

The Predictive Abilities of Financial Ratios in Predicting Company Failure in Malaysia Using a Classic Univariate Approach

¹Ben Chin-Fook Yap, ¹Mohd. Haniff Mohd. Helmi, ¹Shanmugam Munuswamy, and ²Jin-Rui Yap

¹Universiti Tun Abdul Razak, Capital Square, Block C & D, No. 8, Jalan Munshi Abdullah, 50100 Kuala Lumpur, Malaysia

²Kolej Tunku Abdul Rahman, Jalan Genting Kelang, Setapak, 53300 Kuala Lumpur

Abstract: This study examined sixty-four (64) listed companies over a period of ten years using a classic univariate method. Most studies on failure and bankruptcy predictions in the past forty years or more have been dominated by various multivariate statistical methods or some form of artificially intelligent systems. This study however, showed that the predictive powers of the individual ratios used individually and independently of each other has produced highly successful results. The means of the ratios showed significant differences between the companies that failed and those that were non-failed. A dichotomous classification test performed on the holdout sample using the cut-off point obtained from the analysis sample showed average classification accuracy of between 79% and 84%. One ratio, the Cash Flow to Total Debt perform particularly well with correct classification results of failed companies of between 81% and 94% for both the analysis and the holdout sample and for all the four years before actual failure. Being able to classify failed companies with a high degree of accuracy is most significant as minimizing Type I errors are much more important to a wide range of users of financial information as the consequences of failure to predict failed companies are more devastating than failure to predict correctly the non-failed companies. For one individual ratio to achieve such high predictive abilities and for all four years before actual failure is surprising as this result is comparatively better than many studies using the more popular multivariate techniques where multiple ratios are analysed simultaneously. The study showed that financial ratios used individually do have strong predictive abilities though not all the ratios can predict equally well and for every year.

Key words: financial ratios, company failures, failure predictions

INTRODUCTION

The failure of any company has potentially widespread negative effects for those who do business with it as well as many other businesses and individuals including suppliers, customers, employees and their financiers. Though the number of public companies in Malaysia is much smaller compared to the United States or other western countries, we are not shielded from big corporate failures as had happened in the past, though some were rescued through direct government or government agencies intervention, with its resulting adverse financial effects.

There are various ways that can be used to assess the financial health of an organization. Basically, they can be divided into financial and non-financial measures. Financial measures would involve the use of accounting and other numerical data such as ratios and trends to measure a company's growth, profitability, efficient use of its assets and its financial standing at different points in time. Ratio analysis involves comparing the inter-relationships between accounting figures in the financial statements in relative terms. Different user groups of financial reports will focus on different aspects of a company's performance depending on their relationship and involvement with the company. For example, a long term investor will be interested in returns and the level of risks of the company compared to other potential investments, while a trade creditor will be interested in whether goods supplied will be paid in the short term or within the credit period.

Corresponding Author: Ben Chin-Fook Yap, Bank Rakyat of Business and Entrepreneurship, Universiti Tun Abdul Razak, Capital Square, Block C & D, No. 8, Jalan Munshi Abdullah, 50100 Kuala Lumpur, Malaysia
Tel: 603 76277120
E-mail: benyap@unirazak.edu.my

The majority of failure prediction models are developed using various statistical methods or artificially intelligent systems. The most popular statistical models are multiple discriminant analysis such as the study by Altman (1968) where his Z-Score is well known and the work by Ohlso (1980) which is one of the first to use logistic regression for company failure analysis. The most commonly used artificially intelligent systems are artificial neural network including studies by Pramodh and Ravi (2007) and Balcaen and Ooghe (2006) and a type of recursive partitioning method known as the hazard model by Frydman *et al.* (1985). A study by Gepp and Kumar (2008) using a kind of survival analysis model that incorporated time series nature of financial data claimed that such models are more sophisticated than models using different types of discriminant analysis techniques.

