merton model as an explanatory variable in the logit regression analysis. The rightmost column provides the coefficient estimates for a model that includes both DLI and accounting ratios. In addition, the estimates of the Bayesian Information Criteria (BIC) and Psuedo-R^2 for each bankruptcy model are reported in the last two rows.

The parameter estimates of the variables from Altman (1968) show that all coefficients have the expected negative signs but only the coefficient of EBIT/TA ratio is statistically different from zero. Moreover, the coefficient of EBIT/TA at -1.3135 indicates that EBIT/TA has the greatest weight in the bankruptcy equation whereas the highest weight in Altman (1968) belongs to Sales/TA. The results from the Zmijewski model also show that the signs of all coefficients are in line with the expectation. In addition, two out of three variables, namely the TL/TA and NI/TA ratios, are statistically significant. Moreover, the coefficient of TL/TA at 3.5990 suggests that the ratio has the highest influence in the model function. The Shumway model, which incorporates the market-based variables, finds that TL/TA, Sigma, and Ri-Rm are statistically significant. In contrast to the Zmijewski's results, NI/TA, one of the financial ratios in the Shumway model, is not statistically significant and has an unexpected positive sign. In addition, the sign of Rel-Size is positive but statistically insignificant. It is also interesting to note that TL/TA and Sigma have the greatest weight in the Shumway's bankruptcy equation. In the case of the Merton model, the results, not surprisingly, show that the coefficient of DLI is positive and significantly different from zero. Specifically, the DLI coefficient and its Z-statistic are equal to 4.6348 and 14.15 respectively. This Z-statistic represents the most significant value even when compared to the Z-statistic of TL/TA in the univariate logit test (Table 5.3). We also consider a hybrid model which includes the DLI (from the Merton model) and a range of accounting variables. The idea here is to explore whether the predictive ability of the Merton model can be further enhanced by including other accounting ratios in the predictor set. The coefficient estimates for TL/TA, Ri-Rm and relative firm size are 1.8736, -0.8480 and 0.1562 respectively. The signs of these estimates are all in line with expectation. Based on some exploratory data analysis in Tanthanongsakkun and Treepongkaruna (2007) we have included an interaction term between DLI and firm size. The coefficient estimate relating to this term is highly statistically significant and positive. This indicates the different effect on subsequent bankrupty of firm size for firms of different sizes. A high value of the default likelihood indicator is predicted to be more detrimental to the firm's survival prospects in the case of larger firms.

To consider the effectiveness of a bankruptcy model, BIC and Psuedo-R^2 are used as indicators. Our findings in the two last rows show that the Extended Merton has the most explanatory power among other models since it has smallest BIC. The Shumway model performs slightly worse than the Merton model. The results from the two accounting models are rather disappointing. Specifically, BIC values of the Merton, Shumway, Altman, Zmijewski and Merton extended models equal to -0.0562, -0.0574, -0.0665, -0.0645 and -0.0493respectively. Along the same line with BIC, their Psuedo-R^2 values are 0.2469, 0.2319, 0.1092, 0.1358 and 0.3396 respectively.

To summarise, the results of Tables 3 and 4 suggest that the DLI, estimated by the Merton model, provides the most information in explaining corporate bankruptcy. Moreover, apart from DLI, TL/TA and Sigma are the two most significant variables in a bankruptcy model. As can be seen in the univariate logit regression, TL/TA and Sigma have the greatest magnitude among other independent variables with very high Z-statistics. The two variables also play a crucial role in the Zmijewski and Shumway models. Especially in the Shumway model, these two variables have the greatest weight on the bankruptcy function with

Table 4: Parameter Estimates of Bankruptcy Models

The table reports the parameter estimates of bankruptcy models. Using a sample of 6,530 firm-year observations including 93 bankruptcies during 1990-2003, the logit regressions of a 0-1 dummy variable on explanatory variables are performed. The columns labeled Altman, Zmijewski, Shumway, Merton and extended Merton indicate the variables from Altman (1968), Zmijewski (1984), Shumway (2001), and default probability estimated from the Merton model are employed as independent variables to predict the financial distress of firms. BIC is Bayesian Schawarz Information Criteria. The Z-statistics are in parenthesis and are calculated by Huber-White standard errors. *,** indicate that the coefficient is statistically significant at 1%, and 5% respectively.

