PREDICTING FINANCIAL FAILURE: AN EMPIRICAL INVESTGATION ON JORDANIAN INDUSTRIAL AND SERVICE COMPANIES

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ABSTRACT

From year to year, strong attention has been paid to the study of the problems of predicting firms' bankruptcy. Bankruptcy prediction is an essential issue in finance especially in emerging economics. Predicting future financial situations of individual corporate entities is even more significant. Regression analysis is used to develop a prediction model on 22 bankrupt and non-bankrupt Jordanian public listed companies for the period 2000 until 2003. The results show that working capital to total assets, current asset to current liabilities, market value of equity to book value of debt, retained earnings to total asset, and sales to total asset are significant and good indicators of the probability of bankruptcy in Jordan.

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LIST OF ABBREVIATIONS

AID	Agency for International Development
ARM	Adjustable Rate Mortgages
CA / CL	Current Assets / Current Liabilities
C / CL	Cash / Current Liabilities
CFFO	Cash Flow from Operations
CPA	Conditional Probability Analysis
EBIT / I	Earnings before Interest and Tax / Interest
EBIT / TA	Earnings before Interest and Tax / Total Assets
EU	European Union
FCM	Failing Company Model
FDI	Foreign Direct Investment
GDP	General Domestic Product
IMF	International Monetary Fund
JD	Jordanian Dinar
MDA	Multiple Discriminant Analysis
MVE / BVOD	Market Value Equity / Book Value of Total Debt
NI / S	Net Income / Sales
NI / TA	Net Income / Total Assets
RE / TA	Retained Earnings / Total assets
S / TA	Sales / Total Assets
TA / TE	Total Assets / Total Equity
TD / TE	Total Debt / Total Equity

US$	United States Dollar
WC / TA	Working Capital / Total Assets

Chapter 1

Background

1.0 Introduction

A business core aim is to generate profit and by extension, maximization of wealth. In the course of operations, however, a firm might experience financial problems caused by both internal and external environmental factors. These financial factors lead to what we refer to as financial distress.

The failure or bankruptcy of financially distressed companies often results in significant direct and indirect costs to many stakeholders; including shareholders, managers, employees, lenders and clients. Significant cost reductions through failure prevention may arise if financially distressed companies are identified well before failure and estimates then made of their survival probability for a given time frame.

Banks, in operation, have many departments and one of their most important departments is that of credit-risk management because this department makes profits by granting loans. The credit-risk management department needs to make decisions on whether or not they could give loans to their customers. This department normally operates on important procedures based on certain criteria that have been systematized, for example, the extent of customers' credit worthiness prior to getting loans. It is obvious that supporting evidence of credit worthiness will ensure customers' future repayment of loans and therefore critically influence the final decision of the management department. Complete information derived from customers' financial statements plus the banks own instruments for determining the customers' financial solvency are thus indispensable. The customers' financial statements provide objective primary data upon which banks can truly make a creditable judgment and sound evaluation of the customers' financial status. It is for this simple reason that financial statements represent banks' principal requirement in most, if not all, of bank loan applications.

A credit risk analysis is used on consumer credit application and loan. Credit risk is uncertainty in obtaining the return from investing in account receivable. Banks invest in account receivable when they allow the consumer credit who are clearly good, and reject the bad customers very quickly.

In examining this study, insights are derived from previous research studies relating to subjects on risks of bank loans particularly those containing information on certain classification systems. Examples of these studies are those undertaken by Altman (1973, 1984), Frydman, Altman and Kao (1985), Li and Kai (2002), and Shumway (2001).

According to Broecker (1990) banks often have to determine the credit worthiness, i.e. the ability to repay the loan, of their customers'ex-ante. He presented a model where this problem is treated as a binomial decision problem; the bank is able to generate an informative signal about the ability to repay before it has to make its decision. This signal helps to assign the applicants to two risk classes: the high risks versus the low risks.

These researchers examined the worthiness at firm levels focusing, in particular, on the use of financial ratios and mathematical models. They assert that the financial ratios are capable of forecasting risks involved in giving loans irrespective of whether they are classified as high, medium or low risk loans prior. They find that the banks use financial ratios as indices to determine the respective strengths and/or weaknesses of the loan applicants.

According to Mihail, Cetina, Orzan (2006), credit risk is an important issue for any risk manager in the financial and regulation institutions because the largest part of capital from commercial banks is actually utilized for investments schemes that involved credit risks. Moreover, it is this very lucrative investment sector that experienced the intense pressure from the competition between the various rival financial institutions on the market. Such competition obviously has a role to play in determining the degree in the reduction of credit limits.

These credit risk analyses are constrained by limited or incomplete information on default probabilities and have so far not been incorporated into formal bank capital requirements. A basic premise of credit risk modeling is that credit risk managed in the portfolio of holding context and that portfolio is backed with sufficient capital. Portfolio management of credit risk requires knowing the default correlation, both of which are difficult to determine. Data are limited because there are a lot of credits which are not tradable, and model parameters often cannot be estimated and must be preset. However, increasing securitizations of credit allows a market-based risk factor such as credit spreads to be used (Brau, 2004).

It is a fact that banks today do not provide home loans quite as readily because of the sub-prime loans devastating effect. The sub-prime loan crisis began in the United States in 2006 and became a global crisis in July 2007. Subprime loans were created with the realization that a lot of money could be made out of borrowers who could not get conventional loans due to their poor credit history. The story began when banks initiated cheap short term credit for subprime borrowers a few years ago. The huge demands for these loans aroused the mispricing of risk and made it possible for anyone to buy a house, even with little money (Agrawal et al.2007).

According to Agrawal et al (2007) the subprime mortgage crisis is actually an ongoing economic problem manifesting itself through liquidity issues in the banking system, and owing to foreclosures which accelerated in the United States in late 2006 and triggered a global financial crisis during 2007 and 2008.

The sub-prime loan crisis began with the bursting of the US housing bubble and high default rates on "subprime" and other adjustable rate mortgages (ARM) made to higher-risk borrowers with lower income or lesser credit history than "prime" borrowers. Loan incentives and a long-term trend of rising housing prices encouraged borrowers to assume mortgages, believing they would be able to refinance at more favorable terms later. However, once housing prices started to drop moderately in 2006-2007 in many parts of the U.S., refinancing became more difficult. Defaults and foreclosure activity increased dramatically as ARM interest rates reset higher. The mortgage lenders who retained credit risk (the risk of payment default) were the first to be affected, as borrowers became unable or unwilling to make payments. Major banks and other financial institutions around the world reported losses.

The credit crunch crisis which led to the current financial crisis and subsequently global economic crisis motivates this current study because it is obvious from the failure of the US financial institutions that they had not been adequately stringent in giving out the housing loans to customers.

The goal of this study is therefore to analyze credit risk of companies. For this purpose a sample of industrial and service sector in Jordan have chosen for the designated period of (2000 - 2003). Altman model as known as Z-score, is applied on Jordanian companies to determine if they can repay the loan to bank. To date there has been only one study investigating firms' failure in Jordan, that is by (Zeitun et al. , 2007). This current investigation attempts to also look at troubled companies in Jordan. Their result shows that the cash flow variables, as measured by cash flow divided by total debt seems to be correlated to corporate failure. And the free cash flow variable, as measured by returned earnings divided by total assets, has a positive and significant impact on corporate failure in the sample, which that means, it increases the probability of default. The liquidity ratio measured by working capital divided by total assets and current assets divided by current liabilities, seems not to be related to corporate failure in Jordan since it was insignificant in the sample.

1.1 Overview of Economy in Jordan [1]

Jordan is a small Arab country with insufficient supplies of water and other natural resources such as oil and coal. Until the 1950s the economy was underwritten mostly by Britain, and in 1967 foreign aid still represented 60 percent of government revenues. The most important event for the Jordanian economy since the end of the World War II was the quadrupling of world oil prices in October 1973. Although Jordan has nearly no oil itself, it became inextricably linked to other economies in the region. Between 1973 and 1981 the Arab budget (the sum of all Arab governments' budgets) rose more than 16 fold, from US$71.8 million to US$1.179 billion, and during the same period.

Jordanian exports rose almost 13 fold from US$57.6 million to US$734.9 million. In addition, Jordan sent many doctors, scientists, engineers, construction workers, and teachers to the Persian Gulf. These wealthy professionals sent home remittances of more than $US1 billion between 1973 and 1981. Even after deducting the dinars flowing out of the country from the 125,000 foreigners working in unskilled jobs, the net remittances rose from US$15 million in 1970 to US$900 million in 1981. During this oil boom, Jordan's annual real GDP growth averaged 10 percent.

