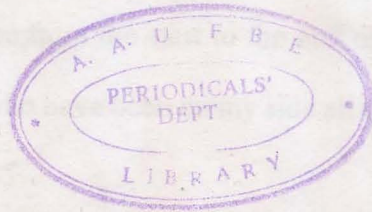




MBA 12

# FIANCIAL FAILURE PREDICTION:

## An Empirical Study on Ethiopian Public Enterprises



A Research Paper Prepared in Partial Fulfillment of the Requirements for Masters Degree in  
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## Abstract

The main purpose of this research is to throw light on a very challenging and perhaps forgotten issue of predicting corporate failure in Ethiopian public enterprises. The study tests and replicates a quantitative model for classifying and predicting serious financial problems of companies. It utilized a failure classification model developed by Altman in 1968 and updated continuously. A sample of 15 serious-problem enterprises is compared with the same number of healthy enterprises. Altman Z-Score Model successfully classified 80 percent of the enterprises one year prior to serious financial problems and as much as 70 percent two years prior. A comparable model replicated for the Ethiopian context, with a revised cut-off point, correctly classified 83 percent of the enterprises one year prior to serious financial problems and as much as 80 percent two years prior. In summary, the outcome of the research is expected to draw pointed attention to managers, government, lending institutions, suppliers, employees, and the community at large in assessing the financial health of an enterprise.

# CHAPTER ONE

## INTRODUCTION

### 1.1 Background

Nowadays, financial failure is becoming one of the most significant threats for many public enterprises in Ethiopia. The economic cost of failures in public enterprises is relatively large since these enterprises play a very significant role in the country's massive effort for rapid economic and social development. The far-reaching implication of public enterprise failures necessitate the need for reliable empirical model that predicts financial failure with reasonable accuracy and that will enable interested parties to take corrective actions.

There are a number of financial failure prediction models that are used in practice. These models have different degree of predictive accuracy; that is, some are weak and others are strong. The most popular of these models is Altman's Z-Score Model developed in 1968 and updated continuously (Altman, 2000). Practitioners as well as academicians are using this model throughout the world.

There is also a growing body of literature addressing the predictive accuracy of Altman's Z-Score Model in forecasting financial failure prior to the failure event. The model has proven to be a reliable tool for failure prediction in a variety of contexts and in different countries. However, such a study is very little in Ethiopia. Hence, the fact that such a study is lacking on Ethiopian public enterprises and the non-existence of a model suitable to the Ethiopian context has triggered the start of this research work.

## 1.2 Working Definition of Terms

The unsuccessful business enterprise has been defined in numerous ways in attempts to depict the formal process confronting the firm and/or to categorize the economic problems involved. Four generic terms that are commonly found in the literature are *failure*, *insolvency*, *default*, and *bankruptcy*. Although these terms are sometimes used interchangeably, they are distinctly different in their formal usage. In view of that, the definitions of relevant terms as used in this research are given below.

- Financial failure – refers to a situation where the average return on investment is significantly and continually lower than the firm's minimum cost of capital – that is, the minimum interest rate paid on bank accounts.
- Failed enterprises – are those enterprises whose average return on investment is significantly and continually lower than the firm's minimum cost of capital – that is, the minimum interest rate paid on bank accounts.
- Non-failed enterprises – are those enterprises whose average return on investment is significantly and continually higher than the firm's minimum cost of capital – that is, the minimum interest rate paid on bank accounts.

## 1.3 Statement of the Problem

### General

The occurrence of public enterprise failure is increasing in Ethiopia. Currently there are certain public enterprises that have failed and are failing. This has put a significant adverse impact on the national economy. With this regard the government of Ethiopia is showing a little concern by structuring and privatizing some financially sick enterprises. However, this concern is put into effect after the failure event is known. Instead the government should take advance measures before the actual failure event is realized.

In order to take advance measures, it is necessary to find or develop a strong model on which to rely on in predicting financial failure. Before using a model, however, one has to test its predictive accuracy. The chosen model, i.e., Altman's Z-Score Model, should be tested on Ethiopian public enterprises before it is applied or otherwise. Thus, testing the predictive accuracy of Altman's Z-Score Model in the Ethiopian context is the first main objective of this paper. The second one is developing a failure prediction model that can be used to classify and predict serious financial problems of enterprises in Ethiopia.

### **Research Hypothesis**

The null and alternative hypotheses are stated as follows:

$H_0$ : *“Altman's Z-Score Model is a strong model for predicting financial failure of public enterprises in Ethiopia.”*

$H_1$ : *“Altman's Z-Score Model is not a strong model for predicting financial failure of public enterprises in Ethiopia.”*

### **Major Research Questions**

This research seeks to investigate answers to certain specific issues that are related to the main theme of the subject matter under study. The major research questions that are addressed in the study are stated as follows:

- Is Altman's Z-Score Model a strong model for predicting financial failure of public enterprises in Ethiopia?
- Do the results of the model for failed enterprises exhibit similarity with what is obtained for non-failed enterprises?
- How best does the model discriminate between failed and non-failed enterprises?

#### **1.4 Objectives of the Study**

The main theme of this study is two-fold. The first main objective is testing the predictive accuracy of Altman's Z-Score Model in predicting financial failure of public enterprises in Ethiopia. If the model turns out to have a strong predictive accuracy, it will help stakeholders to assess the financial health of an enterprise and then take the necessary measure. The second main objective is developing a failure prediction model that is applicable in the Ethiopian context. The specific objectives of the study are stated as follows:

- To test the strength of Altman's Z-Score Model in predicting financial failure of public enterprises in Ethiopia.
- To develop a failure prediction model that is applicable in the Ethiopian context.

#### **1.5 Importance of the Study**

The output of the research is expected to draw pointed attention to managers, government, lending institutions, suppliers, employees, and the community at large while assessing the predictive accuracy of Altman's Z-Score Model and using the new model. The results of the research are also expected to be of great help to interested parties in assessing the financial health of an enterprise. This in turn helps prevent public enterprises from becoming permanent sources of financial loss in the country. Moreover, the findings of the study would open up future directions for further study to those who are interested in dealing with failure prediction.

## **1.6 Scope and Delimitations of the Study**

The research was conducted only based on some selected public enterprises in Ethiopia. The dataset is limited to audited financial statements of 30 manufacturing public enterprises - 15 failed and 15 non-failed. While no doubt the number of enterprises considered in the research is a small percentage of the entire family of public enterprises, the researcher strongly believes that the situation in the selected public enterprises represents the overall picture apparent in the total population. The research is only based on key financial ratios, as required by the Altman's Z-Score Model, without considering such qualitative factors as related to management, labor, market conditions, and other macroeconomic and technical conditions that may have an impact on enterprise performance. Moreover, the limited local research work on related topics has put an impact on the research.

