THE INTERNATIONAL JOURNAL OF BUSINESS & MANAGEMENT

Prediction of Bankruptcy: Evidence from Moroccan Agricultural Companies

Fahd El-Ansari
Ph.D. Candidate, Department of Social Sciences, Hassan II Institute of Agronomy & Veterinary Medicine – Morocco; and Head of Credit Risk Reporting, Credit Agricole du Maroc, Morocco
Pr. Majid Benabdellah
Professor, Department of Agricultural Economics,
Department of Social Sciences, Hassan II Agronomy &Veterinary Institute, Morocco

Abstract:
The aim of this research is to build a bankruptcy prediction model specific to the Moroccan agricultural firms through two methods: multidiscriminant analysis and log it model. The second purpose is to choice the most suitable model for this specific sector. This paper is based on a sample of 75 healthy and 75 companies declared bankrupt. The model aims to test the predictive power of financial ratios reflecting the profitability, the liquidity, the solvency and the activity of companies. The results indicate comfortable prediction accuracy for both models. However, the logistic regression outperforms MDA and has higher classification accuracy prediction. Beside academic contributions, this study may help credit risk managers and investors to provide them useful tools in the assessment of credit risk. The overall difference of this study from previous one is it can be considered the first paper which investigates the bankruptcy prediction in agricultural firms in Morocco.

Keywords: *Agricultural firms, bankruptcy, financial ratios, prediction model*

1. Introduction

Agriculture has always been a strategic sector for Morocco's socio-economic development. In 2015, its contribution in the Moroccan GDP was at 16.5%. Since 2009, agricultural GDP remains above the 100 billion MAD a year, against an average of 75 billion by 2008. In 2015, agriculture generates almost 40% of the Moroccan employment. Finally, since 2009, agricultural exports have represented from 15% to 21% of total exports.

In recent years, Morocco has recorded a worrying increase in number of failures. In 2016, more than 7400 companies file for bankruptcy, of which nearly one third are declared in the agriculture sector and food industries (Inforisk 2016). Moreover the average payment term was 98 days (Coface, Morocco survey; 2015).The correlation between bad payment indicators and the risk of increased failure is frequently confirmed by empirical work. Indeed, given the difficulties that the Moroccan agricultural and agribusiness firms faces, contraction in agricultural production, tightening of margins due to the competition, slowdown in the growth rate of agricultural, and credit rationing, Morocco is included in international ratings among the countries with the highest rates of bankruptcy (Eulers Hermes; 2015).

During 2016, The Central Bank of Morocco has revealed that agricultural sector has the highest level of non-performing loans in Moroccan banks with 13.3 per cent. The sector's default rate remains well above the industry average of 8.3%.

The current increase in the number of failed companies confirms the usefulness of developing predictive models of failure. It is essential to ensure protection of the stakeholders, sustainability of the company, by preventing the economic and financial difficulties that companies may confront which implies an accurate estimate the probability of default.

Since 1960s, many studies have been carried out on the topic of bankruptcy prediction for different countries of the world. The empirical literature reveals some of these research: Pakistan (Abbas and Rashid;2011), India (Bandyopadhyay 2006), Thailand (Sirirattanaphonkun 2012), Sudan (Eljelly et al. 2001), Malaysia (Bidin 1988), Turkey (Erdogan 2008), and Iran (Etemadi et al.; 2009).

Nevertheless, very few studies have been carried out to predict the bankruptcy of Moroccan companies and only a small part of them was devoted to the agricultural sector. Therefore, this paper aim to identify the financial ratios that are most significant in predicting bankruptcy and then develop a bankruptcy model specially designed for Moroccan agricultural firms. In order to achieve this objective, we have applied both multivariate discriminant analysis and the logistic regression method and we have compared performance of each model through classification accuracy. The analysis is based on a sample of firms which became bankrupted over

the time 2014-2015**.** Specifically, we examine ten financial ratios extracted from financial statements and covering four main different aspects, namely liquidity, leverage, profitability, and turnover ratios.
After providing a comprehensive review of bankruptcy concept by presenting some definitions, we expose different techniques of bankruptcy prediction mentioned in the literature. The rest of the study is structured as following. We propose in section III to describe the data and methodology, and set out results and discussions in the section VI before to conclude and make suggestion for the future study in the final section.

