Empirical Tests on Financial Failure Prediction Models
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Abstract

This study aims to empirically testing the effectiveness of financial failure prediction models on forecasting the failure of public shareholding companies. This test will be conducted on a sample of Jordan’s public shareholding companies listed at ASE. Empirical test results will help investors and others concerned to in visualize the ability of shareholding companies for continuation. To realize this objective, the financial statements of a selected sample of companies listed on ASE have been analyzed and the proposed models’ factors have been calculated; the sample included five companies that have been bankrupted and other successful five. The models were: Altman and Sherrod models. Financial statements of afore mentioned companies were analyzed through these models. Study revealed that both models consider mismanagement is the main element in the emergence of imbalance in liquidity, weakness in financial structure, and low profitability of companies been studied. Also, empirical test results revealed that Altman model is able to predict the success or failure of the subject sample. This model was found suitable for the industrial and services sectors, Sherrod model, on the other hand was able to significantly predict the success and failure of services companies, but it gave unreliable values for the industrial sector. The study concludes that Altman model is a reliable financial predictor for all sectors of the public shareholding companies. Also study concluded that Sherrod model was not a reliable predictor for industrial shareholding companies. In general, test results showed a suitability of some financial ratios in both proposed models, but there was no conclusive ability of either model to predict any financial failure of public shareholding companies with a high degree of accuracy, this is probably due to external factors and circumstances.

Key Words: Financial Failure, Altman Test, Sherrod Test, Amman Stock Exchange

Introduction

Companies undergo through various stages which are almost similar to those experienced by humans. Companies usually start by the initiation stage in which the company determines its legal status, this stage is followed by the growth stage where the company starts to grow and people begin to recognize it through its product or service. Then the stage of maturity, which is the highest outstanding stage where the company is recognized by most people's who knowledge its products; and thus significantly increases its sales and achieves high profits. And then company starts to decline or retreat, where its sales begin to decline and unless it initiates new products this decline will lead to bankrupt. Company’s life times usually vary which the company spend s in these stages. However, some companies may shift from deterioration to growth again. One of the most significant threats for many businesses today, despite their size and nature of their operations, is insolvency (Rees, 1995). A company that fails to fulfil its obligations, and especially to repay its debts, may then face a critical situation that, in the worst cases, leads to its failure. Bankruptcy prediction is becoming increasingly important in corporate governance. Global economies have become cautious of the risk involved in corporate liability, especially
after the collapse of giant organizations like WorldCom and Enron. There have been several reviews of this literature on predicting corporate bankruptcy—but those are now either out-of-date (Altman, 1984; Jones, 1987) or too narrowly focused. All the above mentioned researchers focused exclusively on statistical models while others like Jones (1987) and Zopounidis (1996) do not give full coverage of theoretical models. Hu, Z, and Indro (1999) restrict their review to empirical applications of neutral network models while Crouhy, Galai and Mark (2000) cover only the important theoretic current credit risk models. This paper explores empirically two models relating to failure prediction for public shareholding companies listed at ASE-Jordan. This research investigates whether some models are better at differentiating defaulting and non-defaulting firms than others (the "performance" or "power" of models), the extent to which different failure prediction models may yield significantly different rankings for the same firm and the extent of gains that can be realized from combining the predictions of multiple models.

**Literature Review:**

**Financial failure** is the rule rather than the exception in entrepreneurial ventures. Even in well-established businesses the occurrence thereof is alarming. A multitude of reasons for financial failure exist. Sometimes these factors are beyond the reach of management, but most of the times they could have been foreseen and prevented (Venter, W, 2008). The financial failure of a company can have a devastating effect on the all seven users of financial statements i.e.: present and potential investors, customers, creditors, employees, lenders, general public. As a result, users of financial statements are usually interested in predicting on whether a company will fail, and when it will fail. Users of financial statements can predict the financial position of an organization using the Altman Z score, Sherrod, or Argenti models and by looking at the financial statements. Megginson & Smart defined business failure as the unfortunate circumstance of a firm's inability to stay in the business. Business failure occurs when the total liabilities exceeds the total assets of a company. (Megginson & Smart (2006, p.898, para3).

