A Cash Flow Based Model of Corporate Bankruptcy in Australia

Stewart Jones*

Abstract

This study uses a cash flow based model to predict corporate bankruptcies in Australia. Using four cash based variables, the model produces very good out-of-sample predictive accuracy (AUC of around .85) which is better than some of the more complex multivariate models in the literature. The model also outperforms a logit model estimated on Altman Z score variables. The paper illustrates how to calculate and interpret the logit model failure probabilities on the failed Australian company Dick Smith's recent financial statements.

Keywords

Financial Distress Prediction
Logit
Operating Cash Flow
Dick Smith Ltd.

Data Availability

All data available from public and commercial sources identified in the paper

* The University of Sydney

Introduction

The prediction of corporate distress has attracted the attention of accountants, regulators, business analysts and financial economists over the last five decades (Altman 2002). As pointed out by Jones and Hensher (2008) bankruptcy modelling has enjoyed a major resurgence of interest since the global financial crisis. Jones and Hensher (2004) observe that bankruptcy forecasts are now widely used for a range of purposes, including evaluating the solvency of financial institutions and corporations by resource providers and regulators, assessment of debt security by lending organisations, auditor evaluations of going concern, and the pricing of bonds, credit derivatives and other instruments exposed to credit risk.

While more sophisticated modelling techniques have emerged in the literature, much of the extant literature has relied on multiple discriminant analysis (MDA), binary logistic or probit analysis and in a small number of cases multinomial logit models (MNL) (see e.g., Altman 1968; Altman, Haldeman, and Narayanan, 1977; Ohlson, 1980; Zmijewski, 1984; Altman, 2002; Jones and Hensher, 2008). The early work of Altman (1968) championed the use of MDA; however, logit models have become more prevalent in the literature at least from the 1980s, starting with the work of Ohlson (1980). Based on an analysis of 150 empirical studies, Jones et al., (2015) observes that the logit model is the most commonly used statistical model in the corporate bankruptcy literature over the past 50 years.

There are several possible reasons for this. First, logit models are based on less rigid statistical assumptions than MDA. This can be important as bankruptcy datasets tend to "noisy", marred by missing values, incomplete data and input variables which rarely conform to the normality condition (due to the effects of outliers, skewness, kurtosis and other issues in the dataset). Logit models tend to perform better when the dataset is not 'well behaved'. As MDA is based on more rigid econometric assumptions (such as multivariate normality and IID) parameter estimates can easily be biased and predictive performance undermined when these conditions are not fulfilled.

Greene (2008) elegantly describes the differences between MDA and discrete choice models such as logit and probit (in this case he uses the example of loan applicants):

"*It's long track record notwithstanding, one could argue that the underpinning of discriminant analysis is naive. The technique divides the universe of loan applicants into two types, those who* ***will*** *default and those who* ***will not****. The crux of the analysis is that at the time of application, the individual is as if preordained to be a defaulter or a non-defaulter. In point of fact, the same individual might be in either group at any time, depending on a host of attendant circumstances and random elements in their own behaviour. Thus, prediction of default is not a problem of classification the same way as is, say, determining the sex of prehistoric individuals from a fossilized record…Index function based models of discrete choice, such as the probit and logit models, assume that for any individual, given a set of attributes, there is a definable probability that they will actually default on a loan. This interpretation places all individuals in a single population. The observed outcome, default/no default, arises from the characteristics and random behaviour of the individuals.*"

Hence, a second reason for the dominance of logit models in the literature comes down to their intuitive appeal, convenience and practicality. Logit models are probability models and the outputs of these models represent probability estimates of corporate failure. Probability outcomes are relatively easy for practitioners to interpret. However, MDA models produce a Z score, which is a cut-off threshold.

For instance, one of the most well-known of these models, the Z score model of Altman et al., (1977) uses a cut-off score for bankruptcy as Z<=1.80 and a firm is regarded as safe if Z>=3. However, these decision thresholds can be difficult to interpret in practice. For instance, how does the analyst interpret the "grey area" between a Z score 1.8 and 3? Does a Z score of 6 mean a company is twice as strong or healthy as a company with a Z score of 3? The use of probabilities avoids this problem altogether – rather than belonging to "preordained" groups (you are either in or you are out) probabilities recognise the implicit uncertainty about class membership leading up to the failure outcome.

