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Abstract

One criticism of failure prediction models is the bias resulting from pooling failure data over years when economic conditions might influence the failure of a firm. This research incorporates both macroeconomic variables and firm specific variables in explaining corporate failure. The results suggest that including economic variables improve the explanation of failure by ten percent. The economic variables included in the analysis were one-year lag in change in GDP, a two-year lag in interest rates, a one-year lag in the share price index, and a one-year lag in corporate profits. Economic variables were identified using a principal component analysis of key economic variables.

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Introduction

The problem of financial distress takes on increased importance in view of the number and size of company failures, both public and private, following the market failure of the 1987 Market Crash, the Savings and Loan Crisis of the early 1990s, the internet bubble of the late 1990s and the on-going global financial crisis. Numerous studies attempt to predict financial distress based on firm specific (micro) information. However, both anecdotal and empirical evidence (Rose et al., 1982) suggests that macroeconomic conditions are relevant to a firm's success or failure (Bhattacharjee et al., 2009, Fitzpatrick and Ogden, 2011, Liu, 2009). Indeed many firm specific predictors of firm distress may be accurate under certain economic conditions (Cybinski, 1995, McNamara et al., 1988, Kane et al., 1996, Nam et al., 2000, Richardson et al., 1998).

Understanding corporate failure in the context of macroeconomic conditions is important to managers, consultants, creditors, auditors and financial analysts. Managers and consultants need to better understand the interaction between economic conditions and firm performance if they are to develop and manage reconstruction strategies. Lending personnel can better adjust their risk ratings in the light of changing economic circumstances and firm specific characteristics. Auditors' reports are an important signal

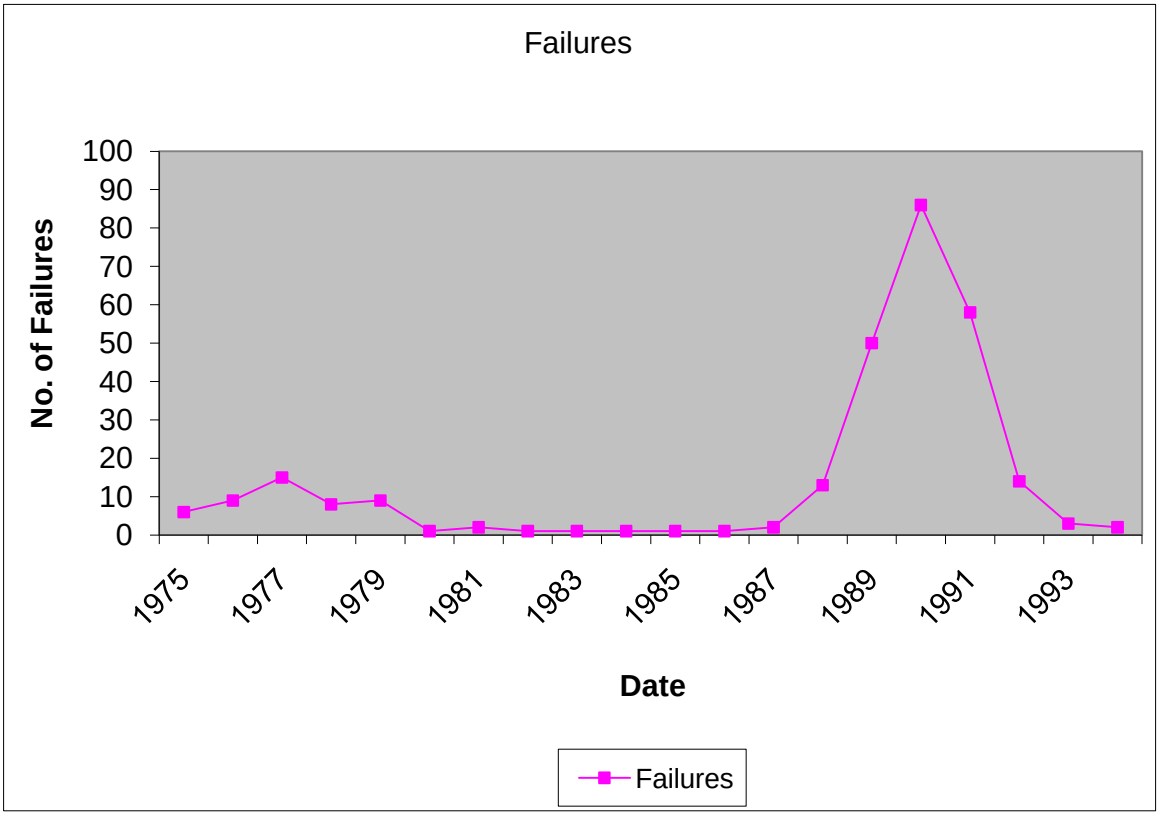
about failing firms through qualifications and going concern exceptions. The cost of not qualifying a set of accounts when they are to fail may result in a significant legal liability to the auditor. Arguing a firm is not a going concern when it can continue its operations can in itself lead to failure. Both these audit risks can be reduced if the auditor appreciates the interaction between a firm's characteristics and the various states of nature the firm may face. Financial analysts need to cast their recommendations in the light of economic conditions. What may appear as viable firm characteristics in an economic boom may be disastrous in a recession.

