THE IMPACT OF CASH FLOW ON BUSINESS FAILURE ANALYSIS AND PREDICTION

Abdelkader Mazouz
Keenan Crane
Hamdan Bin Mohamed University, Dubai, UAE

Patrick A. Gambrel
U.S. Naval Postgraduate School, CA, USA

CITATION: Mazouz, A., & Gambrel, P. A. (2013). The impact of cash flow on business failure analysis and prediction, *International Journal of Social Sciences and Entrepreneurship*, Vol.1, Issue 3, 2013, 1 (3), 14-29

ABSTRACT

The purpose of this study is to determine whether cash flow impacts business failure prediction using a neural network. Using a matched sample of 114 failed and 114 non-failed manufacturing firms selected from the Compustat database, accrual-based and cash flow-based neural network models were developed utilizing financial ratios as input variables. A Z-test was performed to test for significance of any difference at the 0.05 level between the classification results of the two models. The accrual-based model correctly classified 92.55% of firms overall in a training sample and 77.5% of firms overall in a holdout sample. The cash flow-based model correctly classified 94.15% of firms overall in a training sample and 82.5% of firms overall in a holdout sample. While the cash flow-based neural network model outperformed the accrual-based neural network model, results of the Z-test revealed that the difference in classification accuracies between the two models was not significant. This study does not provide evidence that cash flow improves business failure prediction.

***Keywords**: business failure prediction, neural network, Z-Score, accrual-based ratios, cash flow-based ratios*

Introduction

Numerous business failure studies have been performed over time using traditional statistical techniques and financial ratios as input variables. A number of these studies examined whether cash flow improves the prediction of business failure. More recently, researchers are using neural networks to perform business failure studies. Kuruppu, Laswad, & Oyelere (2003), show evidence of the usefulness and efficacy of statistical models such as Altman Z-score discriminant analysis bankruptcy predictive models to assess client ongoing concern status. As shown in previous studies, the bankruptcy models consistently outperform auditor's concerned judgment in discriminating between bankrupt and non-bankrupt companies.

The use of models will alleviate stress levels and can push organizations to reengineer or merge before filing for bankruptcy. Wang & Campbell (2010) provide evidence of failure prediction of various z-score models using China publicly listed companies as test beds. The study shows that the Wang &Campbell model has the higher overall prediction accuracy than the Altman z-score

model and also shows the usefulness of using z-score models. Chava & Jarrow (2004) show bankruptcy prediction with industry effects. The study used an expanded bankruptcy database where three models, Shumway (2001), Altman (1968) & Zmijewski (1984) were tested. The Shumway model provided superior results. The authors then demonstrated the importance of the industry effects in hazard rate estimation. The study divided the industry intofour groups: (i) finance, insurance, and real estate, (ii) transportation, communications and utilities, (iii) manufacturing and mineral, and (iv) miscellaneous industries. The hazard rate model confirmed the industry effects on bankruptcy prediction.
Aziz & Dar (2006) show bankruptcy model findings and substantiate the introduction of artificial intelligence models in predicting bankruptcy. They show evidence that using artificial intelligence models perform marginally better than statistical and theoretical models. Multiple Discriminant Analysis (MDA) and logit models tend to dominate bankruptcy predictive models. The purpose of this study is to determine whether cash flow improves the business failure prediction of manufacturing firms using a neural network.

Procedure

The purpose of this research was to determine if cash flow has an impact on the prediction of business failure. This was accomplished through training, testing, and comparing results of an accrual-based neural network model and a cash flow-based neural network model. Units of analysis for this study are financial ratios derived from raw financial data from balance sheets, income statements, and cash flow statements of both failed and non-failed firms. Raw balance sheet data used to calculate financial ratios include current assets, current liabilities, total assets, total liabilities, market value of equity, and retained earnings. Raw income statement data used to calculate financial ratios include sales and earnings before interest and taxes. Raw cash flow statement data used to calculate financial ratios include cash flow from operations. Financial ratios calculated in this study include (a) working capital: total assets, (b) retained earnings: total assets, (c) earnings before interest and taxes: total assets, (d) market value of equity: book value of total debt, (e) sales: total assets, (f) cash flow from operations: current liabilities, (g) cash flow from operations: total assets, and (h) cash flow from operations: total liabilities.

Failed and non-failed firms were selected for analysis to determine if cash flow improves business failure prediction. The study sample includes 114 failed firms identified for the period 1991 to 2002 and 114 non-failed firms for the same time period. Each failed firm was part of the manufacturing industry and had financial data available one year prior to failure with an asset size of $20 million or greater. Each non-failed firm was part of the manufacturing industry, had an asset size of $20 million or greater, and financial data available the same year as matched failed firms.

