Distressed Company Prediction using Logistic Regression: Tunisian's Case

Faycal Mraihi[1]

[1] Faculty of Law, Economics and Management of Jendouba, Tunisia

Received: 11 February 2015 Accepted: 5 March 2015 Published: 15 March 2015

Abstract

In this study, we try to develop a model for predicting corporate default based on a logistic regression (logit) and applied to the case of Tunisia. Our sample consists of 212 companies in the various industries (106 companies 'healthy' and 106 companies "distressed") over the period 2005-2010. The results of the use of a battery of 87 ratios showed that 12 ratios can build the model and that liquidity and solvency have more weight than profitability and management in predicting the distress. Both on the original sample and the control one, these results are good either in terms of correct percentage of classification or in terms of stability of discriminating power over time (on, two and three years before the distress) and space

Index terms— distressed firms, forecasting model, logistic regression model.

1 Introduction

any firms react very late or improperly facing the first signs of distress. Three to five years elapse, usually between the early difficulties encountered by the company and the first operating mechanisms.

This delay generally results from a lack of understanding of the mechanisms and causes the degradation of process and an obvious lack of foresight. Thus, it is useful to examine the sequence that implies that process and to define, in the area of prevention, methods or models to predict the decline of the company in the medium term.

An objective definition of a distressed company or a firm in a difficult situation does not exist, so we can refer to the definitions suggested by Haehl (1981) and The French Superior Council of Economic Professions (FSCEP).According to the first definition « In state of difficulty the company which, because of certain economic, financial or human imbalance, revealed by the conjunction of diverse indications, ratios, and the examination of all elements, cannot envisage in the predictable, short and medium-term future, to continue its activity in a normal way or could only by proceeding in transactions of partial liquidation, economic transformation, inflow of outer permanent capital or redundancy of a part of the staff ».

For the second definition « In the absence of legal definition on the subject, and to define the firm in difficulties we can base on the criteria of liquidity, solvency, profitability and added value and to consider that a company is in a difficult situation from the moment it evolves in such a way, for economic, financial, organizational, social or other reasons, it will meet sooner or later difficulties to generate the sufficient income to fill its legal and contractual commitments and make the necessary investments ».

In such context, to which is added a bubbling socioeconomic environment, the regular appeal to the diagnosis establishes not only a requirement of good management, but also an imperative for the survival of the company.

A successful diagnostic has to detect, in time, the causes of the distressing. These causes show themselves in the company by a battery of indicators that must be identified as soon as possible to a successful recovery plan.

The diagnostics of default risk knew an important development through the use of multivariate statistical methods to analyze the financial situation from a given set of ratios. Among the most commonly used statistical methods, we find logistic regression. The principle of this method is the following: having the characteristics described by financial ratios, and a sample of companies that cover both "healthy" companies and "distressed" companies, logistic regression leads to determine the best combination of ratios to differentiate the two business groups.

To achieve this goal and to develop a model for predicting corporate default based on a logistic regression, this article will address, in a first section, the methodology through the presentation, writing and justification of the model used, the constitution of the samples and the set of distressed determinants, while being interested in the Tunisian case. The estimate of the discriminatory power of the model in time and space will be in the second section. The third section analyzes the sensitivity that will allow us to test the elasticity of the model results due to the variation of the explanatory variables. Thus, we try to classify, in the fourth section, each ratio according to its degree of participation in the discriminatory power of the model.

2 II.

3 The Methodology

In this work, we use regression for predicting business distress, and then we test its validity in time and space. However, it is primordial to define what a logistic model is, explain its approach and show its usefulness, then present the hypotheses and tests to perform and discuss the constitution of the samples. a) Overview and principle of the logistic model i. Literature review Logistic regression, viewed as a generalization of linear discriminant analysis, has been introduced by Day & Kerridge (1967), Cox (1970), and developed by Anderson (1972Anderson (, 1982)), Martin (1977), **??**lshon (1980) who was the pioneer in the use of logistic regression in the domain of prediction of business distresss. Among the major works that have used this method we can cite Mensah (1984), Albert & Lesaffre (1986), Aziz &al (1988), Bardos (1989) As in multiple linear regression, it is relates to estimate parameters of model, to measure its adequacy (quality of adjustment) and to deduce the significance and the interpretation of the estimated parameters. Logistic regression is an econometric technique with a dichotomous dependent variable yi, representing the state of the company that takes:

-The value 1 if the company is "distressed" -The value 0 if the firm is "healthy".

This type of regression allows to determinate the probability that a firm is classified in the group of « healthy » or the group of « distressed ». At this discrimination, there can be two types of errors:

-The error of the first kind I: classify a distressed company with the healthy ones.

-The type of the second kind II: classify a healthy company with distressed ones.

