

Financial Ratios, Discriminant Analysis and the Prediction of Corporate Distress

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Abstract

This study develops a failure prediction model for Singaporean companies. The results show good performance with a highly correct categorization factuality rate of more than 80 percent. Two ratios were determined significant out of 64 financial ratios utilized in this analysis to discriminate among failed and non-failed companies. The significant variables are Cash flow to Sales (V02) and Days Sales in Receivable (V31).

Keywords: Prediction Model, Discriminant Analysis, Ratio, Cash Flow, Sales

Identification of Distress Firm Characteristics: The Singaporean Case

Introduction

Corporate failures are a common problem of developing and developed economies (Altman et al., 1979). It is commonly described as being when an associate of the firm comes up with a resolution that the firm be wound up and assign a liquidator or the associate of the firm can satisfy a meeting of its creditors to deliberate its proposal for a voluntary winding up of the firm. Corporations are not invulnerable to failure, where commonly the firm is not able to meet its liabilities. In the late 1990s, the economic recession invaded all Asian countries including Singapore, which illustrated the need to develop an early alert method to reduce the circumstance of corporate failure among Singaporean firms.

Table 1 provide the statistics of Singaporean firm's liquidation. The number of companies winding up escalated since year 1985 to 1999 (for 15 years). Most firms illustrated in table 1 are small-scale firms that not listed on the Singapore Stock Exchange. It is difficult to find the failed firms as described above among Singaporean listed firms.

Table 1: Statistics of Singaporean Companies Liquidation

Year	Petitions Filed	Wound-up	Wound-up % over Petitions
1985	688	393	57.1
1986	858	485	56.5
1987	637	449	70.5
1988	503	364	72.4
1989	385	229	59.5
1990	273	161	59
1991	279	174	62.4
1992	318	200	62.9
1993	329	204	62
1994	314	245	78
1995	309	188	60.8
1996	305	222	72.8
1997	340	227	66.8
1998	435	295	68
1999	469	368	78.5

Source: Insolvency & Public Trustee's Office, Ministry Of Law, Singapore. (Singapore's Ministry of Law web site, dated 17.10.2000)

Failure is not an impulsive outcome and it grows constantly in stages. There are unique characteristics of failure in firm's financial levels prior achieving total failures. An impulsive protective effort could be accommodated if the company is foreseen to be proceeding in the direction of potential bankruptcy and this can help allay the financial distress to all investors and abate the costs of bankruptcy. It is clear that notwithstanding the tremendous amount of research that has gone into this topic around the world, the predicament of prediction can by no means be absolutely interpreted. This is because prediction is not an actual science and at best, purely a calculated estimate.

Also, the meaningful variable in determining firm's stability and viability varies from territory to territory as documented in prior researches. In developed economies, most of the users utilized results from the research done in developed economies without making the certain accommodation to regional situations, which will result in misapplication. It is believed that result for Singapore has its particular set of financial ratios in determining company's stability.

In Asian countries, access to literature on this topic is largely unavailable. Business collapses in Asian countries should be deliberately investigated adequate to the increasing expansion of economies that can endanger business performance to meet the treats imposed during economic downturn and this will minimize diminishing credibility of investors and creditors. The objective of this study is to recognize the indicative financial ratios which discriminant between failed and non-failed firms. This study hopes to accommodate some important results relevant to authorities and stakeholders. The capability to detect potential financial problems at a premature stage is absolutely essential because it helps to ensure business, financial, economic and political environment stability.

Literature Review

The earliest study using multivariate data analysis on failure prediction was conducted by Altman (1968) using a set of financial and economic ratios as possible determinants of corporate failures. The study used sixty-six corporations from manufacturing industries comprising of bankrupt and non-bankrupt firms and 22 ratios from five categories, namely, liquidity, profitability, leverage, solvency and activity. Five ratios were finally selected for their performance in the prediction of corporate bankruptcy and the derived model correctly classified 95 percent of the total sample (correctly classifying 94 percent as bankrupt firms and 97 percent as non-bankrupt firms) one-year prior to bankruptcy. The percentage of the accuracy declined with increasing number of years before bankruptcy.