Sample and Data Collection

Standard & Poor's Compustat Research Insight database is the source of raw financial data used for this study. Compustat is the preferred source for raw financial data used in earlier studies performed by researchers (Gentry, Newbold, & Whitford, 1985a; Gombola, et al. (1987); Ohlson, 1980; Platt & Platt, 1990; Zavgren, 1985). The failed manufacturing firms selected from Compustat carry SIC codes 2000-3999 and a deletion code of two for bankruptcy. Failed firms were matched with non-failed manufacturing firms by industry (SIC code of 2000-3999) and asset size, randomly selected from Compustat.

Availability of financial data one year prior to failure was a requirement to qualify as a failed firm in this study. Initially, 118 firms were identified in Standard & Poor's Compustat based on a deletion code of two for bankruptcy. Of the 118 failed firms identified, four firms were missing ~~key balance sheet, income statement, or cash flow statement financial data one year prior to~~ failure. Those firms were removed from the failed sample, reducing the failed firm sample size to 114 firms. Total asset size was used to match the sample of non-failed firms to the sample of failed firms. Total assets for the sample of 114 failed firms one year prior to failure range from a minimum of $20.474 million to a maximum of $2,345.8 million. The mean total asset size for failed firms is $146.769 million with a standard deviation of $298.465 million. The range of total assets for failed firms is $2,325.326 million.

Total assets for the matched sample of 114 non-failed firms range from a minimum of $19.104 million to a maximum of $2,348.616 million. The mean total asset size for failed firms is $146.632 with a standard deviation of $298.505 million. The range of total assets for failed firms is $2,329.512 million.

Descriptive Statistics and Measures of Variables

Descriptive statistics for total asset data are summarized for failed and non-failed firms in Table 1. Financial ratios calculated for this study include (a) working capital: total assets (WC:TA), (b) retained earnings: total assets (RE:TA), (c) earnings before interest and taxes: total assets (EBIT:TA), (d) market value of equity: total debt (MV:TL), (e) sales: total assets (Sales: TA), (f) cash flow from operations: current liabilities (CFFO:CL), (g) cash flow from operations: total assets (CFFO:TA), and (h) cash flow from operations: total liabilities (CFFO:TL). Descriptive statistics for financial ratios are summarized in Table 2 for failed firms and in Table 3 for non-failed firms.

WC:TA compares net liquid assets to the total capitalization of a firm (Altman, 1968). A decline in current assets compared to total assets is indicative of a firm experiencing operating losses. The mean of WC:TA for failed firms was found to be less than that for non-failed firms. Forty-two of 114 failed firms had negative WC:TA compared to only eight non-failed firms.

RE:TA measures cumulative profitability over time (Altman, 1968). Non-failed firms were found to have a higher mean RE:TA than failed firms. Eighty-six of 114 failed firms had negative RE:TA versus 43 of 114 non-failed firms.

EBIT:TA measures the productivity of a firm's assets less the influence of taxes or leveraging factors (Altman, 1968). Higher EBIT performance translates into a firm's ability to remain a viable going concern. More failed firms had a negative EBIT:TA resulting in a negative mean for this ratio. Seventy-five of 114 failed firms had a negative EBIT:TA compared to only 31 of 114 non-failed firms.

MVE:TL measures how much a firm's assets can decline prior to insolvency, due to liabilities exceeding assets (Altman, 1968). Failed firms had a lower average MVE:TL than non-failed firms, suggesting higher risk for failed firms not to meet total debt requirements. Mean MVE:TL for failed firms was 0.2899 compared to 0.7873 for non-failed firms.

Sales:TA measures the ability for a firm's assets to generate sales (Altman, 1968). Therefore, it would be expected that the mean Sales:TA for failed firms would be less than the mean Sales:TA for non-failed firms. Mean Sales:TA for failed firms was 1.306, while the mean Sales:TA for non-failed firms was 1.223. This result suggests that Sales.

CFFO:CL measures the ability of a firm's cash flow to cover short-term liabilities. The mean CFFO:CL for both failed and non-failed firms was negative, suggesting difficulty for all firms to ~~cover short-term debt. The mean CFFO:CL for failed firms was -.3041, which is more negative~~ than the mean CFFO:CL of -.0904 calculated for non-failed firms. Eighty-two of 114 failed firms had negative CFFO:CL compared to 46 of 114 non-failed firms.

CFFO:TA measures the ability of a firm's assets to generate cash. A negative CFFO:TA mean of -.1232 for failed firms suggests difficulty in generating cash flow. The mean CFFO:TA for non-failed firms was positive at 0.0042. Eighty-two of 114 failed firms had negative CFFO:TA compared to 46 of 114 non-failed firms. CFFO:TL measures the ability of a firm's cash flow to cover total debt. The mean CFFO:TL for both failed and non-failed firms was negative, suggesting all firms were challenged with having adequate cash flow to cover short and long-term debt requirements. Eighty-two of 114 failed firms had negative CFFO:TL compared to 46 of 114 non-failed firms.