2. Review of Related Literature
Morocco's bankruptcy law is based on French law. Commercial Courts have jurisdiction over all cases related to insolvency. The law follows the classical scheme in terms of protecting creditors, giving secured debtors priority claim on assets and proceeds over unsecured debtors, who in turn have priority over equity shareholders (USAID; 2008). Recently, bankruptcy law is currently under reviewing in order to shift the focus of bankruptcy from liquidation and restructuring to prevention and settlement.
Casta and Zerbib (1979), define failure of the company by referring to a legal approach. According to these authors, the legal default concerns bankruptcy filing linked to an insolvency situation. Economic failure characterizes the state of a deterioration in the company's situation in terms of performance (Ooghe & Van Wymeersch; 1986), negative added value (Gresse; 1994), or market positioning (Bescos;1989). According to Basel Committee, default may take several forms. Generally, default occurs when debtors are unable to comply with their financial obligations: non-repayment of principal or interest, violation of a covenant.
Concerning the failure's factors, there are a multitude of approaches cited by the literature that contribute to understand and explain causes of failures. The financial and accounting approach seem to be the most used method by analysts. This approach emphasis on financial and accounting indicators such as profitability (Holmen 1988, becchetti & Sierra 2002), cash flow and solvency (Gombola et al. 1987; Abdul Aziz et al.1987; Bernhardsen 2001), and liquidity (Hensher & Jones 2004, Ben Jabeur & Fahmi 2014). The deterioration of those ratios over time could lead the company to bankruptcy. Strategic and managerial approach attributes firm failure causes to internal and external environment of the company (Leidecker & Harder 1987; Lukason & Hoffman 2014). Authors are often inspired by Porter's five forces analysis (1980). Finally, default may be caused by macroeconomic factors such as interest rates and credit constraint (koopman et all 2009; Koopman et al 2009; Liu 2004), and the economic cycle (Altman 1984), inflation (Wadhwani 1986).
The prediction of failure is a phenomenon that goes back to the 1930's with studies of Rosendale (1908) Fitz Patrick (1932), Smith and Winakor (1935) and Merwin (1942). These researchers have applied a simple statistical analysis of a few financial indicators, sometimes expressed in the form of ratios.
Fitzpatrick (1932) classified firms on the basis of individual financial ratios as failed or non-failed. He used a sample of 19 pairs of bankrupt and non-bankrupt firms and he analyzed 13 financial ratios and compared them with trend and standard ratios value. Smith and Winakor (1935) published their study focusing on 183 firms that failed between 1923 and 1931 from several sectors of industries. They analyzed ratios of these firms and concluded that when firms move toward bankruptcy, their ratios of current assets to total assets fall. Furthermore, they showed that it's more relevant the use the ratio of Working Capital to Total Assets than the ratio of Cash to Total Assets as a indicator for predicting financial problems.
Merwin (1942) studied 200 failed firms and 381 non failed firms during the period 1925-1938 in five sectors on small manufacturers. He reported that current ratio, net working capital to asset and net worth to total debt are the most useful ratios to distinguish between those that failed. Beaver (1966) is considered as the most knowledgeable researcher of the univariate analysis. He used univariate discriminant analysis (UDA) to identify financial ratios for corporate failure prediction and to classify both failed and healthy firms. His study tried to understand and measure delay before bankruptcy began to notice differences between firms. By comparing 30 financial ratios of 79 pairs of bankrupt and non-bankrupt firms over the period from 1954 to 1964, he concluded that the best discriminant factor was cash flow to total debt ratio which correctly identified 90 percent of the firms one year prior to failure. Also, he found out that profitable firms had a lower ratio of liabilities to net value than firms with losses. From the 29 financial ratios observed by Beaver, he selected six ratios as the most accurate discriminatory power. While a number of studies devoted to bankruptcy prediction, there have been relatively few studies using the univariate model. Afterwards, the overwhelming majority of researchers used multivariate models.
The pioneer of corporate failure prediction models which used multivariate technique, multiple discriminate analysis–MDA was William Altman (1968) in response to criticism of univariate approach, originally used by Beaver, which suffer from too many deficiencies (classification model was carried out separately for each ratio). In fact, Altman, was the first to use more than a ratio to predict the likelihood of a company going bankrupt (Platt, H.D. & Platt, M.B 2002). His method was based on assessing the overall financial of firm described through a battery of financial ratios. His study covered a sample of 33 pairs of companies (healthy /bankrupted) of the same size and sector over the period 1946-1965. From a battery of 22 ratios, he built a MDA model with five variables as significant bankruptcy predictors. Altman's model was 95% accurate in predicting the bankruptcy of firms a year before. The ability of the model to predict the bankruptcy was 83% two years before occurrence.
This approach offers two significant advantages: in one hand, the model groups five key financial predicator into a simple linear function. In other hand, the model weights these indicators according to their discriminating power. Thereby, Altman's model gives each company a score (Z-Score) that can then be used to classify firms. The Altman Z-scores, is almost certainly the most widely used and applied model for predicting financial distress (Bemmann 2005). The final discriminant function developed by Altman is as follows:

$$Z = 0.012\,\frac{working\ capital}{total\ assets} + 0.014\frac{retained\ earnings}{total\ assets} + 0.033\frac{EBIT}{total\ assets} + 0.006\,\frac{Market\,Value\ Equity}{Market\,Value\ Equity} + 0.999\,\frac{Sales}{total\ assets}$$

According to this model, firms with Z value higher than 2.675 were non-bankrupted firms but all firms with a Z level less than 1.23 are deemed bankrupted firms. Also, Altman found that it wasn't possible to classify accurately all firms with a Z level between 2.675 and 1.23 also called "gray zone".