The remainder of this paper is organized as follows. Chapter Two presents the essence of Altman's Z-Score Model and examines some of the relevant research works related to predicting financial failure. Then, in Chapter 3 the methodological plan of the study is outlined and a description of the essence of the statistical technique used is given – namely, that of linear discriminant analysis. Chapter 4 presents a discussion on the empirical results and its interpretation. Then, Chapter 5 concludes the paper by discussing the study's implications and presenting some remarks.

## CHAPTER TWO

### LITERATURE REVIEW

There are a fair number of previous studies addressing the topic of financial failure prediction. These studies focus on: (i) testing the accuracy of an existing model, and (ii) describing the factors that best explain the financial health of a company. In this chapter, a discussion is presented on the nature of Altman's Z-Score Model and the essence of the model's explanatory variables together with purposefully selected related studies on predicting financial failure.

#### **2.1 Altman's Z-Score Model**

Altman's Z-Score Model is a tried and tested formula for predicting financial failure. The model is developed by Edward I. Altman, who is a world-recognized expert on financial bankruptcy and credit analysis, on a sample of sixty-six companies with thirty-three firms in each the two groups – that is, failed and non-failed enterprise groups.

To develop the Z-Score Model, Altman (1968) compiled a list of twenty-two financial ratios and classified each into one of five categories (liquidity, profitability, leverage, solvency, and activity). The ratios were selected on the basis of their popularity in the literature and Altman's belief about their potential relevancy to financial failure. He estimated the model using multiple discriminant analysis (a statistical tool discussed in Chapter 3), which attempts to derive a linear combination of variables that best discriminates between failed and non-failed enterprise groups.

The linear function that best discriminated between the thirty-three failed and the thirty-three non-failed manufacturing firms was:

$$Z = 1.200X_1 + 1.400X_2 + 3.370X_3 + 0.600X_4 + 0.999X_5$$

Where:

- $X_1$  = working capital/total assets,
- $X_2$  = retained earnings/total assets,
- $X_3$  = earnings before interest and taxes/total assets,
- $X_4$  = **market value** of equity/book value of total liabilities,
- $X_5$  = sales/total assets
- $Z$  = overall index.

The original model has been demonstrated to be quite reliable in a variety of contexts and in different countries. However, it is not designed to be used in every situation. For firms whose stock is not publicly traded, like Ethiopian public enterprises, one has to use the following formula that is modified from the original formula.

$$Z = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5$$

Where:

- $X_1$  = working capital/total assets,
- $X_2$  = retained earnings/total assets,
- $X_3$  = earnings before interest and taxes/total assets,
- $X_4$  = **book value** of equity/book value of total liabilities,
- $X_5$  = sales/total assets
- $Z$  = overall index.

This modified formula is used in this research and it is similar with the original formula described earlier except the  $X_4$  term and the coefficients of the terms. If a firm's stock is not publicly traded, the  $X_4$  term (which is **market value of equity**/book value of total liabilities in the original formula) cannot be calculated. To correct the impact of this problem, the  $X_4$  term is computed using **book value of equity**/book value of total liabilities.

The coefficients of the  $X_i$ s indicate the relative impact of each independent variable on the overall Z-score. The higher the coefficient of the independent variable the stronger will be the impact of the variable on the overall Z-score and vice versa. To assess a firm's likelihood of failure, its Z-score is compared with the predetermined cut-off shown below.

- Failure - if the value of Z is less than 2.065
- Survivor - if the value of Z is greater than 2.065

Altman's Z-Score Model predicts whether or not a company is likely to fail within one or two years. Probabilities of failure in the above ranges are 95 percent for one year and 70 percent within two years. The Z-score is a discriminant value or a figure computed for prediction purpose. A higher Z-score indicates a better financial health and a lower Z-score implies a relatively weak financial health. The Z-score of a firm should be interpreted in a relative sense than in absolute terms.

The 2.065 cut-off point is the point that achieves the best classification accuracy. In setting this cut-off point the aim was minimizing the combined cost of Type I error (classifying a failed enterprise as a non-failed entity) and Type II error (the cost of misclassifying a non-failed enterprise).

Altman's Z-Score Model uses financial ratios to explain failure. This is because the detection of company operating and financial difficulties is a subject that has been amenable to analysis with financial ratios. This implies that there exists a definite potential of ratios as predictors of financial health of a company. In general, ratios measuring profitability, liquidity, and solvency prevailed as the most significant indicators.

Altman has found five ratios to be most significant indicators. These ratios are chosen from many ratios after undertaking a rigorous statistical analysis on each of the variables and the relationship with each other. Starting with twenty-two financial ratios, Altman selected the five that did the best-combined job of predicting financial failure. In order to arrive at a final profile of variables, the following procedures were utilized: (i) observation of the statistical significance of various alternative functions including determination of the relative contributions of each independent variable; (ii) evaluation of inter-correlations among the relevant variables; (iii) observation of the predictive accuracy of the various profiles; and (iv) judgment of the analyst (Altman, 1993).

A brief description about each of the five significant financial ratios is presented in the paragraphs that follow. Note also that these financial ratios are the independent variables that explain failure or survival – the dependent variable.

#### **Working Capital/Total Assets - $X_1$**

The working capital/total assets ratio, frequently found in studies of financial problems, is a measure of the net liquid assets of the firm relative to the total capitalization. Working capital is defined as the difference between current assets and current liabilities. Ordinarily, a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets.

### **Retained Earnings/Total Assets - X<sub>2</sub>**

Retained earnings represents the total amount of reinvested earnings and/or losses of a firm over its entire life. It is a measure of cumulative profitability over time. In addition, this ratio measures the leverage of a firm. Those firms with high retained earnings, relative to total assets, have financed their assets through retention of profits and have not utilized as much debt.

### **Earnings before Interest and Taxes/Total Assets - X<sub>3</sub>**

This ratio is a measure of the true productivity of the firm's assets, independent of any tax or leverage factors. It shows the raw earning power of the firm's assets, before the influence of taxes and leverage. Since a firm's ultimate existence is based on the earning power of its assets, this ratio appears to be particularly appropriate for studies dealing with financial failure. It recognizes operating earnings as a key to long-run viability.