Table 1

Descriptive Statistics for Total Assets of Failed and Non-failed Firms ($, Millions)

Statistic	Failed Firms	Non-failed Firms
Mean	146.769	146.633
Standard of Deviation	298.465	298.505
Range	2,325.326	2,329.512
Minimum	20.474	19.104
Maximum	2,345.800	2,348.616

Table 2

Descriptive Statistics for Financial Ratios of Failed Firms

Statistic	WC:TA	RE: TA	EBIT: TA	MVE: TL	Sales: TA	CFFO: CL	CFFO: TA	CFFO: TL
Mean	.0176	-.7431	-.1573	.2899	1.306	-.3040	.1232	-.2010
Standard of Deviation	.3861	1.264	.2814	.9460	.6686	.7589	.2375	.4798
Range	2.943	9.585	1.703	8.867	3.297	6.473	1.593	3.940
Minimum	-2.140	-9.191	-1.409	0.000	0.000	-3.371	-1.266	-3.181
Maximum	0.803	0.394	0.294	8.867	3.297	3.102	0.327	0.759

Table 3
Descriptive Statistics for Financial Ratios of Non-failed Firms

Statistic	WC: TA	RE: TA	EBIT: TA	MVE: TL	Sales: TA	CFFO: CL	CFFO: TA	CFFO: TL
Mean	.4221	-.1321	.0199	.7873	1.223	-.0904	.0042	-.1342
Standard of Deviation	.4900	.8936	.2179	2.780	1.601	1.325	.1947	1.127
Range	5.397	6.508	1.297	20.766	16.687	7.908	1.290	7.908
Maximum	-0.584	– 5.745	-0.918	0.001	0.000	-5.367	-0.842	-5.367
Minimum	4.813	0.763	0.379	20.767	16.687	2.541	0.448	2.541

Hypotheses

The purpose of this study is to determine whether cash flow improves the business failure prediction of manufacturing firms using a neural network. An artificial Intelligence model is generated using neural networks. A neural network model based on Altman's (1968) variables was compared with a neural network model based on Altman's (1968) variables combined with Gilbert's, Menon's, & Schwartz's (1990) cash flow variables to determine the impact of cash flow on prediction accuracy. The objective is to determine whether cash flow improves the business failure prediction of manufacturing firms using a neural network model. The following three hypotheses, stated in null and alternate form, were formulated to support the purpose of this study:

H01: A neural network model utilizing Altman's (1968) five accrual-based ratios is not able to distinguish between failed and non-failed manufacturing firms.

Ha1: A neural network model utilizing Altman's (1968) five accrual-based ratios is able to distinguish between failed and non-failed manufacturing firms.

H02: A neural network model utilizing Altman's (1968) five accrual-based ratios combined with Gilbert's, Menon's, & Schwartz's (1990) three cash flow-based ratios is not able to distinguish between failed and non-failed manufacturing firms.

Ha2: A neural network model utilizing Altman's (1968) five accrual-based ratios combined with Gilbert's, Menon's, & Schwartz's (1990) three cash flow-based ratios is able to distinguish between failed and non-failed manufacturing firms.

H03: A cash flow-based neural network model does not predict failure of manufacturing firms with a higher degree of accuracy than an accrual-based neural network model.

Ha3: A cash flow-based neural network model predicts failure of manufacturing firms with a higher degree of accuracy than an accrual-based neural network model.

RESULTS

Hypothesis 1 was tested to determine the business failure prediction accuracy of a baseline neural network model using Altman's (1968) five accrual-based financial ratios as input variables. Financial ratios were calculated for 114 failed and 114 non-failed firms from financial statement data one year prior to failure from Standard & Poor's.

The overall sample of firms was split into two groups consisting of 188 firms and 40 firms. The first group was identified as a training group consisting of 94 failed and 94 non- failed firms in order for the baseline neural network model to learn to classify patterns (Coats & Fant, 1992). The baseline neural network model, developed using NeuroShell Classifier, consisted of three layers that included input nodes, hidden nodes, and an output node. The input nodes were represented by Altman's (1968) five accrual-based financial ratios. One output node represented a classification of failed or non-failed for firms. NeuroShell Classifier assigned an optimal number of 106 hidden neurons out of a total of 150 hidden neurons trained.

The baseline accrual -based neural network model correctly classified 92.55% of firms in the training sample, overall, one year prior to failure. The model misclassified 7.45% of firms in the training sample, overall, one year prior to failure.
The baseline model correctly classified 89 of 94 or 94.68% of failed firms one year prior to business failure with Type I errors for 5.32% of failed firms classified. Type I errors represent five of 94 failed firms misclassified as non-failed firms. The model correctly classified 85 of 94 or 90.43% of non- failed firms with Type II errors for 9.57% of non- failed firms classified. Type II errors represent nine of 94 non-failed firms misclassified as failed firms.