Very few studies have used multiple discriminate analysis to predict failure of Moroccan companies. In our opinion, the most important was carried out by Kherrazi & Ahsina (2015) insofar as the authors have tested the multinormality of the financial ratios, have validated the model on a control sample, and have compared results between univariate multivariate techniques. Authors have compared 7 ratios of failed and successful firms (31 of each firm status). Classification accuracy of their model was 93%, while model error was 7%.

The final combination retained by using multiple discriminate analysis is as follows:

$$Z = 0.163 + 0.364\frac{Net\ income}{Permanent\ equity} + 0.097\,\frac{Net\ Income}{Shareholder's\ Equity} + 0.024\frac{Operation\ income}{Revenu}$$

In addition to these aforementioned authors, it is necessary to mention that several experts dealt with the prediction of the failure situation through the multiple discriminate analysis Edmister (1972), Taffler (1984),Dambolena And Khoury (1980), Ooghe and Verbaere (1983), Taffler (1983), Micha (1984), Gloubos and Grammatikos (1988) and Lussier (1995) among many others. Subsequently, Ohlson paper (1980) have introduced significant methodological breakthrough in bankruptcy prediction. In order to overcome problems of using MDA, Ohlson used logistic regression to build his model. Pervan et al (2011) state that MDA suffer from the following main restrictive statistical limitations: requirement for normality of predictors, requirement for the same variance-covariance matrices for both groups, assumptions on a priori probabilities and distribution of predictors and MDA score has little intuitive interpretation. These conditions are unlikely fulfilled (Foster 1986).

The sample used by Ohlson included 105 listed bankruptcy firms and 2,058 listed non bankruptcy firms randomly chosen from public industrial companies from 1970 to 1976. Ohlson's O-Score model (1980) selected nine ratios which he thought should be useful in predicting bankruptcy and was computed including only the following four ratios seemed to be statically significant: net income to total assets, working capital to total assets, total liabilities to total assets and size. Even if Ohlson model didn't reach the same high prediction accuracy as previous papers in the field, e.g. Altman (1968), Logit analysis seemed to be, from a statistical perspective, preferable (Lo 1984).

3. Research Methodology and Materials

3.1. Data Collection

Our methodological approach to data collection is structured in two steps: choosing firms in the database and selection the indicators of financial failure. We use the database OMPIC (The Moroccan Office of Industrial and Commercial Property) for our sample. This database provides access to a fund compounded of more than one hundred thousand enterprises registered in the Central Trade Register. OMPIC database is considered as the most comprehensive basis of financial and general information about Moroccan companies.

The legal definition of the failure was chosen. Companies are selected in the group of defaulters when the president of the commercial court request payment order with the garnishment of the debtor's assets during 2014.

Data studied are organized so that the accounting year is available for 2011, 2012 and 2013. In order to debug the effect of initial mortality; we exclude young companies less than five years given that they carry a natural risk of failure and (Situm;2014). Furthermore, we also ensure that the sample is the most representative by region and by type of crop. Therefore, with the aim of designing a more accurate model, we have eliminated abnormal cases which lay within the bottom 10% and the top 10% of each financial ratio. In accordance with previous bankruptcy studies (Fletcher and Goss, 1993; Matoussi et al, 2010), this paper also adopts a matched-pair approach. The total sample of both bankrupt and non-bankrupt firms meeting the aforementioned selection criteria consists of 100 firms split into two subsamples: 50 healthy firms and 50 bankrupted.

3.2. Variable Collection

In a second step, we have chosen financial ratios. The choice of factors and hypothesis formulation in this study is thus motivated by both theoretical and empirical consideration. Literature review of the last forty years shows that to build models, researchers have used more than 500 different ratios (Du Jardin 2009). A battery of ten financial ratios is considered in this paper. All our chosen financial ratios have been commonly used in previous studies, such as Altman (1968), Conan and Holder (1979), and Ohlson (1980). In accordance with the financial aspects of the business that the variables measure and their relevance to financial analysis, we have categorized these ratios into four themes: liquidity, profitability, solvency and activity.

Liquidity ratios measure a firm's aptitude to meet its short-term obligations as they come due or to cover its long-term liabilities with long-term assets. Foreman (2003) hypothesized in their study concerning southern rice farms that higher liquidity indicates a lower probability of default risk and persisting problems with low liquidity usually indicate problems ahead with meeting long-term liabilities which in the extreme case can result in the company failure. In this study, we approached the liquidity by two ratios: current ratios and quick ratios. Many authors expected that solvency ratios have a negative correlation to the default risk (Heine 2000). Solvency ratios measure the capacity of a firm to repay outstanding financial obligations due to a previous commitment contracted for current operations. In this study, the firm's solvency was measured by three debt ratio: the interest coverage ratio, debt to equity and the debt to assets. The first ratio measures the firm's ability to repay debts, whereas the two latter ratios measure the degree of debt use. In accordance with Balcaen and Ooghe (2004), profitability is a useful predictor of bankruptcy state. As a profit is the main factor for cash generation, high profitability ratios are expected to have a positive impact on cash flows and thus contribute to reduce risk of failure. In this study, the firm's profitability was measured by net profit margin and return on assets. Activity ratios measure the relative efficiency of an organization based on its use of its assets. The most important activity ratios cited by literature include asset turnover ratio and inventory turnover ratio (Veronica & Anantadjay; 2014).). Table 1 describes these ratios and how they are calculated.