The purpose of this paper is to assess whether both firm specific and macroeconomic indicators combine to explain the failure of public companies. The remainder of the paper proceeds as follows. Section two details the literature on firm failure and selected literature on economic variables that a priori give impact on firm performance. The section concludes with a model of firm failure. Section three details the research methods and the data analysis. The final section discusses the findings, limitations, and directions for future research.

Literature Review

Failure prediction, built on the work of Altman (1968) and Beaver (1966), has tested the predictive ability of different combinations of over 100 ratios (Zmijewski, 1984). This research consistently shows that a significant percentage of failed firms can be correctly predicted one year prior (Altman, 1968, Altman, 1971, Altman et al., 1995, Altman et al., 1977, Altman and Narayanan, 1997, Beaver, 1966, Beaver, 1968, Brunner and Krahnen, 2008, Chan and Rotenberg, 1988, Deakin, 1972, Demers and Joos, 2007, Dietrich et al., 2005, Divsalar et al., 2011, Eidleman, 1995, Gilbert et al., 1990, Hensher and Jones,

2007, Hu and Ansell, 2007, McNamara et al., 1988, Neophytou and Molinero, 2004). However, as Johnson (1970) states, "*the ratios to predict failure…do not contain information about the intervening economic conditions…the riskiness for a given value of ratio changes with the business cycle*" (Johnson, 1970; p.1116). McNamara et al. (1988) qualified their findings by stating "*the data employed restricts the generality of the results because we sampled from a period of economic recession. The model therefore has validity for this state of nature only*" (McNamara et al., 1988). A cursory examination of the incidence of corporate failure in Australia supports the proposition that economic



conditions impact on the rate of firm collapse. Figure 1 depicts the incidence of corporate failure from 1975 to 1995 as disclosed in the Australian Stock Exchange Annual Summaries.

Figure 1 Incidence of Public Company Failure

Periods of economic recession, 1976 to 1978 and 1989 to 1992, show significant increases in company failure. High interest rates, recession, squeezed corporate profits, and the heavy debt burdens are anecdotally considered as contributing factors to the increased incidence of corporate distress.

However, the dramatic rise in the number of failures since 1987 suggests some systematic problem among analysts and lenders in their assessments of the viability of publicly listed companies. Alternatively, the firm characteristics that predict success during periods of economic growth may indicate failure during times of recession. Zavgren (1983) suggests that the pooling of failure data over several years may confound prediction results significantly. If different years are characterized by widely differing incidences of firm failure, then prior probabilities will be distorted and hence failure prediction becomes unreliable (Eisenbeis, 1977; p. 892).

This difficulty makes the value of commercial failure-prediction models suspect. The most serious effect would be a tendency to understate the misclassification of surviving companies into the failing group. The costs of such a misclassification would be serious for the company concerned particularly if they approached a provider of capital. The low incidence of failure might also lead users of commercial prediction models to become over confident.

Macroeconomic Variables

Two researchers attempted to assess the impact of economic variables on the corporate failure. Altman (1971)used a first difference regression analysis to explain the number of corporate failures from quarter to quarter. The independent variables used were the

change in Gross National Product, the change in the Standard and Poor's Index of Common Stock Prices, and the change in the national money supply. The R^2 in Altman's equation was 0.19 indicating relatively little explanatory power for economic variables. Rose et al., (1982) argued that business failure is negatively correlated with cyclical changes – rising in periods of recession and falling in periods of economic expansion. They were able to explain the rate of business failure with an R^2 of 0.912. Three significant variables resulted from their step-wise regression; Standards and Poor's Composite Stock Price Index, Corporate Profits, and ninety-day Treasury Bill Rate.