### **Owners' Equity/Total Liabilities - X<sub>4</sub>**

Equity is the difference between total assets and liabilities. This equity divided by the total assets gives the percentage of total assets financed by owners. Firms with high equity to total asset percentage will have a better chance of getting additional financing from creditors and are solvent than those firms with low percentage.

### **Sales / Total Assets - X<sub>5</sub>**

This ratio is a standard financial ratio illustrating the sales generating ability of the firm's assets. It tells us the relative efficiency with which the firm utilizes its resources in order to generate sales. Like the other ratios, this final ratio is found to have significant contribution to the overall discriminating ability of the model.

## **2.2 Related Research on Predicting Financial Failure**

Research in the financial failure prediction area has been very popular among academicians and practitioners during the last four decades. However, as financial failure problem still persists in modern economies, having significant economic and social implications, as an accurate and reliable method for predicting the failure event has not yet been found, research is likely to continue (Neophytou 2001).

Neophytou's (2001) review of modern analyses to failure prediction sites several examples and are presented as follows:

- "Beaver (1966) was among the first to attempt to forecast financial failure and his study is considered a milestone in this area. Beavers' approach was 'univariate' in that each ratio was evaluated in terms of how it alone could be used to predict failure without consideration of the other ratios. Altman (1968) tried to improve Beavers' study by applying multivariate linear discriminant analysis (LDA).
- Researchers, however, continued extending Altman's model, hoping to achieve higher classification accuracy. Some examples of these attempts include among others: (1) assignment of prior probability membership classes (Deakin, 1972), (2) employment of

a more appropriate 'quadratic classifier' (Altman, Haldeman and Narayanan, 1977), (3) use of cash flow based models (Gentry, Newbold and Whitford, 1987), (4) use of quarterly financial statement information (Baldwin and Glezen, 1992), and (5) investigation of the use of current cost information (Aly, Barlow, and Jones, 1992; Keasy and Watson, 1986). Nevertheless, none of these attempts accomplished higher statistically significant results than Altman's earlier work and moreover, in the majority of cases, the practical application of these models presented difficulties due to their complexity."

Altman's (1993) review of modern analyses to failure prediction include the following:

- Libby in 1975 conducted a study to determine whether accounting ratios provide useful information to loan officers trying to predict business failure. Using a subset of Deakin's 14-variable set, commercial bank loan officers were asked to analyze the ratios and then to predict either "failure" or "non-failure." The usefulness of the information was judged on the basis of the accuracy of the loan officers' predictions. Libby found that the loan officers' predictive accuracy was superior to random assignment (i.e., fail - non-fail) and concluded that the ratio information was utilized correctly by the loan officers.
- Edmister in 1972 developed and tested a number of methods of analyzing financial ratios to predict the failure of small businesses. A small business was defined as one with a loan from the Small Business Administration (SBA) of U.S.A. The firms employed were borrowers and guarantee recipients from the SBA for the period 1954 to 1969. Loss borrowers were designated as failures and nonloss borrowers were

considered to be non-failures. Edmister concluded that the predictive power of ratio analysis depends upon both the choice of analytical method and the selection of ratios. Two of the methods he found useful are: (1) dividing a ratio by its respective industry average, and (2) classifying ratios by quartiles.

In addition to the studies described, there has been other empirical work on financial failure prediction. Space does not permit a thorough review, but it is important to mention one additional study. Aziz and Lawson (1989) use a cash-flow-based model (CFB) to predict financial failure. The various components of cash flow – operating, investing, financing, and liquidity changes – are employed. Testing the predictive accuracy of the model for one to five years prior to failure, the authors find 92 percent accuracy for one year prior to the event, declining to 72 percent five years before. In comparing their results with those for Altman's Z-Score Model, the CBF model is found to be slightly more accurate. However, the comparison is mixed with little in the way of statistically significant differences; both models do a good job.

Additional failure prediction studies have used multiple discriminant analysis (MDA) and have reached at a model with a reasonable degree of predictive accuracy (Deakin, 1972; Altman and Lavalley, 1981; Taffler, 1982; Altman and Izan, 1983; Pascal, 1988; Baldwin and Clezen, 1992; Altman, 2000).

Instead of discriminant analysis, other studies in the field of failure prediction have used three different approaches; namely conditional probability analyses (CPA) and neural networks (NNs) to predict financial failure on the basis of financial ratios. Some of these studies are presented in the paragraphs that follow.

Conditional probability analyses (CPA) primarily refers to the discrete choice group of models of which LOGIT and probit are the most common in studies of corporate distress. The main difference between MDA and CPA is that CPA appraises the probability of occurrence of a result, rather than producing a dichotomous analysis of failure/non failure as is the norm with basic discriminant techniques. Ohlson in 1980 applied an alternative LOGIT analysis to predict corporate failure since this method avoids some of the argued limitations of discriminant analysis. Since then, LOGIT analysis has been extensively used for the development of failure classification models. However, Ohlson's results did not improve on the results of discriminant analysis, thus indicating that further refinements of the technique were necessary. Conditional probability models also failed to offer anything more than any other technique to the user (Keasy and Watson, 1991).

Neural networks (NNs) is another technique that has been applied in the corporate insolvency prediction area. NNs are computer systems that take their inspiration from known facts about how the brain works and they can be trained to solve certain problems or identify specific patterns. Coats and Fant (1993) and Wilson and Sharda (1994) compared the results of MDA against NNs and their result suggested that the NNs approach is more effective than MDA in classifying distressed and non-distressed firms, where as Boritz, Kennedy and Albuquerque (1995), after comparing two NNs techniques to MDA, CPA, as well as against Altman's and Ohlson's models, found that the two NNs techniques did not provide superior classification rates. Similar results were reported by Laitinen and Kankaanpaa (1999).

The general conclusions from this extensive research effort seem to be that each study by itself provides a reasonable discrimination between failed and non-failed firms and that the various studies hardly show any agreement on what factors are important for failure prediction. Indeed, it can be said that more than forty years of empirical research on bankruptcy prediction failed to produce agreement on which variables are good predictors and why. This discord of conclusions can, of course, partly be attributed to the fact that the studies refer to different periods, countries and industries. Another factor may be that virtually all of these studies lack a theoretical framework to guide the empirical research effort. In the absence of a theory that provides testable hypotheses, each empirical result has to be evaluated on its own merits and one can only hope that patterns emerge from the multitude of results.

All the aforementioned failure prediction models are based on different assumptions. Though there are a number of models for predicting financial failure, impressive evidence exists about the strong predictive accuracy of Altman's Z-Score Model. In this study the predictive accuracy of Altman's Z-Score Model is tested and a new model suitable for Ethiopian enterprises is developed using adequate sample of public enterprises.