Rushinek and Rushinek (1987) tested data of 30 companies, of which a regional bank believed 13 were bankrupt. The variables utilized were three ratios that the bank believes most essential in making loan decisions, plus four additional ratios preferred by the writer. The variables utilized were net income to sales, EBIT to interest (time interest earned), and Total liabilities/total tangible net worth. They establish that the model precisely categorized 80 percent of the data. This research suffered from constrained sample size and constrained number of ratios included in the model elaboration. However, the researchers recommended the model as only another device to assist bank loan investigation review the perspective of current or future borrowers.

Altman et al. (1994) reported the use of neural network in identification of distressed business by the Italian central bank. Using over 1,000 sampled firms with 10 financial ratios as independent variables, they found that the classification of neural networks was very close to that achieved by discriminant analysis. They concluded that the neural network is not a clearly dominant mathematical technique compared to traditional statistical techniques.

Begley et al. (1995) incorporated the time “bias” factor into the classic business failure prediction model. Using Altman (1968) and Ohlson’s (1980) models to a matched sample of failed and non-failed firms from 1980’s, they found that the predictive accuracy of Altman’s model declined when applied against the 1980’s data. The findings explained the importance of incorporating the time factor in the traditional failure prediction models.

Campbell (1996) constructed a multivariate prediction model that estimates the probability of bankruptcy reorganisation for closely held firms. Six variables were used in developing the hypotheses and five were significant in distinguishing closely held firms that reorganise from those that liquidate. The five factors were firm size, asset profitability, the number of secured creditors, the presence of free assets, and the number of under-secured secured creditors. The prediction model correctly classified 78.5% of the sampled firms. This model is used as a decision aid when forming an expert opinion regarding a debtor’s likelihood of rehabilitation.

Mossman et al. (1998) conducted a study to compare four types of bankruptcy prediction models that are based on financial statement ratios, cash flows, stock returns’, and returns standard deviations. They tested four bankruptcy models: Altman’s (1968) Z-score model based on financial ratios; Aziz et al.’s (1988) model comprised of cash flows; Clark and Weinstein’s (1983) market return model, and Aharony et al.’s (1980) market return variation model. They found that in the year prior to bankruptcy, the ratio model is the most effective in explaining the likelihood of bankruptcy. In the three years preceding bankruptcy, the cash flow model most consistently discriminates between bankrupt and on-bankrupt firms. The findings suggest different uses for the models, as stakeholders might be particularly interested in cash flow variables as an “early warning” indicators of failure. Alternatively, a large negative shift in accounting ratio variables could be a useful indicator of imminent financial collapse.

Methodology

The data utilized in this analysis is extracted from the income statements, balance sheets, and cash flow statements of sampled firms attained from the Companies Annual Report accessible from the Singapore Stock Exchange.

The matched sample design method was applied in this analysis. Each failed company has a non-failed “partner” in the sample. Paired samples of failed and non-failed companies from year of 1990 to 2000 were utilized in this analysis. The definitions of “failure” are:

- i. The firms that approved to undertake a restructuring scheme to revive their financial conditions by the Singaporean authorities
- ii. The firms that were put under receivership.
- iii. The companies had been incurring losses for three years continuously or more.
- iv. The companies had illustrated negative position in cash flow for three years continuously or more.

However, it is difficult to find firms that fall under the first two conditions above. Therefore, our approach is to identify the firms that have the last two definition above in the period observed.

The used of a matched sample of failed and non-failed firms (one-to-one match) might introduce a potential firm failure bias (Palepu, 1986). It is claimed that the potential for failure is overstated using this technique. However, it is stressed that the bias may or may not be important depending on the usage of the model. If the model is used to rank the firms for the potential failure in order to perform a more detailed analysis, then the bias is not important. However, if the model is used to identify investment portfolio selection, then the bias is significant. Furthermore, Zmijewski (1984) reviewed 17 financial distressed studies that used this controversial method found that although a choice based sample bias was present, the results do not indicate significant changes in overall classification and classification rates. Finally, Platt & Platt (1990, 1991) urged that one-to-one sampling technique is still an acceptable method in failure prediction studies.