The ability to predict the financial failure of a firm is crucial for both investors and creditors who wish to ensure that they will be reimbursed on time. For this reason, many banks have developed models to assess the risk associated with their loans or their receivables. These models allow them to decide whether to lend money and on what terms, but also to assess the interest rate depending on the anticipated risk of non-reimbursement (E.I. Altman, 1968). The factors that lead businesses to failure vary. Many economists attribute this phenomenon to high interest rates, recession squeezed profits and heavy debt burdens. Furthermore, industry-specific characteristics, such as government regulation and the nature of operations can contribute to a firm’s financial distress. Studies of patterns of business failure in countries such as UK, US, Canada and Australia found that small, private and newly-founded companies with ineffective control procedures and poor cash flow planning are more vulnerable to financial distress than large well established public firms (Rees, W., 1995).

**Organizational Decline and Turnaround Theory:** organizational decline and turnaround management generally indicate two main research approaches:

1-Content approach that focuses on examining various factors related to organizational decline and turnaround on the basis of cross-sectional statistical analysis of data collected from a number of organizations (Khandwalla, 2001).
2-Process approach which focuses on analyzing the processes within the context of a company in relation to organizational decline and turnaround. In other words, it is a narration of how a sequence of events unfolds to cause a dependent variable to respond to an independent variable (Van de Ven and Huber, 1990). Chowdhury suggests that it is the process through which turnaround strategies are implemented, not the content per se, that explains the difference between successful and unsuccessful turnarounds (Chowdhury, 2002). Therefore, both content and process approaches are linked to each other and are equally important for a good theory.

A financial scoring model is a tool for financial analysis, designed to predict the likelihood of a firm failing based upon an analysis of data determined to have some statistical relationship with failure. It is best understood by examining how it is constructed. Usually two groups of data are compiled, one for a set of failed firms and one for a set of no failed, or healthy, firms. A set of variables is selected which are suspected of predicting failure, are descriptive of a firm’s financial condition or (as is usually the case) some combination of both. Data is collected for those variables for each of the firms in the two sets. A statistical technique designed to discriminate between groups of data - in our case, failed firms versus non-failed firms - is selected and applied to the data, creating a model or equation. When data for a firm is entered into the model, the output of the model will indicate whether or not the firm is expected to fail or remain healthy. Failure is argued as the most critical element of business culture. Theorists view firms as heterogeneous bundles of idiosyncratic, hard-to-imitate resources and capabilities (Conner, 1991); Amit and Schoemaker define resources as “stocks of available factors that are owned or controlled by the firm, Capabilities are “information-based, tangible or intangible processes that are firm-specific and are developed over time through complex interactions among the firm’s resources (Amit and Schoemaker, 1993.)

To predict the event of failure, one must ask what failure is. Definitions previously applied in the private sector have included: negative working capital, court supervised reorganization and protection from creditors (bankruptcy), private asset and financial restructuring, bond interest default, preferred stock dividend default, and complete liquidation. With respect to bankruptcy, what is known is that firms file for reasons of insolvency, reorganization, or even to avoid labor disputes; they enter voluntarily or involuntarily. Claimholders who influence the business to file for bankruptcy protection include equity holders, bond holders, banks or other lending institutions, and trade creditors. These influences are normally asymmetrical and claimholders will behave in such a manner as to maximize their own outcome, if necessary at the expense of the others. Firms are at the greatest risk of failure when they are young and small. Beyond an early peak in mortality rates, often described as the liability of adolescence.