We must notice, however, that the cost associated with the error of the first kind is very different from that associated with type II. Indeed, the first cost is that a creditor support in case of default of the debtor. While the second one is an opportunity cost representing the difference between remuneration that a creditor could collect on the, not accepted, and the rate of return offered by the use of these funds.

To the extent that the cost of a Type I error is much higher than that of a Type II error (about 1 to 20 according to Altman et al. "Zeta analysis" in 1977), then it seems more relevant to judge the quality of the model on the basis of correct classification percentages, in general, and the error rate of type I that it induces, in a particular way.

In general, from a sample of base and a set of ratios, we will proceed as follows:

-Check the distribution normality of selected ratios by eliminating those not responding to the corresponding test.

-Examine the individual discriminating power of these ratios by classifying them by categories.

-Evaluate the existing correlations between the ratios by eliminating those that are redundant.

-Observe the discriminating power of different combinations and select by iteration the combination that offers the best correct percentage of classification with the lowest cost of the first kind, that is the one that provides the best value: intergroup dispersion / intragroup dispersion.

ii. logistic model principle we have : y 1 , y 2 ,......y n : random variables, called dependent variables, each taking the value 1 or 0, values that correspond to groups G1 and G2 to discriminate.

x 1 , x 2 ,........x J : the components of a multidimensional vector X = (x 1 , x 2 ,........x J) and that represent random variables called explanatory or independent variables. (?) = (? 0 , ? 1 ,..........? J): are the unknown coefficients of the model to be estimated.

The idea is to build a model linking ?(x) = p[Y=1/ X] (he probability that Y = 1 given X). With : Formally, the null hypothesis is as follows:0 1 1 2 2 (.......) 1 probability of default ( )] (1/) 1 [K K x x x x P Y X x eH 0 : a 1 = a 2 = ? ? ? = a k = 0

This is a global evaluation assessment of the regression. Indeed, if the null hypothesis is accepted, it would mean that none of the explanatory variables contribute to the explanation of the dependent variable. The model can be rejected.

H1: at least one of the coefficients is non-zero.

The objective of significance tests is to determine the role of each of several or all, of explanatory variables. We have two approaches to test the hypotheses:

4 Global Journal of Management and Business Research

Volume XV Issue III Version I Year ( )

5 C

Use the principle of the likelihood ratio. The approach is generic and consistent with the process of parameter estimation. It can detect better the alternative hypothesis when it is true. The disadvantage is that it is heavier in terms machine. Indeed, every hypothesis to evaluate gives rise to a new estimation of the parameters, so to a process of optimization. Certainly, software and computers today are very efficient, but when the databases processed are important, the calculations to be made will not be as significant as that. Use the asymptotic normality of estimators (maximum likelihood). We talk about Wald test. The main advantage is that the information that we want to use, are all-available when estimating the global mode, including all variables. The obtaining of the results is immediate. A disadvantage is that the Wald test is conservative; it tends to favor the null hypothesis.

6 c) The constitution of samples and variables determination

The choice of the sample posed us serious problems. Indeed, the implementation of logistic regression assumes the existence of two business groups « healthy » and « distressed ». The selection of the reference population leads to a choice between two alternatives:

-Constitute a sample the widest possible, which includes companies from different industries, size, geographical location and economic environments.

-Choose a reference population so as to guarantee the homogeneity of the sample, leave to limit its size.

In practice, and according to most studies [Beaver (1966), Altman (1968), Edmister (1972)], we adopted the option of a larger sample affecting several sectors. Our sample consists of 212Tunisian companies in the various sectors (which will be discussed below), (106 "healthy" companies and 106 "distressed" companies) over the period 2005-2010.

The "healthy" companies were selected from the Tunisian stock exchange and among statutory accountants. While "distressed" companies come from the office of assistance to companies in difficulty, which sits at the Ministry of Industry. The selection of firms in difficulty was based on the following criteria:

-Be suspension of payments for at least six months -Have very serious social problems, -Must be identified by statutory auditors, National Social Security Fund or fiscal institutions From this basic sample, and referring to the approach of Platt and Platt, (1991); Altman et al, (1994); Bardos (1998a) and Varetto (1998), it was possible to set up two sub-samples:

-A first, called "Initial" sample consisting of 152 companies, 76 "healthy" and 76 "distressed". We'll take the last three years of the same companies to form three sub-samples we call "Initial one year prior to distress," "Initial two years before distress" and "Initial three years prior to distress." these subsamples used to develop the model and to test its validity in time.

-A second sample, called "Control" sample, composed of 60 other companies, 30 "healthy" and 30 "distressed". From the last three years of these companies, we will establish three sub-samples that we call "control one year prior to distress," "Control two years prior to distress" and "Control three years prior to distress." These sub-samples are designed to test the validity of the model in space.