A total of 17 failed companies were identified during the year of determination. Table 2, below, disclosed the name of failed firms. The failed companies were paired to the non-failed companies using the following criteria:

- i. same industry
- ii. same failure year
- iii. closest asset size
- iv. same age since incorporation

Table 2: List of Sample Failed Companies.

No.	Company Name
1	Alliance Technology & Dev. Ltd
2	Asiamedic Ltd
3	Easycall International Ltd
4	Eltech Electronics Ltd
5	Falmac Ltd
6	Heshe Holdings Ltd
7	Ho Wah Genting International Ltd
8	Inno Pacific Holdings Ltd
9	Ipcos International Ltd
10	Network Foods International Ltd
11	Pakara Technology Ltd
12	Pokka Corporation, Singapore Ltd
13	Seatown Corporation Ltd
14	SPP Ltd
15	Transmarco Ltd
16	Transpac Industrial Holdings Ltd
17	Tri M Technologies. S Ltd

The sample firms used in this study came from 8 different industries: 2 firms from the investment holding sector, 3 firms from the electronics & information technology, 4 firms from the Sesdaq - manufacturing sector, 4 firms from the food and beverages sector and 1 each firm from the properties, construction, engineering and retailing sectors. Due to the restrained sample volume for each industry, the research focuses on the blended industry sector.

The dependent variable is defined as the dichotomous event named as a failing or non-failing event. The independent variable is interpreted as the commonly used financial ratios. The ratios used are chosen from those utilized by Beaver (1966), Altman (1968) and Ou and Penmen (1989). An itemized listing of the variables is accessible in table 3.

Table 3: List of Ratios Examined

Code	Ratio Name	Code	Ratio Name
V01	Cash flow to Sales	V34	Sales Growth
V02	Cash flow to Assets	V35	Depreciation Growth
V03	Cash flow to Net Worth	V36	Dividend Growth
V04	Cash flow to Total Debt	V37	Return on Opening Equity (ROOE)
V05	Return on Sales (ROS)	V38	Percentage Change in ROOE
V06	Percentage Change in ROS	V39	Equity to Debt
V07	Return on Assets	V40	Percentage Change in Equity to Debt
V08	Return on Equity	V41	Equity to Long Term Debt
V09	Net Income to Total Debt	V42	Percentage Change in Equity to Long Term Debt
V10	Current Liabilities to Total Assets	V43	Equity to Fixed Assets
V11	Long Term Liabilities To Total Assets	V44	Percentage Change in Equity to Fixed Assets
V12	Total Liabilities To Total Assets	V45	Times Interest Earned
V13	Cash To Total Assets	V46	Percentage Change in Times Interest Earned
V14	Quick Assets To Total Assets	V47	Profit Before Depreciation to Sales
V15	Current Assets To Total Assets	V48	Percentage Change in Profit Before Depreciation to Sales
V16	Working Capital To Total Assets	V49	Pretax Income to Sales
V17	Cash to Current Liabilities	V50	Percentage Change in Pretax Income to Sales
V18	Quick Ratio	V51	Sales To Inventory
V19	Percentage Change in Quick Ratio	V52	Percentage Change in Sales to Inventory
V20	Current Ratio	V53	Sales to Fixed Assets
V21	Percentage Change in Current Ratio	V54	Percentage Change in Total Assets
V22	Cash Turnover	V55	Percentage Change in Working Capital to Total Assets
V23	Receivable Turnover	V56	Operating Income to Assets
V24	Quick Asset Turnover	V57	Percentage Change in Operating Income to Asset
V25	Current Asset Turnover	V58	Percentage Change in Long Term Debt
V26	Working Capital Turnover	V59	Dividends to Cash Flows
V27	Percentage Change in Sales to Working Capital	V60	Net Income to Cash Flow
V28	Net Worth to Sales	V61	Operating Profit to Sales
V29	Asset Turnover	V62	Return on Owners Equity
V30	Percentage Change in Sales to Total Assets	V63	Total Assets to Net Worth
V31	Days Sales in Receivable	V64	Earning Power
V32	Inventory To Total Assets		
V33	Inventory Growth		

Normality Tests

Before the discriminant analysis, normality test was carried out to all independent variables. Two generally utilized tests are the Shapiro-Wilks' test and Lillifors test. The Lillifors test based on alteration of the Kolgomorov-Smirnov test is utilized when means and variances are not known but must be approximated from the data (Norusis, 1993). The Shapiro-Wilks test shows better tools in many statistical conditions correlated to other tests of normality (Iman and Conover, 1980). Anyhow, the Shapiro-Wilks' test is well suited to small-size samples.