In this study, most of the failed companies are classified by Bursa Malaysia (formerly the Kuala Lumpur Stock Exchange) as falling either under one of the Practice Notes (PNs) namely PN4, PN10 or PN17. The main reasons for these companies coming under these classifications are due mainly to deficit in their shareholders funds where their financial conditions do not justify continued trading and/or listing in the stock exchange. These companies are given certain time to regularize their financial position or take actions that is necessary to release themselves from those criteria that trigger the specific PN classifications stated above. Failed companies would also include companies that have applied to the Court under Section 176 of the Companies Act 1965, for a Scheme of Arrangement whereby an order is given by the High Court to stay any proceedings against the company whilst the scheme is pending. This study is based on companies in the manufacturing sector. Companies in the trading, services or property sectors are not included as they have different assets and financing requirements compared to companies involved in manufacturing.

Generally, financial distress precedes business failure and eventual collapse. Therefore, assessing the financial trends and financial information of a business on a periodic basis, gives the analysts, credit controllers and financial advisors valuable insights about the performance and status of the business and companies under review. A pre-failure warning system that can anticipate distress and can give indications of financial distress ahead would be very useful in minimizing or total avoidance of exposure to possible risk of substantial monetary losses for their own companies and shareholders or their clients. Having a more reliable and more accurate failure warning model suitable for the Malaysian setting would benefit many interested parties.

The objective of this study is to use the univariate method first developed by Beaver in 1966, in the light of most studies since then that uses various forms of multivariate statistical methods, to test on Malaysian companies. The study is to examine whether financial ratios used individually and independently of each other is effective in classifying failed and non-failed companies in Malaysia at a much later time frame and in a different economic, operating and marketing environment.

Brief Review of past Studies:

The use of ratio analysis is one of several categories of analytical procedures used by auditors, accountants and financial analysts as a useful tool to identify areas in a company's financial statements where errors, misclassifications or potential fraudulent reporting of results and financial status may occur. Green (1978) states that financial ratios have long been regarded as indicators of corporate health, being used for reporting liquidity, leverage, activity and profitability and that an investor may use such ratios to evaluate a company's performance and its future likelihood of success. By comparing with other companies in the same industry, one can gauge whether one's results and financial position are above or below the industry average. If comparisons are made about the sales trend or the net profit margin, such information can help the company as well as external interested parties understand the actual performance and the financial health of the organization.

Empirical studies on the use of financial ratios and its usefulness in corporate health assessments and analysis of corporate failure and demise started in the early part of the last century. Most recently and especially since the 1960's, researchers have used ratios as predictor variables in models to predict companies in financial distress and eventual business failures and bankruptcies. Financial ratios have been found to be useful even in non-profit organizations, as they provide measures and indicators to clarify important and key financial questions about an organisation's performance. Casteuble (1997) found that ratio analysis data provides key information to people charged with responsibilities in managing association financial operations.

According to Green (1978), the earliest studies on company failure prediction were univariate in nature starting with the studies by FitzPatrick in 1932, Winakor and Smith in 1935 and Mervin in 1942. However, the most well know univariate model is probably the 1966 study by Beaver, which since then, has started many other company failure prediction analyses using other statistical techniques such as the multiple discriminant analysis by Ganesalingam and Kumar (2001), Koh and Killough (1990), Mutchler (1985) and

Altman (1968), the logistic regression method by Zavgren and Friedman (1998), Gilbert *et al.* (1990) and Ohlson (1980), and artificial neural network by Pramodh and Ravi (2007), Balcaen and Ooghe (2006). Seaman *et al.* (1990) in their analysis, using different statistical methods to predict bankruptcy, commented that the ability to anticipate corporate bankruptcy is of considerable importance to those who use financial statements in their planning process and that managers equipped with effective bankruptcy prediction models can take corrective measures and possibly prevent failure in their own company.

In 1968, Altman developed a model called the Z-Score that claimed a high level of predictive accuracy and which until today is still subject to academic discourse and evaluation. Since then, many studies have been published using variants of the original Altman model. However, according to the supporters of other statistical techniques such as the study by Seaman *et al.* (1990), multiple discriminant analysis has certain weaknesses, including the violation of the certain assumptions in multivariate statistical techniques. A conditional probabilistic research done by Ohlson in 1980 has the objective of trying to eliminate the critical assumptions used in MDA. The Ohlson model using logistic regression, claimed to have even higher predictive accuracy compared to Altman's model. In their study comparing the multiple discriminant analysis used by Altman and the logistic regression method used by Ohlson, Keating *et al.* (2005) found that Ohlson's model is less parsimonious than other multivariate models. They also stated that the Ohlson model has higher explanatory power than Altman's model in predicting four different measures of financial vulnerability.