Neither Altman et al. (1971) nor Rose et al. (1982) combined their economic variables with firm variables to classify failure of individual firms. However, the variables identified by Rose et al. (1982) confirm the relationship between business cycle indicators and firm failure. Modern European and American economists focus on multiplier interaction models and dynamic structural models of the cyclical process of the economy (Hicks, 1950, Klein, 1964, Smithies, 1957). The extensive body of literature on the business cycle may be classified three major groups:

- Supply or cost-push theories focusing on changes in business costs, net profits, and the cost of labor and other factors of production.

- Monetary theories focus on the cost and availability of credit. Variables identified by these theories include a range of interest rates and money-supply indicators.

- Savings and Investment theories have their origin in nineteenth-century classical general-equilibrium models. As the name suggests, these theories promote variables such as Gross Savings, Change in Business Investment, Industrial Production etc.

In addition, Rose et al. (Rose et al., 1982) included in their study variables identified in previous research that were correlated with cyclical changes. These include indicators such as Share Price Indices, GNP, Unemployment Rates, and Personal Income variables. Detailed procedures are included in the Methods Section.

Ratios

With the exception of Beaver (1966) failure analysis had proceeded without any guiding theory of corporate failure or performance. Beaver suggested that the firm is viewed as a "reservoir of liquid assets which is supplied by inflows and drained by outflows. The solvency of the firms can be defined in terms of the probability that the reservoir will be drained. While this framework was used to guide Beaver's analysis the significant variables in his study were not effectively related to the concept of a firm as a reservoir. An alternate framework is to view the firm as a combination of four related sets of variables:

- Activity Ratios;
- Profitability Ratios;
- Leverage Ratios; and
- Liquidity Ratios

This framework can be related to the cash reservoir formulation of Beaver (1968)

Activity ratios are surrogates for a company's ability to generate sales from its asset base. This measure is similar to Beaver's measure of variables that top up the cash flow

reservoir. A company's survival and long-term success depends on its ability to generate sufficient sales to support the level of assets committed to the business.

Profitability ratios measure the ability of the firm to turn sales into profits. If activity ratios determine the rate of flow of cash into the business, the profitability ratios measure the extent of the firm to control outflows. Activity and profitability measures assess the fundamental viability of the corporation. Failure can occur because the outflows from expenses and overheads are too great relative to the sales generated. Finally, failure can result from a combination of sales generation and profitability problems.

While Activity and Profitability measures indicate the base operating capacity of the firm, Leverage Ratios are surrogates for the financial dimension of the firm. They measure the claims on the cash flows of the firm. How the surplus will be shared and the order in which they will be shared – debt first, and the surplus, if any, goes to equity.

In the Australian context, debt sources of finance come with obligations to meet interest and principal repayments. As these payments are legally enforceable, the commitments in various stages of the business cycle represent varying percentages of a corporation's available cash flow claimed by debt. Modligliani and Miller (1958) propose that, in a world of taxes, firms should have 100% debt in their capital structure. However, in an informed and rational capital market, suppliers of funds would not lend past the capacities of the borrower to pay.

Thus, we would expect the obligation to pay in the lowest stage of the business cycle to represent the limit on the amount of debt acceptable in a company's capital structure. The nature of the legal system also interacts with capital structure considerations to

determine this obligation to pay. In countries where the legal and social attitudes to contracts do not follow the precepts of Judeo-Roman law, capital structure variables show different relationships than those of Australian, British and US economies. For example, average debt levels in Japan range between 70% and 90% of total assets. Australian debt levels and US debt levels average between 40% and 65%. McNamara et al. (1988) found debt levels in propriety companies to average 90% even though the primary source of the funds was the shareholders.

In Japan, it is rare for a listed corporation to be placed in receivership. Under the Japanese system, contracts are renegotiated if they are likely to be breached. In western systems, a breach of a lending contract often leads to corporate distress or liquidation. This is true unless, the major supplier of debt funds also controls the company, as is the case with private companies in Australia. Private companies in Australia have similar capital structures to Japanese public companies. In both cases the holders of debt security are more likely to renegotiate rather than institute bankruptcy proceeding.