The baseline accrual -based neural network model, developed with NeuroShell Classifier utilizing a training sample, was tested on a holdout sample of 40 firms. The holdout sample consisted of 20 failed and 20 non-failed firms. The baseline model consisted of five input nodes, 106 hidden nodes, and one output node. Altman's (1968) five accrual-based financial ratios for holdout sample firms were entered into NeuroShell Classifier with enhanced generalization for results set at 90%. Enhanced generalization smoothes out classification results of the network for out-of-sample or noisy data. The baseline accrual-based neural network model correctly classified 31 of 40 or 77.5% of firms in the holdout sample, overall, one year prior to failure. The model misclassified 9 of 40 or 22.5% of firms overall in the holdout sample.

The model correctly classified 16 of 20 or 80% of failed firms one year prior to failure with Type I errors of 20%. Type I errors represent four of 20 failed firms misclassified as non-failed firms. The model correctly classified 15 of 20 or 75% of non-failed firms with Type II errors of 25%. Type II errors represent five of 20 non-failed firms misclassified as failed firms. Training sample and holdout sample test results for the baseline accrual-based neural network model are summarized in Table 4

Table 4
Classification Results for Accrual-Based Neural Network Model One Year Prior to Business Failure

Sample	Type	Classification	Correctly	% Misclassified Classified	% Error
Training		Overall	92.55	7.45	-
	Type I	Failed		94.68	5.32
	Type II	Non-failed		90.43	9.57
Holdout	-	Overall	77.5		22.50
	Type I	Failed		80.0	20.00
	Type II	Non-failed		75.0	25.00

Hypothesis 1 was tested using the holdout sample of 20 failed and 20 non-failed firms. Null Hypothesis 1 states that the baseline accrual-based neural network is not able to distinguish between failed and non-failed manufacturing firms non-failed firms, and Null Hypothesis 1 cannot be rejected. When the classification of failed and non-failed firms is not equal, the baseline neural network model is able to distinguish between failed and non-failed firms and Null Hypothesis 1 can be rejected.

Test results for Hypothesis 1 indicate the baseline neural network correctly classified 77.5% of firms overall one year prior to failure. Therefore, the model was able to distinguish between failed and non-failed firms, resulting in rejection of Null Hypothesis 1 and support of Alternate Hypothesis 1. The baseline neural network model correctly classified manufacturing firms at a level greater than 50% one year prior to failure.
Hypothesis 2 was tested to determine the business failure prediction accuracy of a cash flow-based neural network model using Altman's (1968) five accrual-based financial ratios and Gilbert's, Menon's, & Schwartz's (1990) three cash flow-based financial ratios as input variables. Financial ratios were calculated for the same 114 failed and 114 non-failed firms used to test Hypothesis I from financial statement data one year prior to failure from Standard & Poor's.

The overall sample of firms was split into two groups consisting of 188 firms and 40 firms. The first group was identified as a training group consisting of 94 failed and 94 non- failed firms for the cash flow-based neural network model to learn to classify patterns (Coats & Fant, 1992). The cash flow-based neural network model developed, using NeuroShell (2003) Classifier, consisted of three layers that included input nodes, hidden nodes, and an output node. The input nodes were represented by Altman's (1968) five accrual-based financial ratios and Gilbert's, Menon's,

& Schwartz's (1990) three cash flow-based financial ratios. There was one output node that represented a classification of failed or non-failed for firms. NeuroShell Classifier assigned an optimal number of 146 hidden neurons out of a total of 150 hidden neurons trained.

The cash flow-based neural network model correctly classified 94.15% of firms in the training sample, overall, one year prior to failure. The model misclassified 5.85% of firms in the training sample, overall, one year prior to failure. The cash flow-based model correctly classified 91 of 94 or 96.81% of failed firms one year prior to business failure with Type I errors for 3.19% of failed firms classified. Type I errors represent three of 94 failed firms misclassified as non-failed firms. The model correctly classified 86 of 94 or 91.49% of non- failed firms with Type II errors for 8.51% of non-failed firms classified. Type II errors represent eight of 94 non-failed firms misclassified as failed firms.

The cash flow-based neural network model developed with NeuroShell (2003) Classifier, utilizing a training sample, was tested on the same holdout sample of 40 firms used to test the baseline accrual-based neural network model. The holdout sample consisted of 20 failed and 20 non-failed firms. The cash flow-based model consisted of eight input nodes, 146 hidden nodes, and one output node. Altman's (1968) five accrual-based financial ratios and Gilbert's, Menon's & Schwartz's (1990) three cash flow-based financial ratios for holdout sample firms were entered into NeuroShell Classifier with enhanced generalization for results set at 90%. Enhanced generalization smoothes out classification results of the network for out-of-sample or noisy data. The cash flow-based neural network model correctly classified 33 of 40 or 82.5% of firms in the holdout sample, overall, one year prior to failure. The model misclassified 7 of 40 or 17.5% of firms in the holdout sample, overall. The model correctly classified 18 of 20 or 90% of failed firms one year prior to failure with Type I errors and Type II errors represent 5 of 20 non-failed firms misclassified as failed firms. Training sample and holdout sample test results for the cash flow-based neural network model are summarized in Table 5.