Since 1990, there appears another different approach for failure prediction using neural networks. This approach used a form of artificial intelligence and is called artificial neural networks (ANN). Boritz and Kennedy (1994 and revised 1995), using different neural network models and comparing them with the traditional bankruptcy prediction techniques like MDA, logit and probit found that the results for Type I and Type II errors varies greatly across the different ANNs techniques.

However, the earliest models to identify failed and non-failed companies were probably univariate in nature. This method uses a single variable such as an accounting ratio, and is examined in isolation and individually and compared against the same ratio over time and against a standard benchmark such as an industry average. The early empirical studies done on company financial health and default predictions in the 1920s and 1930s are all univariate in nature. As mentioned earlier, Beaver (1966) was the first to conduct an extensive study on the relationship between financial ratios and company defaults, comparing companies that had defaulted in paying preferred stock dividends and bond interests with surviving successful ones between 1954 and 1964. He started with 30 financial ratios and eventually chose six for his study. The univariate approach was criticized for various weaknesses (Altman 1968, Morris 1998 etc.), one of which is that when performing inter-company comparisons, companies being compared may be greatly diversified in terms of products and services offered as well as operating in different geographical locations. Another complaint is that the ratios are not allowed to interact with one another as each ratio is examined separately, in isolation from the other ratios. Morris (1998) gave an example to illustrate the above. He states that while low profitability may be one signal of financial distress, it may not necessarily be fatal if a business has a strong liquidity position, and likewise, a company that is profitable but which has low reserves of liquid assets is potentially vulnerable if there should be an unexpected setback.

In univariate financial ratio analysis for bankruptcy prediction purposes, an analyst may have to depend solely on his judgment on say, whether an individual ratio or the combined effect of several ratios calculated separately is good or bad. For example, a very low debt to equity ratio may indicate that there is a very large equity base as the denominator or that the company is averse to borrowings with its inherent risks. Though Beaver's study has been criticized for the above weaknesses, nonetheless the predictive powers of the individual ratios used showed highly successful results with correct classification accuracies of between 69% to 81%.

Holmen (1988)'s study using a sample of 84 bankrupt companies between 1977 and 1984 and using Beaver's model and Altman's model concluded that Beaver's univariate model, especially the Cash Flow to Total Debt ratio predicted bankruptcy with fewer errors than the five ratio Z Score proposed by Altman in both the Type I and Type II errors. In another study by Moyer (1975), he found that certain aspects of Beaver's and Lev's (1973) univariate studies gave better predictive accuracy than studies using MDA.

MATERIALS AND METHODS

Financial Statement data from the annual reports of selected failed and non-failed public companies listed in the Bursa Malaysia were taken from a ten-year period starting 1996 until the end of 2005. Data for these periods is chosen as it covers the period before, during and after the Asian financial crisis that started in

1997/98. Data of the failed companies were obtained for five years prior to failure. Companies selected are from two sectors as classified by Bursa Malaysia namely, the consumer and the industrial product sector. Basically these two sectors are involved in manufacturing as before 1994, the consumer sector companies were grouped under the industrial product sector. A total of 32 failed companies are matched with 32 non-failed companies comprising twenty (20) companies in the consumer sector and forty-four (44) companies in the industrial product sector. Matched pair samples of failed and non-failed companies are used and this is consistent with many past studies, including studies by Beaver (1966), Altman (1968), and Letza *et al.* (2003). As the selection process was based upon a paired-sample design, for each failed company in the sample, a non-failed company in the same industry and with the closest asset size is selected. The paired-sample design is one way of compensating for the effects of industry and asset size differences. Companies with the same financial ratios but with different asset sizes may have different probabilities of failure. It is logical that a larger company with a larger asset base will have a lower probability of failure even if the ratios of the two companies are identical.

The financial statements of the non-failed companies are obtained for the same fiscal years as those of the failed companies, that is, if the failed company has a financial year ending 31 Dec 2006, the non-failed company would be chosen with financial statements ending in the same year. The “first year before failure” is defined as that year included in the most recent financial statement prior to the date that the company failed, i.e., if the company failed in 2005, then the last financial statement data used would be the one prepared for the most recent year before failure. The second year prior to failure would be the fiscal year proceeding the first year. If the first year prior to failure were 31 Dec 2004, then data for the preceding 4 years ending 31 Dec 2000 would be used.