Having prepared the groundwork for understanding the nature and modeling of financial failure, let's turn to the methodological issues covered in this study.

## **CHAPTER THREE**

### **METHOD OF STUDY**

Secondary data drawn from purposefully selected enterprises in the sample are used for this study. The same statistical model used by Altman, namely multiple discriminant analysis (MDA), is used. The result is tested for its significance.

#### **3.1 The Nature of the Sample**

The population is defined as Ethiopian public enterprises that are in the manufacturing sector – food processing, textile firms, beverage companies, leather and shoe factories, garment factories, metal processing, and chemical processing. This selection is made on account of accessibility and taking into consideration the high financial failure event in these enterprises relative to those that are held privately and those enterprises in the service sector. The study was conducted on thirty public enterprises – fifteen failed and fifteen non-failed. Random sampling technique was used to select constituents of the sample. Table 3.1 lists the frequency distribution of the enterprises in the sample in terms of their asset size one year prior to the failure event.

**Table 3.1: Asset Size Distribution of Enterprises in the Sample**

<b>Total Assets (Birr millions)</b>	<b>Non-failed Enterprises</b>	<b>Failed Enterprises</b>	<b>Non-failed and Failed Enterprises</b>
1 – 10	3	4	7
10 – 20	3	5	8
20 – 40	2	4	6
40 – 60	4	1	5
60 – 150	3	1	4
Total	15	15	30
<b>Asset Size (Birr Millions)</b>			
<b>Average</b>	41	25	33
<b>Median</b>	23	18	21

The average asset size was relatively high at Birr 45 million for non-failed enterprises and Birr 25 for failed enterprises, so the results of the study will have relevance over a wide range of companies in terms of size. The failed group sample was actually somewhat smaller, with an average size of around Birr 25 million and a median size of about Birr 18 million. The matching of the failed and non-failed enterprises is only in terms of fiscal year. Matching enterprises in terms of industry, asset size, and age was difficult. This has put its impact on the results of this study.

After the enterprises were selected, balance sheet and income statement data are collected and two separate but related methodologies were used to process the data. The first one is a methodology to test the predictive accuracy of Altman's Z-Score Model and it serves the first main objective of the study. The second is a methodology used to develop the new model suitable to the Ethiopian context and it serves the second main objective of the paper. The two methodologies are presented in the paragraphs that follow.

### 3.2 Methodology to Test the Predictive Accuracy of Altman's Z-Score Model

The data to test the predictive accuracy of Altman's Z-Score Model are composed of audited financial statements (balance sheet and income statement) of the selected public enterprises for two years (1994 and 1995). The failure event is observed during the year 1996. Altman's Z-Score model is tested two years (1994) and one year (1995) prior to the failure event. Thus, the data for 1994 and 1995 are used for prediction purpose and year 1996 is used as a controlling point.

The collected data was analyzed using the required financial ratios so that it would be possible to test the predictive accuracy of Altman's Z-Score Model. The results of the analysis were interpreted in such a way that it would prove or disprove the hypothesis proposed in the statement of the problem.

Inputs for computing the ratios were extracted from financial statement for two consecutive annual reporting periods for each enterprise. Then Z-Score for each public enterprise was computed for each of the two reporting periods using Altman's Z-Score Model presented in the literature. Based on their Z-Score values, the enterprises were classified as failed and non-failed in a table similar to the one presented below.

**Table 3.2: Classification Results Format**

Actual Group Membership	Predicted Group Membership	
	Failed	Non-failed
Failed	H <sub>1</sub>	M <sub>1</sub>
Non-failed	M <sub>2</sub>	H <sub>2</sub>

Where:

Hs stand for correct classifications (hits)

Ms stand for miss-classifications (misses)

M<sub>1</sub> represents a Type I error

M<sub>2</sub> represents a Type II error

The sum of the Hs (H<sub>1</sub> + H<sub>2</sub>) equals the total correct classifications and when it is divided into the total number of enterprises examined (30), it yields the measure of the predictive accuracy of Altman's Z-Score Model, that is, the percentage of enterprises correctly

classified  $\left(\frac{H_1 + H_2}{30}\right)$ .

The initial test was conducted to determine the percentage of enterprises correctly classified using data compiled *two years* before the failure event. The resulting percentage is compared with the 70 percent prediction accuracy described in the literature. The comparison is used as an input to tell about the predictive accuracy of the model prior to *two years* before the failure event.

The second test was conducted to determine the percentage of enterprises correctly classified using data compiled *one year* before the failure event. The resulting percentage is compared with the 95 percent prediction accuracy described in the literature. Again this comparison is used as an input to tell about the predictive accuracy of the model prior to *one year* before the failure event.

### 3.3 Methodology to Develop a New Failure Prediction Model

The methodology to develop a new failure prediction model suitable to the Ethiopian context proceeded as follows: First, two *a priori* groups of firms were categorized as failed and non-failed enterprises and a search for representatives were conducted. A small number of variables were then calculated for each observation (enterprise) in each of those two samples. Data were recorded and variables (financial ratios) were calculated. Data covered the period from one to two annual reporting statements prior to the failure event. These data and the corresponding data for the control sample were then analyzed through the use of linear discriminant analysis in order to determine the failure prediction model.

As noted in the Introduction, the statistical methodology adopted for this study is known as linear discriminant analysis (LDA). Analysis is made only on the linear framework in view of the limited precision of the data available. Discriminant analysis is a multivariate, statistical technique which has been utilized in a variety of disciplines since its first application in the 1930s (Fisher 1936). LDA has been used with increasing frequency in the areas of finance and economics, although neither as well known nor as often as multivariate regression analysis.

Of particular relevance to this study, failure prediction models have been developed over the past four decades using LDA or two-group regressions by many researchers using financial statements of: (i) manufacturers (Altman, 1968; Deakin, 1972; Altman and Izan, 1983; Appetti, 1984); (ii) manufacturers and retailers (Altman, Haldeman, and Narayanan, 1977; Baetge and Niehaus, 1988; Altman, 2000); (iii) small firms (Edmister, 1972); (iv)

public utilities (Baldwin and Glezen, 1992); (v) financial institutions (Shumway, 1999); and (vi) public industrial companies (Neophytou, 2001), among others.

Discriminant analysis is a statistical technique which is used to classify an observation into one of several *a priori* groupings that depend upon the observation's individual characteristics. It is employed primarily to classify and make predictions in situations where the dependent variable (variable to be explained) appears in qualitative form, such as failed vs. non-failed.