Table 5
Classification Results for Cash Flow-Based Neural Network Model One Year Prior to Business Failure

Sample	Classification	% Correctly	% Misclassified Error
Training	Overall -	94.15	5.85
	Failed Type I	96.81	3.19
	Non-failed Type II	91.49	8.51
Holdout	Overall	82.5	17.5
	Failed Type I	90.0	10.0
	Non-failed Type II	75.0	25.0

Hypothesis 2 was tested on the holdout sample of 20 failed and 20 non-failed firms. Null Hypothesis 2 states that the cash flow-based neural network is not able to distinguish between failed and non-failed manufacturing firms. If the classification of failed and non-failed firms is equal, the cash flow-based neural network model cannot distinguish between failed and non-failed firms, and Null Hypothesis 2 cannot be rejected. If the classification of failed and non-failed firms is not equal, the cash flow-based neural network model is able to distinguish between failed and non-failed firms, and Null Hypothesis 2 can be rejected.

Test results for Hypothesis 2 indicate the cash flow-based neural network correctly classified 82.5% of firms, overall, one year prior to failure. Therefore, the model was able to distinguish between failed and non-failed firms, resulting in rejection of Null Hypothesis 2 and support of Alternate Hypothesis 2. The cash flow-based neural network model correctly classified manufacturing firms at a level greater than 50%, one year prior to failure.
Hypothesis 3 was tested to determine whether a cash flow-based neural network model predicted

Table 6
Comparison of Classification Results for an Accrual -Based Neural Network Model and a Cash Flow-Based Neural Network Model One Year Prior to Failure

Classification	Accrual Model		Cash Flow Model	
	Training Sample	Holdout Sample	Training Sample	Holdout Sample
Overall	92.55%	77.5%	94.15%	82.5%
Failed	94.68%	80.0%	96.81%	90.0%
Non-failed	90.43%	75.0%	91.49%	75.0%

The results show that the cash flow-based neural network model attained higher classification accuracy for firms, overall, one year prior to failure than the accrual- based neural network model. The cash flow-based model correctly classified 94.15% of firms overall in the training sample and 82.5% of firms overall in the holdout sample. The accrual-based model correctly classified 92.55% of firms overall in the training sample and 77.5% of firms overall in the holdout sample.

In addition, the results show that the cash flow-based neural network model attained a higher classification accuracy for failed firms than the accrual-based neural network model one year prior to failure. The cash flow-based model correctly classified 96.18% of failed firms in the training sample and 90% of failed firms in the holdout sample. The accrual-based model correctly classified 94.68% of failed firms in the training sample and 80% of failed firms in the holdout sample. The percentage of Type I errors was less for the cash flow-based model compared to the accrual-based model.

Finally, the cash flow-based model attained higher classification accuracy for non-failed firms in the training sample than the accrual-based model one year prior to failure. Results indicate that the classification accuracy of non-failed firms in the holdout sample was the same for both models. The cash flow-based model correctly classified 91.49% of non-failed firms in the training sample and 75% of non-failed firms in the holdout sample. The accrual-based model correctly classified 90.43% of non-failed firms in the training sample and 75% of non-failed firms in the holdout sample. The percentage of Type II errors for the training sample was less for the cash flow-based model compared to the accrual-based model. The percentage of Type II errors for the holdout sample was identical for both models.

A Z-test was performed to test Hypothesis 3 for significance of any differences between classification results of the accrual-based neural network model and the cash flow-based neural network model for the holdout sample. Hypothesis 3 was tested at the 0.05 level of significance. If significant, Null Hypothesis 3 is rejected, indicating a significant difference exists in classification accuracy between the accrual-based model and the cash flow-based model. If the Z-value is less than ±1.96, it is not considered significant at the 0.05 level. If not significant, Null Hypothesis 3 is not rejected, indicating no significant difference in classification accuracy between the accrual-based model and the cash flow-based model.
Results of the Z-test, displayed in Table 7.0, indicate that the difference in overall classification accuracy one year prior to failure between the accrual-based model and the cash flow-based ~~model was not significant at the 0.05 level.~~

Table 7
Z-test Results for Classification Comparison of Accrual-Based Neural Network Model and Cash Flow-Based Neural Network Model One Year Prior to Failure for Holdout Sample

Classification	Accrual Model	Cash Flow Model	Z-Value	Significance Level
Overall	77.5%	82.5%	-0.5601	0.5754
Failed	80.0%	90.0%	-1.2649	0.7942
Non-failed	75.0%	75.0%	0.0000	1.0000

A negative Z-value demonstrates that the cash flow-based model classified with greater accuracy than the accrual-based model. The statistical results indicate that the difference in classification accuracies was not significant. For failed firms, the results show that the difference in classification accuracy one year prior to failure between models was not significant at the 0.05 level. A negative Z-value shows that the cash flow-based model classified firms with greater accuracy than the accrual -based model. Statistical results reveal that the difference in classification accuracy was not significant. For non-failed firms, the results show that the difference in classification accuracy one year prior to failure between models was not significant at the 0.05 level. A Z-value of zero shows that the classification accuracy for failed firms was equal for both models.