Causes of failure and characteristics of failed firms:
Dickerson and Khawaja studied the failure of firms from 1946-1965 on the basis of economic cycles, regions, industries, age of firms, and size of firms. They reached the following conclusions regarding the causes of failure and characteristics of failed firms:

1- Failure rates vary roughly in accordance with business cycles;
2- Failure rates vary among lines of business with the retailing sector showing the highest failure rate;
3- Firm life expectancy increased with age; that is, the longer a firm is in existence, the longer it is expected to remain in existence;
4- Firm size and failure rate are inversely related;
Managers with any prior experience running a business were more likely to have their businesses survive than first-time managers;

The more capital invested and the higher the equity-to-debt ratio, the lower the failure rate;

The failure rate is inversely proportional to the age of the manager;

Management teams were more successful than single managers (Dickerson and Kawaja, 1967).

Corporate financial failure prediction is of critical importance for decision making of managers, investors and shareholders. It is widely recognized that a main cause of financial failure is poor management, and that business operation efficiency is a good reflection of a firm's management. Failure prediction models are defined as models that assign a probability of failure or a credit score to firms over a given time horizon. The development of the Basel II framework has stimulated vendors to offer such models to banks opting to use the internal ratings-based approach for calculating their regulatory capital requirements. Indeed, one of the inputs that banks adopting the internal ratings based approach must provide is an estimate of the probability of default (PD). Failure prediction alternatively, as a basis for development and benchmarking of their internal rating systems. While there exists a large academic literature on failure prediction models; much less is known about failure prediction models offered by vendors (Balcaen and Ooghe, 2006).

Bankruptcy prediction models:

There are many different approaches towards bankruptcy prediction:

A- Altman (1968):

The first to use Multiple Discriminant Analysis (MDA) methodology, to predict failure. Altman set out to combine a number of ratios and developed an insolvency prediction model the Z-Score model. This formula was developed for public manufacturing firms and eliminate all firms with assets less than $1 million. This original model was not intended for small, nonmanufacturing, or non-public companies, yet many credit granters today still use the original Z score for all types of customers. Two further prediction models were formulated by Altman. Model ‘A’ z-score was developed for use with private manufacturing companies. The weighting of the various ratios is different for this model as well as the overall predictability scoring. In addition, while the original score used the market value of equity to calculate the equity to debt formula, model ‘A’ used shareholder’s equity on the balance sheet. Model ‘B’ was developed for private general firms and included the service sector. In this statistical model, the ratio of sales to total assets is not used, the weighting on this model is different.

In its initial test, the Altman Z-Score was found to be 72% accurate in predicting bankruptcy two years prior to the event, with a Type II error (false positives) of 6%. In a series of subsequent tests covering three different time periods over the next 31 years (up until 1999), the model was found to be approximately 80-90% accurate in predicting bankruptcy one year prior to the event, with a Type II error (classifying the firm as bankrupt when it does not go bankrupt) of approximately 15-20% (Altman, 1968). (From about 1985 onwards, the Z-scores gained wide acceptance by auditors, management accountants, courts, and database systems used for loan evaluation (Eidleman, 2003).
Altman's 1968 model took the following form:

\[ Z = 0.012X_1 + 0.014X_2 + 0.33X_3 + 0.006X_4 + X_5 \]

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.

The higher the value \( Z \), it refers to the integrity of the financial position of the company, while a low value implies the possibility of financial failure. Under this model, companies can be classified into three categories according to their ability to continue, and these categories are:

- **Class A**: companies are able to continue, if the value of the \( Z \) (3.0) and bigger.
- **Class B**: companies at risk of financial failure, which could potentially bankrupt, if the value of the \( Z \) (1.81) and less.
- **Class C**: companies that is difficult to give a firm decision on them and that assessor needs to detailed study, when the value of \( Z \) is greater than (1.81), and less than (3.0) is called gray area. Using the above Z-score Altman used a cut-off Z-score of 2.675 resulting in 6% and 3% type I and type II error respectively for sample firms a year prior to failure. An attempt to predict bankruptcy two years in advance, increase the type I and type II errors to 28% and 6% respectively.