	Altman	Zmijewski	Shumway	Merton	Extended Merton
Constant	-3.4700	-6.1474	-6.8126	-5.8888	-5.4624
	(-9.08)	(-23.49)	(-12.40)	(-25.37)	(0.9350)
DLI				4.6348*	9.5803
				(14.15)	(1.6526)
WC/TA	-0.6900				
	(-1.02)				
RE/TA	-0.0204				
	(-0.35)				
EBIT/TA	-1.3135*				
	(-4.01)				
MV/TL	-0.2573				
	(-1.37)				
Sales/TA	-0.0159				
	(-0.11)				
TL/TA		3.5990*	3.6007*		1.8736
		(9.79)	(10.33)		(0.3953)
CA/CL		-0.0169			
		(-1.32)			
NI/TA		-0.4653*	0.2890		
		(-3.28)	(1.42)		
Sigma			3.3425*		
			(3.09)		
Ri-Rm			-1.2469*		-0.8480
			(-6.70)		(0.1534)
Rel-Size			0.0362		0.1562
			(0.66)		(0.0998)
Rel-Size*DLI					0.5005
					(0.1645)
BIC	-0.0665	-0.0645	-0.0574	-0.0562	-0.0493
Psuedo-R^2	0.1092	0.1358	0.2319	0.2469	0.3396

significant Z-statistics. In addition, TL/TA and Sigma are the key inputs of the Merton model[23]. This may be an explanation why the Shumway model performs relatively well in explaining bankruptcy. It is also evident that the market variables size and excess returns along with the ratio of total liabilities to total assets provide some additional predictive power to the model after DLI is already included in the model.

C. Forecasting Accuracy

The classification accuracy for both bankrupt and nonbankrupt firms is reported in Table 5. Panel A of table 5 shows the total performance in correctly predicting both default and non-default firms. The numbers and percentages of classification accuracy and classification errors for both groups are shown. To compute the default probability of each firm-year observation, the estimated parameters for each bankruptcy model from Table 4 are employed. The cutoff point is calculated as the average of the means of the predicted default probabilities for the default and non-default groups. Firms are predicted to be bankrupt if their default probabilities are higher than the cutoff point and vice versa. To measure overall model performance, the study also reports the expected cost measure of classification errors (ECM) at the rightmost column. ECM represents the cost of overall forecasting errors measured as the number of basis points per one dollar invested. By following Altman et al. (1977) and Saretto (2004)[24], ECM can be estimated as follows:

$$ECM = p_1(M_{12} / N_1)C_1 + p_2(M_{21} / N_2)C_2 \ , \tag{12}$$

where p_1, p_2 are the proportions of bankrupt and nonbankrupt observations in the sample respectively. M_{12} and M_{21} represent the number of observations that are misclassified as nonbankrupt (Type I error) and bankrupt (Type II error) firms. N_1 and N_2 are the number of

13 As mentioned earlier, Sigma is not the direct key input but it is positively related to the volatility of asset returns which is the key variable in the Merton model.

14 Saretto (2004) examines how corporate bond defaults can be predicted using financial ratios and how the forecasted probability of default relates to cross-section of expected equity returns.

observations relating to bankrupt and nonbankrupt firms respectively. C_1 is the cost of classifying a bankrupt firm as a nonbankrupt firm whereas C_2 is the cost of classifying a nonbankrupt firm as bankrupt firm. Therefore, C_1 reflects the expected loss when a firm defaults and C_2 represents the opportunity cost that a good investment is avoided. Following Saretto (2004), the study estimates C_1 as the percentage loss of default and C_2 as yield spread between corporate and treasury bonds. C_1 and C_2 are imposed at 50 percent and 1 percent respectively.