Results of the Z-test identify that the difference in classification accuracy between the accrual-based neural network model and the cash flow-based neural network model was not significant at the 0.05 level. Therefore, Null Hypothesis 3 is not rejected and Alternate Hypothesis 3 is not supported. Despite higher classification accuracies, the cash flow-based model was not found statistically different from the accrual-based model. The test for significance of difference between two groups shows that no significant difference exists between the accrual-based model and the cash flow-based model.

The objective was to determine whether cash flow has an impact on business failure prediction. This was accomplished through training and testing and comparison of results between an accrual-based neural network model and a cash flow-based neural network model. Hypothesis 1 was tested to determine the business failure prediction accuracy of a baseline neural network model using Altman's (1968) five accrual-based ratios as input variables. The accrual-based model correctly classified 92.5% of firms overall, 94.68% of failed firms, and 90.43% of non-failed firms in a training sample of 94 failed and 94 non-failed firms, one year prior to business failure. The model also correctly classified 77.5% of firms overall, 80% of failed firms, and 75% of non-failed firms in a holdout sample of 20 failed and 20 non-failed firms, one year prior to business failure. The accrual-based model was able to distinguish between failed and non-failed manufacturing firms, resulting in rejection of Null Hypothesis 1 and support of Alternate Hypothesis 1. Hypothesis 2 was tested to determine the business failure prediction accuracy of a cash flow-based neural network model using Altman's (1968) five accrual-based financial ratios and Gilbert's, Menon's & Schwartz's (1990) three cash flow-based financial ratios as input variables. The cash flow-based model correctly classified 94.15% of firms overall, 96.18% of failed firms, and 91.49% of non-failed firms in a training sample of 94 failed and 94 non-failed firms, one year prior to business failure. The model also correctly classified 82.5% of firms overall, 90% of failed firms, and 75% of non-failed firms in a holdout sample of 20 failed and 20 non-failed firms, one year prior to business failure. The cash flow-based model was able to distinguish between failed and non-failed manufacturing firms, resulting in rejection of Null Hypothesis 2 and support of Alternate Hypothesis 2. Hypothesis 3 was tested to determine whether a cash flow-based neural network model predicted business failure with a higher degree of accuracy than an accrual-based neural network model. A Z-test was performed to test for a significant difference between the two models at the 0.05 significance level.

Despite higher classification accuracies, the difference between the cash flow-based neural network model and the accrual-based neural network model was found not to be statistically significant. Results of the Z-test indicate that the difference in overall classification accuracy one year prior to business failure between the accrual-based model and the cash flow-based model was not significant at the 0.05 level. Therefore, Null Hypothesis 3 was not rejected and Alternate Hypothesis 3 was not supported.

The results of this study demonstrate that the cash flow-based neural network model is a good predictor of business failure. The cash flow-based model outperformed the accrual-based model and classification results are comparable to previous neural network failure study results. While the cash flow-based model achieved a classification accuracy of 94.15% of firms in the training sample, one year prior to business failure overall, the model did not achieve a perfect training forecast as in studies performed by Coats and Fant (1992) and Wilson and Sharda (1994). Holdout sample business failure classification results compare similarly to holdout results achieved by Coats & Fant (1992), Udo (1993), Wilson & Sharda (1994), Rahimian's et al. (1996), and Yang, Platt, & Platt (1999).

The cash flow-based neural network model correctly classified 82.5% of firms in a holdout sample, overall, one year prior to business failure. Overall classification performance of the cash flow-based model compared similarly to (a) Wilson's & Sharda's (1994) overall classification range of 82.64% to 96.49%, (b) Rahimian's et al. (1996) overall classification accuracy of 81.82%, and (c) Yang's, Platt's, & Platt's (1999) overall classification range of 74.0% to 87.0%.

The cash flow-based model correctly classified 90.0% of failed firms in a holdout sample one year prior to business failure. Classification performance of failed firms of the cash flow-based model compared similarly to Coats' & Fant's (1992) classification accuracy of 91.0% of distressed firms. Cash flow-based model classification performace surpassed Udo's (1993) classification performance of 86.0% of failed firms. The cash flow-based model performed well, comparatively, for failed firms, minimizing Type I errors that misclassify a failed firm as a non-failed firm.