This rapid economic growth combined with the increase in oil prices also caused prices and import bills to rise. When world oil prices crashed in the early 1980s, reductions in both Arab aid and worker remittances slowed real economic growth to an

[1] http://www.nationsencyclopedia.com/economies/Asia-and-the-Pacific/Jordan-OVERVIEW-OF-ECONOMY.html

average of roughly 2 percent per year. Imports (mainly oil, capital goods, consumer durables, and food) outstripped exports with the difference mostly covered by aid and borrowing. The Jordanian government was immediately forced to downsize the public sector, stop construction projects, and cut subsidies.

In mid 1989 the Jordanian government embarked upon debt rescheduling discussions and agreed to accept an International Monetary Fund (IMF) structural adjustment program, a lending program designed to correct economies problems. Such programs usually involve devaluing the currency, reducing government spending, lowering the budget deficit, and implementing broad structural reforms. The Gulf War crisis, which began in August 1990, however, aggravated Jordan's already serious economic problems, forcing the government to shelve the IMF program, stop most debt payments, and suspend rescheduling negotiations. Aid from Gulf Arab states, worker remittances, and trade all contracted while refugees flooded into the country, producing serious balance of payments problems. Jordan had to increase its imports, which pushed the trade imbalance further into deficit. This action stunted GDP growth and strained government resources.

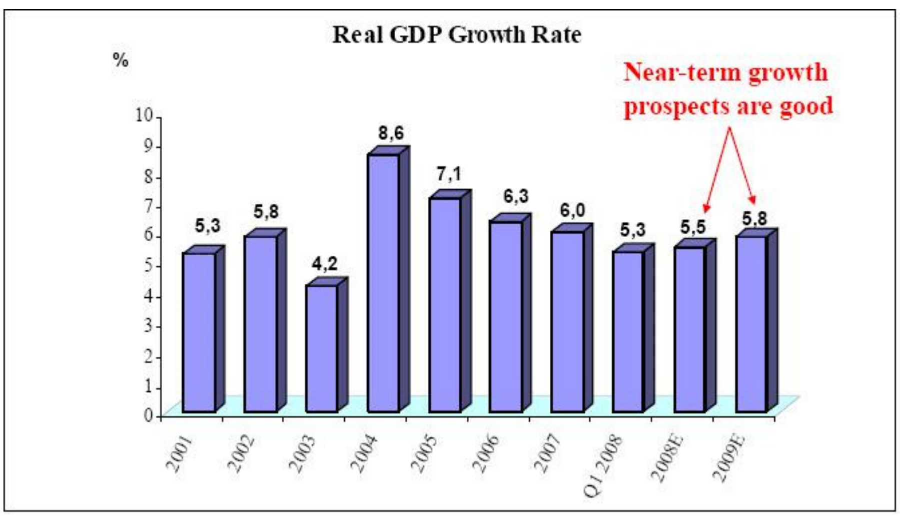
The economy of Jordan rebounded in 1992, largely due to the influx of capital repatriated by workers returning from the Gulf, but the recovery was uneven throughout 1994 and 1995. Jordanian government is currently implementing a reform program adopted in 1992 and continues to secure rescheduling and write-offs of its heavy foreign debt, which amounted to US$8.4billion in 2000. A new IMF package was approved in April 1999 that entitled Jordan to funds worth US$174million over 3 years. The U.S. Agency for International Development (USAID) agreed to an economic assistance program for Jordan in 1999 that amounted to $150 million. However, debt, poverty, and unemployment (which stood officially at 15.5 percent in 1999) remain Jordan's biggest ongoing problems**.**

1.2 Jordanian Economic Performance and Prospects for 2008 and 2009[2]

Despite high oil prices and ongoing instability in the region Jordanian economy continues to perform reasonably well, due to these improvements:

1. The economy was able to achieve an average of 6% growth in real GDP over the last seven years, 5.3% in the first quarter of 2008. Figure 1 illustrates how the economy was able to achieve the average.

Figure 1.1: Real GDP Growth Rate



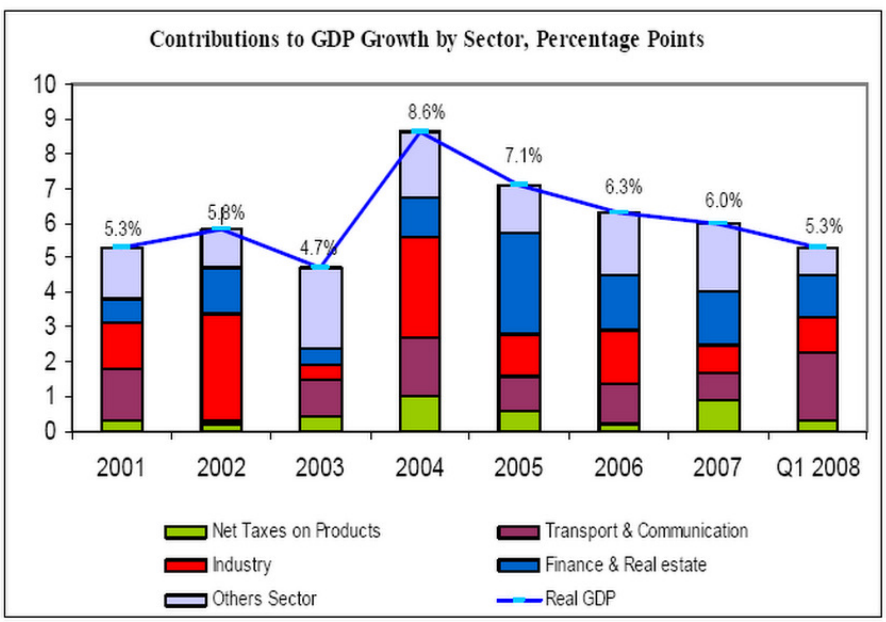
Source: according to Toukan, 2008

[2] Toukan., (2008). Jordanian Economic Performance and Prospects for 2008 and 2009, Governor of the Central Bank of Jordan

Figure 1.1 shows that Jordanian GDP growth has improved noticeably, reaching its peak of 8.6% in financial year 2004 when the instability in the middle east region - due to the gulf war- has been of benefit to the Jordan economic growth. 3 years after, the consequential effects started to diminish again due to the stability of political situations that started to drive the GDP back again to its original ratios until it reached its average of 5.3% in 2008, so, excluding instability that started early in 2003, the GDP is still between 5.3% and 5.8%. This GDP growth can be considered as highly sensitive and responsive towards the middle-eastern political measures.

2. GDP growth was driven mainly by transport and communication, industry, finance and real-estate sectors.

Figure 1.2: Contribution to GDP Growth by Sector, Percentage



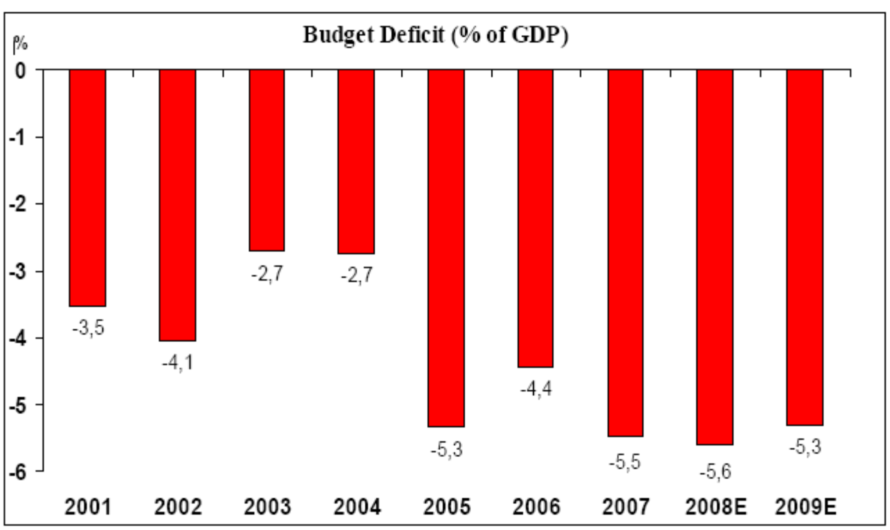
Source: according to Toukan, 2008

Figure 1.2 shows demonstrate the ratios of contributions that mostly determine the growth of the Jordanian GDP. It shows clearly that industry sector represents the main actor that had the major effect particularly in the years 2002 and 2004 because of the enormous external reserve capitals supplied and invested in industry which caused the net taxes on products to be raised. Accordingly, the successful investment on industrial production improved much investment on transportation sector, with finance and real estate as the second main contributors. Other minor sectors had slight effect on the GDP.

Fiscal Performance:

The fiscal deficit has widened, with sharply higher oil and food “compensatory” and “direct” subsidies. As a result, the deficit increased in 2007 to JD615 million (5.5 % of GDP) from JD 443 million (4.4 % of GDP) in 2006. The deficit is projected to narrow gradually over the next couple of years. Figure 1.3 shows the fiscal performance.