The null hypothesis will be rejected for large values of Kolgomorov Smirnov D statistics. According to Norusis (1993), "it is almost impossible to find data that are exactly normally distributed", he advised that for most statistic tests, it is adequate that the data are approximately normally distributed.

Table 4: Normality Tests - Raw Data

Variable	Details	Shape		Normality Test	
		Skewness	Kurtosis	Statistic	Sig.
V01	Cash flow to Sales	-9.176	109.817	0.24	0
V02	Cash flow to Assets	-2.04	6.612	0.147	0
V03	Cash flow to Net Worth	2.758	39.53	0.207	0
V04	Cash flow to Total Debt	-9.599	105.709	0.107	0
V05	Return on Sales	-9.284	112.187	0.242	0
V06	% Change in ROS	8.027	73.613	0.385	0
V07	Return on Assets	-2.376	7.363	0.202	0
V08	Return on Equity	-0.66	16.96	0.234	0
V09	Net Income to Total Debt	-9.522	104.453	0.198	0
V10	Current Liability Percent	0.743	0.389	0.123	0
V11	Long Term Liabilities %	0.438	-0.592	0.083	0.004
V12	Total Liabilities Percent	0.031	-0.208	0.061	0.098
V13	Cash Percent	1.264	1.269	0.14	0
V14	Quick Assets Percent	0.355	-0.168	0.059	0.2
V15	Current Assets Percent	0.173	-0.156	0.043	0.2
V16	Working Capital Percent	0.685	0.829	0.057	0.2
V17	Cash to C. Liabilities	11.285	141.972	0.216	0
V18	Quick Ratio	11.329	143.067	0.149	0
V19	% Change in Quick Ratio	9.598	95.348	0.249	0
V20	Current Ratio	9.482	92.224	0.16	0
V21	% Change in Current Ratio	2.934	12.666	0.173	0
V22	Cash Turnover	3.386	12.931	0.284	0
V23	Receivable Turnover	7.964	67.045	0.533	0
V24	Quick Assets Turnover	3.419	15.727	0.18	0
V25	Current Assets Turnover	2.346	11.173	0.146	0
V26	Working Capital Turnover	8.898	101.991	0.308	0
V27	% Change in Sales to WC	13.355	185.524	0.386	0
V28	Net Worth to Sales	5.119	25.818	0.388	0
V29	Assets Turnover	3.057	15.553	0.137	0
V30	% Chg Sales to Assets	9.647	113.491	0.172	0
V31	Days Sales in Receivable	1.44	4.497	0.099	0
V32	Inventory Percent	2.738	9.51	0.166	0
V33	Inventory Growth	4.931	29.564	0.296	0
V34	Sales Growth	11.133	140.824	0.149	0
V35	Depreciation Growth	4.117	28.248	0.17	0
V37	Return on Operating Equity	-4.134	32.781	0.178	0
V38	% Change in ROOE	6.823	54.125	0.375	0
V39	Equity to Debt	-4.309	20.374	0.248	0
V40	% Change Equity to Debt	-0.261	25.251	0.229	0
V43	Equity to Fixed Assets	3.029	10.641	0.21	0
V44	% Chg Equity to F. Assets	9.739	123.301	0.298	0
V45	Times Interest Earned	-14.014	196.919	0.472	0
V46	% Chg in T. Interest Earned	-13.58	188.462	0.472	0
V47	Profit before Depreciation to Sales	-9.176	109.817	0.24	0
V48	% Chg in Pr Dep. To Sales	10.255	114.829	0.386	0
V49	Pretax Income to Sales	-9.085	108.573	0.245	0
V50	% Chg in Pretax Inc. to Sales	-1.524	86.126	0.423	0
V51	Sales to Inventory	12.238	161.319	0.349	0
V52	% Chg in Sales/Inventory	6.001	40.786	0.331	0
V53	Sales to Fixed Assets	3.367	14.692	0.188	0
V54	% Chg in Total Assets	1.647	6.928	0.12	0
V55	% Chg in WC Percent	-3.999	72.216	0.354	0
V56	Operating Income to Assets	-2.169	6.725	0.167	0
V57	% Chg in Operating Inc. to Assets	-2.08	59.1	0.428	0
V59	Dividends to Cash Flow	-1.62	51.207	0.358	0