Input Variables

A number of financial variables have been tested in prior research over the past five decades (some representative studies include: Beaver, 1966; Altman, 1968; Altman, Haldeman and Narayan 1977; Ohlson, 1980; Zemjewski, 1984; Casey and Bartczak 1985; Gentry, Newbold and Whitford, 1985; Jones 1987; Shumway, 2001; Jones and Hensher, 2004: Beaver et al., 2005; Jones and Hensher, 2008). These financial measures include ratios based on cash position; operating cash flow (CFO); working capital; profitability and earnings performance; asset utilization and turnover; capital structure; and debt servicing capacity, capital expenditure, various growth/change measures and other indicators. More recently there has been a focus on the importance of market price measures, such as abnormal stock returns and stock price volatility (see Hillegeist et al. 2004; Beaver et al., 2005).

The importance of operating cash flows in risk evaluation is not only well established in the literature but has long been recognised by accounting standard setters. For instance, the Australian Accounting Standards Board (AASB) replaced the funds flow statement with the cash flow statement in 1992 recognising the general superiority of this information for liquidity and solvency evaluation (see Jones et al., 1995). Jones et al., (1995) also notes that the shift to the importance of cash flow statements in the late 1980s and early 1990s can be directly attributed to a dramatic increase in the number of corporate bankruptcies over this period.

As stated in paragraph 13 of AASB 107 'Cash Flow Statements':

"The amount of cash flows arising from operating activities is a key indicator of the extent to which the operations of the entity have generated sufficient cash flows to repay loans, maintain the operating capability of the entity, pay dividends and make new investments without recourse to external sources of financing. Information about the specific components of historical operating cash flows is useful, in conjunction with other

information, in forecasting future operating cash flows."

The links to financial risk were also made strongly in the pre-IFRS AASB 1026 "Statement of Cash Flows" (1998) version of the standard which stated (at paragraph 3.1.1):

"The information provided in a statement of cash flows together with other information in the financial report may assist users in assessing the ability of an ***entity*** *to:*

(a) generate ***cash flows***

(b) meet its financial commitments as they fall due, including the servicing of borrowings and the payment of dividends

(c) fund changes in the scope and/or nature of its activities

(d) obtain external finance."

Furthermore, while AASB 107 was amended in 2007 to permit a choice between the direct and indirect methods of reporting cash flows (to be consistent with IFRS) the standard confirmed the superiority of the direct method (at paragraph 19):

"Entities are encouraged to report cash flows from operating activities using the direct method. The direct method provides information which may be useful in estimating future cash flows and which is not available under the indirect method."

Empirical Support

There is strong empirical support for the importance of cash flows in bankruptcy prediction. Beaver (1966) was one of the first to test cash flow based measures (such as cash flow to debt). Beaver (1966, p.101) concluded that: "Not all ratios predict equally well. The cash-flow to total-debt ratio has excellent discriminatory power throughout the five-year period. However, the predictive power of the liquid asset ratios is much weaker." However, cash flow in this study is defined naively as net income plus depreciation, depletion, and amortization.

In the mixed logit analysis of Jones and Hensher (2004), the authors find that measures such as operating cash flow and cash flow cover are highly significant measures in their model. However, with the exception of Beaver (1966) and a few other studies, the importance of cash flow has not been widely tested in the US bankruptcy literature. For instance, none of the Altman studies formally test cash flows (see Altman, 2002). This is perhaps not surprising considering that many of these studies predate the introduction of the cash flow disclosure requirements under SFAS 95 (Casey and Bartczak, 1985) (this standard was introduced by the FASB in 1987).

However, an important difference between the Australian and US cash flow requirements is that SFAS 95 mandated the indirect method of reporting cash flows which requires that operating cash flow be measured/estimated from changes in working capital accounts. Hribar and Collins (2002) provide evidence that empirical studies which uses estimates of CFO (as opposed to reported CFO) are prone to significant measurement errors which can contaminate the empirical results of some of these studies (see also Jones and Hensher, 2004). Previous bankruptcy research testing the predictive performance of CFO has invariably used estimates rather than reported CFO. However, in light of Hribar and Collins (2002), this could also potentially explain why so few of these studies have found any supporting evidence for the usefulness of CFO in distress prediction (see e.g., Neill et al., 1991). For the purposes of this study, all cash flow ratio measures are calculated from the direct method required under AASB 1026/AASB 107. It is noted that while the 2007 version of AASB 107 provided companies a choice to prepare either the direct or indirect method, most companies in Australia continued using the direct method.

The Cash Based Measures

The four cash based measures used in this study are (1) operating cash flow to total assets (or cash flow returns); (2) cash flow cover which is net operating cash flow divided by interest payments, (3) quality of earnings, which is calculated as net operating cash flow divided by EBIT, and (4) cash resources (cash and short term investments) over total assets.