Figure 1.3: Budget Deficit (% of GDP)

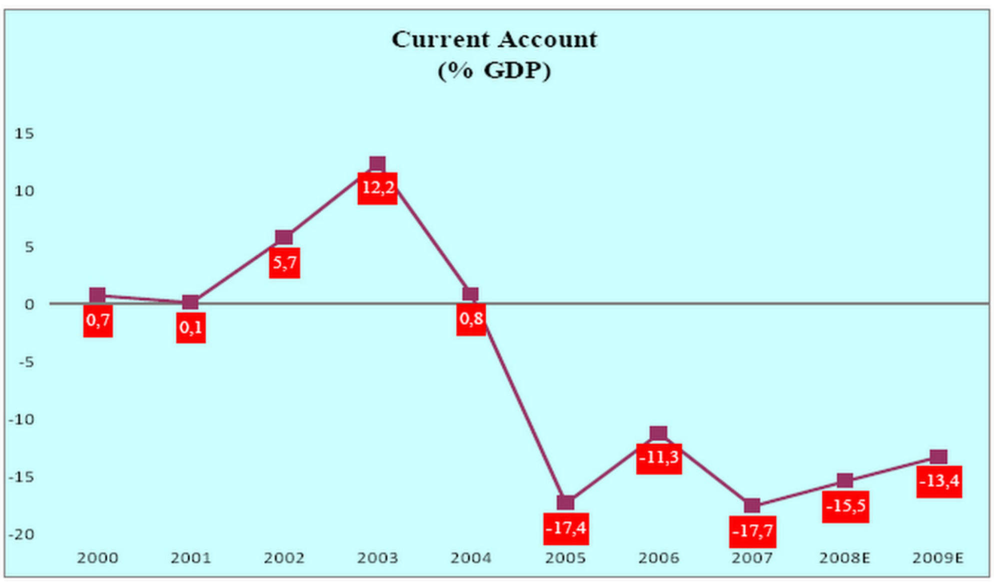


Source: according to Toukan, 2008

Current Account Performance:

Although the current account deficit has widened to 17.7 % of GDP in 2007, a significant increase in foreign direct investment (FDI) inflows has financed the deficit. High oil prices and strong growth in capital imports suggest that the current account deficit will remain uncomfortably large at around 13.4 % of GDP over the next couple of years. However, financing difficulties are not expected to emerge due to anticipated inflows of FDI. Figure 1.4 illustrates about the current account performance.

Figure 1.4: Current account performances (% GDP)



Source: according to Toukan, 2008

1.3 Research Issues and Problems

Since banks are naturally conscious about their financial standing, they often have to determine the credit worthiness of their customers. For this reason, risk analysts are regarded as the most important staff members in the credit facilities department of any bank everywhere in the world (Kim, 2003). Based on the risk classification, a competent officer is expected to be able to identify accurately the level of the risk category to any loan application. In addition she/he must be able to:

- Determine the loan interest rate
- Determine the kind of collateral suitable for the risks carried by the bank's loan
- Predict financial distress that can cause bankruptcy of the firms
- Discover factors contributing to/revealing the credit risk of firms to recognize the risks carried by the loans (Kim, 2003).

Therefore there is a need to resort to department staff to get information on the customer's financial information for the purpose of granting loans by using the appropriate traditional financial analysis upon the ratio of each financial basis. This analysis is able to give the impression whether financial situation of the company is good or bad. If these ratios give bad impression of a company's financial performance, then banks might not give out the loans at all. However, banks often face problems having to determine whether a firm that applies for a loan will later be able to repay its debt or not.

In this research, we attempt to examine a set of financial ratios that influence the worthiness of companies applying for bank loans. With this kind of analysis credit risk officer will be able to recognize the proper ratios to determine the borrower's financial situation and liquidity. The required criteria consist of a group of financial ratios set in one package and when properly applied, the bank officer can get a good, accurate picture of the borrower's financial performance. This will greatly assist the lending bank in deciding whether or not to give any loan to the borrower.

1.4 Research Questions

The purpose of this study is to answer the following questions:

1) Is there any significant relationship between a firm's liquidity ratios and probability of bankruptcy?
2) Is there any significant relationship between a firm's profitability ratios and probability of bankruptcy?
3) Is there any significant relationship between a firm's leverage ratio and probability of bankruptcy?
4) Is there any significant relationship between a firm's solvency ratios and probability of bankruptcy?
5) Is there any significant relationship between a firm's activity ratio and probability of bankruptcy?

1.5 Research Objectives

The main objective of this study is to determine whether among the industrial and service companies in Jordan which have high probability of failure as a result the banks will not grant them the loans.

1.5.1 Specific Objectives

- To identify if liquidity ratios significantly influence the probability of failure.
- To identify if profitability ratios significantly influence the probability of failure.
- To identify if leverage ratio significantly influence the probability of failure.
- To identify if solvency ratios significantly influence the probability of failure.
- To identify if activity ratio profitability significantly influence the probability of failure.

1.6 Significance of Study

This study is designed to help the banks whether should give out bank loans based on the firms' ability to repay the banks i.e. on the firms having lower probability of failure. In addition help the firms in determining its financial position and worthiness, in securing loans from banks. This study is beneficial to investors in making decisions to invest in companies of which their probability of failure has been analyzed by banks.

This study is also designed to benefit banks by helping them to accurately assess the financial status of companies applying for loans from them. It aims to also help them to make justifications of the financial statements given to them by the companies that the banks wish to support financially.

This study is invaluable particularly to help the banks use their time well and also help them to minimize both expense and effort involved in identifying prospective consumers who qualify for the loan. For the bank in question, this implies the availability of a standardized system, method or technique for collecting needed information which will not be forthcoming from the customer.

1.7 Chapter Summary

This chapter discusses the economic condition in Jordan, Jordanian economic performance and prospects for 2008 and 2009, followed by discussion on research issues and problems, research questions, research objective and lastly the significance of this study.

Chapter 2

Literature Review

2.0 Introduction

This chapter discusses ratio analysis methodology and also variables selection followed by empirical evidence of corporate and banks failure. In defining the empirical evidence of corporate failure there will be only one model, the best known bankruptcy prediction model, discussed. In addition, the discussion of this model will be followed by another two models as reference.

2.1 Ratio Analysis Methodology

For a number of years, there was a considerable research by accountants and finance people trying to find a business ratio that would serve as the sole predictor of corporate bankruptcy with research in the corporate failure prediction area being very popular among academics, as well as among practitioners, during the last four decades. William Beaver (1967) conducted a very comprehensive study using a variety of financial ratios. Corporate failure (bankruptcy) problem still persists in modern economies, with significant economic and social implications.

Financial ratios can be applied in many ways. They could be used by managers in any firm in managerial analysis; they also can be used in credit analysis, and by investors in any investment analysis. The financial ratio analysis uses formulas to determine the financial position of the firms compare with the historical data performance. From the balance sheet, the use of financial ratios show that the better idea of the companies' financial position. It is important to note that some ratios will need information from more than one financial statement, such as from the income statement and the balance sheet statement (Figini, 2008).

Ratio analysis is conducted from the perspective of the creditor and equity investors who want to finance a company's investment. To create a center of attention financing for a treatment system, a company must show financial strength both before and, on a projected basis, after the treatment system has been purchased and installed. The ratio analyses undertaken in this section simulate the analyses an investor or creditor would be likely to employ in deciding whether to finance a treatment system or make any other investment in the firm (Altman 1993).

According to Geymueller (2007), in the structure of credit scoring, financial ratios that should be as small as possible would serve as inputs and those ratios that should be as big as possible would serve as outputs. The efficiency of each firm in this situation is equivalent with its credit worthiness relative to the leaders (i.e. the firms with the lowest credit default-risk) in the bank's portfolio.

A common view held by the public is that business entities are incorporated for the sole purpose of profit taking the belief that entity is sustainable indefinitely in the future. Unfortunately not every business works out as planned. One of the most significant threats of many businesses today, despite their size and their nature, is insolvency (Neophytou et al. , 2000). Purnanandam (2004) assumes that apart from the solvent and the insolvent states, a firm faces an intermediate state called financial distress. He defines financial distress as a low cash flow state in which the firm incurs deadweight losses without being insolvent. He again explains that a firm is in financial distress if the assets value falls below some lower threshold during its life.

In general, many approaches of financial distress literature have utilized various statistical methods to predict bankruptcy of firms, with most of these approaches based on financial ratios. A few significant approaches for example are multinomial choice models such as logit and/or probit models (Martin, 1977; Santomero and Vinso, 1997; Ohlson, 1980; Zmijewski, 1984), multiple discriminant analysis (Altman, 1968), recursive partitioning (Frydman, Altman and Kao, 2002), neural networks (Altman, Marco and Varetto, 1994), and discrete hazard models (Hillegeist et al., 2004).