**B-Sherrod’s Failure Prediction Model**

One of the most modern models to predict financial failure, this model depends on the six independent financial indicators, in addition to the relative weights of discrimination function coefficients given for these variables, according to the following formula:

\[ Z = 17X_1 + 9X_2 + 3.5X_3 + 20X_4 + 1.2X_5 + 0.10X_6 \]

**WHEREAS**
- \( X_1 \): Working capital to total assets.
- \( X_2 \): cash assets to total assets.
- \( X_3 \): total shareholders' equity to total assets.
- \( X_4 \): earnings before interest and taxes to total assets.
- \( X_5 \): total assets to total liabilities.
- \( X_6 \): total shareholders' equity to tangible fixed assets.

Based on the number of points (Z scores), companies have been given five categories according to their ability to continue, and these categories are:

<table>
<thead>
<tr>
<th>Category</th>
<th>Risk Degree</th>
<th>( Z )</th>
</tr>
</thead>
<tbody>
<tr>
<td>First</td>
<td>company is not exposed to the risk of bankruptcy</td>
<td>( Z &gt; 25 )</td>
</tr>
<tr>
<td>Second</td>
<td>Little likelihood of exposure to the risk of bankruptcy</td>
<td>( 25 \geq Z &gt; 5 )</td>
</tr>
<tr>
<td>Third</td>
<td>Difficult to predict the risk of bankruptcy</td>
<td>( 20 \geq Z &gt; 5 )</td>
</tr>
<tr>
<td>Fourth</td>
<td>The Company is exposed to the risk of bankruptcy</td>
<td>( 5 \geq Z &gt; -5 )</td>
</tr>
<tr>
<td>Fifth</td>
<td>The Company is exposed significantly to the risk of bankruptcy</td>
<td>( Z \leq 5 )</td>
</tr>
</tbody>
</table>
Problem of the study:
Due to the widespread failure in many public shareholding companies around the world, and the commensurate negative return effects on national economies. Due to the lack of studies to predict failure facing public shareholding corporate, this study is designed to investigate the capability of both aforementioned models to answer the following questions:
- Is Altman model capable to predict the financial failure of public shareholding companies listed in Amman Stock Exchange?
- Is Sherrod’s model capable to predict the financial failure of public shareholding companies listed in Amman Stock Exchange?
- Which of these two models can predict the financial failure with high accuracy?

Study Objectives:
The main objective of this study is to investigate the feasibility of Altman and Sherrod’s models in predicting the financial failure of Jordanian public shareholding companies. To achieve this objective, researchers will use a sample of ten public shareholding companies listed in ASE, five companies are of high degree of success and the other five companies are failures.

Research Hypotheses:
To achieve the objectives of the study, the following hypotheses have been formulated:

H01: Altman model is not a financial predictor for the public shareholding companies listed in ASE.
H02: Sherrod’s model is not a financial predictor for the public shareholding companies listed in ASE.
H03: Neither Altman nor Sherrod models are good predictors of financial failure of the public shareholding companies listed in ASE with a high degree of accuracy