With respect to (1), cash flow returns is similar to Altman's EBIT to total asset measure, however net operating cash flow provides a more relevant measure of a firm's solvency, financial viability and operating performance. While operating cash flows tend to be more volatile than earnings, there is an extensive literature that demonstrates that reported earnings is subjected to systematic managed by companies, whereas operating cash flows are relatively more difficult to manipulate as they do not involve accounting allocations, accruals or deferrals of any kind (see Jones and Belkoui, 2010). Hence, operating cash flows provide a relatively more reliable and objective measure of operating performance (see Jones and Belkaoui, 2010).

With respect to measure (2), cash flow cover has similarities with Beaver's (1966) cash flow to debt measure, but this study utilizes a more refined operating cash flow measure, not a crude "add back" method used by Beaver (net income plus depreciation and amortization). However, instead of using the gross total debt figure, this study uses debt servicing capacity which is arguably a more relevant measure for evaluating a firm's financial solvency.

With respect to measure (3), the quality of earnings indicates the disparity between accrual based earnings and operating cash flow. The greater this disparity (i.e. where earnings are higher than operating cash flow), the lower the quality of earnings. Lower quality earnings often arise from earnings management practices (for instance, companies adopting aggressive revenue recognition practices which leads to higher earnings but lower reported cash flows).

In the context of company failures, Jones (2011) has shown that distressed companies have a high propensity to engage in earnings management which lowers the quality of earnings and increases the risk of failure. Finally, cash position to total assets is an important measure of a firm's liquidity and short term staying power. Even if a firm a has poor operating cash flow performance, low quality earnings and weak cash flow cover, a firm can continue to survive if it has strong cash reserves to draw on.

In certain industries, such as high technology, healthcare and biotechnology, telecommunications and IT firms may not be able to generate positive operating cash flows in the formative years of operation. However, these firms have a higher probability of surviving if they can maintain satisfactory levels of cash resources to finance their operating activities and future growth. However, firms which perform poorly across all four cash based measures are expected to have a much higher chance of financial distress and ultimately failure.

Method

This study employs a binary logistic regression to model failure in two states:
State 0: non-failed firms;
State 1: firms who filed for bankruptcy followed by the appointment of liquidators, insolvency administrators or receivers. Similar to Jones and Hensher (2004) study, the sample includes three forms of bankruptcy proceeding available under the legislative provisions of the Australian *Corporations Act* (2001): (i) voluntary administration, which was first introduced in Australia in June 1993 under the *Corporate Law Reform Act*, 1992); (ii) liquidation and (iii) receivership.

Voluntary administration in Australia shares some of the features of US Chapter 11 provisions, which provide corporations a period of time to reorganize and/or reconstruct their affairs. Under Australian voluntary administration laws, a firm has a limited time to assess its affairs and recommend to the creditors whether the company should be wound up or enter into a deed of arrangement. If the deed of arrangement stage is not reached, the legislation provides for an automatic transition to liquidation.

With respect to liquidation, there are basically two types of winding up procedure available (described in Jones and Hensher, 2004): a creditors' voluntary winding up (decided by special resolution of the company) and a court winding up. In the case of receiverships, the *Corporations Act* (2001) provides that a secured creditor, in the event of a firm's insolvency can appoint a receiver (or a receiver and manager) to recover outstanding claims against the company. Most failed firms in Australia fall under the category of voluntary administrations or liquidations.

Sample Selection

The sample is based on firm financial distress data collected between 2003 and 2010. Over this period I collect a sample of nonfailed firms (state 0) and a sample of bankruptcy firms (state 1). I collected up to three years of data on all firms in both categories. The sample of nonfailed firms is drawn over the same time period range as the firms in states 1. To avoid the "back casting" problem noted by Ohlson (1980) and Jones and Hensher (2004), data are collected only from the financial statements already in the public domain on the date the failure is first made known to the market. The same procedure is followed for firms in state 1. This produces a final useable sample of 2,170 firm years in the non-failed state and 136 firm years in the failure state.

Following Jones and Hensher (2004), only publicly listed firms on the ASX are included in the sample. Only firms who reported cash flow information under requirements of the Approved Australian Accounting Standard AASB 1026 "Statement of Cash Flows" or AASB 107 are the sample. In some cases, firms are removed because no financial statement records could be found. Following the approach of Ohlson (1980) and Jones and Hensher (2004) no firm is deleted simply because it is newly or recently listed, and some firms only had one or two years of financial reports, which is typical in bankruptcy datasets.