Turvey (1991) applied the statistically based models for comparative analyses. These are linear probability, discriminant method, logit and probit models using farm loan observations in Canada. The results show that the model predictive accuracies do not have significant differences among the four approaches. Ziari, Leatham and Turvey (1995) used real loan data to evaluate the risk classification performance of parametric statistical models with nonparametric models. They conclude that two types of models only differ slightly in classifying accuracy.

Splett and Barry (1992) in a survey of 717 agricultural banks find large degree of distribution in the use, implementation and design of lender credit scoring models indicating the lack of efficient data and uniform model for lenders in estimating the creditworthiness of agricultural borrowers.

2.2 Variables Selection

Balance sheet and income statement data were collected for the firms selected. As large number of variables found to be significant indicators of corporate problems in past studies, a list of 22 potentially helpful variables (ratios) are compiled for evaluation. Grice and Ingram (2001) stated that Altman compiled a list of 22 financial ratios and classified each into one of five categories liquidity, profitability, leverage, solvency, and activity. The ratios were not selected on a theoretical basis, but rather, on the basis of their popularity in the literature and Altman's belief about their potential relevancy to bankruptcy.

2.2.1 Liquidity Ratio

The liquidity and size characteristics are explicitly considered. Altman (1993) explained the logic behind this ratio as a firm experiencing consistent operating losses will have shrinking current assets in relation to total assets. This ratio was the most valuable from the three liquidity ratios evaluated. Other two liquidity ratios tested were the current ratio and the quick ratio.

As discussed by Chuvakhin & Gertmenian (2003) a firm with a negative working capital is very likely to experience problems meeting its short-term obligations. Conversely, a firm with a significantly positive working capital rarely has problems paying its bills.

2.2.2 Profitability Ratio

Blum (1974) consisted of 115 firms that failed from 1954 to 1968 with a minimum of $1 million in liabilities at the time of failure, matching with 115 non failed firms on the basis of industry, size, and year. He postulated a general framework for variable selection based upon the concept of a business firm as a reservoir of financial resources with the probability of failure expressed in terms of expected cash flows. By constructing Failing Company Model (FCM), Blum selected 12 variables to measure the cash flow parameters with three common factors underlying the cash flow framework; liquidity, profitability, and variability.

Nam and Jinn (2000) applied the logit likelihood estimator as a statistical technique for a sample of 46 non-financial listed firms from a variety of industries. They studied the predictive model of business failure using the sample of listed companies that went bankrupt over the period from 1997 to 1998, when a deep recession driven by International Monetary Fund sanctions started in Korea. The measure of firm's ability of serving short-term 48 debts, interest expenses to sales and account receivables turnover ratio are variables that comprise the prediction model.

2.2.3 Leverage Ratio

Lin and Piesse (2004) used 32 UK companies from industrial sector for the period 1985 to 1994. They find that a conditional probability analysis (CPA) model is more superior to multivariate discriminat analysis model (MDA). Consistent with previous studies, profitability and liquidity are major factors that can differentiate failed and non failed firms. This finding is consistent with Charitou et, al (2004) finding.

They used 51 matched pairs of failed and healthy UK industrial firms over the period 1988 to 1997. Three variables which are a cash flow, profitability and leverage can classify failure firms.

Routledge and Gadenne (2000) used 20 reorganized and 20 liquidate companies in a sample in Australia by using logistic regression. They find that reorganization decision is more likely to arise if companies have low leverage, higher shareholder equity and more likely rather than to enter liquidation. Reorganization companies are more successful if they are more profitable, are highly levered.

2.2.4 Solvency Ratio

According to Ohlson (1980), Zavgren (1985), Platt and Platt (1994), that the ratios that related with solvency of the firms have a good indicator for the financial distress. Their results show that high values on solvency ratios indicate severe indebtedness, in which case the firms have to generate more income to meet their obligations and repay their debt.

2.2.5 Activity Ratio

Shumway (2001) did a study and the results suggest that the financially distressed companies have lower profitability, bigger size and more highly leverage than active companies. For the sample in this study, liquidity ratios, activity ratios and company age have never been found statistically significant in the model. The insignificance of age implies that there appears to be little duration dependence in financial distress probability.

Chancharat et al (2002) used financially distressed companies in Australia during 1989-2005 using the Cox proportional hazards model. Four main categories of financial ratios; profitability, liquidity, leverage and activity are used as the indicators of financial distress.

2.3 Empirical Evidence of Bankruptcy

2.3.1 Multiple Discriminant Analysis (MDA)

The Altman's Z-score, initially developed in the late of 1960 for industrialized firms, is a multiple discriminant analysis (MDA) which is used to assess bankruptcy. Over the years, the Altman's model has shown acceptance among financial institutions. Altman's Z-score model has added up to of financial ratios at the same time to arrive at a single number to predict and estimate the overall financial health of particular firms. The advantage of the Altman's Z-score model over traditional ratio analysis is its' simulations financial consideration of liquidity, asset management, debt management, profitability, and market value. It addresses an understanding on a series of financial ratios when some financial ratios look good and other look bad (Altman 1993).

Altman (1968) collected data from 33 failed firms and 33 matching firms, during the period 1946 to 1965. To find the discriminating variables for bankruptcy prediction, Altman evaluated 22 potentially significant variables of the 66 firms using multiple discriminat analysis on five variables.

Many researchers have undertaken the development of MDA model over many years. They include Altman (1968, 1980), Marais (1979), Taffler (1982, 1984), Koh and Killough (1990) and Shirata (1998). Beaver (1966) was among the first to attempt forecasting corporate failure Beaver's approach was 'univariate' in that each ratio was evaluated in terms of how it alone could be used to predict failure without consideration of other ratios.

Beaver's univariate analysis led the way to a multivariate analysis by Edward Altman, who used multiple discriminat analysis (MDA) in his effort to find a bankruptcy prediction model. He chose 33 publicly-traded manufacturing bankrupt firms between 1946 and 1965 and matched them to 33 firms on a random basis for a stratified sample (assets and industry). The results of the MDA exercise generated an equation called the Z-score that acceptably classified 94% of the bankrupt companies and 97% of the non-bankrupt companies one year prior to bankruptcy. These percentages dropped when trying to predict bankruptcy two or more years before it occurred. Some ratios used in the Altman model are working capital over total assets, retained earnings over total assets, earnings before interest and taxes over total assets, market value of equity over book value of total liabilities, and sales over total assets (Altman, 1968). The Z-score model has been extended to include privately-held companies (Z' model) and privately-held non-manufacturing firms (Z'' model) (Chuvakhin & Gertmenian, 2003).

Altman (1977) used the multiple discriminate analyses by applying Zeta model to identify bankruptcy risk of corporations. He examined twenty-seven ratios, but the final discriminate function contained only seven ratios. The Zeta model is quite exact up to five years before failure, with successful classification of well over 90% one year before failure, and 70% up to five years before failure.

Piesse and Wood (1992) used the MDA model by examining the independent sample of 261 companies using tests of both ex-post and ex-ante approaches. This study shows ex-post criterion yielded a high rate of classification. In addition, they find that one year before the bankruptcy the data set showed for each one correct failure classification. For Altman model there were 20 incorrect classifications and for Taffler model there were 22 incorrect classifications. But under ex-ante criterion, there was a much higher rate of classification.

Non-metric discriminant analysis is superior to linear discriminat analysis in predicting bankruptcy and bond ratings. Furthermore, cash flow measures have no information content beyond accrual earnings in predicting corporate failure. Information content is defined as the accountability of the data to predict corporate failure and corporate bond ratings. However, accrual earnings have information content over and above cash flow measurements. On the other hand, neither cash flow measures nor accrual earnings improve substantially the classification accuracy of bond ratings (El Shamy et al. 1989).

Regarding the use of cash flows to predict corporate bankruptcy, the common view is that cash flow information does not contain any significant incremental information over the accrual accounting information to discriminate between bankrupt and non bankrupt companies (Watson, 1996).

Viscione (1985) argues that cash flow from operations (CFFO) could be misleading because of management's manipulation of the timing of cash flows, such as not paying bills on time or reducing inventory below desired levels. These maneuvers increase the measure of cash flows from operations reported in the income statement. Such an increase is probably not a good sign, and these distortions arise most often from companies experiencing financial distress. On the other hand, there is the opinion that CFFO has not been properly measured, that some researchers did not validate their model that cash flows and accrual data are highly correlated in the earlier days, and that incomplete information does not allow for study replication. These reasons and additional evidence are used to contest the present state of mind regarding the significance and predictive ability of cash flows for financially distressed companies (Sharma, 2001).

2.3.2 Logit Model

Logit analysis uses a set of accounting variables to predict the probability of borrower default, assuming that the probability of default is logistically distributed i.e., the cumulative probability of default takes a logistic functional form and is, by definition, constrained to fall between 0 and 1.

