A Comparison of the Information Content of Accounting and Market Measures in Distress Prediction.

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Abstract

The literature presents a clear divide between the so called market and accounting based approaches to bankruptcy prediction. With this in mind, this paper employs the discrete time hazard model framework of Shumway (2001) to test the information content of both market and accounting based models using Australian data. We find that market based models significantly outperformed accounting based models in tests of informational content. With many accounting variables become insignificant in a model of bankruptcy already containing market based variables. This paper finds that hybrid models of corporate bankruptcy, containing both accounting and market based variables significantly outperform either of the standalone models. The implication of this result is that, despite the superior performance of market based measures, accounting ratios still add information to a market based approach and therefore have a place in a well defined model of corporate bankruptcy.

1 Introduction

The question of which covariates best predict bankruptcy has been a key focus of the empirical bankruptcy literature. The studies of Beaver (1966), Altman (1968) and Ohlson (1980) typify the accounting or ratio approach to bankruptcy prediction. Regardless of the econometric method used, the underlying concept behind these models is that the accounting numbers published in a firm's yearly (or quarterly) reports contain information that can be used to predict the probability of financial distress in the future.

Agarwal and Taffler (2008) point out some of the common criticisms of accounting information based models: accounting statements present past performance and may or may not be useful in predicting future performance; conservatism and historical cost accounting mean that true asset values may be different from recorded values; accounting numbers are subject to manipulation by management and the 'going concern' principle of accounting may limit the usefulness of accounting ratios as predictors of default. Peat (2007) highlights the lack of theoretical modelling to motivate the use of accounting variables and the tendency for accounting models to approach bankruptcy from a purely forecasting standpoint rather than from the financial theory of the firm.

Despite these drawbacks, proponents of the use of accounting information based models for bankruptcy prediction point to the good predictive performance and simple intuition of such models to justify their use.

As a result of these criticisms, more recent bankruptcy studies have questioned whether or not market based covariates may be more useful in predicting bankruptcy. Market based covariates, such as the distance to default metric derived from the Merton (1974) model, have the following advantages: they provide a theoretical basis for their connection to firm bankruptcy; under the efficient markets hypothesis, market prices reflect all information contained in accounting and non-accounting data and market prices reflect future expected cash flows and hence should be more appropriate for prediction purposes.

The competing market and accounting based approaches to bankruptcy presents an area of academic debate that continues to the present day. We will focus on the literature beginning with the discrete time hazard analysis of Shumway (2001). Results previous to Shumway (2001) may be marred by deficiencies in their econometric approaches. Using the discrete time hazard framework, Shumway (2001) estimated a number of models based on the accounting covariates used by Altman (1968) and Zmijewski (1984) as well as a number of market based covariates.

Using a sample of US firms over the period 1962 to 1992 containing 300 bankruptcies, Shumway (2001) found that many of the covariates used in the accounting models became insignificant in the hazard model framework and that market based variables had greater explanatory power in the context of corporate distress. The market based variables used by Shumway (2001) were: the relative size of the firm (measured by the logarithm of firm market capitalisation over total index market capitalisation); the excess return of the firm's stock over the market and the idiosyncratic volatility of the firm's stock returns.

It is important to note the Merton (1974) model represents a much more complicated and involved measure than the simple market based measures employed by Shumway (2001). As such, this paper will refer to all these variables as 'market based', however, particular focus will be placed on the Merton (1974) distance to default measure. The comparison of this measure to others, both accounting or otherwise, is informative with regard to the ability of the contingent claims approach to correctly explain bankruptcy risk.

Shumway (2001) found that the market based model outperformed both the Altman (1968) and Zmijewski (1984) models in out-of-sample testing. Concluding that market variables are strongly related to bankruptcy probability and should form a part of any well specified bankruptcy prediction model. However, Shumway (2001) also found that a hybrid model including both market and accounting variables provided additional explanatory power above that of the market only model. This finding suggests that accounting variables add additional information not captured in market variables.

Chava and Jarrow (2004) replicated the findings of Shumway (2001) with an expanded data ranging from 1962-1999 including 1461 bankruptcies. Using the covariates of Altman (1968), Zmijewski (1984) and Shumway (2001) they found that accounting variables add little predictive power once market variables are included. Chava and Jarrow (2004) also show a significant industry effect in bankruptcy probabilities and find that the ability to use monthly market based variables, something not possible with accounting variables, improves predictive power. These results are consistent with the theory of market efficiency as market variables incorporate any information found in accounting variables.

Hillegeist et al. (2004) examined a bankruptcy data set ranging from 1980 to 2000 including 756 bankruptcies using the discrete time hazard framework. Unlike the studies above, Hillegeist et al. (2004) incorporate distance to default explicitly as a covariate. In their work, they compare one of the most popular market based default predictors to the accounting based models of Altman (1968) and Ohlson (1980). They found that the distance to default provides significantly more information than either of the two accounting based measures and suggested that future modelling efforts should use the distance to default measure rather than accounting based covariates.

Hilligeist et al. (2004) then test the informational content of their non-nested models using the framework outlined by Vuong (1989) rather than using the out-of-sample predictive accuracy methods more typical of previous literature. They argue that the dichotomous decision assumed in prediction tests, that is classifying a firm as bankrupt or non-bankrupt, is inconsistent with the continuous decisions often face by the end-users of bankruptcy models, for example a bank setting an interest rate based on the probability of default.

Duffie, Saita and Wang (2007) used a competing risk discrete time hazard model that explicitly considered the mean reverting time dynamics of the covariates. Based on a sample period of 1980 to 2004 including 1171 bankruptcies and defaults, they found a model based on the firm specific components of the distance to default measure and stock return, as well as the macroeconomic covariates three-month Treasury bill rates and the trailing one year return on the S&P 500, outperformed previous market and accounting based models in terms of out-of-sample predictive ability. The excellent performance of their model lead them to conclude that market based covariates used in their study represented the most informative with regard to explaining bankruptcy.

In contrast to these findings, Bhararth and Shumway (2004) employ the discrete time hazard framework on a sample of 1449 firm defaults from 1980-2003 finding that the distance to default measure is not a sufficient statistic for bankruptcy prediction and models including this variable only marginally outperformed models that omitted it.

Extending this concept, Agarwal and Taffler (2008) found that not only did the covariates suggested by the accounting based 'Z-score' outlined in Altman (1977) perform comparably with a model based on the contingent claims approach but that a bank using the Z-score would realise greater risk adjusted returns than one employing the market based approach. Similar to prior studies, Agarwal and Taffler (2008) find that the information contained in neither market based or accounting covariates subsumes the other, as shown by the superior performance of a hybrid model including both accounting and market variables.

Using a logit specification, Campbell et al. (2006) estimated a monthly bankruptcy prediction model that included lagged values in order to capture the significance of trends in the covariates. Using data from 1963 to 2003, they find that the distance to default measure adds relatively little to the predictive power of a model that contains a combination of market and accounting based covariates.