V60	Net Income to Cash Flow	-13.015	179.321	0.405	0
V61	Operating Profit	-9.168	109.916	0.258	0
V62	Return on Owners Equity	7.104	109.191	0.39	0
V63	Total Assets to Net Worth	1.393	20.187	0.236	0
V64	Earning Power	-2.229	9.185	0.202	0

Table 4 above, disclosed the Kolgomorov Smirnov tests (altered for Lillifors). Only three variables (V14, V15 and V16) are normal and two variables (V11 and V12) are almost normal out of sixty-four variables were tested. The other variables significantly exit from normality assumptions with excessive skewness statistics and peaked distribution. Accordingly, we exclude the hypothesis null that all of the financial ratios examined are normally distributed.

In order to enhance the normality, data transformation processes were implemented. There are several approaches to data transformation methods supported in the literature, such as natural Log, Square Root, Square and Inverse. Natural logs and square roots suffer in that they cannot be employed if the ratios are negative (Ezammel et al., 1987). Another option that can be utilized to eliminate this complication such as adding or subtracting a constant or engaging squares of ratio or inverse of the ratio. Ezammel et al. suggested that such techniques tend to emphasize the distortion by extreme values giving correlatively more weight to large observations. In this analysis, four accepted transformation approaches are discussed, natural log, square root, square, and inverse transformation were utilized.

Before data transformations were implemented, variable number V14, V15, and V16 are normal and, V11 and V 12 are almost normal. The Kolgomorov-Smirnov statistic (KS) and the significance level was enhanced after elimination of extreme values.

Under the square transformation technique, there is no variable that is normally distributed but variable number V15 is near normally distributed before transformation, the number increased to two under nearly normal distribution when the extreme values were eliminated. The new variable is V12. Under square root transformation, Three variables found normal (V14, V31 and V32) and eight variables found almost normal (V10, V12 V13, V15, V18, V20, V25 and V29) before elimination of extreme values. The number decreased to two in normal (V31 and V32), increased to nine in almost normal (V10, V12, V13 V14, V15, V18, V20, V25 and V29) when the extreme values were eliminated.

Under the natural log transformation, it is found that six variables were normal and three were nearly normal before elimination of extreme values and the number increased to eight (variables number V18 and V 25 are the new variables) in normal distribution and the number decreased to two (V18 was deleted) in near normal distribution. Finally, under inverse transformation, It is found that one variable was normal and nearly normal before elimination of extreme values and the number decreased to zero in normal distribution and the number increased to one (V63 was is the new variable) in near normal distribution

Table 5: Statistic of Normal Variable Under Normality Tests (Untrimmed Vs Trimmed Extreme Values)