Ohlsan (1980) is the first one who applied the logit analysis on the problem of bankruptcy prediction. The sample in his study was discriminated between bankruptcy firms and non-bankruptcy firms; he used 105 bankruptcy firms and 2085 non-bankruptcy firms. He also is the first one who applied a representative sample.

Logit model does not have the same assumption as MDA Mohamed et al. (2001) compares between MDA model and logit model in the prediction of bankruptcy. The sample in this study is 26 distressed companies and 79 non-distressed companies. Using MDA model debt ratio and total assets turnover are found to be significant in predicting bankruptcy. The logit model predicted 80.7% of the companies and in the estimation sample, and 74.4% in the hold out sample. The MDA model on the other hand predicted 81.1% of the companies in the estimation sample and 75.4% in hold out sample.

Lawrence et al. (1992) used the logit model to predict the probability of default on mobile home loans. They found that payment history is by far the most important predictor of default.

Jagtiani (2000) used logit model to analyze financial data from U.S commercial banks with total assets between \$300million and \$1billion, collected from the call Report of Income and condition year-end 1988, 1989, and 1990 using logit model analysis and trait recognition analysis (TRA) model. He considered an early stage of financial distress to occur when the ratio of total equity/ total assets fell below 5.5% which was an initial regulatory threshold capital adequacy purposes during the sample period. Findings showed that bank pending capital deficiency in the near future is much different from other banks in terms of their financial health. Next, bank with higher proportion of assets investing in investment securities have a greater cushion against bad lending decision and, consequently, are less likely to encounter financial distress. They also find that the variables of short term interest rate gap and loans/ total deposits are not important in TRA analysis and tend to also be insignificant in the logit analysis.

Adiana et al. (2008) examine the prediction of corporate failure in Malaysia using MDA, Logit, and Hazard models. In a sample of 52 distressed and non-distressed companies with a holdout sample of 20 companies, matched based on industry and size. They find that logit model could correctly predict corporate failure better than the other models. The logit model predicts 82.7 % of the estimation sample and 80% of the holdout sample.

Zulkarnain et al (2001) did a study on forecasting corporate failure in Malaysian industrial sector firms. They used 24 distressed and non-distressed companies over the period 1980 – 1996; these companies were matched based on the industry, failure year, assets size, and age since incorporation. They found that total liabilities divided by total assets, sales divided by current assets, cash divided by current liabilities, and market value divided by debt were statistically important in determining and forecasting corporate failure in Malaysia.

2.3.2 Hazard Model

The hazard rate (the term was first used by Barlow, 1963) is defined as the probability per time unit from a case that has survived to the beginning of the respective interval will fail in that interval. Specifically, it is computed as the number of failures per time units in the respective interval, divided by the average number of surviving cases at the mid-point of the interval.

Bennett and Loucks (1996) proposed a model to determine whether political influence affects the length of time from initial undercapitalization until ultimate bank failure. Large number of highly technical researches used the survival function and proportional hazards models which developed recently. On the other hand, Lane et al. (1989) and Whalen (1991) find and propose empirically the application of a Cox Proportional Hazards model to predict bank failure.

Wheelock and Wilson (1999) applied proportional hazard model during the 1910-1928 period on a sample of 259 state chartered Kansas banks. They find that coefficient on the ratio of equity / assets is negative and highly significant, implying that banks with low net worth have fewer cushions against losses. Loans / Total assets are insignificant. The authors find that there is no evidence that loan portfolio concentration affects the likelihood of failure. Empirically, the significant negative coefficient on size suggests that larger banks are less prone to failure, perhaps because they are generally better diversified or possibly because regulators devote more resources to avoiding the failure of larger banks.

Hazak and Mannasoo (2007) presented a warning of company failure by employing micro and macro variables within a framework of survival analysis using a sample of 0.4 million companies from the European Union (EU). The sensitivity of the results was checked using two complementary event definitions-bankruptcy and negative equity. The results show that the baseline hazard of a default is a U-shaped function of the time the company has survived. The ratio of leverage and return on assets a high leverage and a low return on assets appear to be strong predictors of the bank-failure.

2.5 Summary

This chapter reviews the literature on the status of corporate failures of firms in countries that have been analyzed to see their state of financial condition. The analyses are carried out by applying several different models which provide a sufficient understanding of the context within which the issues studied and analyzed. The discussion provides an important research framework for this study in terms of the variables to be included and the method of analysis to be utilized

Chapter 3

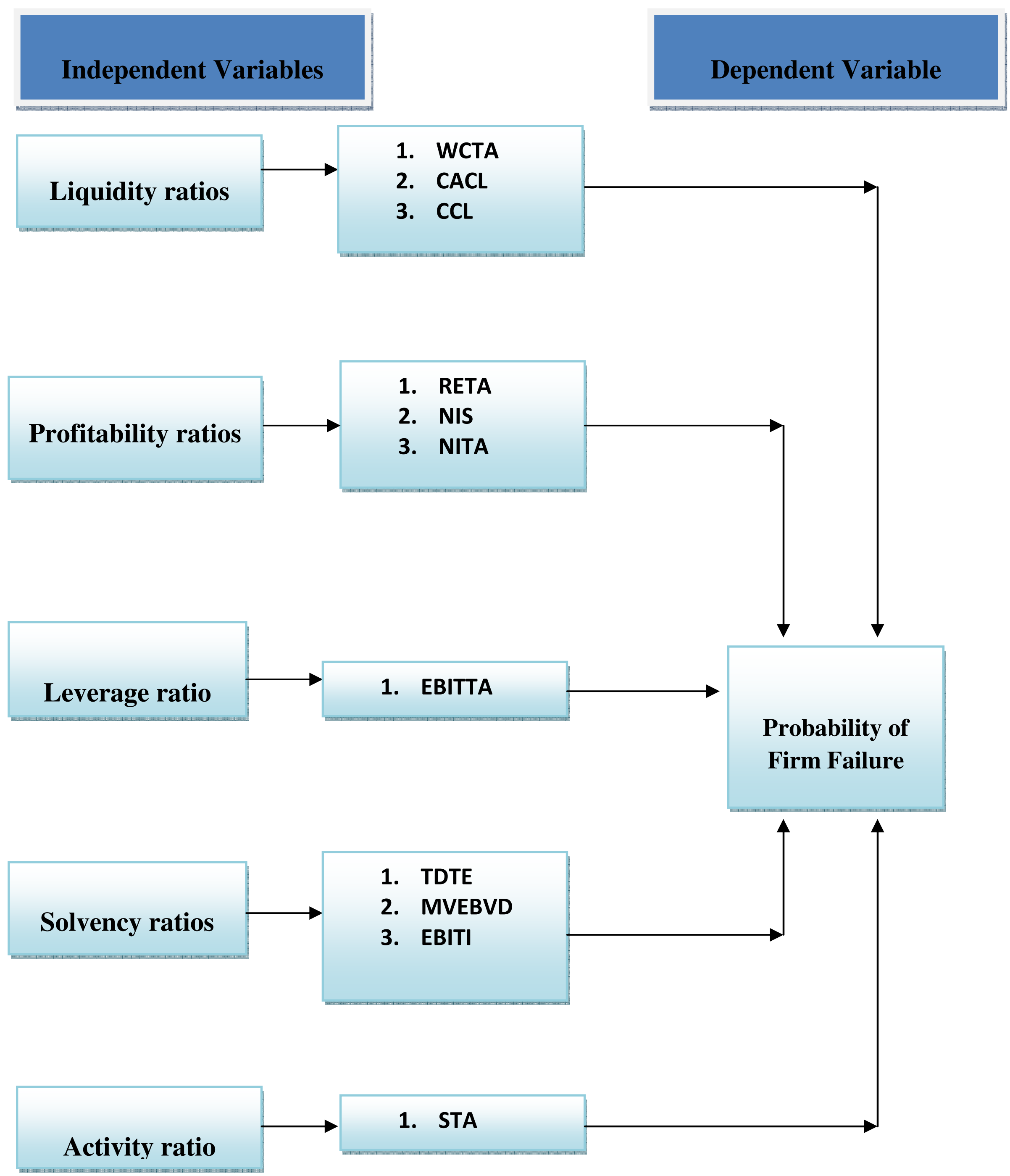
Methodology

3.0 Introduction

This chapter explains the research method that is used to achieve the research objectives which are stated in chapter one. This chapter has four sections; the first section discusses the theoretical framework which includes the dependant variable and independent variables. The second section discusses the hypotheses, followed by the third section which discusses about data collection, and the last section will discuss the model that is used in this study.

The prediction of companies' bankruptcy is used as an expounding case. A group of financial and economic ratios is investigated in a bankruptcy prediction context wherein a logit statistical methodology is employed. Martin (1977) used both logit and discriminat analysis to predict bank failures in the terms of identifying failures / non-failures. West (1985) used the logit model (along with factor analysis) to measure the financial condition and to assign to them a probability of being a problem bank. Platt (1994) applied the logit model to test whether industry-related accounting ratios are better predictors of corporate bankruptcy compared to simple firm specific accounting ratios.