The original six variables used by Beaver (1966) namely, Cash flow to Total Debt (CFTD), Net Income to Total Asset (NITA), Total Debt to Total Assets (TDTA), Working Capital to Total Assets (WCTA), Working Capital Ratio (WCR) and the No-credit interval (NCI) are examined to see whether a relationship exist between the two sectors and between the two groups of companies within each sector. It will determine whether there are significant differences in the mean values between the two groups of failed and non-failed companies for each sector. The analysis will be based on 10 failed companies and 10 non-failed categories in the consumer sector and 22 failed companies and 22 non-failed companies in the industrial product sector.

After the analysis of the means for the failed and non-failed companies in the 2 sectors, a dichotomous classification is then attempted to classify companies into the failed and non-failed categories. Five of the original six ratios are used here with the No-credit interval omitted as this ratios is very similar to the Working Capital Ratio. To classify companies dichotomously, the consumer and industrial product sectors are group together to form a reasonably large enough sample to ensure that the validity of the results are credible. The nature of products and operations are similar in many aspects and as mentioned earlier, they were once grouped together under the manufacturing sector. A total of thirty-two (32) companies comprising ten (10) from the consumer sector and twenty-two (22) from the industrial product sector will form the analysis sample while an equal number of such companies will be grouped to form the holdout sample. The companies are randomly grouped into the two samples so as to avoid bias. The holdout sample will be used to check whether the same cut-off points used to classify the companies in the analysis sample can perform equally well when used to test on the second sample, which is the holdout sample.

Firstly, the means for the analysis sample were computed for each of the companies for the two groups for each of the years before failure. The ratios are then arranged in a descending order. A decision is then made to identify an optimal cut-off point. Trial and error is used for this test until an optimal cut-off point is identified which can correctly classify the most number of companies into the failed and non-failed categories. Depending on the ratios, the companies are then grouped according to whether they are above or below this optimal cut-off point. Beaver (1966) in his seminal study did not indicate what his cut-off points were for each of the ratios though they were estimated through trial and error. After the companies have been classified as either failed or non-failed, percentages of errors are then calculated for each of the five ratios to see whether which of the ratios are useful in the classifications and which ratios gives better predictive accuracy. The smaller the error percentage, the higher the predictive ability of the ratios being considered.

Then, using the cut-off point determined earlier in the analysis sample, a dichotomous classification is attempted on the holdout sample to examine the validity of the results obtained from the analysis sample. The results from the holdout sample will give better explanatory power of the individual ratios as the analysis is considered as ex-ante as opposed to the results of the analysis sample which can be considered as ex-post.

Discussion and Conclusion:

Beaver’s original six variables were tested on the sample of companies in the consumer and industrial product sector. Table 1 below for consumer products showed the mean values for each of the six ratios. The mean of the ratios showed significant differences between the companies that failed and those that are non-failed.

Table 1: Consumer Products: Comparison of Mean Values of Ratios

		WCR	CFTD	TDTA	WCTA	NITA	NCI
Fail	Mean	0.755	-0.077	0.811	-0.277	-0.155	-0.408
Non-fail	Mean	7.148	1.321	0.302	0.386	0.077	0.194

Table 2 below for industrial products showed similar results, that is, there are significant differences in the mean values for companies that failed and those that are successful. The results for both the consumer and industrial products conclusively demonstrated that there are marked differences in the ratios for failed and non-failed companies. Successful companies have more current assets than current liabilities, have more cash compared to debts and higher and positive net income. In terms of debts, failed companies tend to display a much higher debt level compared to their total assets.

Table 2: Industrial Products: Comparison of Mean Values of Ratios

		WCR	CFTD	TDTA	WCTA	NITA	NCI
Fail	Mean	1.214	-0.235	0.762	-0.203	-0.146	-2.950
Non-fail	Mean	3.604	0.547	0.366	0.210	0.030	-0.060

Table 3 for both the consumer and industrial products sectors showed the signs of the direction for each ratio before failure. As can be seen, the difference in the mean values is in the predicted direction for each ratio before failure. This conclusion is not surprising and this is the same as per Beaver’s original findings.