Panel A: Raw Data				
	Rdut		Rdt	
	Stat	Sig	Stat	Sig
V02	-	-	0.093	0.001
V11	0.123	0.004	0.084	0.005
V12	0.061	0.098	0.068	0.058
V14	0.059	0.200	0.066	0.068
V15	0.043	0.200	0.056	0.200
V16	0.057	0.200	0.047	0.200
V29	-	-	0.082	0.007
V30	-	-	0.093	0.001
V31	-	-	0.088	0.003
Panel B: Square				
	Sqreut		Sqreut	
	Stat	Sig	Stat	Sig
V12	-	-	0.089	0.002
V15	0.073	0.018	0.071	0.039
Panel C: Square Root				
	Sqrtut		Sqrtt	
	Stat	Sig	Stat	Sig
V10	0.088	0.001	0.095	0.001
V12	0.084	0.002	0.095	0.001
V13	0.075	0.011	0.069	0.038
V14	0.056	0.200	0.063	0.083
V15	0.071	0.021	0.080	0.008
V18	0.089	0.001	0.093	0.001
V20	0.089	0.001	0.090	0.001
V25	0.086	0.002	0.071	0.029
V29	0.086	0.001	0.070	0.036
V31	0.056	0.200	0.058	0.200
V32	0.051	0.200	0.054	0.200
Panel D: Inverse				
	Invut		Inv	
	Stat	Sig	Stat	Sig
V23	0.094	0.001	0.079	0.014
V63	0.058	0.200	0.067	0.067
Panel E: Natural Log				
	Logut		Logt	
	Stat	Sig	Stat	Sig
V10	0.060	0.200	0.053	0.200
V13	0.086	0.002	0.091	0.001
V17	0.049	0.200	0.058	0.200
V18	0.076	0.012	0.051	0.200
V20	0.058	0.200	0.057	0.200
V22	0.038	0.200	0.041	0.200
V24	0.049	0.200	0.049	0.200
V25	-	-	0.056	0.200
V29	0.081	0.005	0.087	0.003
V53	0.047	0.200	0.050	0.200

Note: Shaded Rows are the Variable Normally Distributed

Annotations:

Rdut: Raw data untrimmed

Rdt: Raw data trimmed

Sqreut: Square untrimmed

Sqret: Square trimmed

Sqrt_{ut}: Square root untrimmed
Sqrt_t: Square root trimmed
Log_{ut}: Log untrimmed
Log_t: Log trimmed
Inv_{ut}: Inverse untrimmed
Inv_t: Inverse trimmed

It is proven that elimination of extreme values enhances the normality degree of variables. Natural log transformation more performed compares to other types of transformation; the square transformation are the worst where no variables were determined normal under this alternative. This condition established the reason developed by Ezammel et al. that the approach would give more weight to large observations.

The natural log transformation is responsive to elimination of extreme values that documented the enhanced number in variables. Also there is an enhancement in KS statistics and significance level.

Findings

Utilizing samples of failed and non-failed companies as the categorization variables and the ratios as the independent variables, a forward stepwise multivariate discriminant analysis was used to determine the discriminating power of the variables. In stepwise estimation, independent variables were entered into the discriminant function one at a time on the basis of their discriminating power. This method starts by selecting the single outstanding discriminating variable. The first variables are then matched with each of the other independent variables one at a time, and the variables that are outstandingly able to enhance the discriminating power of the function in coalition with the first variable are selected. The third and any following variables are selected in the same method.

The normal variables were entered into the discriminant analysis. Five groups of potential variables were examined¹. The Mahalanobis D² method was utilized in this process. Mahalanobis D² was used to select the variable that develops the highest separation for the pair of groups, which are precise at a particular step. This process starts with all of the variables excluded from the model and chooses the variable that's topmost in the Mahalanobis distance between the groups. As an additional means of interpreting the relative discriminating power of the independent variables, F test was utilized.

The prediction model was generated, as illustrated below:

$$Z = 0.873 + 8.951X_1 - 0.138X_2$$

Where, Z = Overall Index

X₁ = Cash flow to Assets (V02)

X₂ = Square root Days Sales in Receivable (V31)

The outcomes show that the failed group centroid (Dependent variable (DV) = 0) is -0.792 and the non-failed group (DV = 1) centroid is 0.775. Z scores measure these centroids. The overall mean or called cutting score is equally to zero².

¹ The correlation analysis were implemented on variables that were normal under the normality tests (constraint to variables that do not have feasibility to be a negative value). Variables probably have negative value, for example, profit and cash flow ratio were eliminated from this analysis due to complication in transforming them utilizing natural log and square root. Also, a number of variables that are statistically normal but with low significance level were incorporated. Our method is to elaborate a number of independent variable groups, which absolutely incorporate the highly correlated variables and analyze them to obtain the power of discrimination among, failed and non-failed groups instead of deleting it. Therefore, a variable selected and associated variable that are highly correlated with it will not incorporate in a similar group and will create other groups for following analysis. The optimum group with elevated achieves ratio will be selected as the final independent variables.