Previous studies:
Neophytou.E., et al developed a failure classification model for UK public industrial companies using logit analysis and Neural Networks. They used a dataset consists of 51 matched-pairs of failed and non failed UK public industrial firms over the period 1988-1997. Research results indicated that a parsimonious model that includes three financial variables, a profitability, an operating cash-flow and a financial leverage variable can yield an overall correct classification accuracy of 83% one year prior to failure (Neophytou.E., et al, 2000). Robert O.E., tested the usefulness of financial ratio analysis for predicting small business failure. His research has indicated that analysis of selected ratios is useful for predicting failure of medium and large asset-size firms. However, these and previous studies have largely ignored small businesses because of the difficulty of obtaining data (Robert O.E., 1972). Jardin, P and Everin, E., aimed to show how a Kohonen map can be used to increase the forecasting horizon of a financial failure model. Indeed, most prediction models fail to forecast accurately the occurrence of failure beyond one year, and their accuracy tends to fall as the prediction horizon recedes. So we propose a new way of using a Kohonen map to improve model reliability. Our results demonstrate that the generalization error achieved with a Kohonen map remains stable over the period studied, unlike that of
other methods, such as discriminant analysis, logistic regression, neural networks and survival analysis, traditionally used for this kind of task (Jardin, P and Everin, E., 2011). Pompe and Bilderbeek have compared the performance of models using financial ratios measured over one year, with other models using ratios measured over several consecutive years, and have analyzed their performance by forecasting horizons of between one and seven years (Pompe, P and Bilderbeek, A., 2005). Appiah, K. examined the phenomenon of bankruptcy prediction for a developing economy using the Altman Z-score model. Drawing on empirical data from a sample of 15 non-failed and failed companies listed in Ghana Stock Exchange, researcher used Altman (1968) model via a cross section of different firms with dataset within 2004 to 2005. Since the literature on corporate failure in African contexts is rather parsimonious, this study makes an important contribution to the global discourse on corporate failure prediction in an increasingly globalised world (Appiah, K., 2011). Apea, C. & Jemime Sezibera, J., explained why banks fail in general, and why Ghana Co-operative Bank Ltd (Co-op) in particular, failed. Many nations have experienced bank failures with very high costs which can lead to systemic risks. The causes of bank failure are numerous, in theory and include regulation of banking activities such as forbearance; asymmetric information leading to a moral hazard problem and connected lending. Continued study of the various causes of banking instability is needed. The thesis extends that area of study with a case study of an African bank which failed, Co-op, a Ghanaian bank, is used to test the theories on some causes of bank failure. Empirical evidence, using Co-op’s financial statements is tested against theory. Competitive theories on causes of bank failure are also used in the analysis (Apea, C. & Jemime Sezibera, J., 2002). Ali, S. studied the causes of financial distress for Islamic banks? To what extent these are unique or similar to those identified for the conventional banks? What lessons can be learned by the stakeholders of Islamic banking from the episodes of financial distress? These and other related questions were important academic and policy concerns for Islamic banking. The banking and financial crisis of 2000-2001 in Turkey provided a natural experiment to gauge the stability of Islamic banks and to analyze the channels and factors that can contribute to the their financial distress during a crisis. His paper utilized this natural experiment by studying the factors that led to the closure of one Islamic finance house in Turkey during which more than twenty conventional banks collapsed. The study drew some lessons for Islamic banks, their regulators, and other stakeholders in such institutions (Ali, S., 2007). Ooghe, H. and Prijcker, S. sought to gain a deeper insight into the failure process of a company, giving it a more grounded understanding of the relationship between the characteristics of a company, the underlying causes of failure and the financial effects. Researchers observed four types of failure processes: the failure process of unsuccessful start-ups, the failure process of ambitious growth companies, the failure process of dazzled growth companies, and the failure process of apathetic established companies. Based on their findings, researchers recommend that stakeholders of a company can have a clearer view of both the time dimension inherent in corporate failure and the impact of their own actions on bankruptcy (Ooghe, H. and Prijcker, S., 2008). Mitchell, J. and Van Roy, P. have addressed a number of comparative issues relating to the failure of prediction models for small, private firms. They used two models provided by vendors, a model developed by the National Bank of Belgium, and the Altman Z-score model to investigate model power, the extent of disagreement between models in the ranking of firms, and the design of internal rating systems. They also examined the potential gains from combining the output of multiple models. Researchers found that the power of these models in
predicting bankruptcies is very good at the one-year horizon, even though not all of the models were developed using bankruptcy data and the models use different statistical methodologies. Disagreements in firm rankings are nevertheless significant across models, and model choice will have an impact on loan pricing and origination decisions. They found that it was possible to realize important gains from combining models with similar power. Also, they showed that it can also be beneficial to combine a weaker model with a stronger one if disagreements across models with respect to failing firms are high enough (Mitchel, J and Van Roy, P, 2007). In their paper, Gerantonis et al conducted analyses on whether Altman Z-score models, can predict correctly company failures. The empirical analysis examines all listed in the Athens Exchange companies, during the period 2002-2008 and discontinuations of operation for these companies during the same period. It is investigated whether Z-score models can predict bankruptcies for a period up to three years earlier. Our study shows that Altman model performs well in predicting failures. This is in line with other findings. The empirical results are interesting since they can be used by company management for financing decisions, by regulatory authorities and by portfolio managers in stock selection (Gerantonis, N. et al, 2009). Mateos-Ronco, A. and López Mas,A Have develops a statistical business failure prediction model specifically for cooperative societies and identifies the most powerful predictive agricultural cooperatives with financial indicators as explanatory variables. The prediction models obtained variables. This is done by applying logistic regression to a sample of Spanish, capable of predicting failures one or two years before they actually happen, reached an accuracy level of more than 94%. The best predictors confirmed the importance to cooperatives of having a minimum amount of capital available to ensure their financial independence, which could be put at risk by virtue of the cooperative principle of “voluntary and open membership”, especially when financial problems appear on the horizon. The importance of the results-based indicators was also shown, which could be considered as obvious, given that the objectives of cooperative societies is to obtain the greatest possible advantage from the activities carried out for their members (Mateos-Ronco, A. and López Mas,A, 2011).