Companies belonging to both sample of "healthy" and the "distressed" companies are distributed between the different sectors as follows: In the absence of a theory of business distress, the choice of indicators is completely subjective. Indeed, it is based on experience and intuition of the one who develops the model. Generally, this choice often results from previous choices, this is to say the choice of all first authors of reference (Ramser and Foster, 1931 ;Fitzpatrick, 1932 ;Winakor and Smith, 1935 ;Merwin, 1942 ;Beaver, 1966 ;Altman, 1968 ;Deakin, 1972 ;Edmister, 1972 ;Blum, 1974 ;Altman and al, 1977 ;Taffler, 1983).

The number of ratios that can be included in a financial analysis is extremely high. To avoid making an excessively statistical treatment, we limited ourselves to ratios calculated on the basis of different valuesrelative to the same year and concerningthe Fundamental and classic aspects of the financial analysis: liquidity, funding, debt, profitability, balance sheet structure and financing costs.

Moreover, for each category, we selected three or four ratios, in order to avoid a high number of ratios for the study to be carried out and thus avoid the redundancy phenomenon. But on the other hand the number of ratios should not be too small for all aspects of business situation are covered.. Despite these limitations, we were finally brought to retain only 87 ratios shown in Appendix 1.

The assignment of a ratio to one or to the other categories can be discussed. Indeed, among selected ratios some are composite in nature and thus reflect, at the same time, several aspects of corporate behavior to be taken into account in the interpretation. This classification has only for objective the convenience of the presentation and the analysis of the results.

7 III. Estimation of the Model Parameters

From the three subsamples which we called "Initial one year prior to distress," "Initial two years before distress" and "Initial three years before distress," each consist of the same 152 firms (76 "distressed" and 76 "healthy") but for different years (each sample is interested in the same year for all companies), and a set of 87 ratios (Appendix 1), we will try to formulate a logistic model, estimate its coefficients, calculate the probability of default in posteriori and develop a decision rule.

To perform the estimation, we used the "SPSS" software. In a first step, it was assumed a model with 87 explanatory variables. The estimated model has provided us with results rather critical because the error rate is 50%: Constant is included in the model.

8 The cut value is ,500

Such an error rate is explained by the importance of correlations between the explanatory variables: collinearity problem, correlation matrix and variance-covariance. Thing that leads us to take great care in selecting all ratios. Indeed, the number of ratios should not be too high for the study to be performed (Rose and Giroux (1984) identified more than 130 different ratios). Also, the phenomenon of redundancy between ratios must be avoided: from the analysis of the correlation matrix, we observed a strong correlation between some explanatory variables; there is a great redundancy (the same information is provided by several ratios).

To solve this problem of collinearity, we opted for the "Feedward" method. It consists in introducing into the model, each time, the most correlated explanatory variable with the dependent variable until the matrix becomes not inversible. During this operation, we must be careful and retain only the independent variables that are significant at the 5% and can improve the 2 R and we will ensure that all aspects of the situation of the company are covered.

Once this is done, based on 87ratios initially taken, we are left with only 12ratios, which will constitute the explanatory variables of the model to be estimated. The estimate by the logit model gives the following results: This ratio, called the ratio of financial autonomy is particularly studied by bankers because their equity represents a guarantee. Indeed, in case of liquidation of the company, share holders will be last served in case of the sale of assets. If the assets are insufficient to cover liabilities, the loss will thus be imputed on stockholders' equity before being on other debts. R 19 = Short-Term Debt / Total Liabilities. It measures the share of short-term debt of the company in all of its liabilities. It is an indicator of the debt structure. R 26 = Amortization of Capital Assets / Gross Fixed Assets. This ratio is often used as an indicator of the degree of aging equipment R 28 = Working Capital / Total Assets. This ratio expresses the degree of liquidity of the firm. Indeed, he reports the excess of current assets after providing for short-term debt relative to total assets. R 33 = current assets (excluding stocks) / current liabilities. The ratio of reduced liquidity is a more restrictive measure of the liquidity of a company than the current ratio. It indicates the portion of current liabilities covered by current assets excluding stocks. R 40 = current assets (excluding stock) / Total assets. This ratio is an indicator of the liquidity of the company; it expresses the proportion represented by trade receivables, investments and other current assets, liquidity and cash equivalents to total assets. R 61 = Medium and long-term debt / Cash flow It is a debt ratio, it gives us information on the proportion that debt in the medium and long terms represents over resources generated by the activity of the company in terms of cash. This cash allows the firm to invest and continue its development. R 74 = Net Income / Total liabilities It is a profitability ratio that expresses the proportion of net income for each currency of liabilities invested in the company. R 79 = Total Liabilities / Total Assets This overall solvency ratio must be significantly less than one. Indeed, if its value is equal to ½, this means that the company has a significant debt capacity because in case of liquidation, for example, the value of its assets can be used to repay twice all its commitments.

