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George Mfune
School of Graduate Studies, Copperbelt University

Dr. Sichinsambwe
Department of Operations and Supply Chain Management, School of Business, Copperbelt University

Humphrey Fandamu
Department of Economics, School of Business, University of Copperbelt

Predicting corporate failure in Zambia: A case of manufacturing firms

George Mfune, Dr. Sichinsambwe, Humphrey Fandamu

Abstract
The major objective this paper was to predict corporate failure of twelve manufacturing firms in Zambia using data from 2000 to 2005. The logistic model developed, used six financial ratios for predicting corporate failure. Out of the six ratios, asset utilization and profitability ratios were found to have significant strongest effect on corporate failure in Zambia. Analysis showed that those firms which managed their assets well and had good profitability ratio had higher probability of not failing while those firms with poor asset management had higher chances of failing. And likewise, less profitable firms were more likely to fail than profitable ones. In terms of prediction the model correctly classified 86.67% of non-failed firms and 73.33% for the failed firms.

Keywords: corporate failure, logistics regression, failed and non-failed firms

1. Introduction

In recent years the Zambian economy has witnessed the collapse of many companies ranging from bank and non-bank institutions. For example, in 1990s the Zambian economy recorded corporate failure of mining companies which included RAMCOZ, ZMCO, ZCCM etc. There are also a number of manufacturing companies in Zambia which failed in 1990s and 2000s namely Kafue Textiles, Copperbelt Steel Manufacturing, Lusaka Engineering (LENCO) and Mulungushi Textiles, among others (Enestelle N. Zimba: 2004) [8].

It should be mentioned here that the likely causes of corporate failure in Zambia for a number of firms that failed have not been empirically ascertained due to lack of research in this area. However, scholars around the world sight insufficient working capital, mismanagement or management errors, excessive debt, falling profit or losses for several years of succession as likely or potential causes of corporate failure in a number of multinational corporations around the world (Fook *et al*., 2012) [9].Whether, these factors can predict corporate failure in a number of failed companies in Zambia; is an empirical question.

The fact that a number of firms failed in Zambia in the past decades could be indicative of failure on the part of managers, creditors and investors to predict corporate failure. The major objective of this study therefore, is to predict corporate or company failure in Zambia in the manufacturing firms. In doing so, the researchers intend to develop the failure prediction model using logistic regression which incorporates a number of financial or and accounting ratios so as to classify rates of failed and non-failed firms in Zambia. As mentioned earlier the study will only focus on manufacturing firms in Zambia where corporate failure has been rampant. It is worth mentioning that this model (logistic regression) has been used by (Foop *et al*., 2012) [9] to evaluate corporate failure in the Malaysian economy and has exhibited higher degree of accuracy in predicting failure among various models of corporate predictions. Therefore, the current study will develop the same model and adapt it to the Zambia economy and thereby use it to predict corporate failure in Zambia.

An empirical assessment of corporate failure in Zambia is very important taking into account of recent events in the Zambian economy. For instance the Engineers institute of Zambia (EIZ) announced deregistration of about 10 companies due to failure to comply with regulations (www.znbc.co.zm). In addition, PACRA too, announced to deregister over 500 companies due to failure to submit annual returns (www.pacra.org). Although some of these companies are not big in nature, this could signal corporate failure in a number of firms in Zambia and a need to address issues relating to corporate failure.

Correspondence
George Mfune
School of Graduate Studies, Copperbelt University

The need to do this study comes from the understanding that company collapses have a lot of devastating multiplier effects on a number of different economic agents. Stakeholders such as creditors, investors, employees, clients and suppliers can be negatively impacted on by corporate failure. For instance when a huge firm collapses, a lot of employees lose jobs and this failure negatively impact on livelihood of the employees thereby leading to misery and poverty. In addition, shareholders and creditors may suffer economic losses because they are the last to be paid in the case where the company is winding up. Besides, corporate failure may have contagion effects on other firms especially those firms that are complementary to the firm in question. For example when a mining firm fails, it means all firms that supply products to the mining firm and those companies that are hired to service mining machinery go under. Thus the economic effects of failure of a single firm may have many unforeseen ramifications than imagined. To add, if there has been rampant corporate failure in the face of well spelt out accounting standards, it could mean that firms do not reveal adequate and truthful information regarding the financial health of their company. This too implies that accounting standards, legal requirements and other regulatory requirements imposed on these firms to avoid corporate failure may not be sufficient and as such it is apparent that any extra improved apparatus or model for detecting symptoms of financial distress of firms would be of great help. Therefore, if the current study can develop a corporate failure prediction model adaptable to the Zambian context; managers of companies, investors and creditors could benefit and such a model could be used to prevent corporate failure or could be used by stake holders to pick signals of corporate failure and thus preventive and corrective measures can be taken to avert company failure.

