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Empirical Model for Predicting Financial Failure

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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.

Keywords

Financial Ratios, Multiple Discriminat Analysis, Bankruptcy, Credit Risk

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1. Introduction

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.

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 (1999), 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.

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

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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.

2. Literature Review

2.1. Credit Risk Measurement

Firm's financial position is important for managers, stockholders, lenders, and employees and firms struggle financially. Stockholder' equity and lender' claim are also not guaranteed. Government, as a regulator in a comparative market, has concern about the consequences of financial distress for the firms. This shared interest among managers, employees, investors, and governments creates continual inquiries and recurrent attempts and to answer about how to predict financial distress or what reveals the credit risk of the firms (Mingo, 2000).

Credit risk (default risk) is defined by Lopez and Saidenberg (2000) as the degree of value fluctuations in debt instruments and derivatives due to changes in the primary credit quality of borrowers and counterparties. The procedure of credit scoring is very important and significant for banks as they need to discriminate whether good financial position from bad financial position in terms of their creditworthiness. This is a classic example of asymmetric information, where a bank has to reveal hidden data about its' customers. Credit risk forecasting is one of the leading topics in modern finance. Gallati (2003) defines risk as a situation with probable exposure to adversity. Risk is defined as a state in which there is a possibility that the real outcome will move away from the expected. According to Barlow (1992), financial distress faced by a developer may cause a default on the repayment of the loan. The earliest stage of poor conditions that may bring the developing banks into failure is ongoing financial distress.

Credit risk is the risk of default or of market value weakening which can be caused by the change in the credit quality of the obligator. Default is a particular case of credit quality reduces when the credit quality deteriorates to the point where the obligator cannot meet its debt obligation. The borrower is either unable to complete the terms promised under the loan contract. Credit risk is the uncertainty of paying the agricultural loan in full in a timely way. Credit risk is a primary source of risk to financial institutions, and the holdings of capital including loan loss allowances and equity assets are main responses to such risk (Barry, 2001).

Lending of money is one of the fundamental functions of banking institution and it is regarded as the essence of banking in driving the economy of a nation. In order to generate more profit. Based on neoclassical economic theory was developed in 1980, the demand for credit is a major influence on the allocation of credit in communities. Hence, increased demand in debt financing may inspire lending institution to make credit more accessible (Green and Kwong, 1995). Firm may be attracted to request bank debt finance over other types of finance because it signals to the market that the firm is creditworthiness (Fama, 1985). A related contribution was made by Stiglitz and Weiss (1988), who argue that a loan made to a firm by a reputable bank, is a signal to others that the firm is likely to stay in business.

The literature on default and credit risk modeling is extensive and growing. A pioneering contribution from the 1960 is Altman's (2002) study of business default risk. Following Altman, many authors have estimated various types of default risk models on cross-sectional data sets (Altman 1973, 1984, Frydman, Altman and Kao 1985, Li (2002), and Shumway (2001). All of these authors have concentrated on the analysis of bankruptcy risk at the firm level.

20 years ago most financial institution relied virtually exclusively on subjective analyses or banker "expert" system to assess the credit risk on corporate loans. Bankers use information on various borrower characteristic such as borrower's character (reputation), capital (leverage), capacity (volatility of earning) and collateral, the so-called 4 "Cs" of credit, to reach a largely subjective judgment (i.e. that of an expert) as to whether or not to grant credit.

In extending credit, one aspect that should be understood by the lender as well as the borrower is the management of credit risk. Credit risk is defined as uncertainty associated with borrower's repayment of loan (Sinkey, 1998). The challenge in credit risk management that is faced by bank is ensuring that the loan is properly structured in order to enhance the likelihood that the facility brings value to the borrower as, ultimately, is repaid (Julie, 1993). It is generally known that debt can be structured in a wide variety of ways. Loan can be long term or short term, secured, unsecured, or partially secured, fixed or variable rate or some other combination (Eli. 1995).

Sommerville and Taffler (1995) find that in the context of the institutional investor's rating of LDC indebtedness (based on bankers' subjective ratings) that: (a) bankers are likely to be overly pessimistic about the credit risk of LDC and (b) multivariate credit scoring system is likely to outperform such expert system. It is not surprising that financial institutions have increasingly moved away from subjective / expert system over the past 20 years towards a system which is more objectively based.

Sobehart and Keenan (2001), Engelmann et al. (2003) and Altman and Sabato (2006) have discussed statistical methods for evaluating default probability estimates. . Statistical credit scoring models try to predict the probability that a loan existing borrower will fail to pay over a given time-horizon. Historically, discriminant analysis and logistic regression have been the most widely used methods for constructing scoring systems. Altman (1968) was the first to use a statistical model to predict default probabilities of firms, calculating his well-known Z-Score using a standard discriminate model.

2.2. Empirical Evidence of Financial Ratio Analysis

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.

2.3. 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).