Ratio	Formulation	Category	Expected sign estimator
R1	current assets/ current liabilities	Liquidity	+
R2	working capital/ total asset	Liquidity	+
R3	EBITDA / total interest charges	Solvency	+
R4	Long termdebt/Equity	Solvency	+
R5	Total debt/ total asset	Solvency	+
R6	net income/ total sales	profitability	-
R7	net income/ total assets	profitability	-
R8	sales/ total Asset	Activity	-
R9	sales/ working capital	Activity	-
R10	stock/sales	Activity	+

Table 1: Description of the selected financial ratios

As the dependent variable for bankruptcy prediction models, we have chosen a dichotomous qualitative dependent variable. We use one dependent variable: Financial Distress. This variable is widely cited in the literature (Ohlson 1980; Foreman 2003; Brédart 2013). For this study, financial distress is a binary variable taking a value of 1 if the firm is in bankruptcy procedure in compliance with (Livre V) of the Moroccan Bankruptcy Code and 0 otherwise.

3.3. Model

To analyze the relationship between the probability of companies' failure and explanatory variables, Multiple Discriminant Analysis and logistic regression are used as statistical methodology.

By using the multivariate technique, we assign a score to each company in a sample, using a combination of independent variables. This numerical score obtained express the risk profile of the firm. State of "healthy firm" is predicted for companies above the cutoff, whereas those below the cutoff are predicted to remain bankrupted (Jones 1987). By developing our model MDA, we proceeded in three steps: estimating the weight of ratios; calculating the discriminant score of each case; and classifying the cases. The model that is developed through MDA takes the form as follows:

$$Zi = \beta_0 + \beta_1 R_1 + \beta_2 R_2 + \beta_3 R_3 + \beta_4 R_4 + \beta_5 R_5 + \beta_6 R_6 + \beta_7 R_7 + \beta_8 R_8 + \beta_9 R_9 + \beta_{10} R_{10}$$

Z is the overall index, β_1, β2, and β_n are discriminant coefficients, R_1, R_2....Rn are independent variables

However, Multiple Discriminant Analysis has two criticisms concern the fact that this method assumes the normality of the distribution of the different ratios and an equal dispersion of covariance matrices for groups defined by dependent variable (Karels and Prakash; 1987). Several studies reveal that the two aforementioned assumptions are often non respected affecting adversely statistical significance of estimation especially in the case of small samples and unequal covariance matrices (Bauer and Agarwal; 2014).

To overcome these problems, we will complete our analysis by regression logistic. Logit is a multivariate statistical method that is most commonly employed in predicting potential company's failure. This model of this current study is adopted from Deakin (1972), Ohslan (1980), and Back et al. (1994).

The advantage of the logistic regression is that it does not have as assumption the normality and the equality of covariance matrices. Therefore, Logit analysis incorporates non-linear effects, uses the logistical cumulative function in predicting a bankruptcy and assumes that the probability of a dichotomous outcome is related to a set of potential predictor variables in the form: $Log\left(\frac{Pi}{(1-Pi)}\right) = \beta 0 + \beta 1 Ri1 + \ldots\ldots + \beta n Rn$

Where: pi = probability of non-bankruptcy in the ith firm, βo = an intercept, R1-Rn = the financial ratios and β1- βn = coefficients of the financial ratios.

4. Empirical Study

4.1. Correlations and Descriptive Statistics

An important problem arise in application of both methods is the multicollinearity of independent variables. Indeed, some of ratios use the same denominator or numerator in the calculation (assets, net income, liabilities, etc). This statistical problem could generate an inefficiently estimated parameters and high standard errors of coefficients and as a result some coefficients for independent variables may be found statistically insignificant. While a model that employs many ratios may be highly successful in classifying the sample data set, it can be less effective in application. A model with many variables is also likely to process substantial multicollinearity (Leksrisakul and Evans; 2005). In order to check this problem of multicollinearity, we have used test Pearson correlation matrix.

	R1	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**	**R9**	**R10**
R1	1	-,015	,012	,034	-,191	,030	,007	-,025	-,023	-,008
R2	-,015	1	,002	-,010	-,016	,007	,012	,000	-,006	-,007
R3	,012	,002	1	,000	-,168	,029	,078	,034	,038	,001
R4	,034	-,010	,000	1	,024	-,016	,007	-,040	-,003	-,014
R5	-,191	-,016	-,168	,024	1	-,049	-.419	,007	-,018	-,032
R6	,030	,007	,029	-,016	-,049	1	,015	,031	,014	,009
R7	,007	,012	,078	,007	-.419	,015	1	-,083	,027	,020
R8	-,025	,000	,034	-,040	,007	,031	-,083	1	,162	-,038
R9	-,023	-,006	,068	-,003	-,018	,014	,027	,162	1	-,018
R10	-,008	-,007	,001	-,014	-,032	,009	,020	-,038	-,018	1

Table 2: Correlation Coefficients of Independent Variables.