Benos and Papanastasopoulos (2007) estimated a single year ordered probit model to explain corporate credit ratings movements, including the movement to default. In their study, they find that an accounting based model outperformed one based on the distance to default measure in predicting credit ratings movements, suggesting that the restrictive assumptions of the Merton (1974) model may limit the ability of the distance to default measure to predict default accurately. The authors find that a hybrid model incorporating both distance to default and accounting variables significantly outperforms either of the standalone models.

It is clear from the literature outlined above that a number of issues remain unresolved in the context of corporate bankruptcy prediction. Firstly, the informational content of accounting based variables remains a topic of empirical debate, particularly with regard to their comparison with market based variables. Secondly, the ability of the contingent claims approach of Merton (1974) to add significantly to the explanatory power of bankruptcy models, especially those constructed using accounting based measures, remains unclear. Finally, whether a hybrid model of bankruptcy, containing both accounting and market covariates, can significantly outperform either of the standalone models. This paper will apply the discrete time hazard model of Shumway (2001) to the Australian bankruptcy context in order to contribute to the literature with regard to these questions.

2 Data and Variable Definitions

The Australian data represents a relatively understudied opportunity. This paper aims to explain the Australian experience. The estimation sample of this paper consists of data collected on 1197 publicly listed non-financial Australian companies over the period 1999 to 2007. The removal of financial firms from the data set is common practice in the previous literature and so, for the sake of consistency, are also removed from this study. Financial firms are complicated in terms of their financial structure, leverage and annual reporting requirements and it is argued that the inclusion of these firms in the sample will confuse the analysis given the difficulty in correctly interpreting the data for these firms. For the sample period, the variables listed in Table 1 were taken from the Worldscope database.

Given that the Australian financial year is from July to June, all data collected represents the fiscal year end values. In this paper each year will be defined as the period from 01/07 to 30/06. For example, 01/07/1999 to 30/06/2000 will be referred to as the year 2000.

Table 1: Data collected for the period 01/07/1998 to 30/06/07

Data Name	Description	Data Code (Source)
Retained Earnings	Retained Earnings represent the accumulated after tax earnings of the company which have not been distributed as dividends to shareholders or allocated to a reserve account.	WS.RetainedEarnings
Market Capitalisation	Market Capitalisation is calculated as the year end value of number of shares outstanding multiplied by share price.	WS.YrEndMarketCap
Working Capital	Working Capital represents the difference between current assets and current liabilities on the balance sheet.	WS.WorkingCapBalSht
Total Debt	Total Debt represents all interest bearing and capitalized lease obligations.	WS.TotalDebt
Total Assets	Total Assets represent the sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets.	WS.TotalAssets
Stock Price	Equity prices adjusted for dividends and splits.	WS.PriceClose
Earnings before Interest and Tax	Earnings before Interest and Tax represent the earnings of a company before interest expense and income taxes.	WS.EarningsBeforeInterestAndTax
Total Sales	Total Sales represent gross sales and other operating revenue less discounts, returns and allowances.	WS.Sales
Total Current Liabilities	Total Current Liabilities represent debt or other obligations that the company expects to satisfy within one year.	WS.TotalCurrentLiabilities
Total Long Term Debt	Total Long Term Debt represents all interest bearing financial obligations, excluding amounts due within one year.	WS.TotalLTDebt
The ASX 200 Index	The level of the ASX 200 index.	Yahoo Finance
One year Australian Treasury bond rates	The yield on one year (or equivalent) zero coupon government borrowings.	The RBA

3 Construction of Covariates

The variables listed below were constructed to match the covariates used in the studies of Altman (1968), Shumway (2001)[1] and the distance to default measure, Merton (1974). The aim of this paper is not to create new or exotic covariates for predicting bankruptcy. With this in mind the selection of covariates was based on the goal of matching those commonly used in the literature to ensure a fair comparison with prior studies. This section briefly discusses the construction of the variables as well as their expected relationship to the probability of bankruptcy. Table 2 summarises the covariates studied in this paper and the expected effect on the probability of bankruptcy of an increase in this covariate.

Table 2: Covariates and Expected Effect on the Probability of Bankruptcy

Covariate	Expected Effect on Bankruptcy	Original Paper
Retained Earnings on Total Assets	-	Altman (1968)
Market Capitalisation on Total Debt	-	Altman (1968)
Working Capital on Total Assets	-	Altman (1968)
Earnings before Interest and Tax on Total Assets	-	Altman (1968)
Total Sales over Total Assets	-	Altman (1968)
Total Liabilities over Total Assets	+	Zmijewski (1984)
Net Income over Total Assets	-	Zmijewski (1984)
Excess Equity Return	-	Shumway (2001)
Equity Volatility (Sigma)	+	Shumway (2001)
Relative Size	-	Shumway (2001)
The Distance to Default	-	Merton (1974)

Many of the covariates listed are relatively self explanatory, some require further explanation, which is given below.

Excess Equity Return
This covariate measures the comparative performance of the company's equity return to the market return, proxied by the return on the ASX 200 index. Ceteris paribus, as the excess return of the company increases, reflecting positive information regarding the firm's current and future performance, the probability of bankruptcy will decrease. This covariate was constructed using the monthly return on each company's equity and the return on the ASX 200 index from the Datastream database and Yahoo Finance.

Equity Volatility
This covariate measures the idiosyncratic risk of a company's equity returns. As the risk of equity increases, representing increase volatility of the underlying assets of the firm, we expect the probability of default to increase. This measure

[1]It should be noted that Shumway (2001) included accounting ratios originally proposed by Zmijewski (1984)

was calculated by annualising the standard deviation of monthly stock returns collected from the Datastream database.

The Distance to Default

Let A_t be the asset value for the firm at time t. The asset value of the firm is assumed to be the sum of the equity and debt of the firm, $A_t = E_t + D_t$. In the Merton (1974) model there is only one type of debt and equity, the debt is a single zero-coupon bond which matures at time T, with a face value of F and the equity is an ordinary share. The value of the firm's assets is assumed to follow a geometric Brownian motion diffusion process:

$$\frac{dA_t}{A_t} = r_A(A_t, t)dt + \sigma_A(A_t, t)dW_{1t} \tag{1}$$

Where, $r_A(A_t, t)$ is the expected growth rate of A and $\sigma_A(A_t, t)$ is the volatility of A and dW_{1t} is a Wiener process. In the Merton (1974) framework, equity holders control the firm and face an economic decision at the maturity of the firm's debt, at time T. The payoff to the equity holder at T is the residual value of the assets of the firm after debt holders have been repaid, $E_T = A_T - F$. However, limited liability means that rational equity holders will only exercise their claim if $E_T > 0$. This implies that $A_T - F > 0$, otherwise the equity holder would liquidate the firm and receive a payoff of 0. Conversely, for debt holder the payoff at time T will be F, if the face value of the debt if it is repaid, or A_T the recovery value of the firm's assets if the firm is liquidated. Before calculating the distance to default metric, we must first estimate the unobserved values of A and σ_A, the value and volatility of firm assets. To do this we employ the observed value of firm equity $\hat{E_t}$ and the volatility of equity returns, $\hat{\sigma_E}$, and substitute these into the Merton (1974) model, with $T - t = 1$ given our time horizon of one year, given by:

$$\begin{aligned}
\frac{\hat{\sigma_E}}{\sigma_A} &= \frac{A_t}{\hat{E_t}} N(d_1) \\
\hat{E_t} &= A_t N(d_1) - F e^{r_f} N(d_2) \\
d_1 &= \frac{\log(A_t/F) + (r_f + \sigma_A^2/2)}{\sigma_A} \\
d_2 &= d_1 - \sigma_A
\end{aligned} \tag{2}$$

One of the weaknesses of the original Merton (1974) model is that it assumes that the firm has only one type of debt with maturity at T. Relaxing this assumption, as the suggested by Vassalou and Xing (2003) and Bharath and Shumway (2004), we define the default point F as current liabilities plus half of long term debt. This modification improves the fit of the distance to default model by more accurately representing the debt structure of the firm[2]. The risk free rate used is the yield on one year Australian Treasury bonds.