Table 3: Consumer and Industrial Products: Predicted Direction of the Ratios.

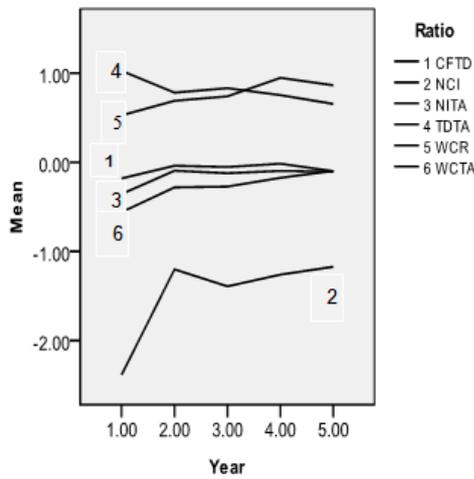
Ratios	Abbreviations	Predictions
Working Capital Ratio	WCR	Non Failed > Failed
Cash Flow to Total Debt	CFTD	Non-Failed > Failed
Total Debt to Total Assets	TDTA	Failed> Non-Failed
Working Capital to Total Assets	WCTA	Non-Failed > Failed
Net Income to Total Assets	NITA	Non-Failed > Failed
No Credit Interval	NCI	Non-Failed> Failed

Graph 1 for the failed companies in the consumer products sector showed the trend of the ratios for the failed companies over the five years period. The differences in means were very clear for at least five years before the actual failure, with the differences widening as the year of failure approaches. For WCR, WCTA, CFTD, NITA and NCI, the trend were downwards from Year 5 before failure to the last year before failure which is expected for companies that are failed. For TDTA the trend was also indicative of a failing company as the debts go upwards.

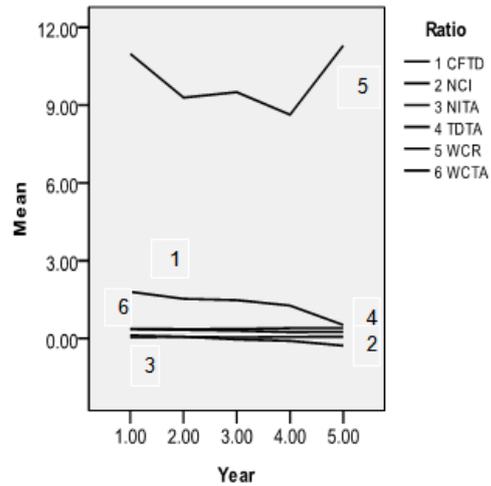
The graph illustrated that failed companies had less cash, less current assets, more current liabilities resulting in less working capital, more and higher debts and also incurring losses in their operations resulting in negative or very low net income. The trends for all the six ratios showed much more marked deteriorations in the last one or two years before the actual failure with negative average mean values for CFTD, NITA, CFTD and NCI. The WCR though on average was positive; they are still below 1.0 which can be interpreted as risky in terms of short term liquidity. It has to be noted that the TDTA was on an upwards slope from years 5 to the year before failure.

Graph 2 for the non-failed companies in the consumer sector generally showed the trend of the ratios going in the opposite directions or at least a zero slope over the five years compared to Graph 1. They also showed a lower and narrower deviations from the trend line compared to those companies that failed where the deviations were more obvious and pronounced. It can be seen that NITA and CFTD were sloping upwards while WCTA and TDTA were maintaining its slope throughout the 5 years.

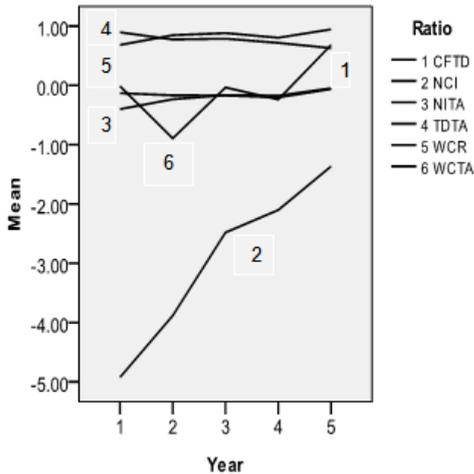
Similarly, for the industrial products sector, the graphs for the failed and non-failed companies (Graph 3 and Graph 4 respectively), showed similar trend lines for all the ratios as in the consumer products sector. The analysis of the ratios and the graphs do not indicate any predictive abilities of the ratios. They just illustrate a general relationship between companies that are healthy and those that are failed or failing.