All other things being equal, we would expect leverage ratios to play a major role in corporate failure for firms operating under Australian legal and business systems. This ratio we would expect to be mitigated by the stage of the business cycle. At the bottom of the business cycle, we would expect leverage ratios to be a major predictor of corporate distress.

Liquidity ratios measure the short-term demand on a firm’s cash reservoir. Fluctuations in the short-term cash inflows and the demand for cash outflows are often cited as a cause of corporate distress. The driver for short-term financial demands may be related the capital structure during times of economic downturn and high interest rates. Specifically,

high interest payments when demand for goods and services are low may lead to a cash shortage. An attempt to remedy this by reducing margins to increase cash inflows can lead to deteriorating liquidity levels.

Whether low liquidity levels cause financial distress depends on the industry and the economic power of the company concerned. For example, Coles Myer Ltd. and Woolworths Ltd. both have acid test ratios around the 0.25 to 0.35 level. However, their economic power enables them to extend their accounts payable turnover and survive what might normally be considered distressing liquidity levels.

In general however, we would expect low liquidity levels to indicate an imbalance between short-term cash inflows and short-term cash outflows. Low liquidity levels would be regarded as indicators of financial distress.

Research Methods

The data analysis comprises four stages:

(1) Principal component analysis of the economic indicators to produce a reduced set of economic factors.

(2) Principal component analysis of accounting ratios to produce a reduced set of ratios to confirm the existence of four factors driving the cash reservoir concept.

(3) Regressing the accounting ratios identified in stage one against a dichotomous variable representing distressed vs. non-distressed firms.

(4) Regressing the accounting and the economic factors identified stages one and two against a dichotomous variable representing distressed vs non-distressed firms.

The Sample

The Annual Summaries of the Australian Stock Exchange list all companies for which a liquidator had been appointed in that year. While there is significant debate over what constitutes financial distress, in the absence of any other compelling argument, the appointment of a liquidator seemed the most objective measure.

Annual financial statement information was gathered manually for the period 1985 to 2000 for companies included in the top 500 of the ASX by market capitalization that subsequently failed. Companies were excluded from the analysis if they had no records in the AGSM microfiche or if any relevant financial data was omitted from their financial statements. The most common missing data for the period 1985 to 1991 was a failure to report Sales Revenue. This information is essential in calculating the profitability of a company and its asset turnover. Failed companies were matched with non-failed companies, as near as possible, on the basis of industry membership and total assets.

A total of 92 companies, 46 failed and 46 non-failed were included in the sample.

For these companies a range of financial ratios was calculated as per Table 1.

The choice of accounting ratios was made after reviewing the literature on corporate distress. However, unlike other studies no market-based variables are included in the analysis. To understand and ultimately predict corporate distress, useful models need to lead the market not follow it.

Code	Variable names
Fail_NF	Fail (0) and Non-Fail (1) Indicator Variable
av1	ROE Before Extraoridnary and Abnormal
av2	ROE Before Extraordinary only
av3	ROE After Extraordinary and Abnormal
av4	Debt to Assets
av5	Debt to Asset before Revaluation after Intangibles
av6	Debt to Equity
av7	Long-term Debt to Total Assets
av8	Long-term Debt to Assets after Intangibles & before Revaluation
av9	Interest Expense to Total Liabilities
av10	Acid Test
av11	Current Ratio
av12	Times Interest Earned
av13	Times Interest Earned After Extraordinaries
av14	Cash Flow to Current Liabilities
av15	Return on Assets
av16	Return on Assets after Intangibles & before Revaluations
av17	Total Asset Turnover before Intangibles
av18	Total Asset Turnover after Intangibles & before Revaluations
av19	Net Profit Margin
av20	Operating Profit Margin
av21	Fixed Asset Turnover before Intangbiles
av22	Fixed Asset Turnover after Intangibles & before Revaluations
av23	Inventory Turnover
av24	Days Receivable Outstanding
av25	EBIT to Total Assets
av26	EBIT to Total Assets after Intangibles & before
av27	Revaluations Operating Income to Operating Assets
av28	Operating Income to Operating Assets before Revaluations & after Intangibles
av29	Liquid Ratio
av30	Total Debt to Total Assets after Intangibles & before Revaluations
CPI	Consumer Price Index
IR2yr	Interest Rates 2 Year
COPRFAT	Corporate Profits After Tax

Table 1 Accounting Ratios for Failure Analysis

These ratios were subject to a factor analysis to test their categorization as compared to the "cash reservoir" perspective on corporate distress/success.