The only unknowns in this system of equations are A and σ_A, however, given the non-linear nature of these equations they are solved iteratively using the Solver function in Excel.

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[2] More complicated approaches to modelling debt structure are summarised by Elizalde (2003), however, the computational burden of these methods prevented their use in this paper

Table 3: Table of Summary Statistics

Variable	Description	Median	Mean	Min	Max	Std
RE/TA	Retained Earnings over Total Assets	-0.127	-0.779	-4.822	0.873	1.403
MC/TD	Market Capitalisation over Total Debt	6.011	43.706	0.877	243.933	77.041
EBIT/TA	Earnings before Interest and Tax over Total Assets	0.030	-0.104	-2.387	1.376	0.429
Sales/TA	Total Sales over Total Assets	0.666	0.938	0.000	4.539	0.985
WC/TA	Working Capital (Current Assets - Current Liabilities) over Total Assets	0.1127	0.126	-4.577	0.955	0.283
NI/TA	Net Income over Total Assets	-0.053	-0.278	-4.680	0.500	0.711
TL/TA	Total Liabilities over Total Assets	0.319	0.368	0.004	2.000	0.333
Excess Return	The excess return of company equity over the ASX 200 index	-0.084	-0.129	-3.834	4.232	0.703
Relative Size	The logarithm of the ratio of company Market Cap to the ASX 200 Market Cap	-10.468	-10.052	-17.783	-1.532	2.092
Sigma	The annualised volatility of company monthly equity returns	0.531	0.609	0.078	4.743	0.376
DtD	The Merton (1974) based Distance to Default	4.639	5.398	0.000	29.286	3.791

As reasonable starting values we set $A = E + F$ and $\sigma_A = \sigma_E$. The Solver function then iterates over these values until model implied E_t and σ_E are equal to observed $\hat{E_t}$ and $\hat{\sigma_E}$. In computing this result the d_2 term is the distance to default metric we require and this is saved for each firm.

Table 3 outlines the summary statistics for the covariates employed in the discrete time hazard regressions of this paper.

4 Data and Methodology

The bankruptcy data for this paper was collected using information from the ASX share registry and Delisted.com.au. All firms which were delisted from the ASX share registry over the period 1999 to 2007 were examined to determine the cause of their delisting, e.g. merger, takeover, voluntary liquidation or bankruptcy. This process lead to approximately 50 bankruptcies being identified over the sample period. A bankruptcy was defined in this study as any firm which was liquidated or deregistered over the sample period.

Some observed bankruptcies could not be included in the final bankruptcy sample as they lacked adequate data for estimating the required models. The final sample consists of 32 bankruptcies. While this number is small, it is almost identical to the sample used by Altman (1968) (33 bankruptcies) and the proportion of bankrupt firms to non-bankrupt firms is consistent with data sets used in Hilligeist et al. (2004) and Chava and Jarrow (2004). To be consistent with the functional form of the discrete time hazard model, a company is coded 1 in year t if it defaulted in that year and zero otherwise. Below is a table which outlines the distribution of defaults across the sample.

Table 4: Bankruptcies by Year

Year	2000	2001	2002	2003	2004	2005	2006	2007
No. of Bankruptcies	2	6	7	9	4	1	3	0

Table 4 highlights the cyclical nature of the occurance of bankruptcy. The high level of defaults in the period from 2000 to 2003 corresponds with a slowdown in the global economy. Australia was not immune to this global downturn and this period includes the collapses of companies such as HIH Insurance and OneTel. In stark contrast to this period, 2004 to 2007 saw strong economic growth both in Australia and the rest of the world and as a result we observe relatively few bankruptcies over this period in our data set.

Each of the explanatory variables is lagged by one year so that the estimated models show how the covariate values in year $t-1$ explain bankruptcy in year t. This means that data for the years 1999-2006 will be matched to bankrupt and non-bankrupt firms over the period 2000-2007. Using the covariates outlined, the aim of this papoer is to replicate the models of Altman (1968) and Shumway (2001), to test the relative information content of the variables suggested by these models in the Australian context and specifically compare the relative strength of accounting based vs market based variables in explaining default.

Also, expanding on these models, this paper aims to add the distance to default measure to compare its information content relative to that of accounting based covariates. Finally, this paper will seek to test whether hybrid models, those containing a mixture of accounting and market variables, are able to significantly outperform the standalone models.
This paper uses a discrete time hazard model framework of Shumway (2001) to estimate a number of models to explore the questions raised by the above discussion. The description of this method and its application is shown below.

Assume we observe a total of n firms ($i = 1, \ldots, n$) with bankruptcy event times for each firm denoted by τ_B^i. As in Kiefer (1988) and Klein and Moeschberger (1997), the hazard rate for the bankruptcy event τ_B^i, is a random variable defined as:

$$\lambda_B^i(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq \tau_B^i < t + \Delta t \,|\, \tau_B^i \geq t)}{\Delta t} \tag{3}$$

This is the instantaneous probability of default for firm i given that firm i has survived up to time t. We only observe these n firms at discret intervals ($t = 1, 2, \ldots, T$) starting at the beginning of our sample period ($t = 1$) until the end ($t = T$) of our sample period. The observation for firm i continues from some starting point t_i until some time $T_i \leq T$ when the firm experiences bankruptcy (τ_B^i) or is censored for some other reason (T_i) . A firm is censored if the firm is observed in period T_i but not $T_i + 1$. Time T_i is usually the last date in the sample but need not be, i.e. the firm may be removed for some other reason (e.g. merger, takeover, voluntary liquidation). It is assumed that any such censoring is non-informative[3].