In the equation used by logistic regression forecasting, we notice the presence of several ratios that have been selected as explanatory variables in previous studies. The overall significance test used in the logistic regression is the chi-square with k degrees of freedom (k is the number of explanatory variables in our case k = 12). If the critical probability is less than the significance level that one is fixed, we can consider that the model is globally significant. In our model the statistical likelihood ratio (chi-square) is equal to 210.717; the critical probability associated is zero. The model is generally very significant, there is indeed a relationship between the explanatory variables and the variable to be explained. Similarly decrease in value -2 logliklihood from one stage to another also indicates the same result, that the introduction of new variables improves the model. In our case, this value down from 210.717 to zero. Cox & Snell R Square and Nagelkerke R Square tests help to determinate the percentage of the binary dependent variable that is explained by the explanatory variables retained confirmed the significativity of our model. Indeed, the Nagelkerke R Square test is an adjusted version of the Cox & Snell R Square one and therefore closer to reality. So, for our model, we notice that 100% of the variation in the dichotomous variable could be explained by the explanatory variables used and retained.

Once the overall significance of the model used is demonstrated, it remains to be seen whether the explanatory variables are significant. The Wald test in the logistic regression (see table above) demonstrates that, the twelve explanatory variables, retained in our model, are significant at 5 %.

The Hosmer and Lemeshow test divided into deciles based on predicted probabilities, then computes a chi-square from observed and expected frequencies. The value p = 100% here is calculated from the chisquare distribution with 6 degrees of freedom, it indicates that the logistic model used is excellent. After checking the overall significance of the model and the significance of the explanatory variables, our job is now to verify the performance and stability of the logit model retained both in time, by applying it to the initial samples a year, two and three years prior to distress and in space using control samples a year, two years and three years before distress (Appendix 3-1, 3-2, 3-3, 3-4 and 3-5).

9 Global Journal of Management and

10 IV. Estimation and Validation of the

Discriminatory Power of the Model in Time and Space a) Estimation of the model discriminatory power one year before distress

The estimation of the logit model on the original sample, one year prior distress, shows that in the "healthy" firms group, the model classifies all "healthy" firms in their original group correctly.

In the distressed companies group, that interests us the most, we find no firm misclassified, so the model classifies successfully both companies "healthy" as "distressed" (Appendix 1 and Appendix 3-1). As far as the error Type I cost is much higher than that of an error type II [about 1 to 20 in Altman and al (1977)], then it seems more appropriate to judge the quality of the model on the base of the correct percentages of classification, in general, and of the error type I rate that it induces, in a particular way. These results "appear" as a whole interesting because they have the advantage of providing a combination of ratios based on which one can make a diagnostic of the company.

We say "appear interesting" because we should not judge the model before testing the performance over time (testing the model on the same companies but for different periods of time, two years and three before distress) and in space (testing the model on a control sample consisting of companies other than those in the sample of origin). b) Validation of the model discriminatory power over time i. For the same companies two years before distress

The validation of model on exercises that come two years before distress gives the results in Appendix 1 and Appendix 3-2.

In the « healthy » companies group, we find that the model correctly classifies all « healthy » firms in their original group. In the « distressed » firms group, there are five firms misclassified, so the firms are considered as "healthy" when they are actually distressed. The model retains thus its discriminatory power, since the percentage of correct classification varies by only 0.66% from 100% to 99.34%, the error type I increases from 0 to 1.32%, while the error type II remains zero.

ii. For the same companies three years before distress We will proceed in the same way as before, the same firms but for three years before distress, we get the results presented in Appendix 1 and Appendix 3-3. In the group of « failed » firms, we find that the model classifies four firms in the group of « healthy » one, while they are « distressed » which produces an error type I of about 5.26%. In the group of « healthy » companies, all companies are correctly classified and we have a percentage of error Type II equal to zero.

The forecasting ability of selected ratios, showed a satisfactory stability over time, since the overall error rate only increased from 0% to 3.29% % over the last three years preceding the distress, particularly some stability is noted for the classification of « healthy » companies .The following table will present a summary of changes in correct percentages of classifications and in errors of type I and II in time. Indeed, we notice that for the model used, the percentage of the error Type I varied only by 6.58% between the first and third years before distress. Furthermore, we find that the correct percentage of classification decreased only by 3.29% (it goes from 100% to 96.71%).

For our model, the most interesting element, in addition to its high correct percentage of classification, it

11 Global Journal of Management and Business Research

Volume XV Issue III Version I Year ( )

12 C

is the weakness of the error Type I whose cost is higher. Concerning the error type II, we see that it remains zero.

13 c) Validation of the model discriminatory power in space

To test the discriminatory power of the model in space, we use a control sample consisting of two new groups. The first contains the distressed firms while the second contains "healthy" companies, each lists 30 firms. The model will be tested on companies other than those that were originated. The application of our Logit model on these samples gives us the estimates presented in Appendix 2 and Appendix 3-1.