Test sample. Based on conventions used in the statistical learning literature, I use an estimation or training sample to estimate the logit models, and a test sample to validate the predictive performance out-of-sample. I randomly allocate 80% of the total observations to the training data and 20% of observations to the test sample (see Hastie et al., 2009).

The Logit Model

The logit model (or "log of the odds" model) used in this study can be conceptualised as log-odds which converts a binary outcome domain (0,1) to the real line (-∞, ∞). For the logit model this index or link function (see Greene, 2008) is based on the logistic distribution. The error structure is assumed to be IID (independent and identically distributed) while explanatory variables have distribution free assumptions. Parameters are estimated using maximum likelihood.

The logit model is set out as follows:

$$\text{Prob}[Y_i = 1|x_i] = \frac{e^{\beta' x_i}}{1 + e^{\beta' x_i}}$$

Which reads as the probability Y_i of a firm observation entering state 1 given a set of risk factors x_i and where $\beta' x_i$ is a vector of parameter estimates and risk factors (ie the four cash based ratios described above).

Empirical Results

The logit results are summarised in Tables 1-2 below and in Figure 1. Table 1 provides the overall model summary. The model shows an excellent area under the ROC curve (AUC) of .8532. The ROC curve is the most widely used measure in the literature for comparing the predictive performance of alternative classifiers (for a technical discussion see Swets et al., 2000; Jones et al., 2015). The ROC curve plots the true positive rate (known as 'sensitivity') relative to the false positive rate (1−specificity) with respect to some cut-off score. For binary (two state) classifiers, this score is the predicted probability of bankruptcy generated from the logit model.

A random guess is characterized by a horizontal curve through the unit interval (this equates to an AUC of precisely 0.5). As a minimum, classifiers are expected to perform >.5 (better than random guessing). An AUC score of 1 represents perfect classification accuracy. In other words the Type I and Type II errors are zero.

Many textbooks recommend that AUC scores greater than 0.9 are an indication of a very strong classifier, which shows an outstanding balance between sensitivity and specificity across different probability thresholds; whereas AUCs between 0.8 and 0.9 are indicative of a very good or strong classifier.

The baseline threshold accuracy in Table 1 is the cut-off threshold that reflects the actual balance of failures and non-failures in the sample: so if the sample has 80% non-failures the cut-off threshold for predicting non-failure .80 and .20 is the cut-off for predicting the failure outcome. The raw classification is based on the default cut-off which is .5. In other words, if an observation has a greater than 50% probability of failure or non-failure, it will be classified into that category.

The model also shows that the log likelihood ratio has improved very significant with a quite good model fit (McFadden's Rho-Squared is .197).

Table 1: Logit Model Summary

Name	Learn	Test
Average LogLikelihood (Negative)	0.51661	0.52278
Misclass Rate Overall (Raw)	0.24193	0.25751
ROC (Area Under Curve)	0.86913	0.85328
Lift	2.33549	2.26038
LogLikelihood (constant model)	-1734.59338	n/a
LogLikelihood	-1392.27722	n/a
McFadden's Rho-Squared	0.19735	n/a
Chi-Sq P-Value	9.992e-016	n/a
Class. Accuracy (Baseline threshold)	0.82560	0.78398

Table 2: Estimated Logit Coefficients

Variable	Coefficients	S.E.	T-Ratio	P-Value
Constant	0.93698	0.048198	19.44	<.0001
NETOPTA	0.089040	0.008587	10.369	<.0001
EQUAL	0.04365	0.016198	2.6947	<.0001
CFCOVER	0.07116	0.010912	6.521	<.0001
CPTA	.0301	.00581	5.178	<.0001

Table 2 shows the estimated coefficients of the model, including coefficients, standard errors and t-values. The net operating cash flow to total assets ratio (NETOPTA) has a positive parameter estimate (.0809) and highly significant *t*-value of 10.36. Increases in this ratio increase the probability of non-failure or reduce the probability failure. The cash flow cover ratio (CFCOVER) also has a positive parameter estimate (.07116) and a significant t-value of 6.52. Increases in this ratio also increase the probability of non-failure or reduce the probability failure. The quality of earnings metric (EQUAL), measured as operating cash flow to EBIT has a positive parameter estimate (.0436) and significant t-value of 2.69. Increases in this ratio indicate higher earnings quality. Hence, higher earnings quality increase the probability of non-failure or lower earnings quality increases the probability failure.