The macro-economic variables

The macro economic variables chosen for this research were the Australian equivalents of the variables identified by Rose et al. (1982). They drew their measures of economic

activity according to the *Leading and Coincident Indicators*, *Supply or Cost-Push Theories*, *Monetary Economics*, and *Savings-Investment* theories. These theories provided an initial data set of 34 variables as listed in Table 2. The DX Statistical Data Base at Bond University provided macroeconomic data for the relevant periods for failed companies.

Leading and Coincident Indicators	**Supply or Cost Push Theories**	**Monetary Theories**	**Savings and Investment Theories**
Average Percapita GDP	Average Weekly Earnings	Monetary Aggregate	Capital Expenditure
Total GDP	Consumer Price Index	Money Supply M3	Dividend Yield
Income Expenditure GDP	Company Profits before tax interest and depreciation	Bank Bill Rate 90 days	Market Capitalisation
Production Expenditure GDP	Company Profits before interest and tax	Bank Bill Rate 180 days	Real Earnings
Gross National Product	Company Profits before tax	Bank Loan Rate – Large	Household Income
Commonwealth Government Deficit/Surplus	Corporate Tax Rate	Bank Loan Rate - Small	Household Savings
Labour Force		Commercial Bill Rate – 180 days	National Income
Real Gross Domestic Income		Treasury Bond Rate – 5 years	
All Industrial Share Price Index		Treasury Bond Rate – 10 years	
All Ordinaries Index		CGS	
Share market ave. daily turnover of equities			
Unemployment			

TABLE 2 MACROECONOMIC VARIABLES

These variables are subject to principal component analysis to form a more parsimonious set for further analysis.