A coefficient of correlation great than 0.8 indicates multicollinearity problem. In our analysis, the Matrix of Pearson Correlation coefficients reveal that all ratios are not highly correlated with each other. Indeed, we can keep all the ten financial ratios.

4.2. Estimation of the MDA Model

In this study, we have applied the stepwise selection technique to develop our MDA model. The discriminant analysis assumes that matrices between the two groups of healthy and bankrupt firms are equal and the data have a multivariate normal distribution. The test of group means equality is considered as a pre-requirement before carrying out the MDA analysis.

	Wilks' Lambda	**F**	**df1**	**df2**	**Sig.**
current assets/ current liabilities	0,957	6,672	1	148	0,011
Working capital/ Total Asset	0,986	2,153	1	148	0,144
EBITDA / Total interest charges	0,981	2,857	1	148	0,093
Long-term debt /Equity	0,983	2,492	1	148	0,117
Total debt/Total Asset	0,888	18,579	1	148	0
Net income/ Total sales	0,993	1,114	1	148	0,293
Net income/ Total assets	0,942	9,071	1	148	0,003
Sales/ Total Asset	0,978	3,318	1	148	0,071
Sales/ Working capital	0,939	9,645	1	148	0,002
Stock/Sales	0,99	1,564	1	148	0,213

Table 3: Tests of Equality of Group Means

According to table 3, four of ten independent variables are significant and contribute to the model: current assets/ current liabilities, debt/Total Asset, net income/ Total assets and Sales/Working capital, whereas the others variables seem to be insignificant to discriminate between healthy and non healthy firms.

To verify the second assumption related to the equality of covariance within group, we have performed Box’s M test. Results of this test are exposed in Table 4.

Box's M		4784,782
F	Approx.	80,81
	df1	55
	df2	70734,818
	Sig.	0

Table 4: Box's M test

Box M test with a p-value< 0.05 revealed that the two groups of firms did not have equal covariance matrices, indicating that second DA assumption is valid.
To identify how much discriminating ability a function possesses, we have effectuated canonical correlation and Wilks' Lambda statistics (Table 5).

Eigen value	% of Variance	Cumulative %	Canonical Correlation	Wilks' Lambda	Chi-square	Df	Sig.
.326	100	100	0,496	0,754	41,218	4	0

Table 5: Eigen value and Wilks' Lambda Statistics

The canonical correlation is 0.496, which means that formed model explains almost 50 % variance of dependent variables. Thus, Wilks Lambda statistic was 0.75 indicating that 25% of the variance in the dependent variable is accounted for by this model.
To show the correlation between each ratio and discrimination function and to evaluate the significance of independent ratios, we have used the structure matrix reported in Table 6.

Total debt/Total Asset	0,62
Sales/ Working capital	-0,447
Net income/ Total assets	-0,433
Current assets/ Current liabilities	0,372

Table 6 : Structure Matrix

The coefficients of Structure Matrix reveal that we can discriminate among bankrupted and healthy Moroccan agricultural firm by four financial ratios. Debt/asset and current assets/current liabilities have positive sign meaning that increase of these variables increase probability of being bankrupted. Contrary to such finding, sales/working capital and net income/ assets have a negative sign, meaning that increase of these variables causes decreasing the probability of the firm to be non healthy.
In this case, discriminant functions are linear combination of four independent variables and can be described as follows:
Healthy firms (1): $Y = -6.848 + 0.187\ R1 + 13.81\ R5 + 9.595\ R7 - 0.005\ R9$
Bankrupt (0): $Y = -4.464 + 0.112\ R1 + 10.841\ R5 + 8.947 R7 + 0.003\ R9$

The success of the discriminant analysis leans on the percentage of correct classification. Assessing the accuracy of the discriminant function was carried by using cross-validated procedure of classification. A higher percentage of correct classification means that the analysis is the more successful. The results obtained are presented in Table 7.

DEFAULT			Predicted Group Membership		Total
			0	1	
Cross-validated	Count	0	56	19	75
		1	22	53	75

Table 7: Classification Results

Although 56 of 75 successful firms are predicted correctly, 19 of 75 successful firms are classified incorrectly. Besides, 53 of 75 unsuccessful firms are predicted correctly, 22 of 75 unsuccessful firms are classified incorrectly. Thus, the model accuracy is 75% for healthy firms, 71 % for bankrupted firms and 73% in total.

4.3. Estimation Results of the Logit Model

In order to estimate the likelihood of a firm to belong to the group of solvent companies or to the group of insolvent companies, we used, in this section, the logistic regression model offered by SPSS software. The result of regression test is 0.000. It means that the regression test is significance. The overall significance test used in the logistic regression is The Omnibus test. It indicates of how well the model performs, which refers to as a goodness-of-fit test. Table 8 illustrates that the model is significant, meaning that the estimated Logit model provide generally a good fit to data. Indeed, explanatory variables in the model jointly are capable of predicting the dependent variable.