Let the point process N_t^i be defined as:

$$N_t^i = \begin{cases} 1 & \text{if} \quad \tau_B^i \leq t \\ 0 & \text{if} \quad \tau_B^i > t \end{cases} \tag{4}$$

The random time $Y_i = \min(\tau_B^i, T_i)$ corresponds to the last date that we observe firm i within the sample period. Let X_{it} denote the time varying covariates (market variables, accounting variables, etc.) of firm i at time t. Following Allison (1982), the discrete time conditional hazard rate is defined as:

$$P_t^i = \Pr(\tau_B^i = t | \tau_B^i \geq t, X_{it_i}, \ldots, X_{iY_i}) \quad \text{for} \quad t_i + 1 \leq t \leq T_i \tag{5}$$

This is the probability of a firm i experiencing bankruptcy in the discrete time period t conditional on the firms survival up to time t and the values of the the time varying covariates for firm i

It is assumed, given the information sets generated by the covariates X_{it} for all firms and times, that default times τ_B^i are independent. This conditional independence is standard assumption in hazard modelling[4]. For firm i $N_{Y_i}^i$, is either 1 if $Y_i = \tau_B^i$ and bankruptcy occurs at time τ_B^i, or 0 if $Y_i = T_i$ and the firm is censored at time T_i. The likelihood function L of the firm i's data conditioned on the covariates is:

[3] This is a common assumption in previous studies, see Chava and Jarrow (2004) and Shumway (2001), however, the testing of this assumption is recognised as a possible extension of this work.

[4] See Chava and Jarrow (2004)

$$L(N^i_{Y_i}|X_{it_i},\dots,X_{iY_i}) = \begin{cases} \Pr(\tau^i_B = Y_i) & \text{if} \quad N^i_{Y_i} = 1, \\ \Pr(\tau^i_B > Y_i) & \text{if} \quad N^i_{Y_i} = 0 \end{cases} \tag{6}$$

$$= \Pr(\tau^i_B = Y_i)^{N^i_{Y_i}} \Pr(\tau^i_B > Y_i)^{1-N^i_{Y_i}} \tag{7}$$

Let, for simplicity of notation, $\Pr(.) = \Pr(.|X_{it},\dots,X_{iY_i})$. Using the properties of conditional probabilities we can write

$$\Pr(\tau^i_B = Y_i) = P^i_{Y_i} \prod_{t=t_i+1}^{Y_i-1} (1-P^i_t) \quad \text{and} \quad \Pr(\tau^i_B > Y_i) = \prod_{t=t_i+1}^{Y_i} (1-P^i_t) \tag{8}$$

Substituting into the likelihood function and taking logarithms yields the log-likelihood function:

$$\begin{aligned} \log L(N^i_{Y_i}\,|\,X_{it_i},...,X_{iY_i}) &= N^i_{Y_i} \log\left(P^i_{Y_i} \prod_{t=t_i+1}^{Y_i-1} (1-P^i_t)\right) \\ &\quad + (1-N^i_{Y_i}) \log\left(\prod_{t=t_i+1}^{Y_i} (1-P^i_t)\right) \\ &= N^i_{Y_i} \log\left(\frac{P^i_{Y_i}}{1-P^i_{Y_i}}\right) + \sum_{t=t_i+1}^{Y_i} \log(1-P^i_{Y_i}) \end{aligned} \tag{9}$$

$$\begin{aligned} &\log L(N^1_{Y_1},\dots,N^n_{Y_n}\,|\,X_{1t_1},\dots,X_{1Y_1};\dots;X_{nt_n},\dots,X_{nY_n}) \\ &\qquad = \sum_{i=1}^{n} N^i_{Y_i} \log\left(\frac{P^i_{Y_i}}{1-P^i_{Y_i}}\right) + \sum_{i=1}^{n}\sum_{t-t_i}^{Y_i} \log(1-P^i_t) \end{aligned} \tag{10}$$

For a point process we have that $N^i_{Y_i} = \sum_{t=t_i+1}^{Y_i}(N^i_t - N^i_{t-1})$. Substitution yields:

$$\begin{aligned} &\log(N^1_{Y_1},\dots,N^n_{Y_n}\,|\,X_{1t_1},\dots,X_{1Y_1};\dots;X_{nt_n},\dots,X_{nY_n}) \\ &= \sum_{i=1}^{n}\sum_{t=t_i+1}^{Y_i} (N^i_t - N^i_{t-1}) \log\left(\frac{P^i_t}{1-P^i_t}\right) + \sum_{i=1}^{n}\sum_{t=t_i+1}^{Y_i} \log(1-P^i_t) \end{aligned} \tag{11}$$

Cox (1970) shows that this is identical, with respect to maximisation over the data, to the log-likelihood function for a logit model. The implication of this result is that computer programs that are used for analysis of logit models can also be used to estimate discrete time hazard models.[5]

This result becomes clearer when the functional form of the logit model is compared with that of the discrete time hazard model. The familiar logit model

[5] Brown (1975) noted that the discrete time hazard models could be estimated using programs that analysis dichotomous data. This paper uses the statistical package SAS to do the maximum likelihood estimation.

links the probability of bankruptcy for firm i, P_i, to set of covariates in the following function form:

$$P_i = \frac{1}{\exp -(\alpha + \beta^{'} X_i)} \tag{12}$$

This can be compared to the discrete time hazard model:

$$P_{it} = \frac{1}{\exp -(\alpha_t + \beta^{'} X_{it})} \tag{13}$$

Hillegeist et al. (2004) note that the discrete time hazard model differs from the logit model in two important ways. Firstly, the hazard model is able to incorporate all firm years of data. This is advantageous for a number of reasons;the increase in the sample improves the accuracy of our estimates, the ability to include bankrupt firms in all years for which they survive in the sample rather than just the year of bankruptcy should eliminate the selection bias inherent in the static logit approach. The hazard model incorporates a time varying baseline hazard rate, α_t. This baseline hazard rate captures the tendency for bankruptcy to be correlated to macroeconomic cycles. For example, it is likely that more bankruptcies will occur during a recession than an expansion of the economy.

We follow Hilligeist et al. (2004), in using the proportion of bankruptcies in the previous year, as a percentage of total firms in the sample, as a proxy for the baseline hazard rate. The use of this proxy ensures that our statistical model yields unbiased and consistent results. If we assume that the percentage of bankruptcies observed in the sample in any given year is a function of underlying macroeconomic variables (such as GDP, inflation, interest rates, etc.) so that $B_t = f(GDP_t, \pi_t, i_t, \ldots)$, then using the annual bankruptcy rate, B_t, as a proxy for these unobserved variables should yield unbiased and consistent results, while still incorporating their effects and avoiding a mis-specification of the model.

5 Results

This section details the results of the discrete time hazard regressions and discusses the implications of these results. Estimated models, which are based on the papers of Altman (1968), Shumway (2001) and Merton (1974), are presented to enable a comparison of the results of this study with those of the previous literature. This analysis is motivated by the aim of directly comparing the results found using Australian data with previous models, which have typically been based on United States data. An analysis of the individual covariates under different model specifications, specifically examining which variables are statistically significant in these models is followed by a comparison of the overall models in terms of their in-sample goodness of fit and informational content, consistent with the approach of Hillegeist et al. (2004).

5.1 Altman's Model

The MDA analysis of Altman (1968) represents a cornerstone of the bankruptcy prediction literature, despite the subsequent changes in econometric approach suggested by Ohlson (1980) and then Shumway (2001). The variables suggested by Altman (1968) have been included in the discrete time hazard models by Shumway (2001), Chava and Jarrow (2004) and Hillegeist et al. (2004).