Panel B of table 5 reports the classification default accuracy for each decile portfolio. By following Shumway (2001), all firm-year observations are sorted into deciles based on their fitted default probability. The numbers and percentages of bankrupt observations classified into each decile are reported. Deciles 1 through 5 represent the five highest default probability deciles whereas bankrupt firms that are classified in the five lowest default probability deciles are pooled in the last row (Deciles 6-10).

The results from Panel A of Table 5 suggest that the Merton model and its extended version which includes accounting ratios as predictors perform the best in predicting firm bankruptcy. While the Altman model becomes the next best model, Shumway and Zmijewski have relatively low Type I accuracy. Specifically, The Merton, Altman, Shumway, and Zmijewski models can correctly classify corporate bankruptcy about 56, 54, 44 and 37 percent of the time respectively. The extended Merton model classifies corporate bankruptcy correctly 51% of the time. However, results from Type II accuracy are slightly different. The extended Merton model performs best by correctly classifying about 97% of the non-bankrupt firms. The Shumway model performs the next best with 96% of nonbankrupt observations correctly classified, whereas the Merton model become the third best by classifying about 94% of nonbankrupt firms correctly. The Zmijewski and Altman models have marginally lower accuracy. To determine the overall performance, the rightmost column reports the ECM values of each bankruptcy model. As can be seen, the Merton model and its extended version have the lowest cost of incorrect classification with the ECM at 34.24 and 34.40 basis points respectively. The ECM value at 38.19 basis points leads Altman to the next best model. Shumway and Zmijewski come in the fourth and fifth places with ECM at 41.07 and 48.99 basis points respectively.

The results in Panel B of table 5 are quite similar to those of Panel A of table 5. The extended Merton model has the most accuracy, which can classify 71 bankruptcies or about 76.3 percent in the highest default probability decile (Decile 1). The Merton model also performs very well with 62 default firms classified as being in the top 10% of risky firms. The Shumway model also performs well with the accuracy rate at 65.59 percent whereas Altman and Zmijewski can explain about 59.14 and 49.46 percent respectively. In addition, the Merton model still outperforms the other three models with accuracy rate at 96.77 percent when the accuracy is based the number of bankrupt firms classified above the median probability (Decile 1-5).

In summary, Table 5 confirms the previous findings that the DLI estimated by the Merton model has the most explanatory power in predicting firm bankruptcy. The performances of the remaining models have rather mixed results. However, it seems that the market-driven model of Shumway (2001) is superior to the two accounting-based models.

The logistic regression modeling framework adopted in this paper involves the estimation of a number of regression coefficients. Each of these coefficient estimates involves some error and so there is a reduction in the ability of the models to accurately make predictions when more covariates are included. To investigate this further, in this section we consider 95% confidence intervals for the predicted probabilities of failure for each of the firms in the dataset, for each of the five models discussed in this paper. This analysis provides striking evidence that the Merton model is superior to any of the other models considered. First, we form 95% confidence intervals for the probability of default for each of the firms in the dataset for each model. These intervals are formed as $\hat{p} \pm 1.96\hat{p}\left(1-\hat{p}\right)\sqrt{\underset{\sim}{x}'V\underset{\sim}{x}}$, (13),

Table 5: Forecasting Accuracy

The table shows the performance of each bankruptcy model in predicting firm default. Using a sample of 6,530 firm-year observations including 93 bankruptcies during 1990-2003, the estimated coefficients of logit regression for each bankruptcy model are used to calculate default probabilities of firms. Panel A reports the total performance in correctly predicting both default and non-default firms. The numbers and percentages of classification accuracy and classification errors both bankrupt and nonbankrupt firms are shown. In addition, the expected cost measure of classification errors (ECM) is presented. The ECM represents the cost that a model predicts incorrectly measured as the number of basis points per one dollar invested.