Figure 3.1: Study Framework



The above framework shows the contact between the descriptive variables in failure risk. Each of the variables will be discussed further in the following section**.** Altman (1968) recommend the following parameters in his model: working capital divided by total assets; retained earnings divided by the total assets, earnings before interest and taxes divided by total assets, market value equity divided by book value of total debt, and sales divided by total assets. These ratios are chosen because of several reasons. A total asset is related to the size of the firms and provides an indication of the firm's size. It is frequently used as a normalizing factor. Working capital shows the ability of the firm to pay short-term obligations. Return earnings refer to the net income and is important because it gives an idea on how competitive a company is. Too low a decrease in return earnings may be an indicator for the loss of competitive edge.

In the 1968 study, Altman used the first sample to obtain the coefficient of his Z-score model. When the Z-score was applied, the accuracy of predicting bankruptcy for the firms was very high. The results show that about 95% of the total sample was predicted correctly. He classifies the companies in two parts: Type 1 classifies companies as non-bankrupt, while Type 2 classifies companies as bankrupt.

3.1 Hypothesis Development and Variable Selection Criteria

Financial literature has identified a number of variables as significant indicators of corporate failure. The choice of factors and hypothesis formulation in this study is thus motivated by both theoretical and empirical consideration. Related variables are selected to determine the financial condition of the companies with the debt obligation and distress condition. To test whether the sign and significance of the coefficients reject the hypothesis or not, an appropriate statistical model is selected.

3.1.1 Liquidity Ratios

A firm with a negative working capital is very likely to experience problems meeting its short-term obligations. Conversely, a firm with a significantly positive working capital rarely has problems paying its bills Chuvakhin & Gertmenian (2003).

Firms need liquidity to cover its short-term obligations. This ratio is found in studies in corporate problems. Net working capital to total assets, ratio defined as the net current assets of a company and expressed as a percentage of its total assets, means the difference between current assets and current liabilities. Generally, firms experiencing consistent operating losses will reduce the current assets in relative to the total assets. Basically it is the amount of net current assets that a company has to meet current debts and take advantage of purchase discounts and profitable short term investments. The purchase discount is normally available to customers who pay up within a short period of time, thus companies with more money on hand will have an advantage. Liquidity ratio X_1 (Altman, 1968) is in principle, a measure of the net liquid assets relative to the total capitalization. He regards this ratio is as being more important compared to the other two liquidity ratios, current ratio and the quick ratio. Therefore, I hypothesize the following:

H 1: Liquidity ratios are expected to have a significant relationship to the probability of corporate failure.

3.1.2 Profitability Ratios

Retained earnings generally consist of a company's increasing net income less any net losses and dividends declared. This ratio takes into account the age of a corporation. For example, a young company will have a lower ratio as it has less accumulated earnings. Thus, one might say that young firms are discriminated against using this ratio but on a closer look, this is in fact in line with reality. The chances of bankruptcy for a young firm are higher because of the lower accumulated earnings. Companies with net accumulated losses may refer to negative shareholder's equity. A complete report of the retained losses is presented in the statement of retained losses. In general, a firm with a poor profitability and or solvency record may be regarded as a potential bankrupt Altman (2000) and Sloan (1996). Therefore, I hypothesize the following:

H 2: Profitability ratios are expected to have a significant relationship to the probability of corporate failure.

3.1.3 Leverage Ratio

Leverage ratio calculates the real productivity of the firm's assets without consideration of tax and leverage factors. Companies that are highly leveraged may be at higher risk of default if they are unable to make payment on their liabilities or unable to attract external finance. This ratio is calculated by dividing total assets of a firm with its earnings before interest and tax reductions. In essence, it is a measure of the true productivity of the firm's assets, abstracting from any tax or leverage factors. 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 corporate failure. Furthermore, insolvency in bankruptcy sense occurs when the total liabilities exceed a fair valuation of the firm's assets with value determined by the earning power of the assets Hazak and Hazak and Mannasoo (2007). Therefore, I hypothesize the following:

H 3: Leverage ratio is expected to have a significant relationship to the probability of corporate failure.

3.1.4 Solvency Ratios

Equity value is a market based measure of the equity value of the firm. It is also called market capitalization; the value goes to all stockholders of equity. This ratio measures solvency of the firm, which means that the solvency ratio measures the amount of debt and other expenses obligations used in the firm business relative to the amount of owner equity invested in the business. In other word, solvency ratio provides an indication of the business's ability to repay all financial obligations if all assets were sold, as well as an indication of the ability to continue operation as a viable farm business after a financial adversity. Kim (2003) using the Altman Z-score, finds that market value of equity is the most significant ratio than the others in predicting corporate failure.

Solvency ratios are a good indicator for predicting bankruptcy and financial distress, because the solvency ratio measures the amount of debt and the expenses obligations that used in the firm business Ohlson (1980). Therefore, I hypothesize the following:

H 4: Solvency ratios are expected to have a significant relationship to the probability of corporate failure.

3.1.5 Activity Ratio

Activity ratio exhibits the ability of the company to generate sales from its assets. The uniqueness of this ratio is that if it is applied independently to predict bankruptcy, it will be very useless. Only when it is applied in combination of the Z-score model then it becomes very useful. The higher ratio is the more efficiently a company is using its capital. It is a ratio which measures management's capability in dealing with competitive condition. Chancharat et al (2002) find that the activity ratio considers as a good indicator to predict bankruptcy of the firms and it significantly related with firm failure. Therefore, I hypothesize the following:

H 5: Activity ratio is expected to have a significant relationship to the probability of corporate failure.

3.3 Data Collection

The sample used in this study is derived from publicly listed companies on the Amman stock exchange (ASE), over the period 2000-2003. This period has complete data available. For data analyses a clear and consistent definition of failure or bankruptcy is required. While failure is usually defined as a corporation not being able to meet its obligation, different researchers have used different criteria for definition of default. For example, Beaver (1968) used a wider definition of default, which included default on loan and an overdrawn bank account. In the present study, default or bankruptcy for the Jordanian companies is defined as a corporation that is unable to meet its debt obligations, or a company that stopped issuing financial statements for two years or more[3]. For this present study, samples are taken from two sectors (industrial sector and service) for bankrupt and non-bankrupt companies. The final sample consists of 11 bankrupt companies and 11 non-bankrupt companies matched based on the size.

Table 3.1: Summary of Ratios (Independent Variables)

Used in Study

Measurement	Description	Abbreviation	Expected sign
Liquidity ratios	Working capital / Total assets	WC / TA	+
	Current Assets / Current Liabilities	CA / CL	-
	Cash / Current Liabilities	C / CL	-
Profitability ratios	Retained Earnings / Total assets	RE / TA	+
	Net Income / Sales	NI / S	+
	Net Income / Total Assets	NI / TA	-
Leverage ratio	Earnings before Interest and Tax / Total Assets	EBIT / TA	-
Solvency ratios	Total Debt / Total Equity	TD / TE	+
	Market Value Equity / Book Value of Total Debt	MVE / BVOD	+
	Earnings before Interest and Tax / Interest	EBIT / I	+
Activity ratio	Sales / Total Assets	S / TA	-

[3] Amman stock exchange (ASE)

3.4 Model

To analyze the relationship between the probability of companies' failure and explanatory variables, logit model is used in this study. The univariate analysis is used to evaluate the predictive ability of the individual variables, while the multivariate logit analysis is used to find the best combination of explanatory variables for predicting the failure of the Jordanian companies.

Logit is a multivariate statistical method that is used to predict company's failure and is one of the most commonly employed parameter in detecting potential failure risk. The logit model assumes that there is underlying response variable, Z_i, which is defined by the regression relationship. This model of this current study is adopted from Martin (1977), Ohlsan (1980), and Gujarati (1995).It formulates a multiple regression model consisting of a combination of variables, which best distinguished distress and the non-distress firms. This model can be showed as:

$$\boldsymbol{p_i}\, \mathbf{E(Y = 1|\ X1i, X2i \ldots Xk)} = \frac{\mathbf{1}}{\mathbf{1+e^{-zi}}} \qquad (1)$$

Where

p_i = Probability of bankruptcy for firm i

Y = 1 bankruptcy company

E(Y) = cumulative probability function that take value between 0 and 1

And,

$$\mathbf{Z_i = B_0 + B_1\, X_1 + B_2\, X_2 + B_3\, X_3 + B_4\, X_4 + B_5\, X_5 + B_6\, X_6 + B_7\, X_7 + B_8\, X_8 + B_9\, X_9 + B_{10}\, X_{10} + B_{11}\, X_{11}} \qquad (2)$$

Where,

$\mathbf{Z_i}$ = B_0 + B_1 Working capital / Total assets + B_2 Current Assets / Current Liabilities + B_3 Cash / Current Liabilities + B_4 Total Debt / Total Equity + B_5 Market Value Equity / Book Value of Total Debt + B_6 Earnings before Interest and Tax / Interest + B_7 Retained Earnings / Total assets + B_8 Net Income / Sales + B_9 Net Income / Total Assets + B_{10} Sales / Total Assets + B_{11} Earnings before Interest and Tax / Total Assets

Chapter Four

Data Analysis and Finding

4.0 Introduction

In this chapter, the results of this study on the relationship between the explanatory variables in explaining the probability of companies' bankruptcy are discussed. The discussion is segmented into four sections. The first section provides the descriptive analysis of the data and variables for this study, followed by the second section which discusses correlation analysis that demonstrates the strength of relationship between the dependant variable and independent variables. The third section discusses the outcomes of the regression analysis and data analysis that compose the main findings of this study. The last section is the application model.