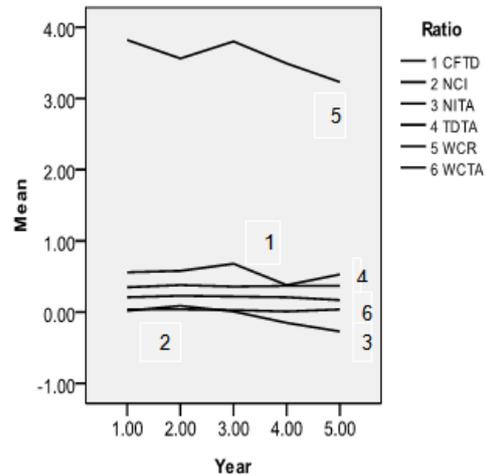
Graph 1: Trend: Failed Co.-Consumer Year 5 to Year 1 preceding Failure.



Graph 2: Trend: Non-failed Co.-Consumer Year 5 to Year 1 preceding Failure.



Graph 3: Trend: Failed Co.-Industrial Year 5 to Year 1 preceding Failure



Graph 4: Trend: Non-failed Co.-Industrial Year 5 to Year 1 preceding Failure

Dichotomous Classification Tests:

The results shown in Table 4 below for the analysis sample revealed correct average classification accuracy of between 73% and 79% for the five years. To predict accurately the failed companies is more significant and beneficial as the consequences of not identifying a potential failure are more devastating financially than identifying a successful non-failed company. Based on this measure, the ratio that stands out is CFTD which managed correct “hit” rates of 94% for the second, third and fourth year before failure and 81% for the last year before failure.

The cut-off points used for each of the five ratios to determine the results above are as shown in Table 5 below:-

The cut-off points mean that any ratio values of less than 1.0, 0.1, 0.15 and -0.001 for WCR, WCTA, CFTD and NITA, respectively will be classified as failed. Similarly any of the ratios above the values mentioned will be classified as non-failed. As for TDTA, any values above 0.5 will result in a failed classification and any values below 0.5 will result in a non-failed classification.

The same cut-off points determined in analysis sample above will be used on the holdout sample to see whether they can predict with the least misclassification errors. The results on the holdout sample (Table 6) are more relevant compared to the results from the analysis sample which can be considered as predicting *ex-post*.

Table 4: Consumer and Industrial Products: Analysis Sample: Dichotomous Classification Results.

		1 yr (%)	2 yrs (%)	3 yrs (%)	4 yrs(%)	5 yrs(%)	Average
WCR	Fail	63	50	75	56	63	61
	Non-Fail	88	88	88	81	81	85
	Average	75	69	81	69	72	73
WCTA	Fail	81	69	81	75	75	77
	Non-Fail	75	75	75	69	63	71
	Average	78	72	78	72	69	74
CFTD	Fail	81	94	94	94	63	85
	Non-Fail	75	75	88	75	50	73
	Average	78	84	91	84	56	79
NITA	Fail	75	88	81	69	75	78
	Non-Fail	75	75	81	75	81	77
	Average	75	81	81	72	78	77
TDTA	Fail	75	75	81	69	63	73
	Non-Fail	75	75	88	94	88	84
	Average	75	75	84	81	75	79

Table 5: Cut-off points.

Ratios	WCR	WCTA	CFTD	NITA	TDTA
Cut-off points	1.0	0.1	0.15	-0.001	0.5

Average correct classification results for the five ratios obtained range from 79% to 84% when failed and non-failed companies are classified together which is better than the results obtained from the analysis sample. The results showed that not all ratios predict equally well and not for every year. However, the results do indicate that ratios do have some predictive abilities when used individually. Again, the ratio that stands out is CFTD which managed to produce the least misclassification errors for the failed companies, meaning that Type I error are minimized. This ratio achieved correct classification results of 88% for the third, fourth and fifth year before failure and 81% and 94% for the second and last year before failure respectively.