Analysis of the classification matrix shows that the model is 81.34% accurate in predicting non-failures and 82.26% accurate in predicting failures on the test sample. The overall percent correct is 81.69%. Figure 1 plots the ROC curve for the estimation and test samples.

Figure 1: ROC Curve for Logit Model reported in Table 1

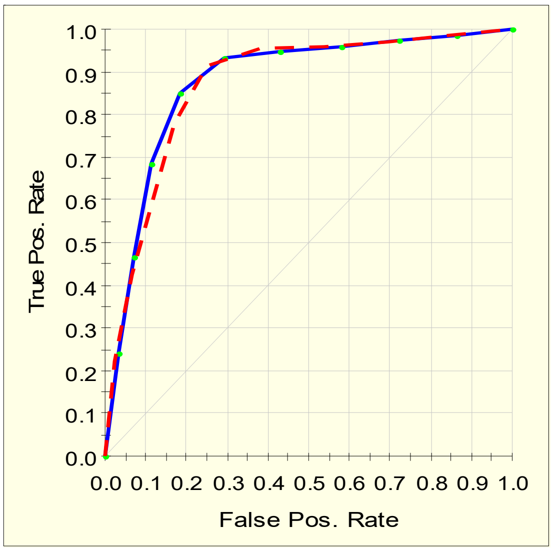

Table 3: Estimated Logit Coefficients for Altman Variables

Variable	Coefficients	S.E.	T-Ratio	P-Value
Constant	1.49195	0.085916	17.365	1.9984e-015
Earnings Before Interest and Taxes/Total Assets	0.03730	0.0034344	10.861	1.9984e-015
Market Value of Equity/Book Value of Total Liabilities	0.00003	6.7577e-005	0.46949	0.63872
Working Capital to Total Assets	0.00433	0.0022674	1.9098	0.056158
Retained Earnings/Total Assets	0.00024	0.00025958	0.93555	0.3495
Sales/Total Assets.	-0.00008	0.00038014	-0.19922	0.84209

It is interesting to contrast these results with a logit model estimated on the well-known Altman et al., (1977) parameters: EBIT to total assets; working capital to total assets; retained earnings to total assets; sales to total assets and market capitalization to total book value of debt. Tables 3 show the key results. Table 3 shows the coefficients for the Altman variables – only two variables are statistically significant: EBIT to total assets and working capital to total assets.

Analysis of the classification matrix shows that the predictive power of the Altman variables is weaker overall than the cash flow model reported in Tables 1-2. The Altman variables are 78.06% accurate in predictive failures and 79.59% accurate in predicting non-failures. The overall accuracy rate of the Altman model is 78.46%.

Interpreting the Models

An Application to Dick Smith's Financial Statements

As an illustration, we apply the Altman model and the cash flow model introduced in this study to the recent failure of Dick Smith. Dick Smith was suspended from official quotation on 5th January 2016 and receivers were appointed shortly after. A number of large stockholders did not anticipate the collapse and analyst growth forecasts and recommendations tended to be positive prior to the failure.[1]

In a trading update provided by Dick Smith to the market on 18th October 2015, the CEO stated: "Sales for the first quarter have improved on the prior year and last quarter (4Q2015), with New Zealand experiencing its best quarterly sales performance since acquisition." Further, while the company expected trading conditions would be challenging moving into the Xmas period, the company was clearly not expecting a financial catastrophe. The 18th October, 2015 updated stated:

"Reflecting this caution, the Company presently anticipates FY2016 NPAT could be $5 million to $8 million below previous guidance of $45 million to $48 million… Cash conversion is expected to improve year on year for 1H2016 and FY2016, as the Company continues to unwind the working capital position at June 2015".

The failure of Dick Smith was a surprise to the market – the stock price reaction was slow and there was no sharp correction in price until the later stages of the collapse. Many institutional investors were still listed as major shareholders at the time of the collapse. The Appendix provides the balance sheet, income statement and statement of cash flows from 2012-2015.

While the cash flow model has outperformed a logit model estimated on the Altman variables, how does one apply and interpret the logit model on Dick Smith's financial data? One of the major benefits of the Altman Z score model is that it is very easy to apply and interpret. For

[1] The company's growth prospects appeared upbeat on 8th October when the company released its Bank of America Merrill Lynch Emerging Stars Symposium strategy.

instance, the most popular Z score model has the following fitted form:

$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.99X_5$,

where $X_1 – X_5$ represent financial ratios, respectively Working Capital/Total Assets; Retained Earnings/Total Assets; Earnings Before Interest and Taxes/Total Assets; Market Value of Equity/Book Value of Total Liabilities; and Sales/Total Assets.