2. Literature

Research done so far regarding corporate failure shows that various authors have different interpretations of corporate failure, and therefore, no universal definition of corporate faliure exist (Pretorious, 2009) [12]. Since many researchers have failed to propose a definition to guide their research but depend on the general understanding about the phenomenon; many definitions with varying viewpoints have been found (Shepherd, 2005) [14]. Shepherd (2005) [14] also says that the lack of a single definition of failure could partly be responsible for the poor understanding of the phenomenon.

According to Valley (2008) [17] corporate failure is caused by the inefficient risk assessment and management of the organization. Valley (2008) [17] cites inadequate financial planning and budget control, fraud, quality problems, change of customer tastes as some of the prominent issues that have direct positive relationship with corporate failure.

Uchena and Okelue (2008) describe corporate failure as the increasing inability of a company to meet its financial obligations such as debts, tax, dividends etc as they fall due. In other words, when there is a mismatch between current assets and financial obligations company failure is eminent. This is because such a mismatch leads to inability to fulfill required financial commitments. Thus when liabilities of a corporate entity exceed its cash flows, it means the operating activities are not able to sustain the debts of the company and this leads to corporate failure.

Some theories of corporate failure such as resource dependence theory spearheaded by Sheppard (1995) have asserted that organisations fail or dissolve due to resource insufficiency.

In another theory called resources combination theory, Sheppard (1995), claims that when an organization is unable to obtain a proper mix of resources, such a firm is likely to fail. The theory is based on the understanding that a lack of sustainable resources contributes to failure. The theory to a great extent explains why some organisations succeed and others don't, when they are all exposed to the same risks, opportunities and business challenges. Therefore, each resource choice has an important implication for business growth and survival. The choices are expected to show negative consequences if the wrong resources are acquired. According to this theory firms can gain competitive advantage over their competitors if they can obtain a resource supply that is unique when compared to their competitors. Organisations that are unable to guard their resource base have high prospects of failure (Sheppard, 1995).

The Corporate governance (CG) theory stress that corporate failure is a result of poor corporate governance (Maher and Anderson, 1999) [10]. Maher and Anderson (1999) [10] say that CG are internal structures and processes used in the managing of the company, and also it's a system which provides sound and honest leadership, observance and regulatory frameworks of being conscious of corporate ethics. In addition, corporate governance is all about the shareholders, management, auditor and other stakeholders and how they relate to each other in the interest of the company. Maher and Anderson (1999) [10] ague that failure to adhere to or the absence of CG structure in a company has often led to poor financial and operational performance of most failed companies.

There are a number of studies that have been done in evaluating and predicting corporate failure. In the 1930s, agencies were established to supply qualitative type of information assessing the creditworthiness of a particular enterprise. This had so many shortcomings because the assessment of an enterprise was not resulting in the correct knowledge of the status of the business. Studies were done later at the time and concluded that failing firms exhibited significantly different ratio measurements than continuing entities. This evidence made scholars to conclude that financial ratio analysis was adequate in assessing the performance of san enterprise (Altman, 1968) [1]. From that time financial ratios have been used to compare a firm's financial data at different points in time, or with other firms. Financial ratios are often employed to provide a clue to a number of questions concerning the financial health of an organisation.

Taani and Barnykhaled (2011) [15] state that the financial ratios analysis can assist investors in making investment decisions and predicting the firms future performance. Ohlson (1980) [13] also adds to say that financial ratios can give an early warning about the slowdown of the firm's financial condition. Fook *et al.*, (2012) [9] argues that financial ratios play a dominant role in almost all the variables used as predictors attesting to the fact that ratios do contribute substantially and immeasurably to understanding financial performance and financial status.

From these explanations, it is very clear that financial ratios such as profitability, leverage, liquidity, efficiency or asset management and investment ratios, obtainable from data from the financial reports, are very important in analyzing the financial condition of the firm.