In the « healthy » companies group, we find that the model classifies two firms in the « distressed » group when they are « healthy ». In the « distressed » group, there are also misclassified firms so they are considered by the model « healthy » when they are actually distressed.

This model has a remarkable accuracy by classifying 95% of the control sample correctly. The error Type I is around 10% while the error type II is zero. Studying companies' exercises of control sample in case of two years before distress, we get the results announced at Appendix 2 and Appendix 3-4.

In the « healthy » companies group, we find that the model classifies all firms correctly so we conclude an error type II equal to zero. While in the group of distressed companies, there is a single firm misclassified, giving us an error Type I of about 3.33%. The increase of the efficiency of the Logit function, in this validation test (it passed from 5% to 98.33%), is due to the fact that the two samples of distressed firms (the initial sample and the control one) are randomly selected from a pool of 106failed firms. Moreover, as the samples are both small, the distributions of firms by size and industry differ considerably and this affects the efficiency of the function.

If we further increase the time period between the prediction date and the advent of distress, using the same control sample but for three years before distress, we obtain the results reported in Appendix 2 and Appendix 3-5

In the « healthy » companies group, all firms are correctly classified. But, in the « distressed » firms group, there are two misclassified companies so they are considered as "healthy" when they are actually distressed.

If we summarize, we get the following table **??** Table 10 : Results of estimation in the time and space We notice that the percentage of correct classification, in the initial sample, varies from 100% to 96.71% (a change of 3.29%). It is a result that remains well above those achieved by Ohlson (1980) and Olson et al (2012). Note that Ohlson was the pioneer in the use of logistic regression in the prediction of business distresss. For the control sample that percentage increased from 95% to 96.67%, a negative variation of 1.67%. Overall, the results provided by our model outperforms those presented by Wilcox (1973), Zavgren (1985), Flagg and al (1991), **??**arniv and Mcdonald (1992), Back and al (1996)

14 V. The Determinant Power of Variables

The basic equation of the model is: Z = Our objective now is to classify each ratio according to its degree of participation in the discriminatory power of the model to deduce the most determinant ones.

The observation of the coefficients of the previous equation does not allow us to evaluate the contribution of each ratio. To do this, we made an adjustment by multiplying the coefficients of these variables by their standard deviation, in order to transform them into a scalar vector. Indeed, since the variance matrix is as follows: The contribution of the j variable j = ?b j ? j ?with bj : Ratio weighting coefficient of R j in the function LOGIT ?j :standard deviation of ratio R j for all companies of initial sample.

From this table, we can conclude that the three most significant variables of distress risk in the model are: R28, R06and R07.

Thus, we see that the liquidity and solvency have more weight in predicting the distress than profitability and management. This is logical and consistent with reality since the filing of corporate balance sheets is never caused by the deficits, but rather a cash flow problem that is manifested by the inability of the company to meet its obligations or an insolvency problem.

15 VI.

16 Conclusion

Both on the original sample as the control sample, the results provided by the method used are very efficient either in terms of correct percentage of classification or in terms of discriminative power stability over time and space.

The ratios selected and used in the model can cover all aspects of the company: its solvency, its degree of liquidity, financial independence sees its financial structure, the level of payment of its debts, and the degree of ageing its equipment.

Despite the relevance of the results obtained by logistic regression, the presence of several predicting methods allows us a wider choice and therefore more satisfaction and confidence.

Indeed, if the application of models for the same company, gives us the same result (different models apply the same classification) then the creditor or financial analyst make its decision with more confidence. If instead the models give contradictory results, then the decision maker is forced to push more research on this company. [1] [2] [3] [4]

[1] 1

[2] Conan & Holder (1979) ; Holder & al (1984)

[3] Distressed Company Prediction using Logistic Regression: Tunisian's Case

[4]

Figure 1:

1

Companies

Figure 2: Table 1 :

2

Observed		Predicted Y 0	1	Percentage Correct
Step 0 Y	0	0	76	,0
	1	0	76	100,0
OverallPercentage				50,0

Figure 3: Table 2 :

3

Year
Volume XV Issue III Version I
( ) C
Global Journal of Management and Business Research

		B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1 a	R 5	14,088	15960,342	,000***	1	,999	1312882,320	,000	.
	R 6	-131,311	43256,749	,000***	1	,998	,000	,000	.
	R 7	-272,144	40875,140	,000***	1	,995	,000	,000	.

[Note: Z]

Figure 4: Table 3 :

4

Ratio	Authors
R 6	

Figure 5: Table 4 :

5

Chi-square	Df	Sig.

Figure 6: Table 5 :

6

Itération		-2 Log likelihood	Coefficients Constant
Step 0	1	210,717	,000

a. Constant is included in the model.
b. Initial -2 Log Likelihood: 210,717

[Note: c. Estimation terminated at iteration number 1 because parameter estimates changed by less than ,001.]