The cash flow-based model correctly classified 75.0% of non-failed firms in a holdout sample, one year prior to business failure. The cash flow-based model classification performance was inferior to (a) Coats'& Fant's (1992) classification accuracy of 96.0% for healthy firms and (b) Udo's (1993) classification results of 90% for healthy firms. The cash flow model did not perform well, comparatively, for non-failed firms, with increased Type II errors that misclassify a non-failed firm as a failed firm.

The business failure classification results of the cash flow-based neural network model also compared similarly to results of cash flow oriented failure studies. The cash flow-based model correctly classified 94.15% of firms overall, 96.81% of failed firms, and 91.49% of non-failed firms in a training sample, one year prior to business failure. The cash flow-based model results for the training sample outperformed Gentry's, Newbold's & Whitford's (1985a) failed firms in an estimation sample. The cash flow-based model results also outperformed Gentry's, Newbold's & Whitford's (1985b) classification results of 83.3% of firms overall, 78.8% of failed firms, and 87.9% of non-failed firms in an estimation sample.

In addition, the cash flow-based neural network model achieved better results overall on a training sample than previous cash flow-based failure study overall results on estimation samples. The cash flow-based model outperformed (a) Casey's & Bartczak's (1984) classification results of 86.0% of firms overall, (b) Gombola's et al. (1987) classification results of 85.0% of firms overall, (c) Dambolena's & Shulman's (1988) classification results of 74.0% and 89.0% of firms overall, (d) Gilbert's, Menon's & Schwartz's (1990) results of 81.9% of firms overall, and (e) Rujoub's, Cook's & Hay's (1995) classification results of 86.36% of firms overall.

The cash flow-based neural network model achieved higher holdout test classification results when compared to holdout test results of previous cash flow failure studies. The cash flow-based neural network model correctly classified 82.5% of firms overall, 90.0% of failed firms, and 75.0% of non-failed firms for a holdout sample, one year prior to business failure. Gentry, Newbold, and Whitford (1985a) achieved classification results of 71.74% of firms overall, 69.57% of weak firms, and 73.91% of nonweak firms. Gilbert, Menon & Schwartz (1990) achieved a classification result of 78.3% of firms overall for a holdout sample.

The classification results of the cash flow-based neural network model compared similarly to Altman's (1968) classification results. The cash flow-based model correctly classified 94.15% of firms overall in the training sample, one year prior to business failure compared to 95.0% overall for Altman (1968). Altman's (1968) multiple discriminant model correctly classified 96% of bankrupt firms and 79% of non bankrupt firms in a secondary sample test. The cash flow-based model correctly classified 90.0% of failed firms and 75% of non-failed firms in a holdout sample test.

T able 8

Summary of Hypothesis Testing

	Hypotheses	Outcome
H 01	A neural network model utilizing Altman's (1968) five accrual-based ratios is not able to distinguish between failed and non-failed manufacturing firms.	Rejected
H 02	A neural network model utilizing Altman's (1968) five accrual-based ratios combined with Gilbert's, Menon's & Schwartz's (1990) three cash flow-based ratios is not able to distinguish between failed and non-failed manufacturing firms.	Rejected
H 03	A cash flow-based neural network model does not predict failure of manufacturing firms with a higher degree of accuracy than an accrual-based neural network model.	Accepted

Conclusions

Several key conclusions result from the research performed in this study. First, the results of the study reveal that an accrual-based neural network model utilizing Altman's (1968) five accrual-based financial ratios is a good predictor of business failure. The accrual-based model is able to distinguish between failed and non-failed manufacturing firms one year prior to business failure. The classification results of this model are only generalizable to publicly traded manufacturing firms. The question remains whether the model would be a good predictor of business failure for privately held manufacturing firms or other industries, more than one year prior to business failure.

Second, the results of the study confirm that a cash flow-based neural network model utilizing Altman's (1968) five accrual -based financial ratios and Gilbert's, Menon's, & Schwartz's (1990) three cash flow-based financial ratios is a good predictor of business failure. The cash flow-based model also is able to distinguish between failed and non-failed manufacturing firms, one year prior to business failure. The classification results of this model are only generalizable to publicly traded manufacturing firms. The question remains whether this model would also be a good predictor of business failure for privately held manufacturing firms or other industries, more than one year prior to business failure.

Third, the results of the study demonstrate that cash flow does not impact business failure classification using a neural network. While both models were found to be good predictors of business failure, and the cash flow-based model had a higher classification accuracy than the accrual-based model, the difference in results is found not to be statistically significant. Toward classification accuracy compared to the contribution by Gilbert, Menon, & Schwartz, (1990) cash flow-based financial ratios. This suggests that no one model is able to classify business failure with considerably increased accuracy over other models. Accrual-based and cash flow-based business failure models were developed using neural networks with financial ratios as input variables. Both were found to be good predictors of business failure. Because the difference in results of the two models proved not to be significant, either model can serve as a financial tool to assist financial managers in manufacturing firms, creditors, and investors and analysts.