Beaver (1966) [4] carried out a study on predicting corporate failure using financial ratios and found a number of ratios that could discriminate between matched samples of failed and non-failed entities. Using a sample of 79 failed and 79 non-failed companies (period 1954 to 1964), Beaver used 30 financial ratios and compared the mean values of ratios for the two groups of firms and found that failed and non- failed firms differed significantly with regards to six financial ratios. The six financial ratios that Beaver (1966) [4] identified to be superior in the study were the cash flow to debt, net income to total assets, and total debt to total assets, working capital to total assets, current ratio and defensive interval. For instance, working capital/debt ratio as a discriminant factor, correctly identified 90 percent of the firms one year prior to failure whereas net income/total assets ratio, accurately identified 88 percent of firms one year prior to failure.

A major weakness of Beaver's study is that his study was based on the univariate discriminant analysis in which a single variable was used to predict corporate failure. Though he achieved a moderate level of predictive accuracy, the univariate approach has various weaknesses. One of the major weaknesses of using the univariate method is that the financial ratios are not allowed to interact with one another as each ratio is examined separately, in isolation from the other ratios (Altman, 1968) [1]. For instance Morris (1998) illustrated in his study that while low profitability may be one signal of financial distress, it may not necessarily be fatal if a business has a strong liquidity position. Likewise, a company that is profitable but which has low reserves of liquid assets is potentially vulnerable if there should be an unexpected set back. Thus using a single variable to determine a financial distress situation is risky (Fook *et al*; 2012) [9].

In response to criticism levelled against Beaver (1966) [4], Altman (1968) [1] developed a multivariate discriminant analysis (MDA) model called Linear Discriminant Analysis (LDA) model to discriminate failure from non-failure firms using a Z score. The analysis was based on 33 failure and 33 non-failure USA manufacturing companies over the period 1946 to 1965. Altman (1968) [1] used 22 financial ratios, all of which were categorized under the 5 broad groups. Five of the 22 were eventually chosen to form discriminant scores of Z values. The model correctly classified 94% failed companies, and 97% non- failed companies. Altman further applied the model on 21 failed and 21 non failed rail road firms for the period 1939 to 1970. One year prior to failure the model classified 95% of failed companies and 100% non- failed companies. However, misclassification of failed companies increased significantly with increase in prediction time (28% at 2 years, 52% at 3 years and 71% at 4 years.

Blum (1974) also investigated 115 failed and 115 non-failed which had at least 3 years of accounting and financial data in the period 1954 to 1968. He also used the LDA that he developed. The results were 94% classification on failed companies (one year prior to failure), 80% classification (two years prior to failure) and 70% for 3, 4 and 5 years prior to failure. This was quite encouraging.

Ohlson (1980) [13] utilized a sample of 105 failed and 2058 non failed companies in the period 1970 to 1976 with a probabilistic logistic model for bankruptcy prediction. The strength of the study was the calculation of the optimal cut off point (to separate failed and non- failed companies) which minimized the sum of errors. The model predicted 82.6% of failed companies one year prior to failure, and also classified 87.6% non -failed companies, correctly.

Zavgren (1986) developed a model that improved prediction accuracy as compared to the Altman (Z) model. He used the Logit analysis to predict failure. Unlike the MDA which is based on the assumption of normality and similar dispersion measures of the data, the Logit analysis did not require that, to produce good predictive results. Marco and Varetto (1994) also did studies on the Logit analysis and found that it performed better than many methods such as the MDA and Neural networks models.

This paper therefore applies the logit model to predict corporate failure in the Zambian context.

3. Methodology

3.1 Data collection and sample

Financial data from the annual reports of the selected failed and non-failed companies were collected. In certain circumstances, a specific questionnaire was used to collect data on specific data used where financial reports posed to be difficult to obtain. The data so collected was mostly for the period 2000 - 2005, that is for 5 years prior to failure for failed companies. And it was the same period adopted for the non-failed companies. The data collected was for purposes of computing the required financial ratios. Except for that on questionnaire, which was primary data, most data collected was secondary. A specific questionnaire was also given to ZAM, a reliable source of information on the manufacturing sector in Zambia.

Due to limitations that will be adequately highlighted later, the preferred sample size was 16 failed companies and 16 non failed companies (the sample covered both public and private companies from the manufacturing sector). Ten (10) failed and 10 none failed were to be used for model development, while 6 failed and 6 none failed were to be used for the validation or Holdout sample. However, only 6 failed and 6 none failed were used for model development and 1 failed and 1 none failed were used for the Holdout sample. This is simply because collection of financial data was very difficult. Companies and organisations were not willing to share the information.