		Chi-square	df	Sig.
Step 1	Step	111,431	10	0
	Block	111,431	10	0
	Model	111,431	10	0

Table 8: Significant regression test: Omnibus Tests of Model Coefficients

The Cox & Snell R square and Nagelkerke R values provide an indication of the amount of variation in the binary dependent variable that is explained by the explanatory variables.

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	96,513	0,524	0,699

Table 9: The Regression Coefficient

As depicted in Table 10, and according to Cox & Snell, Coefficient of determination is 0.52. It means that around 52% of variation in the dependent variable is explained by these explanatory predictors. Indeed, by using the Nagelkerke R Square test which is an adjusted version of the Cox & Snell test, we notice that in our model 700\% of the changes in the dependent variable may be explained by the model's accounting variables.
The Hosmer and Lemeshow test assesses whether or not the observed event rates match expected event rates in subgroups of the model population (Hosmer & Lemeshow; 2000). The value in this study is 9.9 calculated from the chisquare distribution with 8 degrees of freedom, suggesting that the model fits the data well since there is no significant discrepancy between the predicted and observed classifications.

Step	Chi-square	df	Sig.
1	9,918	8	0,271

Table10: Hosmer and Lemeshow Test

Observed			Predicted		
			Default		Percentage Correct
			0	1	
Step 1	Default	0	62	13	82,7
		1	14	61	81,3
	Overall Percentage				82

Table 11: Classification table

The validity of the model to estimate the probability bankruptcy is 82 percent. Therefore, this model is able to identify 82 percent of "healthy" firms group. In the distressed companies group, that interests us the most, we find that the model misclassify 19%.

Wald test is usually used to test the significance of the individual coefficient for each predictor in Logit model (Hair, et al.; 1998). As shown in column B which represent the estimated values of the coefficients of the independent variables, and with significance level sets at p-value=0.05, the Logit forward stepwise procedure retained four predictors from ten candidate variables which might best discriminate the bankrupt firm from the healthy firms: Current asset/current liability, Debt/Asset, Sales/Working capitaland Stock/sales.

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1	Current assets current liabilities	0,546	0,171	10,24	1	0,001	1,726
	Working capital Total Asset	-0,326	0,227	2,056	1	0,152	0,722
	EBITDA Total interest charges	-0,004	0,006	0,43	1	0,512	0,996
	Long term debt Equity	0,055	0,081	0,465	1	0,495	1,057
	Total debt Total Asset	4,635	1,232	14,143	1	0	103,038
	Net income Total sales	0	0	0,024	1	0,877	1
	Net income Total assets	-0,782	2,776	0,079	1	0,778	0,458
	Sales Total Asset	-0,167	0,352	0,225	1	0,636	0,846
	Sales Working capital	-0,079	0,025	9,942	1	0,002	0,924
	Stock sales	1,639	0,853	3,696	1	0,055	5,152
	Constant	-4,19	1,084	14,947	1	0	0,015

Table 12: Coefficient of Independent variable

The values in Exp (B) column are the odds ratios for each selected predictor. According to Tabachnick and Fidell (2001), the values which are greater than one indicate a greater chance of success than failure. Also, the values which is less than one, means the chance of failure is less than success. According to the results of this study, bankruptcy risk has increases when debt and stock decrease.
Logistic regression model is reported in this Equation:
$Zi = 0.54\ R1 + 4.63\ R5 - 0.08\ R9 + 1.65\ R10 - 4.19$

5. Conclusion

Although many academics researchers have been interested about the financial distress and bankruptcy prediction, a limited part of them was devoted to the agricultural sector in Morocco.

The main objective of this study is to develop and compare the performance of bankruptcy prediction models using multiple discriminant analysis and logistic regression. The dataset of this research consists of 75 matched pairs of bankrupted and healthy Moroccan firms in agriculture sector.

The estimated model using MDA has shown that from ten financial ratios covering several categories: solvency, liquidity, profitability and activity, only four ratios: Debt/asset, current assets/current liabilities, sales/working capital and net income/ assets can be efficiently used to determine the financial distress of the firm. MDA models accuracy in prediction of bankrupted companies is 71%. Logistic regression model is more robust since it does not have the two assumptions: data normality and equality of covariance matrices. The Logit forward stepwise procedure has shown that asset/current liability, debt/asset, sales/working capital and stock/sales can be effectively used for bankruptcy prediction. The results indicate that from the classification result, logistic regression has higher classification accuracy prediction bankruptcy (82%) in comparison to multiple discriminant analysis. Indeed, logistic model outperforms MDA in detecting the insolvent firms.

The study has several limitations that might be overcome in future research. First, and as shown by others authors (Tinoco and Wilson 2013) combing financial, non-financial and macroeconomic variables might strengthen the model of prediction, help to assess the default risk of companies and improve the accuracies prediction bankruptcy.