Table 5: Model based on Altman (1968)

Parameter	Estimate	Standard Error	Wald χ^2	P-value
Intercept	-5.7997	0.4801	145.9024	<0.001
Annual Rate	0.6704	0.3145	4.5444	0.0330
RE/TA	0.0223	0.1225	0.0330	0.8558
EBIT/TA	-0.5397	0.2231	5.8518	0.0156
MC/TD	-0.00067	0.000916	0.5347	0.4647
WC/TA	-0.2962	0.3945	0.5637	0.4528
Sales/TA	0.1599	0.1262	1.6053	0.2052

Table 5 shows the result of the hazard model estimated with Altman (1968) covariates. The most important aspects of the results are the signs of the parameter estimates and the statistical significance of these estimates. The sign of the coefficients can be viewed as the effect that an increase in that covariate will have on the probability of bankruptcy in the estimated model. For example, the negative coefficient of EBIT/TA implies that as this covariate increases the predicted probability of default decreases.

The sign of the estimated coefficients that are consistent with a priori predictions with the expectation of RE/TA and Sales/TA. This unexpected result is not unique to this study and similar results for these covariates can be found in Chava and Jarrow (2004) (Shumway (2001) also finds the same result for the sign of the coefficient of Sales/TA). Excluding the result for RE/TA, these results are similar to those reported by Shumway (2001) and other empirical studies.

Examining these results we see that the variables Annual Rate and EBIT/TA are significant at the 5% level, suggesting that these variables are driving the explanatory power of the model. The significance of the Annual Rate variable serves to highlight the importance of the time varying baseline hazard. The coefficient of this variable is consistent with the intuition that an increase in the percentage of defaults in the previous year, that is, an increase in the baseline hazard rate, implies an increase in the probability of bankruptcy. The failure of the remaining variables to be significant in the estimated model suggest that these accounting variablesdo not add to the fit of the model.

5.2 Shumway's Market Model

Shumway (2001) proposed a market based alternative to the models of Altman (1968) and Zmijewski (1984). The covariates proposed in this model have been used extensively in the literature including Duffie, Saita and Wang (2007), Campbell et al. (2006), Beaver, McNichols and Rhie (2005) and Chava and Jarrow (2004).

Table 6: Model based on Shumway (2001) using Market Variables

Parameter	Estimate	Standard Error	Wald χ^2	P-value
Intercept	-4.9296	0.9175	28.8670	<0.001
Annual Rate	0.8166	0.3544	5.3105	0.0212
Excess Return	-0.8751	0.2047	18.2784	<0.001
Relative Size	0.1994	0.0897	4.9452	0.0262
Sigma	1.0193	0.3250	9.8361	0.0017

Table 6 shows the results of the model estimated with the market variables proposede by Shumway (2001). All estimated coefficients have the expected signs and are similar to the results reported in Shumway (2001) with the exception of Relative Size. This result may be a function of the bankruptcies of two large companies, OneTel and HIH insurance, within the sample. Given the size of these bankrupt firms relative to others in the index, their inclusion in the sample may be influencing the coefficient of Relative Size. However, this result is not unique to this study as Campbell et al. (2006) also find that Relative Size has a positive coefficient suggesting that the simple intuition that as a company grows in size its bankruptcy probability falls may not hold.

The standard view on company size and bankruptcy risk is that as a firm grows it will be able to deal with shocks to liquidity and profitability due to its its improved access to capital markets and its broader base of underlying cash flows. However, an argument can be made for the reverse to hold true. Jensen (1986) notes, the large size of firms may reflect the failure of managers to redistribute earnings to shareholders thus increasing the firm beyond its optimal size. Also, the complexity of large firms may serve to mask their true financial position and thus their true bankruptcy probability from outside observers.

All variables in the model are significant at the 5% level, suggesting that these market based variables add significantly to a model explaining bankruptcy. As in the model based on Altman (1968), the term Annual Rate remains significant consistent with the hypothesis that the underlying baseline hazard rate is an important determinant of bankruptcy.

5.3 Shumway's Hybrid Model

As well as the model above, Shumway (2001) also estimated a hybrid model of bankruptcy incorporating the additional accounting terms NI/TA and TL/TA suggested by Zmijewski (1984). Table 7 shows the result of a model estimated using these covariates.

Comparing this model to the purely market based model estimated above, we see that only the term TL/TA enters the model significantly and with the correct sign. NI/TA has the opposite sign to our a priori expectation and is statistically insignificant. Even without comparing the goodness of fit of the two models, the statistical significance of TL/TA suggests that this variable contains information that is incrementally informative over the market based measures included in the model.

Table 7: Model based on Shumway (2001) using Market and Accounting Variables

Parameter	Estimate	Standard Error	Wald χ^2	P-value
Intercept	-5.4872	0.9454	33.6876	<0.001
Annual Rate	0.8146	0.3648	4.9850	0.0256
Excess Return	-0.7542	0.2115	12.7182	0.0004
Relative Size	0.1925	0.0923	4.3495	0.0370
Sigma	0.9167	0.3407	7.2381	0.0071
NI/TA	0.0371	0.1884	0.0387	0.8440
TL/TA	1.2440	0.3655	11.5832	0.0007

5.4 Distance to Default Model

The Merton distance to default metric is used as the only covariate in the model shown in Table 8.

Table 8: Model based on Merton Distance to Default

Parameter	Estimate	Standard Error	Wald χ^2	P-value
Intercept	-4.6674	0.4969	88.2464	<0.001
Annual Rate	1.0529	0.4176	6.3581	0.0117
DtD	-0.4111	0.0896	21.0444	<0.001

In the estimated model both variables are significant at the 5% level. The coefficient of the distance to default has the expected sign, that is, as the distance to default increases the probability of bankruptcy falls. As in previous models the Annual Rate covariate is significant. This result provides a strong indication of the explanatory power of the Merton model and suggest that this measure will be useful in a model explaining corporate bankruptcy.

5.5 Accounting Variables Model

This model represents a combination of all the accounting ratios used in the models of Altman (1968) and Zmijewski (1984). The combination of all accounting ratios makes this the most general form of any of the accounting based models estimated in this paper. The results of this model are presented in Table 9.

The only variables significant at the 5% level in the model are Annual Rate and TL/TA, with both variables displaying the expected sign, all other variables are insignificant. Most of the variables enter the model with the correct sign, with the exception of RE/TA, WC/TA and Sales/TA, given the insignificance of these variables this result is not of great concern. The insignificance of the EBIT/TA variable is surprising given its significance in the Altman (1968) Model. This may be explained by the presence of multicollinearity in the variables included

Table 9: Model built using Accounting Variables

Parameter	Estimate	Standard Error	Wald χ^2	P-value
Intercept	-6.3926	0.5858	119.0686	<0.001
Annual Rate	0.5480	0.2583	4.5024	0.0338
RE/TA	0.1211	0.1321	0.8407	0.3592
EBIT/TA	-0.3789	0.6485	0.3414	0.5590
MC/TD	-0.00027	0.000665	0.1654	0.6842
WC/TA	0.1315	0.6106	0.0464	0.8294
Sales/TA	0.0395	0.1355	0.0852	0.7704
TL/TA	1.5906	0.6581	5.8423	0.0156
NI/TA	-0.3160	0.7664	0.1700	0.6801

in this model, especially with the NI/TA term which is likely to be highly correlated with EBIT/TA. In order to produce a more parsimonious model, the variables in this model where used in a stepwise regression in order to estimate the best accounting based model. The results of this analysis are shown in Table 10.