3.2 Logistic regression

The Logistic model computes a probability of failure or success based on probability distribution. Like the discriminant analysis, Logit model weighs the independent variables and assigns a score in the form of failure probability to each company in the sample. Thus this statistical procedure not only groups a firm to either fail or non-fail, based on the financial factors but also incorporates or considers other shocks of external factors that could determine probability of failure or success of a firm. In addition, the Logit model utilizes the coefficients of the independent variables to predict the probability of failed and non-failed dependent variable. This technique weighs the independent variables and creates a score for each company in order to classify it as a failed or non-failed. (Fook *et al.* 2012) [9].

Ohlson (1980) [13] expresses the Logistic function which this study also adopt, as follows;

$\int(\beta) = \sum \log P(Xi, \beta) + \sum \log(1-P(Xi, \beta))$, where

Xi = vector of predictors for I observation

ß = vector of unknown parameter

P = some probability function, $0 \leq P \leq 1$

P (Xi, ß) = the probability of failure for any given Xi and ß.

However, the Logistic equation adopted in this research makes use of the probabilities. The computed probability in the Logistic regression determines whether a company is a failed or non-failed one. The general formula is

$P = e^{(a+bX)} / 1 + e^{(a+bX)}$, which is the same as $P = 1/ 1 + e^{-(a-bX)}$, Where P is the probability, e is the base of the logarithm (about 2.718), and a and b are parameters of the model and X is the independent variable (Landau and Everitt, 2004) [8].

The model utilizes the coefficients of independent variables to predict the probability of occurrence of the dichotomous dependent variable (Dielman, 1996) [7]. The Logistic regression tool was chosen in this research because of the remarkable results it has given in many studies. Unlike the Discriminant analysis, another statistical tool, the Logistic regression does not require that variance-covariance matrices of the predictor variables be the same for both groups that is the failed and non-failed and also that predictor variables need not to be normally distributed. Both Constand and Yazdipoor (2011) [6]. Express that the Logistic models predicted rate of corporate failure, has more significance than the Z-score values by the Discriminant analysis. The Logistic regression is a robust tool and outliers in this model does not affect its performance.

This type of regression model being applied is specifically called the Binary Logit model with dichotomous variables (failed and non-failed). While the predictor variables are independent variables with continuous data, the dependant variable can only take one result either fail or non-fail that is 1 or 0 respectively.

4. Data Presentation and Analysis

The statistical package used in this study for data analysis was EVIEWS which is a powerful user friendly software package for the manipulation and statistical analysis of data. It is a core program which houses many modules, including the logistic regression.

Note that failed companies are represented by 1 (for the dependent variable) while the non-failed by 0 (another kind of dependent variable). The default probability in the regression of. 05, was adopted when entering the predictor variables and. 10 is also a default probability of removal. Using the logistic regression the model so developed was tested for fitness using the -2log likelihood value (-2LL), the Chi-square Goodness-of-fit tests, the Cox and Snell R2 as well as the Nagerkerke R2 measures. The results were presented in tables and interpreted accordingly.

The model was then tested on the analysis sample and Holdout sample, separately. The idea was to attain the classification accuracy of the model, that is, how the model was classifying failed and non-failed companies. Again, it was the means of the significant variables in the hold out sample that were used to test the model. Due to limited sample size, the test was also done on variable for each year in the hold out sample.

4.1 Findings and discussions

The following variables, were used in the model to predict corporate failure namely;

1. **PBITS;** this is another profitability measurement ratio that is computed by dividing the profit before interest and taxes by the sales made.
2. **NWTD;** this is another leverage ratio. It measures the Net worth to the total debt of the company. The Net worth is basically the Total Assets less Total Liabilities.
3. **NWTA;** this is a liquidity measurement ratio. It is calculated by dividing the Networth or working capital by the total assets value.
4. **TDTA;** this is another liquidity measurement ratio and it measures the total debt to the total assets. It is simply calculated by dividing the total debt by the total assets value.
5. **STA;** this is an efficiency measurement ratio and it measures the firm's asset utilization. The ratio is computed by dividing the sales by the total assets.
6. **EBBITA;** this is a profitability ratio which is calculated by simply dividing the earnings or profit before interest and tax by the total asset value of the firm.

Note that not too many financial ratios were used in the logistic regression for analysis due to lack of data. Below are the results for logistic regression on corporate failure.