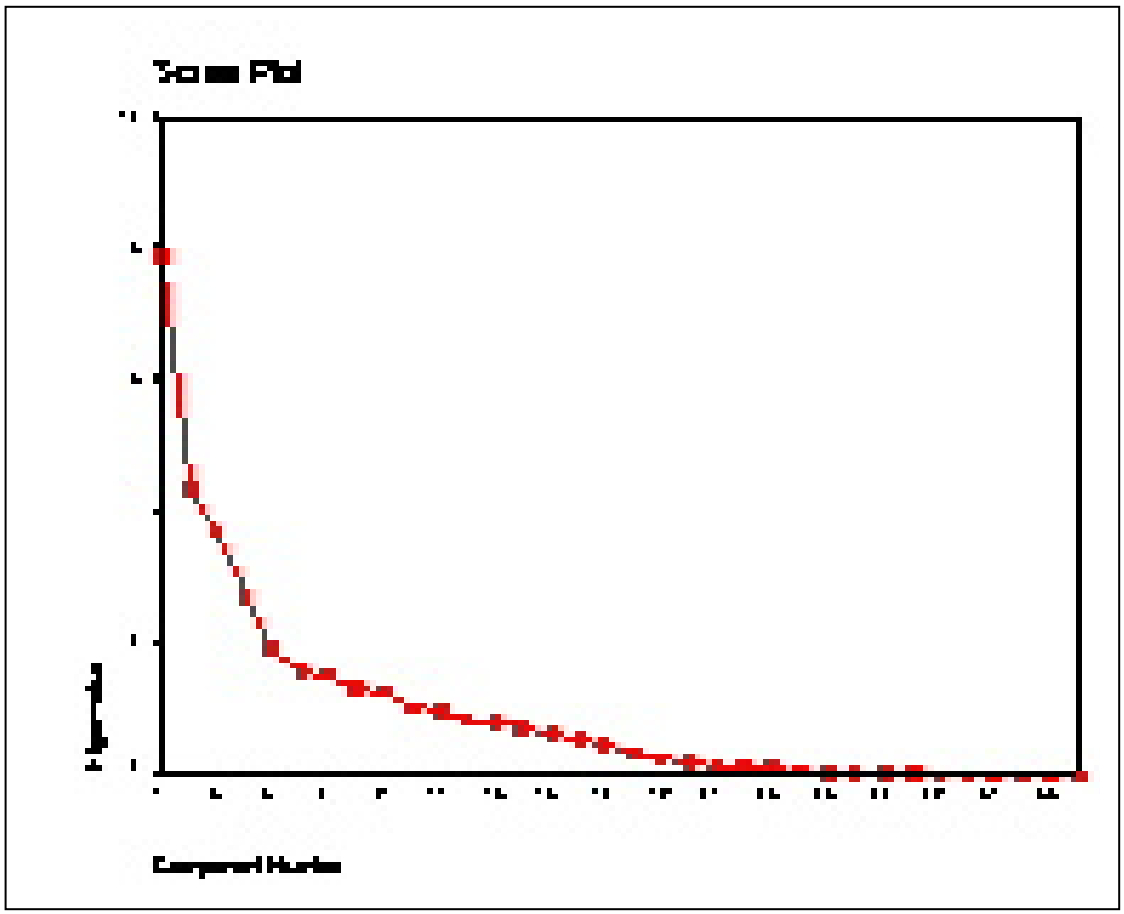
Data Analysis

An analysis of the failed companies shows a decline in share value of 86% from three years prior to failure to the suspension of trading. The fall in value from three years prior to one-year prior was only 20%. This suggests that the market had not, in general, anticipated the failure of the companies.

Stage 1: Principal Components Analysis – Macroeconomic Variables

The variables suggested by the various macroeconomic theories are undoubtedly correlated. Accordingly, the purpose of principal component stage of the analysis is to identify those variables whose variability is related to some underlying factor. The factors found in this stage of the analysis will be the result of a varimax rotation and thus their orthogonality is enhanced.

A varimax principal component analysis was applied to the macro economic variables. Three factors were extracted based on a scree test applied to the eigen values. The eigen value graph is shown in Figure 2. Based on the scree test there may be between four and six factors. The number of factors rotated can affect the structure that emerges. Francis (1974) proved that the rotation of too few factors distorts the factor pattern such that it may bear no relation to the true underlying pattern. Rummel (1970)concluded that it is preferable to rotate too many factors rather than too few.



In accord with the scree tests, four, five and six factor rotations were undertaken. The rotated factor matrix for the principal component analysis is shown in Table 2 (only loading greater than .3 are reported). Four interpretable factors emerged and were labeled as an Output Factor, Interest Factor, Market Factor, and a Corporate Activity Factor. These three factors accounted for seventy percent of the total variance. It would appear that no one macro-economic theory explains the nature of the factors that emerged from the analysis.

The purpose of the factor analysis was to reduce the macro economic variables to a parsimonious-orthogonal set. Based on the high loadings in the factor analysis stage, total GDP (TO_GDP), the 90 day Bill Rate (BB_90), the Share Price All Industrials

Index (SPI) and aggregate corporate profits before tax (CP_EBT) were used in the prediction of failure. This choice was primarily on loading and intuitive appeal.

Variable	Component				
Factor	1	2	3	4	5
AVPC_GDP	.924				
TO_GDP	.918				
GDP_INC	.903				
R_GDI	.888				
GNP	.873				
GDP_P	.738				
UN_EPLY	-.503				
CAP_EXP	.379	.345			
DIV_YLD	.355				
BB_180		.946			
BB_90		.926			
TB_5Y		.787			
BBL_SML		.781			
BBL_LRG		.771			
TB_10Y		.708			
SPI_AI			.953		
SPI_AORD			.945		
MKT_CAP			.935		
MKT_TO			.822		
R_EARN					
CP_EBITD				.934	
CP_EBIT				.928	
CP_EBT				.900	
HHLD_INC				.802	
D_BASED				.604	
LBR_FRC					
CGS_THLD					.576
AVE_ERN					
CPI_AGRP					.440
CW_DEF					.421
D_SP					
CORP_TAX					
NAT_INC					
HHL_SAV					

Table 3: Rotated Component Matrix

The alternative would be the use of a composite score for each factor based on the factor coefficients obtained from the analysis. Because of the inherent susceptibility of factor analysis to the errors in the value of the coefficients and to the variables included/excluded in the analysis, one variable was chosen to represent each factor. That

variable was one, if any, that best related to our cash-reservoir model and had a loading greater than 0.8

Stage 2: Principal Components Analysis – Accounting Variables

Principal component analysis of accounting ratios produced a reduced set of ratios to confirm the existence of five factors driving the cash reservoir concept. These are shown in Table 3.