All the analyst has to do is compute the required ratios and then multiply the ratios by the parameter estimates provided, then sum them. If the Z score is below a certain threshold (1.80) the company is predicted to fail (see Altman, 2002). It can be seen from Table 4 below that the Z score for Dick Smith based on the 2015 financial statements is 4.33 (or financially safe) as shown in the following calculation:

Z = 1.2*.1434 + 1.4*.318 + 3.3*.1159 + 0.6*1.24+ 0.99*2.59 = 4.33 (financially safe).

How does the cash flow model fair? A logit model produces probabilities, not cut-off scores. Hence, we need to calculate probabilities from the Table 2 model. This is easily achieved in two simple steps:

Step 1: From Table 2, calculate the value of the logistic regression equation:

$Y = 0.93698 + 0.089040*X_1 + 0.04365*X_2 + 0.07116*X_3 + .030*X_4$

where X_1 = net operating cash flow to total assets, X_2 = quality of earnings, and X_3 = cash flow cover, and X_4 cash position to total assets.

Step 2: Convert Y to the probability of failure. As non-failure is coded 1 in the dataset, the probability of failure is simply calculated as:

1-(Exp(Y)/(1+Exp(Y))

where 'Exp' is the exponential function. It can be seen from Table 4, that Dick Smith has a probability of failure of 28%. The calculation is shown as follows:

Y = 0.93698 + 0.089040*.789 + 0.04365*-.0677 + 0.07116*-1 + .030*5.89%. Y sums to .97.

The failure probability is calculated as:

1-(Exp(Y)/(1+Exp(Y)), or
1-Exp(.97)/(1+Exp(.97)) = 28%.

Table 4: Key Ratios of Dick Smith (2015 Financial Statement Data)

Cash Flow Model		**Altman Model**	
Operating cash flow to total assets (%)	-4/509 = .789%	Working Capital to Total Assets	390-317/509 = .1434
Quality of earnings (X)	-4/59 = -.0677	Retained Earnings/Total Assets	162/509 = .318
Cash flow cover (X)	-4/4 =-1	Earnings Before Interest and Taxes/Total Assets	59/509 = .1159
Cash position to total assets (%)	30/509 = 5.89%	Market Value of Equity/Book Value of Total Liabilities	422/339 =1.24
		Sales/Total Assets.	1320/509 = 2.59
Failure Probability	28%	**Z score**	4.33

While a 28% probability of failure represents no certainty of Dick Smith's demise, this is a very high failure probability compared to what we might expect from a healthy company. Most strong Australian companies should have a less than a 5% chance of failure if they score reasonably well on the cash flow variables shown in Table 2. For instance, a financially solid company with operating cash flow greater that EBIT (i.e. >1 or good quality of earnings), a net operating cash flow to total assets of at least 15%, cash flow cover of around 4 times, and cash resources to total assets of around 25% will have less than a 3% chance of failure based on the cash flow model. Hence, the cash flow model appears to provide a much better indication of Dick Smith's financial woes 6 months prior to failure compared to the Altman Z score which provides no indication of the company's looming financial distress.

Conclusions

This study develops a simple cash flow based model based on four variables of interest: net operating cash flow to total assets, quality of earning (operating cash flow to EBIT), cash flow cover and cash position to total assets.

The logistic regression results indicate that all four parameters are statistically significant and have consistent signs. The overall area under the ROC curve (AUC) is around .85, indicating the model has very good predictive accuracy and actually improves on some of the more complex multivariate models in the literature.

The cash flow model also outperforms a logit model estimated on Altman Z score variables.

Using the 2015 financial statements of Dick Smith, the paper illustrates how to calculate and interpret probability outputs from a logit model.

The study shows that the Altman Z score model failed to pick up the financial distress of Dick Smith, but the cash flow model provided a much better indication that the company was in serious financial trouble at least 6 months before the collapse of the company.

References

Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance,* 23 (1): 589-609.

Altman, E., Haldeman, R. and Narayan, P. (1977). ZETA Analysis: a new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance,* June, Vol 1 (1), :29-54.

Altman, E. (2001). *Bankruptcy, Credit Risk and High Yield Junk Bonds,* Blackwell Publishers, New York, NY, USA.
Australian Accounting Standards Board. (1992). *Approved Australian Accounting Standard AASB 1026: Statement of Cash Flows*. Australian Accounting Research Foundation, Melbourne, Australia.