Table 10: Stepwise Accounting Model

Parameter	Estimate	Standard Error	Wald χ^2	P-value
Intercept	-6.4183	0.4876	173.2670	<0.001
Annual Rate	0.5821	0.2553	5.1986	0.0226
EBIT/TA	-0.4706	0.1436	10.7407	0.0010
TL/TA	1.4787	0.4141	12.7492	0.0004

The covariates in the model, EBIT/TA, Annual Rate and TL/TA, were the only variables to be chosen via the stepwise regression process. The removal of insignificant but correlated variables improves the fit of the model with EBIT/TA and TL/TA becoming significant at the one percent level. The fact that the model selects EBIT/TA and TL/TA implies that these accounting ratios are informative.

5.6 Market Variables Model

In similar fashion to the accounting section above, this section will examine the results of a model containing only market based covariates. The model estimated is similar to the Shumway (2001) market model, however, the distance to default metric is included as a covariate.

Table 11 details the results of the market based model. All variables enter the model with the expected sign except for Relative Size which, as before, is opposite to our a priori expectation. The covariates Annual Rate and Sigma are the

Table 11: Model built using Market Variables

Parameter	Estimate	Standard Error	Wald χ^2	P-value
Intercept	-1.3820	1.5257	0.8206	0.3650
Annual Rate	0.3295	0.2587	1.6225	0.2027
DtD	-0.4533	0.1626	7.7730	0.0053
Excess Return	-0.6546	0.2092	9.7922	0.0018
Relative Size	0.2522	0.1019	6.1280	0.0133
Sigma	0.0620	0.6091	0.0104	0.9189

only variables to be insignificant in the model at the 5% level. Given the important role that Sigma, the volatility of a firm's equity, plays in calculating the distance to default, it is likely that the distance to default metric is capturing the informational content of Sigma and rendering it insignificant in the model. The insignificance of Annual Rate in the model is notable. Given that the only change between this model and the Shumway (2001) market model is the addition of the distance to default variable, this result is surprising. Despite these results, the significance of the remaining variables in the model demonstrates the explanatory power of the market based covariates.

Table 12: Stepwise Market Model

Parameter	Estimate	Standard Error	Wald χ^2	P-value
Intercept	-1.3663	1.2799	1.1396	0.2857
Annual Rate	0.3406	0.2572	1.7540	0.1854
DtD	-0.4548	0.1164	15.2766	<0.001
Excess Return	-0.6610	0.2085	10.0475	0.0015
Relative Size	0.2510	0.1019	6.0716	0.0137

Using a s stepwise regression, the model in Table 12 was constructed as the 'best' market based model. It differs from the previous model in its exclusion of Sigma, however, all other variables are retained. Despite its insignificance, Annual Rate is included in the final model to be consistent with the underlying assumptions of the discrete time hazard framework. Not including this variable may lead to a cross sectional time dependence within the data which would result in biased and inconsistent estimates.[6]. All variables enter the model with the correct sign with the coefficient of Relative Size continuing to remain positive

5.7 The Hybrid Model

One of the aims of this work is to test whether or not hybrid models of bankruptcy are able to significantly outperform either accounting or market based models. In order to test this hypothesis, the model in Table 13, including all available variables, was estimated.

[6] Shumway (2001)

Table 13: Hybrid Model including all covariates

Parameter	Estimate	Standard Error	Wald χ^2	P-value
Intercept	-2.6003	1.7638	2.1734	0.1404
Annual Rate	0.3015	0.2673	1.2721	0.2594
DtD	-0.3473	0.1632	4.5270	0.0334
Excess Return	-0.5538	0.2282	5.8916	0.0152
Relative Size	0.2457	0.1134	4.6952	0.0302
Sigma	0.3332	0.6295	0.2802	0.5966
NITA	0.2563	0.8368	0.0938	0.7594
TLTA	1.0003	0.6966	2.0618	0.1510
RETA	0.0996	0.1384	0.5179	0.4717
EBITTA	-0.6201	0.6907	0.8061	0.3693
MCTD	-0.00010	0.000521	0.0381	0.8453
WCTA	0.3694	0.6059	0.3717	0.5421
Sales/TA	0.1283	0.1377	0.8684	0.3514

The results of the model are quite striking, in that none of the accounting based covariates are significant in this model. Given the tendency for the accounting covariates to be highly correlated this result may be a sign of multicollinearity amongst these variables. Despite this possibility, the market based variables, with the exception of the Sigma term, remain significant at the 5% level. The model above provides evidence that the market based covariates are capturing the fundamental determinants of the bankruptcy process and that accounting based covariates add relatively little, in terms of explanatory power, to a model already containing market based variables. The insignificance of the Annual Rate variable suggests that once conditioned on all available covarites, the underlying baseline hazard rate does not add significantly to the predictive power of the model.

Table 14: Stepwise Hybrid Model

Parameter	Estimate	Standard Error	Wald χ^2	P-value
Intercept	-2.6003	1.3023	0.6215	0.4305
Annual Rate	0.2704	0.2656	1.0369	0.3085
DtD	-0.4436	0.1166	14.4653	0.0001
Excess Return	-0.5354	0.2144	6.2341	0.0125
Relative Size	0.2871	0.1048	7.5057	0.0062
EBITTA	-0.3968	0.1550	6.5502	0.0105

In order to further test the explanatory power of the covariate set, the model in Table 14 was estimated using a series of stepwise regressions. One of the advantages of this technique is that, since variables are added to the model one at a time, it can avoid the problems of multicollinearity . The model represents the 'best' model constructed from all available covariates. The inference that can be drawn from the results above is that all of these variables add explanatory power to a model of bankruptcy.

As in all previous models, the market based covariates of distance to default, excess return and relative size are found to be significant. Interestingly, the accounting ratio earnings before interest and tax over total assets also enters the reduced form model[7]. This result is consistent with the findings of Agarwal and Taffler (2008), Beaver, McNichols and Rhie (2005) and Shumway (2001) in that accounting ratios add explanatory power to a bankruptcy model containing market covariates. It is clear that from a comparison of these results that market based covariates significantly outperform accounting ratios, in terms of informational content.

5.8 Comparing the Models

This section aims to assess the informational content of the models estimated and compare their relative in-sample predictive ability. To do this three measure are employed: the pseudo R^2 coefficient; area under the Receiver Operating Characteristic (ROC) curve and $-2LogL$.