Figure 7: Table 6 :

7

Step	-2 Log likelihood	Cox &Snell R Square	Nagelkerke R Square
	,000 a	,750	1,000

a. Estimation terminated at iteration number 20 because maximum iterations has been reached.

Figure 8: Table 7 :

8

Year
Volume XV Issue III Version I
( )
Business Research

[Note: C]

Figure 9: Table 8 :

9

	1 year before distress	2 years before distress	3 years before distress
% of correct classification	100 %	99. 34 %	96.71 %
% of classement error	0 %	0. 66 %	3.29 %
% of error type I	0 %	1. 32 %	6.58 %
% of error type II	0 %	0 %	0 %

Figure 10: Table 9 :

Figure 11:

11

Ratio	Variance
R 5	0,08

Figure 12: Table 11 :

12

	Coefficients b j	standard deviation ? j	Scalar vector ?b j ? j ?	classification
R 5	14,088	0,282842712	3,984688133	12
R 6	-131,311	0,793725393	-104,2248751	2
R 7	-272,144	0,264575131	-72,00253448	3
R 15	10,482	0,804363102	8,431334036	8
R 19	-23,35	0,266458252	-6,221800182	9
R 26	66,129	0,242899156	16,06267829	6
R 28	178,682	0,80311892	143,5028949	1
R 33	-13,401	0,779743548	-10,44934328	7
R 40	87,654	0,242899156	21,29108262	5
R 61	-0,502	11,70794602	-5,877388902	10
R 74	-15,515	0,367423461	-5,700575004	11
R 79	52,925	0,831865374	44,0264749	

Figure 13: Table 12 :

[Winakor and Smith ()] , A H Winakor , R F Smith . *Changes in the Financial Structure of Unsuccessful Industrial Corporations* 1935. 51 p. 44. University of Illinois, Bureau of Business Research (Bulletin)

[Fitzpatrick (1932)] *A Comparison of Ratios of Successful Industrial Enterprises with Those of Failed Firms*, P J Fitzpatrick . 1932. October 1932. The Certified Public Accountant. p. .

[Ramser and Foster ()] 'A Demonstration of Ratio Analysis'. J Ramser , L Foster . *Bulletin* 1931. 40. University of Illinois, Bureau of Business Research

[Deakin ()] 'A discriminant analysis of predictors of business failure'. E B Deakin . *Journal of accounting research* 1972. p. .

[Lau ()] 'A five-state financial distress prediction model'. A H Lau , .-L . *Journal of accounting research* 1987. p. .

[Day and Kerridge ()] 'A general maximum likelihood discriminant'. N E D F Day , Kerridge . *Biometrics* 1967. 23 (2) p. .

[Platt and Platt ()] 'A note on the use of industry-relative ratios in bankruptcy prediction'. H D M B Platt , Platt . *journal of banking &* 1991. 15 (6) p. .

[Mahmood and Lawrence ()] 'A Performance Analysis of Parametric and Nonparametric Discriminant Approaches to Business Decision Making'. M A Mahmood , E C Lawrence . *Decision Sciences* 1987. 18 p. .

[Wilcox ()] 'A prediction of business failure using accounting data'. J W Wilcox . *Journal of accounting research* 1973. p. .

[Wu ()] 'A real-valued genetic algorithm to optimize the parameters of support vector machine for predicting bankruptcy'. C.-H Wu . *Expert Systems with* 2007. 32 (2) p. .

[Mossman ()] 'An empirical comparison of bankruptcy models'. C E Mossman . *Financial Review* 1998. 33 (2) p. .

[Edmister ()] 'An empirical test of financial ratio analysis for small business failure prediction'. R O Edmister . *Journal of Financial and Quantitative* 1972. 7 (02) p. .

[Tserng ()] 'An enforced support vector machine model for construction contractor default prediction'. H P Tserng . *Automation in Construction* 2011. 20 (8) p. .

[Mensah ()] 'An examination of the stationarity of multivariate bankruptcy prediction models: a methodological study'. Y M Mensah . *Journal of accounting research* 1984. p. .

[Wang et al. (2014)] 'An improved boosting based on feature selection for corporate bankruptcy prediction'. Jian Wang , Shanlin Ma , Yang . *Expert Systems with Applications* 2014. April. 41 (5) p. .

[Cox ()] *Analysis of binary data*, D Cox . 1970. 1970. Methuen, London. p. .

[Zavgren ()] 'Assessing the vulnerability to failure of American industrial firms: a logistic analysis'. C V Zavgren . *Journal of Business Finance and Accounting* 1985. 12 (1) p. .

[Yu ()] 'Bankruptcy prediction using Extreme Learning Machine and financial expertise'. Q Yu . *Neurocomputing* 2014. 128 p. .

[Min and Lee ()] 'Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters'. J H Min , & Y.-C Lee . *Expert Systems with Applications* 2005. 28 (4) p. .