$$ECM = p_1(M_{12} / N_1)C_1 + p_2(M_{21} / N_2)C_2$$

where C_1 is the cost of classifying an bankrupt firm as a nonbankrupt firm (Type I error), and C_2 is the cost of classifying a nonbankrupt firm as bankrupt firm (Type II error). C_1 and C_2 are imposed at 50% and 1% respectively. p_1, p_2 are the proportions of bankrupt and nonbankrupt observations in the sample respectively. M_{12} and M_{21} represent the number of observations that are misclassified as nonbankrupt and bankrupt firms. N_1 and N_2 are the number of observations in both bankrupt and nonbankrupt groups respectively. Panel B reports numbers and percentages of default classification accuracy in each decile. All observations are sorted into deciles based on their fitted default probability. The default classification accuracy can be calculated by counting the number of bankrupt observations in each decile.

Panel A : Total Performance

	Default		Non-Default		ECM
	Correct	Incorrect	Correct	Incorrect	
Altman	54	39	5893	544	38.19
	(58.06)	*(41.94)*	*(91.55)*	*(8.45)*	
Zmijewski	37	56	6038	399	48.99
	(39.78)	*(60.22)*	*(93.80)*	*(6.20)*	
Shumway	44	49	6205	232	41.07
	(47.31)	*(52.69)*	*(96.40)*	*(3.60)*	
Merton	56	37	6051	386	34.24
	(60.22)	*(39.78)*	*(94.00)*	*(6.00)*	
Extended Merton	*51*	*42*	*6292*	*146*	34.40
	(54.84)	*(45.16)*	*(97.7)*	*(2.27)*	

Panel B : Default Classification Accuracy

Decile	Altman	Zmijewski	Shumway	Merton	Extended Merton
1	55	46	61	62	71
	(59.14)	*(49.46)*	*(65.59)*	*(66.67)*	*(76.34)*
2	10	18	10	11	10
	(10.75)	*(19.35)*	*(10.75)*	*(11.83)*	*(10.75)*
3	11	10	8	6	2
	(11.83)	*(10.75)*	*(8.60)*	*(6.45)*	*(2.15)*
4	6	5	7	8	1
	(6.45)	*(5.38)*	*(7.530*	*(8.60)*	*(4.3)*
5	4	2	3	3	4
	(4.30)	*(2.15)*	*(3.23)*	*(3.23)*	*(1.08)*
6-10	7	12	4	3	5
	(7.53)	*(12.90)*	*(4.30)*	*(3.23)*	*(5.38)*

where $\hat{p}$ denotes the estimated probability of default, $\underset{\sim}{x}$ is a column vector containing the predictor variables and V is the estimated variance-covariance matrix of the logistic regression coefficient estimators. Table 6 shows the 95^{th}, 90^{th}, 85^{th}, 80^{th}, 75^{th} and 70^{th} percentiles of the distribution of upper bounds of the confidence intervals calculated using (13) for firms that did not default. We then calculate the number of default firms which have 95% confidence intervals for the default probability entirely above the various percentiles shown in Table 6. We note that the Altman and Zimjewski models do not perform well here. For the Altman model, less than 10% of the default firms have predicted 95% confidence intervals for default that are above 70% of the corresponding intervals for non-default firms. In contrast, the Merton model and the extended Merton model perform very well. In particular, 46.2% of the 95% confidence intervals for estimated default probabilities for firms that actually default lie entirely above 95% of the corresponding confidence intervals for non-default firms. The extended Merton model does not perform any significantly better than the Merton model in Table 6. This is most likely due to the increased number of regression coefficients estimated in the extended Merton model compared to the Merton model. This over-estimation significantly increases the variance associated with prediction probabilities and in turn produces wider confidence intervals associated with these probability estimates.