Therefore, the first step in LDA is to establish explicit, inclusive, non-overlapping, group classifications. The number of original groups can be two or more. After the groups are established, data are collected for each object in the groups. Discriminant analysis then attempts to derive a combination (in this study in linear form) of these characteristics which best discriminates between groups. In essence what is performed is the separation of, to the greatest extent possible, of the group means of  $G$  groups (in this study two) while at the same time trying to cluster each of the individual observations around its own group mean. That unique set of weights (or coefficients) for each of the explanatory variables, which maximizes the function, will usually achieve maximum classification accuracy of the original observations. Thus, to find the coefficient or weight of each of the significant independent variables (financial ratios), one may use the following formula.

$$\lambda = \frac{\sum_{g=1}^G (\bar{x}_g - \bar{x})^2}{\sum_g \sum_{i=1}^N (x_{ig} - \bar{x}_g)^2}$$

Where:

$\bar{x}_g$  = Group Mean Value

$x_{ig}$  = Individual observations in Group  $g$  of  $i$  ratio.

$\bar{x}$  = Overall Sample Mean Value

Discriminant coefficients ( $\lambda_i$ ) are computed for all the independent variables or financial ratios ( $x_i$ ) with the objective of maximizing the between group variance while minimizing the within group variance. The sum of the discriminant coefficients multiplied by the related independent variables gives us the discriminant function. The function takes the following form:

$$Z = \lambda_1 x_1 + \lambda_2 x_2 + \lambda_3 x_3 + \lambda_4 x_4 + \lambda_5 x_5$$

Where:

$Z$  = Discriminant Score

$\lambda_i$  = Discriminant Coefficients

$x_i$  = Independent or explanatory variables

The result of this formula is a discriminant score ( $Z$ ) which is used to classify an observation (an enterprise) as either failed or survivor on the basis of a single cut-off point. This cut-off point is developed based Z-Scores of the actual observations (failed and non-failed enterprises) using the new model.

The next chapter presents a discussion on the empirical results and its interpretation.

## CHAPTER FOUR

### DISCUSSION OF THE RESULTS

The empirical results will be discussed in two sections. The section tests the predictive accuracy of Altman's Z-Score Model and the second section presents a new model that is most suitable to the Ethiopian context. These objectives are met using a sample of fifteen failed and fifteen non-failed manufacturing enterprises. The failure event is only on the financial dimension rather than overall enterprise failure.

Before discussing the results, it might be helpful to present the Z-Score calculated two years (1994) and one year (1995) prior to failure (1996) for each of the enterprises in the sample. This is shown in Table 4.1 below. In order to preserve confidentiality, the names of enterprises are not given in this research. Instead a code is given to each enterprise for easier identification. Codes 1 to 15 represent non-failed enterprises and Codes 16 to 30 represent failed enterprises. The values in Table 4.1 are computed based on the  $X_i$  values – values for the independent variables – for each enterprise two years and one year prior to the failure event. See Appendix-1 for  $X_i$  values of each enterprise.

**Table 4.1: Z-Score**  
**Altman's Z-Score Model**  
 $(Z = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5)$

<b>Group Membership</b>	<b>Enterprise Code</b>	<b>Z-Score Two Years Prior to Failure (1994)</b>	<b>Z-Score One Year Prior to Failure (1995)</b>
<b>Non-failed</b>	1	3.713	3.805
	2	2.351	2.517
	3	2.599	3.498
	4	2.208	2.110
	5	2.247	3.982
	6	1.980	2.398
	7	2.961	2.705
	8	1.970	2.116
	9	2.178	2.391
	10	1.948	2.528
	11	2.067	1.730
	12	1.703	1.078
	13	0.874	1.827
	14	3.536	3.353
	15	2.396	2.152
<b>Failed</b>	16	-0.071	-0.306
	17	0.774	0.803
	18	2.152	1.620
	19	1.808	2.927
	20	0.395	0.311
	21	1.232	1.396
	22	-0.417	-0.984
	23	1.036	1.328
	24	3.307	2.124
	25	0.852	1.338
	26	2.237	1.808
	27	-1.904	-1.365
	28	2.623	3.261
	29	0.903	1.970
	30	-0.736	-0.060

#### 4.1 Testing the Predictive Accuracy of Altman's Z-Score Model

At the outset, it might be helpful to present the format for presenting the test results. Given the two classes of enterprises, results are shown in a classification chart or accuracy matrix. Table 4.2 shows how the chart is set up. This table is the same as the one presented in the methodology part on page 18. It is reproduced here for the sake of easier reference.

**Table 4.2: Classification Results Format**

Actual Group Membership	Predicted Group Membership	
	Failed	Non-failed
Failed	H <sub>1</sub>	M <sub>1</sub>
Non-failed	M <sub>2</sub>	H <sub>2</sub>

The Hs stand for correct classifications and Ms stand for misclassifications. M<sub>1</sub> represents a Type I error and M<sub>2</sub> a Type II error. The sum of the diagonal elements (H<sub>1</sub> + H<sub>2</sub>) equals the total correct classifications, and when it is divided into the total number of firms classified (30), it yields the measure of the predictive accuracy of Altman's Z-Score Model in classifying the enterprises, that is, the percentage of enterprises correctly classified  $\left(\frac{H_1 + H_2}{30}\right)$ .

#### Results Two Years Prior to Failure

The initial test examines the percentage of enterprises correctly classified using data compiled *two years* before the failure event. The following classification table is generated on the basis of the Z-Score for each of the enterprises computed based on Altman's Z-Score Model.

**Table 4.3: Classification Results Two Years Prior to Failure**

Actual Group Membership	Predicted Group Membership	
	Failed	Non-failed
Failed	11 <sup>a</sup>	4 <sup>b</sup>
Non-failed	5 <sup>c</sup>	10 <sup>d</sup>

<sup>a</sup> Failed enterprises with Z value less than 2.065 – correctly classified.

<sup>b</sup> Failed enterprises with Z value greater than 2.065 – incorrectly classified.

<sup>c</sup> Non-failed enterprises with Z value less than 2.065 – correctly classified.

<sup>d</sup> Non-failed enterprises with Z value greater than 2.065 – incorrectly classified.

Altman's Z-Score Model has a cut-off point which is equal to 2.065. This Z value is used to discriminate failed enterprises from non-failed, i.e., enterprises with Z values less than 2.065 have 70 percent probability of failure within two years. From Column three of Table 4.1 (page 24) it can be shown that 11 failed and 10 non-failed enterprises are correctly classified based on their individual Z value and Altman's Z-Score Model cut-off point.