[Aziz ()] 'Bankruptcy prediction-an investigation of cash flow based models [1]'. A Aziz . *Journal of Management Studies* 1988. 25 (5) p. .

[Laitinen and Laitinen ()] 'Bankruptcy prediction: application of the Taylor's expansion in logistic regression'. E K. & T Laitinen , Laitinen . *International Review of Financial Analysis* 2001. 9 (4) p. .

[Nam and Jinn ()] 'Bankruptcy prediction: Evidence from Korean listed companies during the IMF crisis'. J H. & T Nam , Jinn . *Journal of International Financial Management and Accounting* 2000. 11 (3) p. .

[Dimitras ()] 'Business failure prediction using rough s & s'. A Dimitras . *European Journal of Operational Research* 1999. 114 (2) p. .

[Laitinen and Laitinen ()] 'Cash management behavior and failure prediction'. E K. & T Laitinen , Laitinen . *Journal of Business Finance and Accounting* 1998. 25 (7-8) p. .

[Dwyer W ()] 'Changes in the Helping Behaviors of Adult Children as Caregivers'. . J Dwyer W . *Research on Aging September*, 1992. 1992. 14 p. .

[Burgstahler ()] 'Changes in the probability of bankruptcy and equity value'. D Burgstahler . *Journal of Accounting* 1989. 11 (2) p. .

[Kim and Kang ()] 'Classifiers selection in ensembles using genetic algorithms for bankruptcy prediction'. M.-J. & D.-K Kim , Kang . *Expert Systems with Applications* 2012. 39 (10) p. .

[Barniv and Hershbarger ()] 'Classifying financial distress in the life insurance industry'. R R A Barniv , Hershbarger . *Journal of Risk and Insurance* 1990. p. .

[Bardos and Zhu ()] *Comparaison de l'analyse discriminante linéaire et des réseaux de neurones: Application à la détection de défaillance d'entreprises*, M & W Bardos , Zhu . 1997. 45 p. . (Revue de statistique appliquée)

[Charalambous ()] 'Comparative analysis of artificial neural n&work models: Application in bankruptcy prediction'. C Charalambous . *Annals of operations research* 2000. 99 (1-4) p. .

[Olson ()] 'Comparative analysis of data mining m&hods for bankruptcy prediction'. D L Olson . *Decision Support* 2012. 52 (2) p. .

[Altman ()] 'Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience)'. E I Altman . *journal of banking* 1994. 18 (3) p. .

[Zeitun ()] 'Default probability for the Jordanian companies: A test of cash flow theory'. R Zeitun . *International Research Journal of Finance and Economics* Zopounidis, C. (ed.) 2007. 1995. 8 p. . (Economica)

[Distressed Company Prediction using Logistic Regression: Tunisian's Case] *Distressed Company Prediction using Logistic Regression: Tunisian's Case*,

[Martin ()] 'Early warning of bank failure: A logit regression approach'. D Martin . *journal of banking* 1977. 1 (3) p. .

[Li and Sun ()] 'Empirical research of hybridizing principal component analysis with multivariate discriminant analysis and logistic regression for business failure prediction'. H Li , & J Sun . *Expert Systems with Applications* 2011. 38 (5) p. .

[Blum ()] 'Failing Company Discriminant Analysis'. M Blum . *Journal of Accounting Research* 1974. 12 (1) p. .

[Chen ()] 'Financial distress prediction in China'. J Chen . *Review of Pacific Basin Financial Mark&s and Policies* 2006. 9 (02) p. .

[Ohlson ()] 'Financial ratios and the probabilistic prediction of bankruptcy'. J A Ohlson . *Journal of accounting research* 1980. p. .

[Beaver ()] 'Financial ratios as predictors of failure'. W H Beaver . *Journal of accounting research* 1966. p. .

[Altman ()] 'Financial ratios, discriminant analysis and the prediction of corporate bankruptcy'. E I Altman . *The journal of finance* 1968. 23 (4) p. .

[Merwin ()] 'Financing Small Corporations in Five Manufacturing Industries'. C L Merwin . *Studies in Business Financing, 172 p. December*, 1942. p. . National Bureau of Economic Research, Financial Research Program III

[Taffler ()] 'Forecasting company failure in the UK using discriminant analysis and financial ratio data'. R J Taffler . *Journal of the Royal Statistical Soci&y. Series A (General* 1982. p. .

[Jones and Hensher ()] 'Forecasting corporate bankruptcy: optimizing the performance of the mixed logit model'. S Jones , D A Hensher . *Abacus* 2007a. 43 (3) p. .

[Varetto (1998)] 'Genetic Algorithms Applications in the Analysis of Insolvency Risk'. F Varetto . *Journal of Banking and Finance* 1998. October. 22 p. .

[Haehl ()] J Haehl . *« Les techniques de renflouement des entreprises en difficulté », Librairies techniques*, 1981.