4.1 Descriptive Analysis

Descriptive analysis describes the response for the major variables studied. The descriptive analysis include mean and standard deviation on the dependant variables and independent variables.. The results of the descriptive analysis are shown in Tables 4.1 and 4.2. In addition are the results of the descriptive analysis for the whole sample of both bankrupt and non-bankrupt companies.

Table 4.1: Descriptive Analysis for the Dependant Variable and Independent Variables (All companies)

Variables	N	Minimum	Maximum	Mean	Std. Deviation
WCTA	88	-3.11	.88	.0271	.63058
CACL	88	.00	465.38	10.2309	50.14974
CCL	88	.00	464.03	7.9335	49.86105
TDTE	88	-4.16	13.19	.6694	2.04458
MVEBVD	88	.00	8082.60	96.5953	861.17076
EBITI	58	-154.41	51.10	-6.6566	25.70101
RETA	88	-4.37	.13	-.4637	.77380
NIS	80	-9.25	14.30	-.3525	2.16354
NITA	88	-.63	.47	-.0638	.14656
STA	88	.00	.83	.2460	.18002
EBITTA	88	-.59	.53	-.0355	.13515
Valid N (listwise)	57				

From the results in Table 4.1, it can be observed that the means for the all variables fall between a minimum -6.6566 and maximum 96.5953. However, there are three of the variables chosen which have higher mean them the rest; two of the variables belong to the liquidity measurement and another one belongs to the solvency measurement. These are MVEBVD (solvency ratio) with a mean of 96.5953 and Liquidity ratios, CACL, with a mean of 10.2309 and CCL with a mean of 7.9335 ratios. This large average, such as the solvency ratio, with the highest mean (96.5953) is as expected since the core functions of companies are firstly and primarily to manage their solvency. Therefore companies which have higher market capitalizations are deemed to be much healthier. On other hand, companies would be in serious financial condition if they lack a sufficiently large market capitalization.

Liquidity ratio is just as important because it measures a company's ability to meet its short term obligations. Generally, a high liquidity ratio (as in the case of the sampled companies with high means) indicate that companies can convert their assets to cash in the short time easily. In other word, companies which have more cash and current assets are seemed to be more liquid. On other hand, companies are in the serious financial trouble if they lack cash and current assets, resulting in it being illiquid, a condition of which, if persists, will make the companies financially distressed.

4.2 Correlation analysis

Correlation analysis is executed to test the strength of relationships between variables. Statistical test at 5% level is used to test the significance of the relationships between the independent variables in this study. It is also used to examine the potential issue of multicollinearity that exists when two explanatory variables are highly correlated. A superior financial distress prediction model should avoid from multicollinearity among explanatory variables, because the information in one variable is already demonstrated by another variables. Table 4.2 shows the correlation matrix among the independent variables.

Table 4.2: Correlation Matrix among the Independent Variables

		WCTA	CACL	CCL	TDTE	MVEBVD	EBITI	RETA	NIS	NITA	STA	EBITTA
	N											
WCTA	Pearson Correlation	1										
	Sig. (2-tailed)											
	N	88										
CACL	Pearson Correlation	.104	1									
	Sig. (2-tailed)	.335										
	N	88	88									
CCL	Pearson Correlation	.079	.996(**)	1								
	Sig. (2-tailed)	.466	.000									
	N	88	88	88								
TDTE	Pearson Correlation	.095	-.061	-.052	1							
	Sig. (2-tailed)	.378	.573	.632								
	N	88	88	88	88							
MVEBVD	Pearson Correlation	-.002	.052	-.018	-.037	1						
	Sig. (2-tailed)	.985	.631	.869	.734							
	N	88	88	88	88	88						
EBITI	Pearson Correlation	-.016	-.011	.293(*)	.242	-.043	1					
	Sig. (2-tailed)	.905	.935	.026	.068	.749						
	N	58	58	58	58	58	58					
RETA	Pearson Correlation	.789(**)	.094	.081	.311(**)	.066	.213	1				
	Sig. (2-tailed)	.000	.381	.451	.003	.538	.109					
	N	88	88	88	88	88	58	88				
NIS	Pearson Correlation	.209	.016	-.007	-.006	.016	.082	.228(*)	1			
	Sig. (2-tailed)	.062	.885	.948	.959	.886	.544	.042				
	N	80	80	80	80	80	57	80	80			
NITA	Pearson Correlation	.415(**)	.056	.048	.007	.048	.188	.527(**)	.585(**)	1		
	Sig. (2-tailed)	.000	.604	.660	.946	.657	.158	.000	.000			
	N	88	88	88	88	88	58	88	80	88		
STA	Pearson Correlation	.117	-.159	-.157	.092	-.147	-.140	-.121	.074	-.165	1	
	Sig. (2-tailed)	.277	.140	.145	.392	.172	.296	.261	.514	.125		
	N	88	88	88	88	88	58	88	80	88	88	
EBITTA	Pearson Correlation	.199	.021	.018	-.023	.029	.261(*)	.346(**)	.597(**)	.963(**)	-.157	1
	Sig. (2-tailed)	.064	.843	.866	.831	.791	.048	.001	.000	.000	.143	
	N	88	88	88	88	88	58	88	80	88	88	88

** Correlation is significant at the 0.001 level (2-tailed)
** Correlation is significant at the 0.001 level (2-tailed

The correlation matrix is a powerful tool for getting a rough idea of the relationship between predictors (Alsaeed, 2005). If Pearson correlation result is higher than 0.7, then there is relation among independent variables (Anderson, Sweeney, and Williams, 1996). As displayed in Table 4.2, the results indicate that except for four correlations (EBITTA and NITA, CCL and CACL, TDTE and CCCL, and RETA and WCTA) all other Pearson correlations between the independent variables are lower than 0.7, generally therefore there is no multicollinearity problem can be seen from Table 4.2 few significant correlations are observed between the independent variables 0.05 level.

4.4 Regression Analysis

4.4.1 Regression Analysis for All Observations

Table 4.3: Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.818[a]	.670	.589	.31733

a. Predictors: (Constant), EBITTA, CACL, TDTE, CCL, STA, EBITI, RETA, NIS, MVEBVD, WCTA, NITA

R square is the relative predictive power of a model and it is a measure between 0 and 1. The closer it is to one, which that means the closer to one is the significant model. In this analysis, it can be seen the R square is 0.670. It considered and expected a good indicator because it is closer to one. So 0.670 of variation in lymphocyte count can be predicted using a function of reticulates.

Table 4.4: Regression Analysis for All Observations

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.409	.162		2.522	.015		
	WCTA	-1.003	.244	-1.403	-4.104	.000	.063	15.928
	CACL	.117	.042	.426	2.808	.007	.320	3.130
	CCL	-.011	.255	-.005	-.041	.967	.571	1.752
	TDTE	-.050	.023	-.244	-2.146	.037	.566	1.767
	MVEBVD	.099	.039	.361	2.535	.015	.363	2.754
	EBITI	.003	.002	.177	1.374	.176	.442	2.264
	RETA	.514	.132	.920	3.900	.000	.132	7.582
	NIS	.055	.025	.281	2.223	.031	.458	2.183
	NITA	7.417	2.862	2.414	2.592	.013	.008	118.218
	STA	.780	.275	.280	2.835	.007	.750	1.334
	EBITTA	-8.273	2.928	-2.524	-2.825	.007	.009	108.774

a Dependent Variable: Pi

Variance Inflation Factor: VIF = 1/ (1-R^2)

According to the results in the table above, it can be observed that all the variables are significant except CCL (0.967) and EBITI (0.176). But the multicollinearity[4] as be shown in the table for some ratios are above 10 The ratios are WCTA, NITA, AND EBITTA, which affect the other ratios and the model. WCTA is thus omitted from the regression analysis to see whether multicollinearity still between the remaining independent variables.