6. Conclusion

This paper examines how effectively the default likelihood indicator (DLI) estimated from the Merton model can predict corporate bankruptcy in Australia. Moreover, the performance between the Merton model and the three well-cited bankruptcy models i.e. Altman (1968), Zmijewski (1984), and Shumway (2001) is compared. By using 6,530 firm-year observations and the idiosyncratic standard deviation of stock returns (Sigma) are the most significant variables, among accounting and market-based variables, in bankruptcy models. These two variables play a crucial role in the Zmijewski and Shumway models. The forecasting accuracy including 93 firm bankruptcies during 1990-2003, the logit regression analysis of each bankruptcy model is

Table 6: Forecasting Accuracy – Confidence Intervals

Table 6 shows the 95th, 90th, 85th, 80th, 75th and 70th percentiles of the distribution of upper bounds of the confidence intervals calculated using (13) for firms that did not default. Columns 3 and 4 report the number of default firms which have 95% confidence intervals for the default probability entirely above the various percentiles shown in Column 2.

Model and Percentile	Percentiles of Upper 95%Confidence Limits for Non-Default Firms	Number of Default Firms where the 95% confidence interval for default probability lies above Percentile in Column 2	Percentage of Default Firms where the 95% confidence interval for default probability lies above Percentile in Column 2
Altman 95%	0.05379	1	1.1%
Altman 90%	0.04162	2	2.2%
Altman 85%	0.03648	3	3.2%
Altman 80%	0.03290	4	4.3%
Altman 75%	0.03004	6	6.5%
Altman 70%	0.02738	7	7.5%
Zimjewski 95%	0.04930	20	21.5%
Zimjewski 90%	0.03224	28	30.1%
Zimjewski 85%	0.02565	35	37.6%
Zimjewski 80%	0.02176	40	43.0%
Zimjewski 75%	0.01891	50	53.8%
Zimjewski 70%	0.01686	54	58.1%

Shumway 95%	0.06382	28	30.1%
Shumway 95%	0.03291	40	43.0%
Shumway 95%	0.02329	49	52.7%
Shumway 95%	0.01815	51	54.8%
Shumway 95%	0.01479	55	59.1%
Shumway 95%	0.01255	58	62.4%
Merton 95%	0.08472	43	46.2%
Merton 90%	0.03292	62	66.7%
Merton 85%	0.01671	70	75.3%
Merton 80%	0.00981	70	75.3%
Merton 75%	0.00706	71	76.3%
Merton 70%	0.00564	71	76.3%
Extended Merton 95%	0.06804	44	47.3%
Extended Merton 90%	0.02991	62	66.7%
Extended Merton 85%	0.01507	70	75.3%
Extended Merton 80%	0.01114	70	75.3%
Extended Merton 75%	0.00990	72	77.4%
Extended Merton 70%	0.00759	73	78.5%

estimated. The model selection criteria based on the Bayesian Information Criteria (BIC) and the goodness of fit (Psuedo-R^2) are employed as indicators for the effectiveness of each bankruptcy model. The results suggest that the Merton model is the most informative model in explaining corporate bankruptcy. The Shumway model, which incorporates two financial ratios with three market-driven variables, becomes the second best candidate. Furthermore, the results seem to suggest that the ratio of total liabilities to total assets (TL/TA) results also confirm the performance of the Merton model. The model has the highest Type I accuracy and performs relatively well in predicting Type II accuracy.

In conclusion, the study shows that DLI computed from the Merton model has the most explanatory power to predict corporate bankruptcy in Australia. The plausible explanation is that the Merton model incorporates correct variables (default risk determinants) into the model and uses the right functional form to estimate default probability. The results also suggest that market-based variables perform more favorably than accounting variables. However, TL/TA is the only financial ratio that still seems to be a very significant variable in a bankruptcy model.

Acknowledgement

We are grateful to Tom Smith for invaluable comments.

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