[Barniv and Mc Donald ()] 'Identifying financial distress in the insurance industry: A synthesis of m & hodological and empirical issues'. R J B Barniv , Mc Donald . *Journal of Risk and Insurance* 1992. 59 p. .

[Holder ()] 'Le score de l'entreprise'. M Holder . *Nouvelles Editions Fiduciaires*, (Paris) 1984.

[Tam and Kiang ()] 'Managerial applications of neural n&works: the case of bank failure predictions'. K Y M Y Tam , Kiang . *Management Science* 1992. 38 (7) p. .

[Jones and Hensher ()] 'Modelling corporate failure: A multinomial nested logit analysis for unordered outcomes'. S D A Jones , Hensher . *The British Accounting Review* 2007. 39 (1) p. .

[Albert and Lesaffre ()] 'Multiple group logistic discrimination'. A E Albert , Lesaffre . *Computers and mathematics with applications* 1986. 12 (2) p. .

[Back ()] 'Neural networks and genetic algorithms for bankruptcy predictions'. B Back . *Expert Systems with Applications* 1996. 11 (4) p. .

[Serrano-Cinca and Gutiérrez-Nieto ()] 'Partial least square discriminant analysis for bankruptcy prediction'. C & B Serrano-Cinca , Gutiérrez-Nieto . *Decision Support Systems* 2013. 54 (3) p. .

[Anderson and Blair ()] 'Penalized maximum likelihood estimation in logistic regression and discrimination'. J Anderson , & V Blair . *Biometrika* 1982. 69 (1) p. .

[Boyacioglu ()] 'Predicting bank financial failures using neural n&works, support vector machines and multivariate statistical m & hods: A comparative analysis in the sample of savings deposit insurance fund (SDIF) transferred banks in Turkey'. M A Boyacioglu . *Expert Systems with Applications* 2009. 36 (2) p. .

[Flagg ()] 'Predicting corporate bankruptcy using failing firms'. J C Flagg . *Review of financial Economics1* 1991. (1) p. .

[Rose and Giroux ()] 'Predicting Corporate Bankruptcy: An Analytical and Empirical Evaluation'. P S Rose , G A Giroux . *Review of Business and Economic Research* 1984. XIX (2) p. .

[Charitou ()] 'Predicting corporate failure: empirical evidence for the UK'. A Charitou . *European Accounting* 2004. 13 (3) p. .

[Jones and Hensher ()] 'Predicting firm financial distress: a mixed logit model'. S Jones , D A Hensher . *The Accounting Review* 2004. 79 (4) p. .

[Anderson ()] 'Separate sample logistic discrimination'. J A Anderson . *Biometrika* 1972. 59 (1) p. .

[Peel and Peel ()] 'Some further empirical evidence on predicting private company failure'. M Peel , & D Peel . *Accounting and Business Research* 1987. 18 (69) p. .

[Gloubos and Grammatikos] *Success of bankruptcy prediction models in Greece. Studies in Banking and Finance: International business failure prediction models*, G Gloubos , T Grammatikos . 7 p. . (1 (988))

[Taffler ()] 'The Assessment of Company Solvency and Performance Using a Statistical Model'. R J Taffler . *Accounting and Business Research* 1983. 13 p. .

[Houghton and Sengupta ()] 'The effect of prior probability disclosure and information set construction on bankers' ability to predict failure'. K A. & R Houghton , Sengupta . *Journal of accounting research* 1984. p. .

[Altman ()] 'The Link between Default and Recovery Rates: Theory, Empirical Evidence, and Implications*'. E I Altman . *The Journal of Business* 2005. 78 (6) p. .

[Ahn ()] 'Trade finance and the great trade collapse'. J Ahn . *The American Economic Review* 2011. 101 (3) p. .

[Bardos ()] 'Trois méthodes d'analyse discriminante'. M Bardos . *Cahiers économiques et monétaires* 1989. 33 p. .

[Conan and Holder ()] 'Variables explicatives de performances & contrôle de gestion dans les PMI'. J & M Conan , Holder . *These d' & at*, 1979. CERG, Université Paris Dauphine

[Altman ()] 'Zeta Analyses : A new model to identify bankruptcy risk of corporations'. E I Altman . *journal of banking and finance* 1977. 1 (1) p. .

[Ngnyen (1997)] *« An application of artificial neutral networks and statistical methods in qualitative evaluation of small business loans*, KiraD S , Doreen D Ngnyen , D . 1997. April. ASMD Summer.

[Bardos ()] '« Detecting the risk of company failure at the Banque de France'. M Bardos . *Journal of Banking and Finance* 1998a. 22 p. .

[Bardos ()] *« Le risque de défaillance d'entreprise » Cahiers économiques et monétaires de la banque de France*, M Bardos . 1984. 190 p. 19.