**Methodology of the study:**
The study has adopted the applied research method which aims to empirically test two financial failure models. The study follows the case study approach using financial data of ten shareholding companies listed on Jordan’s ASE files. The researchers have used a purposeful sample which was selected to get the information from specific sectors to provide information and to get rich and accurate information on the status of stock companies.

**Framework for the study:**
Practical application of the proposed models on the financial data of the ASE companies and using Altman and Sherrod models in the analyses.

- Jordanian companies are divided into two sections:

A - Successful companies, namely:
  - Paper and cardboard factories in Jordan.
  - Mediterranean Tourism Investment.
  - Jordanian Duty Free Shops.
  - Jordan Press Foundation / Alrai
  - International Brokerage and Financial Markets.
B - Companies declared bankruptcy, namely:

- Trust International Transport.
- Investments and integrated industries.
- Investment Advisory Group.
- Canadian Pharmaceutical Industries.
- United for regulated road transport.

These companies were selected to represent different sectors in Jordan’s ASE and financial statements for the years 2010/2011 were used for the purposes of this study.

Analysis of the results:

From Table -1, Altman Model data showed Z scores ranging between 1.85 and 19.45 for the highly successful companies; however, Z scores for Paper and Card Company in and International Brokerage and Financial Markets Company in 2011 both fell below the required minimum Z score(+ 2.99). In 2.99 and are failing companies.

Table -2, Altman Z scores for the failing companies ranged between -0.619 and 0.675, which are below were in category one of the successful companies which are not expected to suffer any bankruptcy for the near future, however, Jordan Duty Free Shop Company was considered as a successful company As for Sherrod model results, Table – 3, showed Z scores ranging between 9.575 and 38.65; two in 2010 with Z score 28.38 and had fell into category two in 2011 with Z score 20.52, a situation that contradicts the real status. Table – 4 reflects that all companies had Z scores below 20 and thus were ranked as third category and are difficult to predict their failure and to be bankrupt, and others were in the fourth category(Z was below 5 ) and are exposed to the risk of bankruptcy. Table – 5, shows that Altman's model was able to predict companies' bankruptcy in the second year prior to the bankruptcy by 77%, while Sherrod’s model was able to predict bankruptcy by 69% for the same year. The results of the year that preceded the bankruptcy, an improvement is noted in the predictive ability of Altman's model where the rate reached 94%, compared to predictive ability of Sherrod’s model having a predictive ability at the rate of 77%. These results support the rejection of the first hypothesis which stated that Altman model is not a financial predictor for the public shareholding companies listed in ASE. And the second hypothesis which stated that Sherrod model is unable to predict companies' bankruptcy during the two years prior to liquidation. It is also noted from table 5-3 that the Altman models' predictive ability has significantly improved in the first year prior to bankruptcy where the rate has reached 91%. While the predictive ability of Sherrod’s model has reached 77% only.