3. Methodology

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 1 illustrates the conceptual framework used in this study

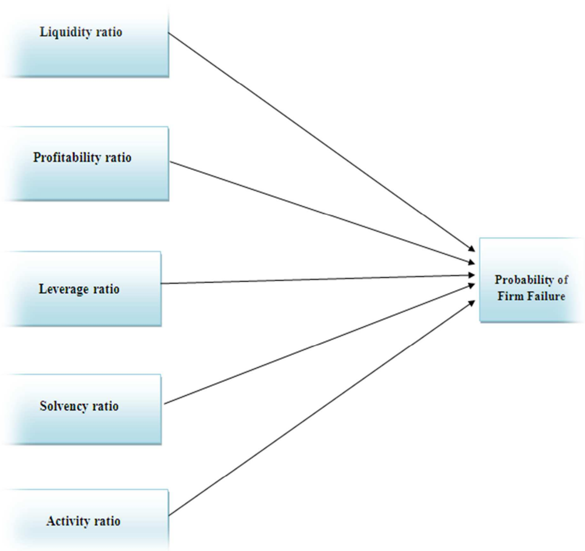

Figure 1. Conceptual Framework Used in this Study

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.

3.2. Liquidity Ratios

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 ratio is expected to have a significant relationship to the probability of corporate failure.*

3.3. Profitability Ratio

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). Therefore, I hypothesize the following: *H 2: Profitability ratio is expected to have a significant relationship to the probability of corporate failure.*

3.4. 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 Mannasoo (2007). Therefore, I hypothesize the following: *H 3: Leverage ratio is expected to have a significant relationship to the probability of corporate failure.*

3.5. Solvency Ratio

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.. Therefore, I hypothesize the following: *H 4: Solvency ratio is expected to have a significant relationship to the probability of corporate failure.*

3.6. 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. Therefore, I hypothesize the following: *H 5: Activity ratio is expected to have a significant relationship to the probability of corporate failure.* Table 1 illustrates the financial ratios used in this study.

Table 1. Summary of Financial Ratios

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

3.7. 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[1]. 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.

3.8. 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), Ohslan (1980), and Gujerati (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:

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

[1] Amman stock exchange (ASE)

Where

p_i = Probability of bankruptcy for firm iY = 1 bankruptcy company E(Y) = cumulative probability function that take value between 0 and 1

And,

$$Zi = B0 + B1\ X1 + B2\ X2 + B3\ X3 + B4\ X4 + B5\ X5 + B6\ X6 + B7\ X7 + B8\ X8 + B9\ X9 + B10\ X10 + B11\ X11 + B12\ X12 \quad (2)$$

Where, 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 Total Assets / Total Equity + B_6 Market Value Equity / Book Value of Total Debt + B_7 Earnings before Interest and Tax / Interest + B_8 Retained Earnings / Total assets + B_9 Net Income / Sales + B_{10} Net Income / Total Assets + B_{11} Sales / Total Assets + B_{12} Earnings before Interest and Tax / Total Assets.

4. Data Analysis and Finding

4.1. 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 2 shows the correlation matrix among the independent variables.

Table 2. Correlation Matrix among the Independent Variables

	N	WCTA	CACL	CCL	TDTE	MVEBVD	EBITI	RETA	NIS	NITA	STA	EBITTA
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 001 level (2-tailed)
* Correlation is significant at the 005 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 07, then there is relation among independent variables (Anderson, Sweeney, and Williams, 1996) As displayed in Table 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 07, generally therefore there is no multicollinearity problem can be seen from Table 2 few significant correlations are observed between the independent variables 005 level.

Table 3. Regression Analysis

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig
		B	Std Error	Beta		
1	(Constant)	128	128		1000	323
	WCTA	-570	189	-798	-3014	004
	CACL	085	042	309	2012	050
	CCL	140	263	062	533	596
	TDTE	-028	023	-140	-1243	220
	MVEBVD	126	040	459	3156	003
	EBITI	000007	002	004	034	973
	RETA	509	140	911	3643	001
	NIS	038	025	192	1486	144
	STA	687	289	247	2374	022
	EBITTA	-754	424	-230	-1779	082
R^2		0788				
Heteroscedasticity		No				
VIF		No				

4.2. Regression Analysis

In the table above it can be observed that the R^2 is 0788, which that means that 0788 of variation in lymphocyte count can be predicted using a function of reticulates However, 0292 are external factors that could affect the predictable model The development of the prediction model is applied by using the coefficient for each explanatory variable which can be seen in Table 3 It can be observed from the table that 5 of 12 variables are statistically significant at $P < 005$ These variables are WCTA (0004), CACL (0050), MVEBVD (0003), RETA (0001), and STA (0022) The values of the weights can be seen by observing the "B" column under unstandardized coefficients Therefore the predictable model is as follow:

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

$$Z_i = 0165 - 0570\ \text{WCTA} + 0085\ \text{CACL} + 0126\ \text{MVEBVD} + 0509\ \text{RETA} + 0687\ \text{STA}$$

The probability of bankruptcy is calculated using this formula:

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

Moreover, table 4 shows the estimated coefficients for the participation model

Table 4. Estimated Coefficients for the Participation Model

Variables	Sig	Ratios
WCTA	-0570	0288
CACL	0085	2308
MVEBVD	0126	0006
RETA	0509	-0016
STA	0687	0003
Constant	0128	
Z_i	1911	
Percent of Success (P_i)	087	

5. 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.

6. Suggestion for the Future Researches

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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