Australian Corporations Act 2001. Cwt (http://www.asic.gov.au/asic/ASIC).
Australian Stock Exchange. 2003. *Listing Rules*. Sydney, Australia. http://www.asx.com.au/about/l3/ListingRules.

Australian Stock Exchange. 2003. *Market Comparative Analysis*, Sydney, Australia. http://www.asxtra.asx.com.au.

Beaver, W. (1966). *Financial ratios as predictors of failure.* Empirical Research in Accounting: Selected Studies*, Journal of Accounting Research,* 4 *Supplement*: 71-111.

Beaver, W.H, McNichols, M.F., Rhie, J.W. (2005). Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy, *Review of Accounting Studies*, 10 (1): 93–122.

Casey, C. and Bartczak, N. (1985). Using operating cash flow data to predict financial distress: Some extensions, *Journal of Accounting Research,* 23 (Spring): 384-401.

Clark, K., and Ofek, E. (1994). Mergers as a means of restructuring distressed firms: and empirical investigation. *Journal of Financial and Quantitative Analysis,* 29 (2): 541-565.

Duffie, D., and Singleton, K. (2003). *Credit Risk: Pricing, Measurement and Management,* Princeton University Press, Princeton, NJ, USA.

Financial Accounting Standards Board. (1987). *Statement of Financial Accounting Standards 95, Statement of Cash Flows,* FASB, Stamford, CT, USA.

Gentry, J., Newbold, P. and Whitford, D. (1985). Classifying bankrupt firms with funds flow components. *Journal of Accounting Research,* 23(Spring): 146-160.

Greene, W. (2008). *A Statistical Model for Credit Scoring*. In Jones, S., and D. A. Hensher *Advances in Credit Risk Modelling and Corporate Bankruptcy Prediction,* 14-44. Cambridge University Press, Cambridge, UK.
Hastie, T., Tibshirani, R., Friedman. J. (2009). *The Elements of Statistical Learning: Data*

Mining, Inference and Prediction (2nd edition). Springer, New York, USA.

Hillegeist, S. A., Keating, E. K., Cram, D. P. and Lundstedt, K. G. (2004), Assessing the probability of bankruptcy *Review of Accounting Studies*, 9 (1): 5-34.

Hribar, P. and Collins, D. (2002). Errors in estimating accruals: implications for empirical research. *Journal of Accounting Research,* 40(2):105-134.

Jones, F. (1987). Current techniques in bankruptcy prediction. *Journal of Accounting Literature,* 6(?):131-164.

Jones, S, and Hensher, D. A. (2004) Predicting firm financial distress: A mixed logit model, *The Accounting Review*, 79 (4): 1011-1038.

Jones, S, and Hensher, D. A. (2008) *Advances in credit risk modelling and corporate bankruptcy prediction*, S. Jones and D.A. Hensher (Editors), Cambridge University Press, Cambridge, UK.

Jones, S, and Belkaoui, R. H. (2010) *Financial Accounting Theory* (3rd Edition), Cengage, Sydney, Australia.

Jones, S. (2011) Does the capitalization of intangible assets increase the predictability of corporate failure, *Accounting Horizons*, 25 (1): 41-70.

Joy, M., and Tollefson, J. (1975). On the financial applications of discriminant analysis. *Journal of Financial and Quantitative Analysis,* December, Vol 10 (1): 723-739.

Neill, J. D., Schaefer, T.F., Bahnson, P.R. and Bradbury, M.E. (1991). The usefulness of cash flow data: A review and synthesis. *Journal of Accounting Literature,* 10: 117-150.

Ohlson, J. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research,* 18(1): 109-131.

Shumway, T. (2001). Forecasting bankruptcy more accurately: a simple hazard model. *Journal of Business,* 74(1): 101-124.

Swets, J.A., Dawes, R.M., Monahan, J. (2000). Better decisions through science. *Scientific American*, 283(4): 82-7.

Zmijewski, M. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research,* 22 (3): Supplement, 59-82.
Vol

Appendix

Dick Smith Financial Statements

Balance Sheet

All numbers in thousands

Period Ending	28/06/2015	29/06/2014	30/06/2013	30/06/2012
Assets				
Current Assets				
Cash And Cash Equivalents	30,000	30,000	47,000	-
Short Term Investments	-	-	-	-
Net Receivables	64,000	49,000	10,000	-
Inventory	293,000	254,000	171,000	-
Other Current Assets	2,000	-	6,000	-
Total Current Assets	**390,000**	**336,000**	**241,000**	**-**
Long Term Investments	-	-	-	-
Property Plant and Equipment	-	-	-	-
Goodwill	-	-	-	-
Intangible Assets	-	-	-	-
Accumulated Amortisation	-	-	-	-
Other Assets	-	-	-	-
Deferred Long Term Asset Charges	26,000	37,000	43,000	-
Total Assets	**509,000**	**451,000**	**344,000**	**-**
Liabilities				
Current Liabilities				
Accounts Payable	201,000	217,000	74,000	-
Short/Current Long Term Debt	71,000	-	-	-
Other Current Liabilities	16,000	23,000	68,000	-
Total Current Liabilities	**317,000**	**267,000**	**172,000**	**-**