However, the average predictive ability of business discontinuation two years prior to bankruptcy were 84% for Altman Model and 73% for Sherrod Model respectively.

CONCLUSIONS:

From these results, researchers concluded that Altman model was a better reflector to screen out success companies from failing ones. As for the companies that entered the circle of bankruptcy, they had exited results that placed non stable companies and announced their liquidation.

It is worth to conclude that there is no sharp judgment ability to a one particular model to predict the financial failure of the shareholding companies at a high degree.
of accuracy, because of differences in the terms and conditions of their failure phenomena and what they might have faced due to external factors.

Recommendations:
1-For any project or investment, Management has to determine the project objectives in a clear and valid form and carry out economic feasibility study of the project before the direct implementation.
2-To study and in-depth the financial matters and conduct relevant financial analysis to find out the feasibility of the project.
3-Develop the capacity of officials concerned in the financial and accounting departments to cope with the relevant international standards.
4-Conduct studies and surveys of the strength of competition of rivals in the market.
5-To seek the assistance of administrative and accounting expertise before taking any administrative and financial decisions for projects.
References


Jardin, P. and Everin, E., 2013, Predicting corporate bankruptcy using a self-organizing map: An empirical study to improve the forecasting horizon of a financial failure model, MPRA Paper No. 44262, posted 14, UTC.


### Table 1
**A1:** The first group – Successful companies: Sherrod model analyses of successful companies

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<tbody>
<tr>
<td>1.2Xₐ</td>
<td>0.157</td>
<td>0.059</td>
<td>0.803</td>
<td>0.783</td>
</tr>
<tr>
<td>1.4Xₐ</td>
<td>0.08</td>
<td>0.068</td>
<td>0.166</td>
<td>0.172</td>
</tr>
<tr>
<td>3.3Xₐ</td>
<td>0.352</td>
<td>0.232</td>
<td>1.047</td>
<td>0.981</td>
</tr>
<tr>
<td>0.6Xₐ</td>
<td>2.85</td>
<td>2.198</td>
<td>10.83</td>
<td>8.139</td>
</tr>
<tr>
<td>0.99Xₐ</td>
<td>0.477</td>
<td>0.375</td>
<td>1.379</td>
<td>1.331</td>
</tr>
<tr>
<td>Altman Z</td>
<td>3.77</td>
<td>2.93</td>
<td>14.23</td>
<td>11.4</td>
</tr>
<tr>
<td>Mk. Val (1000)</td>
<td>225</td>
<td>232.5</td>
<td>325</td>
<td>479.5</td>
</tr>
</tbody>
</table>

### Table 2
**A2:** The first group – Successful companies: Sherrod model analyses of successful companies

<table>
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<tr>
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<tbody>
<tr>
<td>17X₁</td>
<td>2.23</td>
<td>0.842</td>
<td>11.45</td>
<td>11.09</td>
</tr>
<tr>
<td>9X₂</td>
<td>2.62</td>
<td>2.34</td>
<td>6.78</td>
<td>7.25</td>
</tr>
<tr>
<td>3.5X₃</td>
<td>2.4</td>
<td>2.035</td>
<td>3.027</td>
<td>2.804</td>
</tr>
<tr>
<td>20X₄</td>
<td>2.133</td>
<td>1.409</td>
<td>6.348</td>
<td>5.944</td>
</tr>
<tr>
<td>0.1X₆</td>
<td>0.098</td>
<td>0.079</td>
<td>1.056</td>
<td>0.895</td>
</tr>
<tr>
<td>Sherrod Z</td>
<td>13.304</td>
<td>9.575</td>
<td>37.49</td>
<td>34.03</td>
</tr>
</tbody>
</table>