² The overall mean was calculated as follow; $Z = (N_0Z_0 + N_1Z_1) / (N_0 + N_1)$; where Z is a critical cutting score, N₀ are the number of observations in non-failed group, Z₀ is the centroid for non-failed group, N₁ are the number of observations in failed group and Z₁ is centroid for failed group.

Table 6 lists down the statistics indicated, captioned together with the significant variables, which were examined by the stepwise process, and two variables were determined to be significant.

Table 6: Summary of Interpretative Measures

Variables	Standard Weight Value	Discriminant Loading		Univariate F Ratio	
		Value	Rank	Value	Rank
V02	0.951	0.935	1	101.909	1
V12	NI	-0.064	5	NI	NI
V14	NI	0.120	3	NI	NI
V16	NI	0.042	4	NI	NI
V18	NI	-0.020	7	NI	NI
V31	-0.355	-0.312	2	57.968	2
V33	NI	0.067	4	NI	NI

Note: NI = Not Included

Utilizing the stepwise process, the significant variable has been recognized and this process eliminates the non-significant variables from entering the function. According the analysis carried out, variables V02, V12, V14, V16, V18, V31 and V33, the discriminant loadings and univariate F values, the ranking of discriminating power of variables are recognized. In two variables function, V02 discriminates the most with the topmost discriminant loading and F statistics, and V18 discriminates the least.

Validation of the Discriminant Outcomes

This section elaborate on the validity of the discriminant function. For that reason, we are required to elaborate validation matrices for both the analysis sample and the cross-validated validation. In the earlier section, we have determined the cutting score, which is equal to zero. The process is as follows:

- (1). Categorize a company as failed companies if its discriminant score is positive value
- (2). Categorize a company as non-failed company if its discriminant score is negative value.

Utilizing this precedent, the SPSS generated validation matrices for the observations in the examine sample. The validation outcome of the analysis sample is illustrated in table 7.

Table 7: Validation Outcomes.

		Predicted Group Membership		Total	
		DV	0	1	
Original	Count	0	72	22	94
		1	12	84	96
	%	0	76.6	23.4	100
		1	12.5	87.5	100
Cross-validated	Count	0	71	23	94
		1	12	84	96
	%	0	75.5	24.5	100
		1	12.5	87.5	100

It is determined that the model factuality is up to 82.1 percent (average of correct categorization of DV=0 at 76.6 percent and DV=1 at 87.5 percent). In the cross-validated approach, the categorization factuality was determined at 81.6 percent (average of correct categorization of DV=0 at 75.5 percent and DV=1 at 87.5 percent). This outcome indicates that the model is valid for application.

Conclusion

The outcome shows good performance with a highly correct categorization factuality rate of more than 80 percent. The outcomes (V02 and V31) are very significant variables to identifying distress of the Singaporean firms.

Two ratios were determined significant out of 64 financial ratios utilized in this analysis to discriminate among failed and non-failed companies. The significant variables stated below are in accord with their discriminating power or position in condescending series:

- (1). Cash flow to Sales (V02)
- (2). Days Sales in Receivable (V31)

The significant variables captioned could assist the users of the results to generate a similar framework of advanced indicator mode to either avoid or mitigate impending difficulty.

The following are the possible entities to utilize the characteristic failure and non- failure result:

- (1). Malaysian Business Counterpart/Supplier/Customer Neighboring Country
The results can be utilized as an apparatus in determining future borrowers or credit applicants. The result can determine the risk postulate to that future customer. Additionally, this result can be utilized as a yearly appraisal of customer's financial situation in making decisions to renew or continue the loan provided.
- (2). Investors/Stakeholders
In recognizing suitable portfolio of investment, investor can utilize the results to reach a certain conclusion. The result can contribute in advance an indication of the financial situation to aid the investor's selection of companies.

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