Long Term Debt	-	-	-	-
Other Liabilities	-	-	-	-
Deferred Long Term Liability Charges	-	-	-	-
Minority Interest	-	-	-	-
Negative Goodwill	-	-	-	-
Total Liabilities	**339,000**	**284,000**	**188,000**	**-**
Stockholders' Equity				
Misc Stocks Options Warrants	-	-	-	-
Redeemable Preferred Stock	-	-	-	-
Preferred Stock	-	-	-	-
Common Stock	346,000	346,000	10,000	-
Retained Earnings	162,000	160,000	140,000	-
Treasury Stock	(339,000)	(339,000)	6,000	-
Capital Surplus	-	-	-	-
Other Stockholder Equity	-	-	-	-
Total Stockholder Equity	**169,000**	**167.000**	**156,000**	**-**

Income Statement

Period Ending	28/06/2015	29/06/2014	30/06/2013	30/06/2012
Total Revenue	**1,320,000**	**1,228,000**	**950,000**	**1,370,000**
Cost of Revenue	993,000	920,000	728,000	1,030,000
Gross Profit	**327,000**	**308,000**	**221,000**	**340,000**
Operating Expenses				
Research Development	-	-	-	-
Selling General and Administrative	-	-	-	-
Non-Recurring	-	-	-	-
Others	-	-	-	-
Total Operating Expenses	1,260,000	1,197,000	953,000	1,349,000
Operating Income or Loss	**59,000**	**30,000**	**(3,000)**	**20,000**
Income from Continuing Operations				
Total Other Income/Expenses Net	-	-	-	-
Earnings Before Interest and Taxes	59,000	30,000	(3,000)	20,000
Interest Expense	(4,000)	(3,000)	(3,000)	(1,000)
Income Before Tax	-	-	-	-
Income Tax Expense	15,000	9,000	(2,000)	6,000
Minority Interest	-	-	-	-
Net Income from Continuing Ops	38,000	20,000	168,000	13,000

Discontinued Operations	-	-	-	-
Extraordinary Items	-	-	-	-
Effect of Accounting Changes	-	-	-	-
Other Items	-	-	-	-
Net Income	**38,000**	**20,000**	**168,000**	**13,000**
Preferred Stock and Other Adjustments	-	-	-	-
Net Income Applicable to Common Shares	**-**	**-**	**-**	**-**

Currency in AUD.

Statement of Cash Flows

All numbers in thousands

Period Ending	28/06/2015	29/06/2014	30/06/2013	30/06/2012
Net Income	**38,000**	**20,000**	**168,000**	**13,000**
Operating Activities, Cash Flows Provided by or Used In				
Depreciation	15,000	12,000	9,000	-
Adjustments to Net Income	-	-	-	-
Changes in Accounts Receivables	(7,000)	(36,000)	22,000	-
Changes in Liabilities	-	-	-	-
Changes in Inventories	(39,000)	(85,000)	170,000	-
Changes in Other Operating Activities	4,000	18,000	3,000	-
Total Cash Flow from Operating Activities	**(4,000)**	**52,000**	**141,000**	**-**
Investing Activities, Cash Flows Provided by or Used in				
Capital Expenditures	(32,000)	(31,000)	(3,000)	-
Investments	-	-	-	-
Other Cash flows from Investing Activities	-	-	-	-
Total Cash Flows from Investing Activities	**(32,000)**	**(54,000)**	**(97,000)**	**-**
Financing Activities, Cash Flows Provided by or Used In				
Dividends Paid	-	-	-	-
Sale Purchase of Stock	-	-	-	-
Net Borrowings	-	-	-	-
Other Cash Flows from Financing Activities	-	-	-	-
Total Cash Flows from Financing Activities	**35,000**	**(15,000)**	**12,000**	**-**
Effect of Exchange Rate Changes	-	-	-	-
Change in Cash and Cash Equivalents	**-**	**(17,000)**	**56,000**	**-**

Currency in AUD.

Source: Yahoo Finance