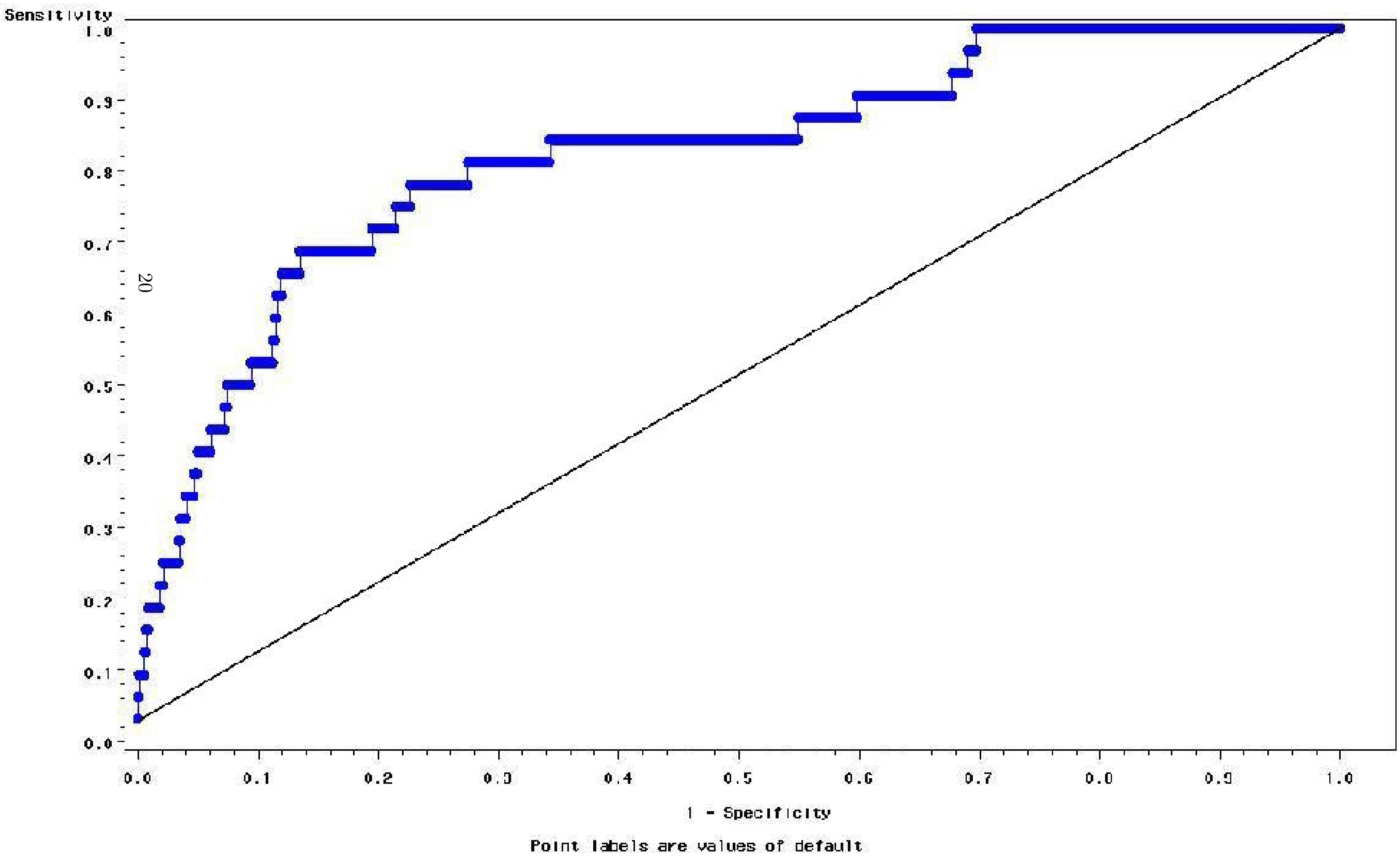
The R^2 value represents the most well known of these, however, given the nature of the discrete time hazard model, this statistic represents the pseudo R^2 of McFadden (1973). Despite this, its interpretation remains consistent with that of the more familiar OLS statistic, that is, that an increase in this statistic represents a increase in the ability of the independent variables in the model to explain the variation in the dependent variable.

The area under the ROC curve represents a measure of in-sample predictive performance based on the ROC curve method. The ROC curve is a graphical representation of a binary prediction model's trade-off between the ability to maximise sensitivity (the percentage of true positives) and minimise 1-specificity (the percentage of false positives) predicted by the model. The intuition behind this analysis is relatively simple, using the predicted bankruptcy probabilities estimated in the discrete time hazard model, each observation is predicted to be either bankrupt or not bankrupt based on some cut off probability that separates the two groups. This cut off criterion is varied across the range of estimated probabilities and the percentage of true positives and false positives is recorded for each step. The ROC curve is the plot of these recorded coordinates with sensitivity as the y-axis and 1-specificity on the x-axis. Given that sensitivity and specificity are percentage terms, the ROC curve is defined between 0 and 1 on both the x and y axes. Figure 1 represents the ROC curve constructed for the Hybrid model including all available covariates.

The aim in any binary prediction model is to maximise true positives (sensitivity) and minimise false positives (1-specificity) do the optimal point is represented by (1,0) implying that all positive predictions hold true in the observed data. A model with no predictive ability is represented by the 45^o line as it has a equal proportion of true and false positives, this is equivalent to a random guess. As the ROC curve moves closer to the optimal point (1,0) in the upper

[7] The TLTA term was only excluded from the final model as it was marginally insignificant at the 10% level

ROC plot for Hybrid Model



left corner of the graph this indicates an improvement in the predictive power of the model. As the area under the ROC curve increases this indicates an improvement in predictive power. The area under the ROC curve provides another useful metric for model comparison and evaluating the information content of different models.

The $-2LogL$ term represents negative two times the log likelihood function found under the maximum likelihood estimation process. This statistic may be interpreted by noting that as the informational content of the model increases then this term will approach zero. The use of this statistic is consistent with the approach of Hillegeist et al. (2004) in assessing the informational content of our estimated models.

Table 15 and 16 outline the key statistics for each of the models estimated. The results are split into two sections for ease of comparison.

Table 15: Comparison of Model Fit: Section 1

Model	R^2	Area under the ROC curve	$-2LogL$
Altman	0.0746	0.699	335.644
Shumway Market	0.0998	0.776	329.093
Shumway Hybrid	0.1295	0.808	316.613
Distance to Default	0.1049	0.796	327.145

Table 16: Comparison of Model Fit: Section 2

Model	R^2	Area under the ROC curve	$-2LogL$
All Market	0.1398	0.811	315.692
Stepwise Market	0.1391	0.811	316.060
All Accounting	0.1015	0.746	329.236
Stepwise Accounting	0.0965	0.747	330.990
Hybrid	0.1680	0.829	305.782
Stepwise Hybrid	0.1530	0.815	311.176

The relatively low values for R^2 in the tables above is typical of the discrete time hazard model. Given the cross sectional nature of the data under analysis and the low frequency of bankruptcies as a percentage of the overall data set, the R^2 values of such models are usually quite low. These values are similar to, if slightly lower than, many of the results reported in the literature.[8] All models achieve a significantly higher area under the ROC curve than that of the naive model (0.5), indicating explanatory power for all models.