A comparison of the average results of this study with Beaver’s results done more than forty years earlier is shown in

Table 7 below. Both results are quite similar on average over the five years.

The purpose of this study is to examine the extent to which financial ratios predict company failures using the univariate analysis method in the Malaysian context under different economic, operating and marketing environment and at a much later time frame. Most studies on failure and bankruptcy predictions in the past forty years or more have been dominated by various multivariate statistical methods or some form of artificially intelligent systems. This study however, showed that the predictive powers of the individual ratios used individually and independently of each other has produced highly successful results. A total of 64 companies were analyzed using the financial ratios that were originally used by Beaver in his often cited study. The findings showed that there is a general relationship between healthy companies and distressed and failed companies. The differences in means are very clear for at least five years before the actual failure, with the differences widening as the year of failure approaches. Failed companies have less cash, less current assets, more current liabilities resulting in less working capital, more and higher debts and also incurring losses in their operations resulting in negative or very low net income.

Table 6: Consumer and Industrial Products: Holdout Sample: Dichotomous Classification Results.

		1 yr (%)	2 yrs (%)	3 yrs (%)	4 yrs(%)	5 yrs(%)	Average
WCR	Failed	88	69	56	81	63	71
	Non-Failed	94	88	88	81	88	88
	Average	91	78	72	81	75	79
WCTA	Failed	88	81	81	88	81	84
	Non-Failed	81	81	75	81	81	80
	Average	84	81	78	84	81	82
CFTD	Failed	94	81	88	88	88	88
	Non-Failed	75	81	81	75	88	80
	Average	84	81	84	81	88	84
NITA	Failed	88	63	81	69	63	73
	Non-Failed	81	81	81	81	81	81
	Average	84	72	81	75	72	77
TDTA	Failed	94	75	94	88	81	86
	Non-Failed	69	75	69	75	75	73
	Average	81	75	81	81	78	80

Table 7: Comparison with Beaver's Average Classification Results.

	1 yr (%)	2 yrs (%)	3 yrs (%)	4 yrs(%)	5 yrs(%)	Average
WCR	<i>75</i>	<i>69</i>	<i>81</i>	<i>69</i>	<i>72</i>	<i>73</i>
	91	78	72	81	75	79
	(-80)	(-73)	(-69)	(-68)	(-69)	(-72)
WCTA	<i>78</i>	<i>72</i>	<i>78</i>	<i>72</i>	<i>69</i>	<i>74</i>
	84	81	78	84	81	82
	(-80)	(-70)	(-67)	(-65)	(-65)	(-69)
CFTD	<i>78</i>	<i>84</i>	<i>91</i>	<i>84</i>	<i>56</i>	<i>79</i>
	84	81	84	81	88	84
	(-90)	(-82)	(-79)	(-76)	(-78)	(-81)
NITA	<i>75</i>	<i>81</i>	<i>81</i>	<i>72</i>	<i>78</i>	<i>77</i>
	84	72	81	75	72	77
	(-88)	(-85)	(-78)	(-72)	(-75)	(-80)
TDTA	<i>75</i>	<i>75</i>	<i>84</i>	<i>81</i>	<i>75</i>	<i>79</i>
	81	75	81	81	78	80
	(-81)	(-76)	(-72)	(-76)	(-73)	(-76)

note: first row (*italic*) are results from the first (analysis) sample

second row are results from the second (holdout) sample

third row (in brackets) are Beaver's original results

A dichotomous classification test performed on the holdout sample using the cut-off point that were obtained from the analysis sample showed average classification accuracy of between 79% and 84%. One ratio, the Cash Flow to Total Debt perform particularly well with correct classification results of failed companies of between 81% and 94% for both the analysis and the holdout sample and for all the four years before actual failure. Being able to classify failed companies with a high degree of accuracy is most significant as minimizing Type I errors are much more important to a wide range of users of financial information as the consequences of failure to predict failed companies are more devastating than failure to predict correctly the non-failed companies. For one individual ratio to achieve such high predictive abilities and for all four years before actual failure is surprising as this result is comparatively better than many studies using the more popular multivariate techniques where multiple ratios are analysed simultaneously. The study showed that financial ratios used individually do have predictive abilities though not all the ratios can predict equally well and for every year. Overall, the findings indicate that financial ratios used individually and in isolation with other ratios do have strong predictive abilities.