Financial managers are responsible for manufacturing firm financial performance through the management of balance sheet, income statement, and cash flow financial information. Financial performance is assessed through comparisons with competition and with published industry information. In addition, financial managers are concerned with the financial viability of their firms. The accrual-based or cash flow-based model could be used as a supplemental financial tool to determine whether the firm's financial condition is indicative of a failed or non-failed firm. Depending on results of the analysis, management can take corrective action to adjust appropriately the firm's financial condition.

Creditors are concerned with financial viability when making determinations whether to offer credit to firms. Lending institutions could use the accrual-based or cash flow-based model as an additional tool to further analyze the financial condition of potential borrowers. The outcome of the analysis could determine whether or not to lend to potential borrowers or if further analysis is required before granting credit.

When providing advice and recommendations to investors, financial analysts are concerned with the financial viability of manufacturing firms. Investors are also concerned with the financial viability of firms when making investment decisions. In each case, investors and financial analysts want to avoid Type I errors or firms that are failing but emerge as non-failed firms. The accrual-based or cash flow-based model can be used as a supplemental financial tool to assist investors and analysts to assess the viability of manufacturing firms. The outcome of the analysis could assist in avoiding unfavorable recommendations and investments that lead to potential financial loss to investors.

References

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, 23(4), 589-609.

Aziz, M.A., & Dar, H.A. (2006) Predicting corporate bankruptcy: where we stand?, *Corporate Governance*, 6(1), 18-33.

Casey, C. J., & Bartczak, N. J. (1984). Cash flow – it's not the bottom line. *Harvard Business Review*, 62(4), 61-66.

Coats, P. K., & Fant, L. F. (1992). A neural network approach to forecasting financial distress. *The Journal of Business Forecasting Methods & Systems*, 10(4), 9-12.

Chava, S., & Jarrow, R. (2004) Bankruptcy Predictions with Industry Effects. *Review of Finance*,

Dambolena, I. G. & Shulman, J. M. (1988). A primary rule for detecting bankruptcy: Watch the cash. *Financial Analysts Journal*, 44(5), 74-78.

Gentry, J. A., Newbold, P. & Whitford, D. T. (1985a). Classifying bankrupt firms with funds flow components. *Journal of Accounting Research*, 23(1), 146-160.

Gentry, J. A., Newbold, P. & Whitford, D. T. (1985b). Predicting bankruptcy: If cash flow's not the bottom line, what is? Financial Analysts Journal, 41(5), 47-56.

Gilbert, L. R., Menon, K. & Schwartz, K. B. (1990). Predicting bankruptcy for firms in financial distress. *Journal of Business Finance & Accounting*, 17(1), 161-171.

Gombola, M. J., Haskins, M. E., Ketz, J. E. & Williams, D. D. (1987). Cash flow in bankruptcy prediction. Financial Management, 16(4), 55-65.

Kuruppu, N., Laswad, F. & Oyelere, P. (2003), The efficacy of liquidation and bankruptcy prediction models for assessing going concern. *Managerial Auditing Journal* 18, 577-590.

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

Platt, H.D. & Platt, M.B. (1990). Development of a class of stable predictive variables: the case of bankruptcy prediction. *Journal of Business Finance & Accounting*, 17(1), 31-51.

Rahimian, E., Singh, S., Thammachote, T. & Virmani, R. (1996). Bankruptcy prediction by neural network. In R. Trippi & E. Turban (Eds.), *Neural networks in finance and investing: Using artificial intelligence to improve real-world performance* (pp. 243-259). New York: McGraw-Hill.

Rujoub, M. A., Cook, D. M. & Hay, L. E. (1995). Using cash flow ratios to predict business failures. *Journal of Managerial Issues*, 7(1), 75-90.

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

Udo, G. (1993). Neural network performance on the bankruptcy classification problem. *Computers & Industrial Engineering*, 25(1), 377-380.

Wilson, R. L. & Sharda, R. (1994). Bankruptcy prediction using neural networks. Decision Support Systems, 11(5), 545-557.

Yang, Z. R., Platt, M. B., & Platt, H. D. (1999). Probabilistic neural networks in bankruptcy prediction. *Journal of Business Research*, 44(2), 67-74

Wang, Y. & Campbell (2010) Do Bankruptcy Models Really Have Predictive Ability? Evidence using China Publicly Listed Companies. *International Management Journal*, 6(2)

Zavgren, C.V. (1985). Assessing the vulnerability to failure of American industrial firms: a logistic analysis. *Journal of Business Finance & Accounting*, 12(1), 19-45.

Zmijewski, M. E. (1984) Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research*, 22, 59–82.