Owing to the availability of financial statement this study covers only medium-sized enterprises and large corporations. The future analysis might be done through integration small sized agricultural companies.

And finally, with regard to others studies which confirm the theoretical superiority of non-parametric statistical techniques (Classification regression trees) on the classic logistic regression (LR) analysis, testing whether this new techniques to Moroccan context are capable of enhance the overall predictive accuracy is primordial.

Also, this study can be further improved in future research by taking in account the data for a longer period. Analyzing of a company's financial statements over a certain period might highlight the relevance of a time dimension in the bankruptcy prediction**.**

6. References

i. Abbas ,Q. and Rashid,A. (2011). Modeling Bankruptcy Prediction for Non-Financial Firms: The Case of Pakistan, Munich Personal RePEc Archive, 28161:14
ii. Alsaeed, K. (2006). The Association between Firm-specific Characteristics and Disclosure: the Case of Saudi Arabia, Managerial Auditing Journal, 21(5), 476-96.
iii. Altman, E.I. (1984). The success of business failure prediction models, Journal of Banking and Finance, Vol. 8, pp. 171-98
iv. Back, B., Laitinen, T. and Sere, K.(1994). Neural Networks and Bankruptcy Prediction. Paper presented at the 17th Annual Congress of the European Accounting Association, Italy, April, 1994
v. Balcaen, S. and Ooghe, H. (2004). 35 years of studies on business failure: an overview of the classical statistical methodologies and their related problems, Working paper. Ghent University, June, 248: 1–62
vi. Bauer, J. and Agarwal,V. (2014). Are hazard models superior to traditional bankruptcy prediction approaches? A comprehensive test, Journal of Banking and Finance, vol. 40, p. 432–442
vii. Bandyopadhyay, A. (2006). Predicting probability of default of Indian corporate bonds : logistic and Z-score model approaches, The Journal of Risk Finance, 7(3), 255-272.
viii. Beaver, W. (1966). Financial ratios as predictors of failure, Journal of Accounting Research
ix. Becchetti, L. and Sierra, J. (2002). Bankruptcy risk and productive efficiency in manufacturing firms, Journal of Banking and Finance, 27, 2099-2120
x. Bemmann, M. (2005). Improving the Comparability of Insolvency Predictions. Dresden Economics Discussion Paper (June 23, 2005)
xi. Ben jabeur, S. and Fahmi,Y. (2014). Predicting business failure using data-mining methods, Working paper research No 2014-308, IPAG Business School
xii. Bernhardsen, E. (2001). A model of bankruptcy prediction. Technical report, Norges Bank.
xiii. Bescos,P.L. (1989). Les facteurs de réussite dans le redressement des PMI en difficulté, Revue Française de Gestion, 74, 55-67.
xiv. Bongini, P., Claessens, S. and Ferri, G. (2001). The political economy of distress in East Asian financial institutions, Journal of Financial Services Research 19 (1), 5–25.
xv. Bruno, A., Leidecker, J. and Harder, J. (1987). Why Firms Fail. Business Horizons (March/April),
xvi. Casta, J.F. and Zerbib, J.P. (1979). Prévoir la défaillance des entreprises, Revue française de comptabilité , 97, 506 - 526.
xvii. Charitou, A., Clubb, C., and Andreou, A. (2000). The Value Relevance of Earnings and Cash Flows: Empirical Evidence for Japan, Journal of International Financial Management & Accounting
xviii. Dambolena, I. G. and Khoury, S. J. (1980). Ratio stability and corporate failure, Journal of Finance, 35(4), 1017-1026.
xix. DuJardin,P. (2015). Bankruptcy prediction using terminal failure processes, European Journal of Operational Research Volume 242, Issue 1, 1 April 2015, Pages 286–303
xx. Deakin, E. (1972). A discriminant analysis of predictors of business failure, Journal of Accounting Research 10(1): 167-179.
xxi. Edmister, R. (1972). An empirical test of financial ratio analysis for small business failure prediction, Journal of Financial and Quantitative Analysis 7(2): 1477-1493.
xxii. Eljelly, A.M. and Mansour, I.H.F. (2001). Predicting Private Companies Failure in the Sudan, Journal of African Business, Hawarthpress, USA, Vol. 2 (2), p.23-43.