Further studies will need to be carried out using other ratios which may give better predictive abilities. Much larger sample sizes for both the failed and non-failed categories may give better or more credible results than the sample used in this study.

REFERENCES

- Altman, E.I., 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance*, 23(4): 589-609.
- Balcaen, S. and H. Ooghe, 2006. 35 Years of Studies on Business failures. An overview of the classic statistical methodologies and their related problems. *The British Accounting review*, 38(1): 63-93.
- Beaver, W.H., 1966. Financial Ratios as Predictors of Failure. *Journal of Accounting Research*, 4: 71-111.
- Boritz, J.E. and D.B. Kennedy, 1994 and revised 1995. Effectiveness of Neural Network Types for Prediction of Business Failures. School of Accountancy, University of Waterloo, Canada. Retrieved 15 May, 2006, from <http://landing.netmyne.com/index.jsp? mode=search&nlia =google+scholar>.
- Casteuble, T., 1997. Using financial ratios to assess performance. *Association Management*, 49(7): 29-36.
- Frydman, H., E.I. Altman and D.L. Kao, 1985. Introducing recursive partitioning for financial classification: The case of financial distress. *The Journal of Finance*, 40(1): 269-291.
- Ganesalingam, S. and K. Kumar, 2001. Detection of Financial distress via Multivariate Statistical Analysis. *Managerial Finance*, 27(4): 45-55.
- Gepp, A., K. Kumar, 2008. The Role of Survival Analysis in Financial Distress Predictions. *International Research Journal of Finance and Economics*, 16: 13-34.
- Green, D., 1978. To Predict Failure. *Management Accounting July*: 39-45.
- Gilbert, L.R., K. Menon and K.B. Schwartz, 1990. Predicting bankruptcy for companies in financial distress. *Journal of Business, Finance and Accounting*, 17(1): 161-171.
- Holmen, J.S., 1988. Using financial ratios to predict bankruptcy: An evaluation. *Akron Business and Economic Review*, 19(1): 52-63.

Keating, E.K., M. Fischer, T.P. Gordon and J. Greenlee, 2005. Assessing financial vulnerability in the nonprofit sector. KSG Faculty Research Working Paper Series, Harvard University. Retrieved 20 May 2006 from:<http://www.philanthropy.iupui.edu/Education/Greenlee.pdf>.

Koh, H.C. and L.N. Killough, 1990. The Use of Discriminant Analysis in the Assessment of the Going Concern Status of an Audit Client. *Journal of Business Finance and Accounting*, 17(2): 179-192.

Lev, B., 1973. Decomposition Measures for Financial Analysis. *Financial Management*, Spring: 56-63

Letza, S.R., L. Kalupa and T. Kowalski, 2003. Predicting corporate failure: How useful are multi-discriminant analysis models? *The Poznan University of Economics Review*, 3/2: 5-11.

Morris, R., 1998. Bankruptcy prediction models: Just how useful are they? *Credit Management*, 43-45. Retrieved 10 May 2006, http://findarticles.com/p/articles/mi_qa_5308/is_199805/ai_n21421946.

Moyer, R.C., 1977. Forecasting Financial Failure: A Re-Examination, *Financial Management*, 6(1): 11-17.

Mutchler, J.F., 1985. A Multivariate Analysis of the Auditor's Going Concern Opinion Decision. *Journal of Accounting research*, 23(2): 668-682.

Ohlson, J.A., 1980. Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, Spring, 109-131.

Pramodh, C. and V. Ravi, 2007. Modified Great Deluge Algorithm based Auto Associative Neural Network for Bankruptcy Prediction in Banks. *International Journal of Computational Intelligence Research*, 3(4): 363-370.

Seaman, S.L., D.M. Young and J.N. Baldwin, 1990. How to predict bankruptcy. *The Journal of Business Forecasting Methods & Systems*, 9(3): 23-27.

Zavgren, C.V. and G.E. Friedman, 1988. Are bankruptcy prediction models worthwhile? An application in securities analysis. *Management International Review*, 28(1): 34-44.