It can be concluded that Altman's Z-Score Model has 70 percent  $\left[ \frac{11+10}{30} \right]$  probability of predicting failure event within *two years* applied in the Ethiopian context. Surprisingly, this result is exactly the same as the one required by the model – i.e. according to Altman's, probability of failure is 70 percent within *two years* for a 2.065 cut of point. Thus, the model, applied in the Ethiopian context, has a relatively similar predictive accuracy *two years* prior to the failure event.

The results of the model show similarity between predicting failed and non-failed enterprises. Relatively, however, the model discriminates failed enterprises

$\left[ \frac{11}{15} \text{ or } 73 \text{ percent} \right]$  better than survivors  $\left[ \frac{10}{15} \text{ or } 67 \text{ percent} \right]$ .

### Results One Year Prior to Failure

The second test was conducted to determine the percentage of enterprises correctly classified using data compiled *one year* before the failure event. The following classification table is generated on the basis of the Z-Score of each of the enterprises computed based on Altman's Z-Score Model.

**Table 4.4: Classification Results One Year Prior to Failure**

Actual Group Membership	Predicted Group Membership	
	Failed	Non-failed
Failed	12 <sup>a</sup>	3 <sup>b</sup>
Non-failed	3 <sup>c</sup>	12 <sup>d</sup>

<sup>a</sup> Failed enterprises with Z value less than 2.065 – correctly classified.

<sup>b</sup> Failed enterprises with Z value greater than 2.065 – incorrectly classified.

<sup>c</sup> Non-failed enterprises with Z value less than 2.065 – correctly classified.

<sup>d</sup> Non-failed enterprises with Z value greater than 2.065 – incorrectly classified.

From column four of Table 4.1 (page 24) and in the above classification matrix, it can be shown that 12 failed and 12 non-failed enterprises are correctly classified based on their individual Z value and Altman's Z-Score Model cut-off point.

It can be concluded that Altman's Z-Score Model has 80 percent  $\left[ \frac{12+12}{30} \right]$  probability of predicting failure event within *one year* applied in the Ethiopian context. This result is slightly lower than the one required by the model - i.e. according to Altman's, probability of failure is 95 percent within *one year* for a 2.065 cut of point. Thus, the model has a relatively weak predictive accuracy *one year* prior to the failure event. Besides, the model equally predicts failed  $\left[ \frac{12}{15} \text{ or } 80 \text{ percent} \right]$  and non-failed enterprises  $\left[ \frac{12}{15} \text{ or } 80 \text{ percent} \right]$ .

In general, a success rate of 70 percent is obtained in applying Altman's Z-Score Model in the Ethiopian context two years prior to the failure event. This result is surprising in that it is exactly the same success rate as the one obtained by Altman. However, the success rate of the model applied one year prior to the failure event is slightly lower than the one obtained by Altman; that is, 80 percent applied in the Ethiopian context and 95 percent obtained by Altman. This result is attention-grabbing and at the same time anomaly in that the strength of the model decreases as time moves towards the failure event. But under normal circumstances the strength of a model increases when it is tested in a period near to the failure event. This is not true in applying Altman's Z-Score Model in the Ethiopian context suggesting the need for further research.

Altman's Z-Score Model has been found to be relatively dependable. However, in order to minimize the risk of contextual differences in applying the model, a new model is needed with best performance in predicting enterprise probability of failure. Three approaches can be used to develop a new model, given the five financial ratios (independent variables), which are found to be strong predictors of financial failure in the literature. The first approach is to revise the cut-off point for discrimination without changing the coefficients of the independent variables. The second is to revise the coefficients without changing the cut-off point. The third one is to revise both the coefficients of the independent variables and the cut-off point. In this study the third approach is employed.

The rational for choosing the third approach is the fact that only revising the cut-off point (the first approach) or the coefficients (the second approach) will not help much in minimizing the effect of contextual differences in applying a model. Rather revising both

the cut-off point and the coefficients (the third approach) will result in a model that can help to minimize contextual differences. Thus, the third approach is taken as a strategy to develop the new model in this study.

#### 4.2 The New Failure Prediction Model

The new model, which is deemed to be suitable to the Ethiopian context, is developed using the five financial ratios discussed in the literature. These ratios have been proven by most researches to be relatively accurate and reliable in predicting the financial failure of a company. The new model is of the form

$$Z = 0.0165X_1 + 0.0229X_2 + 0.0344X_3 + 0.0068X_4 + 0.0032X_5$$

Where:

$X_1$  = working capital/total assets,

$X_2$  = retained earnings/total assets,

$X_3$  = earnings before interest and taxes/total assets,

$X_4$  = book value of equity/book value of total liabilities,

$X_5$  = sales/total assets

$Z$  = overall index.

The coefficients for each of the independent variables are computed using the following formula. This formula is the same as the one presented in the methodology part on page 17.

It is reproduced here for the sake of easier reference.

$$\lambda = \frac{\sum_{g=1}^G (\bar{x}_g - \bar{x})^2}{\sum_g \sum_{i=1}^N (x_{ig} - \bar{x}_g)^2}$$

Where:

$\bar{x}_g$  = Group Mean Value

$x_{ig}$  = Individual observations in Group  $g$  of  $i$  ratio.

$\bar{x}$  = Overall Sample Mean Value

Table 4.5 lists the mean values for the five financial ratios for both failed and non-failed groups and also the overall sample mean values.

**Table 4.5: Variable Means**

	$X_1$	$X_2$	$X_3$	$X_4$	$X_5$
Non-failed group mean ( $\bar{x}_g$ )	0.220	0.087	0.258	0.627	1.137
Failed group mean ( $\bar{x}_g$ )	-0.084	-0.119	0.058	0.232	0.898
Overall sample mean ( $\bar{x}$ )	0.068	-0.016	0.158	0.429	1.018

The mean values in Table 4.5 are computed based on the individual values for each enterprise from Appendix-1. Based on mean values from Table 4.5, individual  $X_i$  observations from Appendix-1, and the above formula, we compute the discriminant coefficients for each of the independent variables.

Table 4.6 lists the coefficients for the new model and Altman's Z-Score Model and indicates the relative importance of each of the five variables. In terms of the new model, the ranks of the relative importance of the five variables are  $X_3$ ,  $X_2$ ,  $X_1$ ,  $X_4$ , and  $X_5$ . The order in Altman's Z-Score Model is  $X_3$ ,  $X_5$ ,  $X_2$ ,  $X_1$ , and  $X_4$ .