Table 1: Logit estimation of the probability of company failure

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	172.8042	165.3539	1.045057	0.2960
EBBITA	2.099087	2.162413	0.970715	0.3317
NWTA	-171.9218	165.5023	-1.038788	0.2989
NWTD	0.076634	0.174693	0.438681	0.6609
PBITS	-13.85246	7.028324	-1.970948	0.0487
STA	-1.674373	0.519513	-3.222966	0.0013
TDTA	-169.1166	164.9771	-1.025092	0.3053
McFadden R-squared	0.384479	Mean dependent var		0.500000
S.D. dependent var	0.504219	S.E. of regression		0.398945
Akaike info criterion	1.086626	Sum squared resid		8.435307
Schwarz criterion	1.330966	Log likelihood		-25.59879
Hannan-Quinn criter.	1.182201	Deviance		51.19758
Restr. deviance	83.17766	Restr. log likelihood		-41.58883
LR statistic	31.98009	Avg. log likelihood		-0.426646
Prob(LR statistic)	0.000016			

As results in the table above show, only two variables were significant. The asset utilization ratio also called efficiency measurement ratio is significant at all levels of significance with the probability of 0.0013 and with a correct negative sign which entails that there is a negative relationship between company failure and asset utilisation. Since asset utilization reflect how well a company utilises its assets, it means good management of asset reduces probability of failure. Thus if a company is managing its assets poorly, it is likely to fail.

Profitability measure (PBITS) was found to be statistically significant at 5% level of significance with a correct negative sign implying that there is a negative relationship between profitability and probability of corporate failure. This means a more profitable entity is less likely to fail than the less

profitable entity. The other financial ratios were found to be statistically insignificant however with correct signs.
However, the LR statistics of 31.89 with a probability of 0.000016 indicates joint significance of the variables included in the logistic regression. However this could be indicative of the low power of the test when all the variables are jointly examined.
The Pseudo-R squared (the McFadden R-squared) of 34.5% are low but not too low and this could be indicative of a fairly good model. As (Chris, 2008) site, the McFadden R-squared are quiet low often times in limited dependent variable model. A further check of the adequacy of the model through the Chi-Square test as shown below in the table indicated a P-value of 0.5128 and 0.1031 for H-L Statistic and Andrews Statistic respectively. Since the probabilities of the two statistics are greater than 0.05 it means insignificance and that the model is a good fit.

Table 2: Goodness of Fit Evaluation test (Chi-square test)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	5.E-28	0.0779	6	5.82595	0	0.17405	6	0.17925
2	0.0785	0.1435	4	5.37021	2	0.62979	6	3.33069
3	0.1692	0.2530	5	4.71860	1	1.28140	6	0.07858
4	0.2836	0.3984	5	3.84110	1	2.15890	6	0.97175
5	0.4415	0.4754	4	3.26632	2	2.73368	6	0.36171
6	0.4809	0.5187	3	3.02335	3	2.97665	6	0.00036
7	0.5427	0.6639	3	2.42074	3	3.57926	6	0.23236
8	0.6832	0.8138	0	1.47744	6	4.52256	6	1.96010
9	0.9704	1.0000	0	0.05630	6	5.94370	6	0.05683
10	1.0000	1.0000	0	1.2E-08	6	6.00000	6	1.2E-08
		Total	30	30.0000	30	30.0000	60	7.17163
H-L Statistic		7.1716		Prob. Chi-Sq(8)		0.5182	
Andrews Statistic		15.8794		Prob. Chi-Sq(10)		0.1031	

In terms of classification, the model correctly classifies 86.67% of non-failed firms and incorrectly classifies the non-failed firms with 13.33%. As indicated in table 3, for the failed firms, the model correctly classifies the failed firms with 73.33% level of accuracy but incorrectly classifies the failed firms by 26.67%. Therefore, overall, the model correctly predict 80% of the observations and incorrectly predict 20% of the observations.

Table 3: Predictive accuracy and classification table

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	26	8	34	30	30	60
P(Dep=1)>C	4	22	26	0	0	0
Total	30	30	60	30	30	60
Correct	26	22	48	30	0	30
% Correct	86.67	73.33	80.00	100.00	0.00	50.00
% Incorrect	13.33	26.67	20.00	0.00	100.00	50.00
Total Gain*	-13.33	73.33	30.00			
Percent Gain**	NA	73.33	60.00			

Conclusion

The purpose of this study was to examine the ability of the logit model in predicting corporate failure in Zambia for a five years period. A logistic regression model was developed with six financial ratios. Out of the six ratios asset utilization and profitability ratio seem to have the greater effect on corporate failure or success in Zambia. Analysis showed that those firms which managed their assets were and had good profitability ratio had higher probability of not failing while those firms with poor asset management had higher chances of failing. And likewise, less profitable firms are more likely to fail than profitable ones. In terms of prediction the model correctly classified 86.67% of non-failed firms and 73.33% for the failed firms.

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