Variable	1	2	3	4	5	
AV16	0.96754	0.05709	0.05248	0.01827	0.08444	ROA
AV27	0.96223	0.0643	0.07872	-0.06325	0.12577	
AV15	0.95874	0.10124	0.05484	0.00512	0.08743	
AV25	0.95484	0.11442	0.07043	-0.07275	0.13084	
AV12	0.36886	0.29343	0.09239	-0.17247	-0.03092	
AV17	0.11506	0.92126	-0.05328	-0.10591	0.11606	Asset Turnover
AV18	0.01081	0.91679	-0.07505	-0.06276	0.09622	
AV21	0.00818	0.87277	-0.03231	-0.14725	0.06792	
AV22	0.17045	0.72791	0.06639	0.05097	-0.09897	
AV10	0.10996	0.00486	0.93245	-0.06008	0.07959	Acid Test Rat
AV11	0.08356	-0.07247	0.93238	-0.0336	0.03857	
AV29	0.02801	0.0477	0.83428	0.0295	0.02125	
AV14	0.21361	-0.06458	0.56728	-0.06921	0.05375	
AV9	-0.09912	-0.22971	0.38541	0.12003	-0.11324	
AV8	-0.03511	-0.15406	0.00789	0.95603	-0.0791	Debt Ratio
AV7	0.0108	-0.17764	0.03582	0.94579	-0.08239	
AV4	-0.54484	0.06223	-0.26769	0.61718	-0.07638	
AV30	-0.63696	0.10467	-0.29463	0.59274	-0.06365	
AV28	0.29103	0.11405	0.02991	-0.05553	0.85276	Oper. Income to Oper. Assets
AV3	0.2861	0.11693	0.12572	-0.05101	0.83443	ROE
AV26	-0.15326	-0.04111	-0.0676	0.20873	0.34199	
AV2	-0.14366	0.14659	0.02234	0.12907	0.20599	
AV19	0.22145	0.04943	0.15954	0.06216	0.1735	
AV5	0.03799	0.03864	-0.02968	-0.06232	0.13309	
AV13	0.14881	-0.00484	-0.01065	-0.0236	0.08817	
AV20	0.18857	0.01149	-0.00762	0.10881	0.06763	
AV24	-0.06096	-0.05112	0.25134	0.04928	-0.05732	
AV6	0.04519	-0.16567	-0.15106	0.03923	-0.18804	
AV1	-0.0947	0.06528	0.00447	0.1329	-0.29286	
AV23	0.02336	-0.00917	-0.02472	0.09386	-0.57551	

Table 3: Rotated Component Matrix

As with the factor analysis of the macroeconomic variables, the scree test provided the number of factors to rotate. The factor analysis confirmed the cash reservoir framework with the four factors in Table 3 named a Profitability Factor, an Activity Factor; a Liquidity Factor, and a Leverage Factor plus an additional factor, Return on Equity. Five variables, representative of these factors were used in stage 3 and stage 4 of the analysis. These were, earning before tax to assets (ROA), asset turnover (ASSTO), acid-test ratio (ACIDRAT) and the debt ratio (DTOASS) and return on equity (ROE).

Stage 3: Accounting Ratios and Corporate Failure

Four accounting variables were regressed on a dichotomous dependent variable coded 1 for fail and 0 for nonfail. Logit analysis was used to detemine the drivers of failure. The logit function for failure prediction is shown in Table 4

Variable	**B**	**S.E.**	**Wald**	**df**	**Sig**	**R**	**Exp B**
DTO	6.7046	2.8937	5.3682	1	.0205	.1625	816.1821
ACIDRAT	2.1570	1.1947	3.2601	1	.0710	.0994	8.6455
EBT2ASS	-2.8716	.8192	12.2884	1	.0005	-.2840	.0566
ROE	.5303	.9900	.2870	1	.5922	.0000	1.6995
ASSTOo	-2.7914	.9889	7.9682	1	.0047	-2.163	.0613
Constant	-4.8394	3.2094	2.2737	1	.1316		

TABLE 4 Logit Function – Accounting Variables

The initial log likelihood function (-2LL) reflects the error associated with the model when only the intercept is included in the model. The inclusion of the accounting ratios reduces –2LL from its initial value of 127.53 to 78.981, signifying an improvement in the model. The Chi-Square of 48.558 indicates the model is significant, rejecting the null hypothesis that none of the independent variables are linearly related to the log odds of the dependent. It should be noted that this test does not assure that every independent variable is significant.