**Table 4.6: Coefficients for the New Model and Altman's Z-Score Model**

Independent Variable	The New Model		Altman's Z-Score Model	
	Coefficient or $\lambda_i$	Rank	Coefficient or $\lambda_i$	Rank
X <sub>1</sub>	0.0165	3	0.717	4
X <sub>2</sub>	0.0229	2	0.847	3
X <sub>3</sub>	0.0344	1	3.107	1
X <sub>4</sub>	0.0068	4	0.420	5
X <sub>5</sub>	0.0032	5	0.998	2

All of the coefficients for variables X<sub>1</sub> to X<sub>5</sub> are changed as are the group means. These lower coefficients imply that the independent variables have lower impact on the overall Z-score and that the variables are not as good indicators as they were in the Altman's Z-Score Model.

When the discriminant coefficients are entered in to the general discriminant function

$$Z = \lambda_1 X_1 + \lambda_2 X_2 + \lambda_3 X_3 + \lambda_4 X_4 + \lambda_5 X_5$$

we find the following model

$$Z = 0.0165X_1 + 0.0229X_2 + 0.0344X_3 + 0.0068X_4 + 0.0032X_5$$

This model is deemed to be suitable to the Ethiopian context. The reliability of the replicated model when applied to enterprises from various industries depends on the stationary of failure conditions across industries and time, the velocity of business activities, and the nature of the economic environment in which the enterprises operate.

Additionally, the relative importance of the variables may change over time, and, consequently, the coefficients may not be stable even if the variables included in the model are accurate predictors.

We now need to determine the cut-off value of the function. To determine the cut-off value, the actual scores for the sample enterprises for each of the two years was computed. This is noted in Table 4.7.

**Table 4.7: Z-Score  
The New Model**

$$(Z = 0.0165X_1 + 0.0229X_2 + 0.0344X_3 + 0.0068X_4 + 0.0032X_5)$$

Actual Group Membership	Enterprise Code	Z-Score Two Years Prior to Failure (1994)	Z-Score One Year Prior to Failure (1995)
Non-failed	1	0.039	0.035
	2	0.034	0.033
	3	0.020	0.022
	4	0.015	0.013
	5	0.015	0.026
	6	0.015	0.018
	7	0.022	0.022
	8	0.019	0.021
	9	0.017	0.021
	10	0.025	0.030
	11	0.023	0.021
	12	0.020	0.015
	13	0.009	0.018
	14	0.030	0.031
	15	0.022	0.019
Failed	16	-0.012	-0.020
	17	0.015	0.015
	18	0.015	0.012
	19	0.012	0.020
	20	-0.001	-0.004
	21	0.009	0.009
	22	-0.012	-0.025
	23	0.007	0.009
	24	0.028	0.013
	25	0.004	0.009
	26	0.023	0.018
	27	-0.037	-0.034
	28	0.015	0.020
	29	-0.001	0.006
	30	-0.022	-0.024

Analysis was made about the distribution of Z score for both failed and non-failed groups. Classification accuracy of the model will change depending on the cut-off point. The balance of Type I error cost and Type II error cost should be considered. By rearranging the actual scores in ascending order, as show in Appendix-2, it is evident that 0.016 is the most approximate cut-off point for the new model. Thus, any enterprise with a score greater than 0.016 is classified as having a profile similar to continuing entities and those with a score less than 0.016 as having characteristics similar to entities which experienced serious problems.

The lower cut-off point indicates that the revised model is probably less reliable than Altman's Z-Score Model. The efficiency with which the new model accurately predicts failure relative to Altman's is 0.78 percent  $\left[ \frac{0.016}{2.065} \right]$ . This result correlates with the very low discriminant coefficients of the independent variables and is in some way related to contextual differences in applying models. But this low efficiency doesn't imply that the new model is of no use. As all developers of prediction models warn that the model should be considered as just another tool of the user and that it is not intended to replace experienced and informed personal evaluation. Perhaps the best use of this model is as a filter to identify companies requiring further review or to establish a trend for a company over a number of years.

In the paragraphs that follow the accuracy of the new model is examined two years and one year prior to the failure event given a 0.016 cut-off point. The whole exercise is based on inputs from Appendix-2.

### Results Two Years Prior to the Failure Event

Table 4.8 lists both the classification and validation results of the new model *two years* prior to the failure event.

**Table 4.8: Classification Results Two Years Prior to the Failure Event**

#### The New Model

$$(Z = 0.0165X_1 + 0.0229X_2 + 0.0344X_3 + 0.0068X_4 + 0.0032X_5)$$

Actual Group Membership	No. of Enterprises	Predicted Group Membership		Percent Error
		Failed	Non-failed	
Failed	15 (100.0%)	13 (87.0%)	2 (13.0%)	13.0%
Non-failed	15 (100.0%)	4 (27.0%)	11 (73.0%)	27.0%
Overall	30			20.0%

Of the 30 enterprises in the overall sample, 6 are misclassified, yielding an overall accuracy of 80 percent. The Type I error (that of classifying a failed enterprise as a non-failed entity) was 13 percent (two out-of fifteen misclassified) and the Type II error (that of classifying a non-failed enterprise) was slightly higher at 27 percent (four of fifteen).

### Results One Year Prior to the Failure Event

Table 4.9 lists both the classification and validation results of the new model *one year* prior to the failure event.

**Table 4.8: Classification Results One Year Prior to the Failure Event****The New Model**

$$(Z = 0.0165X_1 + 0.0229X_2 + 0.0344X_3 + 0.0068X_4 + 0.0032X_5)$$

Actual Group Membership	No. of Enterprises	Predicted Group Membership		Percent Error
		Failed	Non-failed	
Failed	15 (100.0%)	12 (80.0%)	3 (20.0%)	20.0%
Non-failed	15 (100.0%)	2 (13.0%)	13 (87.0%)	13.0%
Overall	30			17.0%

Of the 30 enterprises in the overall sample, 5 are misclassified, yielding an overall accuracy of 83 percent. The Type I error (that of classifying a failed enterprise as a non-failed entity) was 20 percent (three out-of fifteen misclassified) and the Type II error (that of classifying a non-failed enterprise) was slightly higher at 13 percent (two of fifteen).

In summary, the new model developed for the Ethiopian context correctly classifies 83 percent of the enterprises one year prior to financial failure and as much as 80 percent two years prior. These results are quite impressive since they indicate that published financial data, when correctly interpreted and rigorously analyzed, does indeed provide important information. Even more impressive results could be obtained by increasing the sample size and employing more rigorous validation testing techniques.