The first comparison that is striking is that the Shumway (2001) market model and the distance to default model significantly outperform the Altman

[8] Hillegeist et al. (2004) find values between 0.06 to 0.16 for similar models based on the models of Merton (1974), Altman (1968) and Ohlson (1980)

(1968) model in terms of both R^2, area under the ROC curve and the $-2LogL$ statistic . This result is consistent with Hilligeist et al. (2004), Shumway (2001) and Duffie, Saita and Wang (2007) in finding that market based models outperform accounting based models in explaining bankruptcy. However, the strong performance of the Shumway (2001) hybrid model in comparison to all other models highlights the ability of accounting variables to add to the predictive power of a model of bankruptcy. These findings suggest that market variables are unable to subsume the information found in accounting ratios and that accounting ratios have a role to play in a well defined model of bankruptcy.

The testing of the information content of the distance to default metric in comparison to accounting based covariates and, to a lesser extent, other market based covariates was an important aim of this study. The results in Table 15 show that the distance to default, in a univariate discrete time hazard model, outperforms both the Altman (1968) model and Shumway (2001) market model in terms of R^2 and area under the ROC curve. This result highlights the information content of the distance to default measure and shows that, despite the restrictive assumptions that underlie its construction, the Merton framework is able to capture the underlying process that drives bankruptcy. This finding is consistent with those of Hillegeist et al. (2004), however, as in Bharath and Shumway (2004) this paper finds that the distance to default measure is not a sufficient statistic for summarising bankruptcy risk. This is shown above by the fact that other covariates are found to be significant in a model already containing the distance to default measure. The improved R^2 and area under the ROC curve values of these models, that either do not contain the distance to default measure or include other variables, reiterates this fact.

Considering the second section of the results in Table 16, all of the stepwise models under perform their generalised counterparts. This result is unsurprising given that adding more variables, despite their individual significance in the model, will typically inflate the R^2 value, increase the area under the ROC curve and improve the $-2LogL$ metric. Consistent with the results above, the market based model out performs the accounting based model in terms of R^2, area under the ROC curve and the $-2LogL$ statistic. The stepwise hybrid model is found to have a higher R^2 value, a greater area under the ROC curve and lower $-2LogL$ than either of the standalone models. Once again, this result supports the notion that both accounting and market based covariates add incrementally to a model of corporate bankruptcy.

To supplement the analysis above the in-sample predictive power of the individual models was assessed by looking at their ability to correctly rank firms into deciles based on their bankruptcy risk. This method, used by both the studies of Beaver, McNichols and Rhie (2005) and Shumway (2001), sorts companies based on their model implied probability of bankruptcy into deciles with the lowest decile (10) representing the highest probability of bankruptcy and the highest decile (1) representing the lowest. The number of actual bankruptcies, as a percentage of total bankruptcies, in each of these deciles is calculated. The model with no predictive power would have an average of 10 percent of actual bankruptcies in each decile. The theoretical 'best' model would have all actual bankruptcies placed in the lowest decile. The output of these tests are shown in Table 17.

Examining Table 17 , it is clear that all models have some explanatory

Table 17: Bankruptcies per Decile: Section 1

Decile	Altman	Shumway Market	Shumway Hybrid	DtD
10	28.13	40.63	53.13	53.13
9	40.63	65.63	71.88	65.63
8	53.13	78.13	81.25	78.13
7	62.50	78.13	84.38	81.25
6	78.13	81.25	87.50	84.38
5	90.63	81.25	87.50	90.63
4	93.75	93.75	90.63	96.88
3	93.75	93.75	96.88	100.00
2	96.88	93.75	100.00	100.00
1	100.00	100.00	100.00	100.00

power above the naive model, as actual bankruptcies are found mostly in the lower deciles of the model implied probabilities of bankruptcy. For example, the distance to default metric is able to place 53.13% (17/32) of the total bankruptcies in the data in the decile with the highest model implied probability of bankruptcy. Examining the results above we may draw similar conclusions as those based on the R^2 comparison above. The market based models significantly outperform the Altman (1968) model and the Shumway (2001) hybrid model and the distance to default metric outperform both the Altman (1968) and Shumway (2001) market models. The comparison between the Shumway (2001) hybrid model and distance to default model is less clear. Both these models perform well with 53.13% of the observed defaults placed in the lowest decile by each model. As we proceed further down the table the two models mirror each other quite closely, indicating that the distance to default measure compares favorably with the hybrid model in terms of predictive ability.

Table 18: Bankruptcies per Decile: Section 2

Decile	Market	Reduced Market	Accounting	Reduced Accounting	Hybrid	Reduced Hybrid
10	53.13	53.13	28.13	31.25	53.13	50.00
9	65.63	62.50	53.13	53.13	71.88	65.63
8	78.13	78.13	71.88	68.75	81.25	81.25
7	84.38	84.38	78.13	71.88	84.38	84.38
6	87.50	87.50	81.25	84.38	84.38	87.50
5	90.63	90.63	84.38	87.50	87.50	90.63
4	93.75	93.75	93.75	93.75	100.00	93.75
3	96.88	96.88	93.75	96.88	100.00	96.88
2	100.00	100.00	96.88	96.88	100.00	100.00
1	100.00	100.00	100.00	100.00	100.00	100.00

Table 18 compares the in-sample predictive ability of the remaining models. All models are shown to have significant predictive power above the naive model and all stepwise models are slightly less accurate than their generalised counterparts, as expected. The most striking feature of these results is the performance of the hybrid model. This performance is demonstrates the ability of the hybrid model to incorporate the information contained in accounting and market based variables. The inclusion of accounting and market variables implies that neither subsumes the other and both have a place in a well defined model of corporate bankruptcy.

6 Conclusion

This paper has explored corporate bankruptcy in Australia in order to add to the debate over how best to construct a model for bankruptcy prediction. The previous literature presents a clear divide between the so called market and accounting based approaches to this problem. With this in mind, this paper employs the discrete time hazard model framework of Shumway (2001) to test the information content of both market and accounting based models in Australia.

This study has found that market based models outperformed accounting based models in tests of informational content. Further, many accounting variables become insignificant in a model of bankruptcy already containing market based variables. The conclusion drawn from these results is consistent with the findings of Hillegeist et al. (2004), Chava and Jarrow (2004) and Duffie, Saita and Wang (2007) in suggesting that market based covariates should form the basis for any well defined model of corporate bankruptcy. However, as in Shumway (2001), Bharath and Shumway (2004) and Benos and Papanstasapoulos (2007), this paper finds that hybrid models of corporate bankruptcy, containing both accounting and market based variables outperform either of the standalone models. The implication of this result is that, despite the superior performance of market based measures, accounting ratios still hold information that increases the explanatory power of market based model and therefore have a place in a well defined model of corporate bankruptcy.

This work can be extended in a number of ways. An increase in the size of the bankruptcy database, increasing the length of the sample period and the sophistication of the screening process. Also, increasing the number and creativity of covariates tested may provide further insight and improve the fit of the models presented. Further, an out-of-sample test of the predictive power of the estimated models would allow further evaluation of their comparative merit. Finally, the inclusion of macroeconomic or industry level variables, as suggested by Chava and Jarrow (2004), may lead to greater insight into these important determinates of bankruptcy in the Australian context.

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