### Table 3
**B1:** The second group: Altman model analyses of bankrupt companies:

| Trust Intern.Tra Invest.&Industr Invest.Advis.Gr Canad.Pharma United Road |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| 1.2X₁           | -0.198          | -0.579          | 0.033           | -0.218          | -0.054          | -0.0914         | -0.132          | -0.241          | -0.261          | -0.311          |
| 1.4X₂           | -0.313          | -1.169          | -0.017          | -0.075          | -0.013          | -0.062          | -0.276          | -0.337          | 0.025           | -0.036          |
| 3.3X₃           | -0.108          | -1.154          | 0.299           | -0.111          | 0.462           | -0.0353         | -0.0647         | 0.129           | 0.0555          | -0.147          |
| 0.6X₄           | -              | -              | 0.18            | -              | -              | 0.005           | 0.252           | 0.244           | 0.287           | 0.450           |
| 0.99X₄          | -0.945          | 0.5010         | 0.522           | 0.853           | 0.465           |
| Altman Z        | -0.619          | -0.319          | 0.046           | -0.218          | -0.249          | 0.0559          | 0.316           | 0.522           | 0.675           | 0.084           |
| Mkt.Ca p(1000)  | -              | -              | 440             | -              | -              | 2347.02         | 2347.0          | 1145.9          | 6756.16         |
Table 4 - The second group: Sherrod model analyses of bankrupt companies

<table>
<thead>
<tr>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td>17X1</td>
<td>-2.803</td>
<td>-8.202</td>
<td>0.464</td>
<td>-3.09</td>
<td>0.774</td>
<td>-1.295</td>
<td>-1.866</td>
<td>-3.419</td>
<td>-3.691</td>
<td>-4.41</td>
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<tr>
<td>9X2</td>
<td>0.113</td>
<td>0.999</td>
<td>0.993</td>
<td>1.46</td>
<td>6.123</td>
<td>6.556</td>
<td>1.072</td>
<td>0.991</td>
<td>1.378</td>
<td>1.349</td>
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<tr>
<td>3.5X3</td>
<td>2.547</td>
<td>1.916</td>
<td>2.812</td>
<td>2.047</td>
<td>0.213</td>
<td>-0.0002</td>
<td>1.562</td>
<td>1.535</td>
<td>5.952</td>
<td>5.049</td>
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<tr>
<td>20X4</td>
<td>0.0006</td>
<td>7.077</td>
<td>1.815</td>
<td>-0.671</td>
<td>-2.805</td>
<td>-0.215</td>
<td>0.392</td>
<td>0.078</td>
<td>0.336</td>
<td>-0.848</td>
</tr>
<tr>
<td>0.1X6</td>
<td>0.087</td>
<td>0.039</td>
<td>0.121</td>
<td>0.111</td>
<td>0.037</td>
<td>-0.0005</td>
<td>0.0633</td>
<td>0.0623</td>
<td>0.085</td>
<td>0.074</td>
</tr>
</tbody>
</table>

Table 5 - Comparative results of Altman and Sherrod models in terms of bankruptcy predictive ability two years prior to the bankruptcy incident

<table>
<thead>
<tr>
<th>Statement</th>
<th>Altman Model</th>
<th>Sherrod Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predictive ability of business discontinuation two years prior to bankruptcy</td>
<td>12</td>
<td>77%</td>
</tr>
<tr>
<td>Predictive ability of business discontinuation one year prior to bankruptcy</td>
<td>15</td>
<td>91%</td>
</tr>
<tr>
<td>Average predictive ability of business discontinuation two years prior to bankruptcy</td>
<td>--</td>
<td>84%</td>
</tr>
</tbody>
</table>

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