xxiii. Erdogan,B.(2008). Bankruptcy Prediction of Turkish Commercial Banks Using Financial Ratios, Applied Mathematical Sciences, Vol. 2, no. 60, 2973 – 2982.
xxiv. Etemadi, H., Rostamy, A., and Dehkordi, H. (2009) A genetic programming model for bankruptcy prediction: Empirical evidence from Iran, Expert Systems with Applications, 36 (2), 3199-3207.
xxv. Fletcher, D., and Goss, E. (1993). Forecasting with neural networks: an application using bankruptcy data, Information and Management, 24(3), 159–167.
xxvi. Foreman,RD. (2003). A logistic analysis of bankruptcy within the US local telecommunications industry, Journal of Economics and Business 55(2): 135–166.
xxvii. Gloubos, G. and Grammatikos, T .(1988). The success of bankruptcy prediction models in Greece, Studies in Banking and Finance. 7: 37–46.
xxviii. Gombola, M., Haskins, M., and Ketz, J, Williams D. (1987). Cash flow in bankruptcy prediction, Financial Management: 55–65.
xxix. Gresse , C. (1994). Les entreprises en difficulté, Paris, Economica.
xxx. Heine, M.,L. (2000). Predicting financial distress: Revisiting the Z-score and ZETA Models, Stern School of Business, New York University.
xxxi. Hernandez Tinoco, M., and Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables, International Review of Financial Analysis, 30, 394-419. DO
xxxii. Holder,S. (1979). Variables explicatives de performances et controle de gestion dans les P.M.I, Universite Paris Dauphine.
xxxiii. Holmen, J. S. (1988). Using financial ratios to predict bankruptcy: An evaluation of classic models using recent evidence, Akron Business and Economic Review, 19(1), 52-64.
xxxiv. Jones, S., Hensher, D. A. (2004). Predicting firm financial distress: A mixed logit model, Acounting Review 79 (4), 1011-1038
xxxv. Karels,G. and Prakash,A. (1987). Multivariate normality and forecasting of business bankruptcy, Journal of Business Finance & Accounting 14(4): 573-593.
xxxvi. Kherrazi and Ahsina. (2016). Défaillance et politique d'entreprises : modélisation financière déployée sous un modèle logistique appliqué aux PME marocaines, La Revue Gestion et Organisation Volume 8, Issue 1, March 2016,
xxxvii. Koopman, S. J., Kräussl, R., Lucas, A. & Monteiro, A. B. (2009). Credit cycles and macro fundamentals, Journal of Empirical Finance, 16(1), 42-54.
xxxviii. Leksrisakul, P. and Evans, M. (2005). A model of corporate bankruptcy in Thailand using multiple discriminant analysis, Journal of Economic and Social Policy, 10(1), 5, p. 1-35.
xxxix. Liu, J. (2004). Macroeconomic determinants of corporate failures: evidence from the UK, Applied Economics, 36, pp. 939-945. ISSN 0003-684
xl. Lo, A. (1984). Essays in financial and quantitative economics. Ph.D. dissertation, Harvard University.
xli. Lukason,O and Hoffman,R.(2014). Firm Bankruptcy Probability and Causes: An Integrated Study, International Journal of Business and Management; Vol. 9, No. 11; 2014
xlii. Lussier, R. N. (1995). A Nonfinancial Business Success versus Failure Prediction Model for Young Firms, Journal of Small Business Management, vol. 33, n° 1, pp. 8-20.
xliii. Matoussi, H. and Krichène. A. (2010). Credit risk evaluation of a Tunisian commercial : Bank: logistic regression versus Neural Network Modelling , Journal of accounting and management information systems,vol 9, number 1 2010
xliv. Merwin, C. (1942). Financing small corporations in five manufB.cturing industries, 1926- 1936 New York, National Bureau of Economic Research.
xlv. Morocco., The Bankruptcy Reform Process in Morocco Improving the Business Climate in Morocco Program. (2008), *USAID country report*. Washington, DC: USAID.
xlvi. Ooghe, H. and Van Wymeersch,C. (1996). Traité d'analyse financière. 6th Edition. Brussels, Wolters Kluwer Belgique & Presses Universitaires de Namur.
xlvii. Rosendale, W. M. (1908). Credit Department Methods. Bankers' magazine, 183-194.
xlviii. Pervan, I., Pervan, M., and Vukoja, B. (2011). Prediction of company bankruptcy using statistical techniques – Case of Croatia. Croatian Operational Research Review, 2(1), 158–167.
xlix. Platt, H. D. and Platt, M. B. (2002). Predicting Corporate Financial Distress: Reflections on Choice-Based Sample Bias. Journal of Economics and Finance, 26(2), 184-199
l. Situm, M., (2014), 'The inability of gearing-ratio as predictor for early warning systems', Business Systems Research Journal, 5 (2): 23 – 45
li. Sirirattanaphonkun, W. and Pattarathammas, S. (Dec. 2012). Default Prediction for Small-Medium Enterprises in Emerging Markets: Evidence from Thailand, Seoul Journal of Business, 18(2), 25-54.
lii. Smith, R. and. Winakor, A. (1935).Changes in Financial Structure of Unsuccessful Industrial Corporations, Bureau of Business Research, Bulletin No. 51. Urbana: University of Illinois Press.
liii. Tabachnick, B. G. and Fidell, L. S. (2000). Using Multivariate Statistics, Allyn and Bacon Press, UK. 2000
liv. Taffler, R.J. (1984). Empirical models for the monitoring of UK corporations, Journal of Banking and Finance
lv. Wadhwani, S. (1986). Bankruptcy, Default and the Stock Market, Economic Journal, 96, 120-138.