The Cox & Snell R^2 and the Nagelkerke R^2 are similar to the R^2 in OLS regression. The Nagelkerke R^2 modifies the Cox & Snell R^2 so that the measure ranges from 0 to 1. For the accounting variables only the Nagelkerke R^2 was 54.7%.

In conclusion the model is significant with reasonable explanatory power. The prediction rates for the accounting variables are shown in Table 5.

	Predicted		
Obeserved	Survive	Fail	Percent Correct
Survive	39	7	84.78%
Fail	11	35	76.09%
Overall			80.43%

TABLE 5 – Prediction Results for Accounting variables

Stage 4: Accounting Ratios, Macroeconomic Variables and Corporate Failure

A logit model was used to regress the accounting and the economic factors identified in the stages one and two against a dichotomous variable representing distressed vs non-distressed firms. Various combinations of lag factors were considered for the macro economic variables. To be of any use as explanatory variables, the macroeconomic variables must lead the failure of firms. A priori, one would expect a two year lag in interest rates, and a one year lag in the other economic variables.

This analysis resulted in only two accounting variables being significant and three macroeconomic variables being significant. This combined model had significantly better explanatory power then the model using accounting variables only as shown by the Nagelkerke R^2 of 71.4%. The –2LL is further reduced by this model to 56.987.

The Chi-Square for the model is 70.552 which indicate that the model is significant. Homer and Lemeshow's Goodness of Fit Index is an alternative measure of the model's significance. This model has a Goodness of Fit Index of 465.676 compared with a value of 81.943 for the accounting variables model, providing further support for the inclusion for macro-economic variables.

The logit model is shown in Table 6. All variables except the debt ratio (DTOASS) are significant at the .05 level. The debt ratio is significant at the .10 level. The constant is not significant.

Variable	B	S.E.	Wald	df	Sig	R	Exp B
DTOASS	4.0458	2.3703	2.9135	1	.0878	.0846	57.1597
ASSTO	-6.3957	1.8956	11.3836	1	.0007	-.2712	.0017
LAG2BB90	.66672	.2116	9.9422	1	.0016	.2495	1.9488
LAGGDP	55.9047	20.0081	7.8070	1	.0052	.2134	1.90E24
LAGCPEBT	-16.9547	5.5600	9.2990	1	.0023	-.2392	.0000
Constant	-3.0974	2.7461	1.2721	1	.2594		

TABLE 6: Logit Function – Combined Model

This model has significantly improved explanatory power as shown in Table 7. The results of the analysis were cross validate by holding out each case and testing the predictive ability of the model. There is insufficient data on failed public companies to establish a reliable test using a holdout sample. Test on two companies that are not included in the data set, Brashs Ltd. and Burns Phillip confirmed the predictive ability of the model one year prior to their failure.

	Predicted		
Observed	Survive	Fail	Percent Correct
Survive	42	4	91.30%
Fail	5	41	90.22%

Overall			80.43%

TABLE 7 – Prediction Results for Combined Model

Conclusions

The purpose of this study was to determine if economic variables provide any additional explanation of financial distress for a firm compared with accounting variables. The results, though preliminary, are promising. Three economic variables, interest rates lagged two years, gross domestic product lagged one year, and changes in corporate profits before tax have a significant influence on firm survival. The three economic variables have some intuitive appeal. That fact that some economic research suggests a two lag between changes in interest rates and their translation into the cost structures of businesses makes the two year failure effect appealing.

When economic variables are included in an explanatory model, only asset turnover, the ability to generate sales from assets, has explanatory power.

Without economic variables in consideration four accounting variables, that are surrogates for increasing/decreasing a firm's cash reservoir, have explanatory power. The failure of all the accounting variables to remain in the explanatory model suggests that the macroeconomic environment plays a central role in determine corporate survival.

To the extent that macro-economic variables are influenced by government policy this research shows the connection between that policy and firm survival.

There are several limitations to the generalizations possible from this research. First, is the common criticism that using a matched pairs design distorts the proportion of failures in the sample relative to the total population? Because of the relatively small number of

failed firms for which data exists, the methodological gains from using a matched design outweigh the restrictions in generalizability. The failure to use a holdout sample to test the predictive accuracy of the logit model seriously limits the models use as a predictive tool.

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