## CHAPTER FIVE

### CONCLUSION

The results of this study, combining published data and rigorous statistical techniques, are quite promising. Altman's Z-Score Model successfully classified 80 percent of the enterprises one year prior to failure and as much as 70 percent two years prior. The new model developed for the Ethiopia context yielded an accuracy of approximately 83 percent based on data from one reporting period prior to the failure event and almost 80 percent accuracy as much as two years prior, given a revised cut-off point.

In applying prediction models there has to be a considerable emphasis on contextual differences. The models are developed by utilizing data from enterprises operating in different economic conditions. Thus, in transferring or replicating a model due consideration should be given to these changes in economic conditions, the type and size of enterprises to be considered, and the strength of the explanatory or independent variables. Additionally, the relative accuracy of the models may change over time. The accuracy of any model may decline as we go far behind the failure event. This is observed in Altman's Z-Score Model and the model replicated in this study.

The implications and applications of models designed for assessing the potential for financial failure are many. This is true especially in a developing country, like Ethiopia, where an epidemic of business failures could have drastic effects on the economy as a whole. If a model, such as the one developed in this study, is used to identify potential problems, then in many cases preventive or rehabilitative action can be taken. This

involves a conscious internal effort, by the enterprises themselves, to prevent critical situation as soon as a potential problem is detected. Besides internal efforts, a program of financial and managerial assistance by interested stakeholders is a potential outcome.

It should also be noted that unqualified application of failure prediction models could cause some problems. Obviously, if a firm demonstrates a profile similar to past failed entities and the model is used by all or most of the organizations providing credit to firms, the prediction exercise will become a self-fulfilling insight. While some firms cease operations due to qualitative inefficiency, one may advocate the potential of such prognostications to help rebuild and restructure a temporarily flustering operation.

From the standpoint of financial institutions, which are probably the first potential users of models such as the one developed in this study, a better allocation of their scarce resources for loan evaluation and loan review is advocated. A check on internal problem screening procedures seems to be an appropriate application.

Finally, it is important to mention that the topics of the applicability of financial failure prediction models and testing their accuracy are surely worthy of continued study. These topics have been under-researched in the Ethiopian context and it is the belief of the researcher that further study of these topics would yield new and interesting results.

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# APPENDICES

**APPENDIX-1**  
**X<sub>I</sub> Values for Each Enterprise**

Year	Enterprise Code	Non-failed					Enterprise Code	Failed				
		X <sub>1</sub>	X <sub>2</sub>	X <sub>3</sub>	X <sub>4</sub>	X <sub>5</sub>		X <sub>1</sub>	X <sub>2</sub>	X <sub>3</sub>	X <sub>4</sub>	X <sub>5</sub>
1994	1	0.527	0.021	0.309	2.159	1.453	16	-0.310	-0.283	-0.097	0.161	0.627
	2	0.495	-0.012	0.040	3.456	0.432	17	0.818	-0.041	0.039	0.054	0.077
	3	0.086	0.102	0.311	0.137	1.431	18	0.167	0.017	0.129	0.444	1.433
	4	-0.034	0.024	0.270	0.248	1.272	19	-0.070	0.017	0.187	0.502	1.053
	5	-0.053	0.022	0.233	0.471	1.349	20	-0.083	-0.108	0.035	0.122	0.388
	6	0.060	0.034	0.275	0.076	1.025	21	0.143	0.010	0.070	0.222	0.810
	7	0.037	0.079	0.383	0.197	1.597	22	-0.485	-0.158	-0.064	0.178	0.188
	8	0.279	0.045	0.256	0.327	0.801	23	0.067	0.003	0.043	0.224	0.760
	9	0.006	0.060	0.282	0.385	1.085	24	0.008	0.111	0.554	0.240	1.388
	10	0.231	0.368	0.083	1.015	0.789	25	-0.151	-0.028	0.018	0.675	0.644
	11	0.596	0.023	0.243	0.209	0.778	26	0.396	0.008	0.116	1.288	1.046
	12	0.305	0.154	0.182	0.448	0.600	27	-0.602	-0.620	-0.341	-0.255	0.219
	13	0.346	-0.070	0.103	-0.025	0.378	28	-0.085	0.129	0.170	0.226	1.955
	14	0.096	0.139	0.505	0.415	1.610	29	-0.271	-0.118	0.084	0.069	0.909
	15	0.198	0.113	0.294	0.369	1.092	30	-0.518	-0.363	-0.201	0.014	0.564
1995	1	0.331	0.042	0.456	1.192	1.618	16	-0.434	-0.498	-0.085	-0.062	0.718
	2	0.493	0.009	0.077	2.979	0.666	17	0.839	-0.028	0.041	0.065	0.071
	3	0.059	0.146	0.247	0.201	2.484	18	0.257	0.019	0.061	0.294	1.108
	4	-0.015	0.041	0.213	0.165	1.357	19	0.009	0.038	0.284	0.436	1.828
	5	0.064	0.041	0.385	0.429	2.531	20	-0.144	-0.182	0.006	0.064	0.524
	6	0.030	0.086	0.323	0.130	1.248	21	0.083	0.022	0.089	0.204	0.957
	7	0.083	0.107	0.346	0.214	1.393	22	-0.765	-0.430	-0.069	-0.094	0.183
	8	0.307	0.077	0.264	0.403	0.842	23	0.012	0.015	0.124	0.217	0.831
	9	0.060	0.104	0.338	0.458	1.019	24	0.007	0.101	0.143	0.192	1.513
	10	0.277	0.382	0.152	1.199	1.033	25	-0.053	0.002	0.076	0.721	0.838
	11	0.625	0.051	0.163	0.252	0.628	26	0.310	0.011	0.128	0.825	0.834
	12	0.294	0.156	0.087	0.435	0.282	27	-0.755	-0.716	-0.116	-0.323	0.279
	13	0.453	0.002	0.226	0.051	0.779	28	-0.027	0.162	0.226	0.281	2.328
	14	0.151	0.191	0.481	0.424	1.414	29	-0.230	-0.109	0.176	0.088	1.646
	15	0.202	0.082	0.204	0.398	1.139	30	-0.648	-0.546	-0.101	-0.124	1.234

**N.B:** In order to preserve confidentiality, the names of enterprises are not given in this table. Instead a code is given to each enterprise for easier identification. Codes 1 to 15 represent non-failed enterprises and Codes 16 to 30 represent failed enterprises.