4.4.2 Regression Analysis for All Observations Except WCTA Ratio

4.5: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.739(a)	.546	.447	.36794

a Predictors: (Constant), EBITTA, CACL, TDTE, CCL, STA, EBITI, RETA, NIS, MVEBVD, NITA

In this table we can observe that the R square is 0.546, which that means that 0.546 of variation in lymphocyte count can be predicted using a function of reticulates,

[4] Multicollinearity exists when one or more of the explanatory variables are highly collinear with other variables in the regression model. In this study, each of the explanatory variables is regressed on the remaining explanatory variables to compute R square values.

Table 4.6: Regression Analysis for All Observations Except WCTA Ratio

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.101	.167		.608	.546		
	CACL	.001	.036	.005	.036	.971	.589	1.697
	CCL	-.037	.296	-.016	-.124	.902	.571	1.751
	TDTE	-.018	.025	-.088	-.707	.483	.637	1.569
	MVEBVD	.161	.042	.589	3.880	.000	.429	2.333
	EBITI	.003	.003	.135	.908	.369	.444	2.250
	RETA	.158	.115	.283	1.375	.176	.232	4.305
	NIS	.024	.027	.124	.886	.380	.505	1.982
	NITA	-.608	2.423	-.198	-.251	.803	.016	63.022
	STA	.474	.307	.170	1.543	.130	.809	1.236
	EBITTA	-.015	2.467	-.005	-.006	.995	.017	57.424

a Dependent Variable: Pi

Variance Inflation Factor: VIF = 1/ (1-R^2)

According to the results in the Table 4.6. , and after omitting WCTA, it can be observed that only one independent variable is significant, which is MVEBVD. And the others are not significant. And the multicollinearity in the table above shows that all VIFs for the independent variables are less than 10 except NITA (63.002) and EBITTA (57.424). NITA is now taken out and the regression analysis is performed again to see whether multicollinearity still exists for the independent variables.

4.4.3 Regression Analysis for All Observations Except NITA Ratio

Table 4.7: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.788(a)	.620	.538	.33647

a Predictors: (Constant), WCTA, EBITI, NIS, STA, TDTE, CCL, CACL, EBITTA, MVEBVD, RETA

In the table above we can observe that the R square is 0.620, which that means that 0.620 of variation in lymphocyte count can be predicted using a function of reticulates, and it consider better than the earlier regression in which WCTA was excluded.

Table 4.8: Regression Analysis for All Observations Except NITA Ratio

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.128	.128		1.000	.323		
	WCTA	-.570	.189	-.798	-3.014	.004	.118	8.491
	CACL	.085	.042	.309	2.012	.050	.351	2.852
	CCL	.140	.263	.062	.533	.596	.602	1.660
	TDTE	-.028	.023	-.140	-1.243	.220	.646	1.548
	MVEBVD	.126	.040	.459	3.156	.003	.391	2.559
	EBITI	7.494E-5	.002	.004	.034	.973	.604	1.656
	RETA	.509	.140	.911	3.643	.001	.132	7.580
	NIS	.038	.025	.192	1.486	.144	.495	2.020
	STA	.687	.289	.247	2.374	.022	.763	1.311
	EBITTA	-.754	.424	-.230	-1.779	.082	.493	2.030

a Dependent Variable: Pi

Variance Inflation Factor: VIF = 1/ (1-R^2)

From Table 4.8 above, it is observed that multicollinearity problem has been eliminated since all the VIFs of the independent variables are less than 10. The independent variables which are statistically significant are WCTA (0.004), CACL (0.050), MVEBVD (0.003), RETA (0.001), and (0.002).

4.5 Application of the Prediction Model

The development of the prediction model is applied by using the coefficient for each explanatory variable which can be seen in Table 4.20. It can be observed from the table that 5 of 12 variables are statistically significant at $P < 0.05$. These are WCTA (0.004), CACL (0.050), MVEBVD (0.003), RETA (0.001), and STA (0.022). The values of the weights can be seen by observing the "B" column under unstandardized coefficients.

$$Z_i = B_0 + B_1 \text{ WCTA} + B_2 \text{ CACL} + B_3 \text{ MVEBVD} + B_4 \text{ RETA} + B_5 \text{ STA}$$

$$Z_i = 0.165 - 0.570 \text{ WCTA} + 0.085 \text{ CACL} + 0.126 \text{ MVEBVD} + 0.509 \text{ RETA} + 0.687 \text{ STA}$$

The probability of bankruptcy is calculated using this formula:

$$\boldsymbol{p_i}\, \mathbf{E(Y = 1 |\, X1i, X2i \ldots Xk)} = \frac{\mathbf{1}}{\mathbf{1} + \boldsymbol{e^{-zi}}}$$

Table 4.23 shows the probability of bankruptcy between bankrupt firms and non bankruptcy firms. It can be observed that the bankrupt firms have higher probability of bankrupt at 96%, and 86% than the non bankrupt firms at 54% and 55%. Thus we can conclude that the bankrupt firms exhibit more likelihood to fail.

Table 4.9: Estimated Coefficients for the Participation Model

Variables	Sig.	Ratio
WCTA	-0.57	0.288479
CACL	0.085	23.08112
MVEBVD	0.126	0.006
RETA	0.509	-0.01641
STA	0.687	0.003
Constant	0.128	
Z_i	1.919929	
Percent of Success (P_i)	0.87	

Chapter 5

Conclusion

5.0 Introduction

This chapter summarizes the interpretations of results presented in the previous chapter and provides conclusion of this study.

5.1 Interpretations

The purpose of this study is to investigate the relationship between selected accounting ratios and bankruptcy on Jordanian firms, and to determine whether these ratios are effective in predicting the probability of bankruptcy. The sample used in this study is derived from publicly listed companies on the Amman stock exchange (ASE), over the period of 2000-2003 of which data is available. For data analyses a clear and consistent definition of failure or bankruptcy is required. Failure is usually defined as a corporation not being able to meet its obligation. In the case of Jordan, default or bankruptcy is defined as a corporation not being able to meet its obligations, or a company that stops issuing financial statements for two years or more. Samples are taken from two sectors, industrial and service sectors. The financial data is analyzed to test the predictive ability of the variables, regression analysis estimated and the significance of the overall model and individual variables examined.

Empirical analysis shows that all the predictive variables exhibited different performance between bankrupt firms and non bankrupt firms for the period of study. The results of the study using regression analysis show that there are five ratios which are significant: WC/TA and CA/CL which belong to liquidity ratio, MVE/BVD which belongs to solvency ratio, RE/TA which belongs to profitability ratio, and S/TA which belongs to activity ratio. The development of prediction model leads to a more accurate and stable coefficient estimation of variables in the model.

The WC/TA ratio is found to be positively and highly significant correlated with the probability of companies bankrupt. This means that if the companies have high working capital, they are less likely to be bankrupt which that because of the multicollinearity. CA/CL and C/CL ratio are found to be negatively and insignificantly correlated with the probability of companies bankrupt, which means that the higher the liquidity, the less is the probability to bankrupt and this finding is consistent with a study conducted by (Zeitun et al 2007).

For the solvency ratio, TA/TE ratio is found to be negatively and insignificantly correlated with the probability of companies bankrupt, which means that the higher the solvency, the less probability to bankrupt. But MVE/BVD and EBIT/I ratio are found to be positively and insignificantly correlated with the probability of companies being bankrupt, which means that the higher the solvency, the more is the probability to bankrupt.

For the profitability ratio, the RE/TA ratio is found to be positively and significantly correlated with the probability of companies bankrupt, which that means that the higher the profitability, the more is the probability to bankrupt and this finding is consistent with a study conducted by (Zeitun et al 2007). But NI/S ratio is found to be positively and insignificantly correlated with the probability of companies bankrupt, which means that the higher profitability, the more is the probability to bankrupt which that because of the multicollinearity.

For the activity and leverage ratio, S/TA is found to be positively significantly to predict corporate bankruptcy. But EBIT/TA ratio are found to be positively and insignificantly correlated with the probability of companies bankrupt, which means that the higher activity ratio, the more is the probability to bankrupt.

5.2 Suggestion for the Future Research

An extension of this study for future study can be developed in several areas. First, interested parties can develop a prediction model for the non-publicly traded firms especially small and medium enterprises (SMSs) firms. Rather than focusing on publicly traded firms, it will be a valuable and applicable to develop a prediction model for the SME firms because may have different characteristics.

Second, the prediction model could be developed on other sectors in Jordan, such as insurance and bank sectors not only focusing on industrial and service sector. Results from the different models using different predictive variables could be compared to indicate whether the estimated prediction model(s) applied to different sectors could improve classification accuracy.

Finally, non-financial information such as disclosure on corporate governance, marketing strategy, human resource management etc can be utilized either alone or in conjunction with financial information to predict the characteristics of distressed and healthy firms.

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