INTERNATIONAL JOURNAL OF BUSINESS, 15(2), 2010 ISSN: 1083–4346

Corporate Default Analysis in Tunisia Using Credit Scoring Techniques

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ABSTRACT

The present paper aims at empirically comparing the performance of the different scoring techniques in detecting corporate default on a corporate loan portfolio of 151 big size companies hold by one of the biggest banks in Tunisia. Our objective is to identify the most performing internal credit scoring model for Tunisian banks which aim at improving their current predictive power of financial risk factors. Our results show that on our sample of Tunisian corporate loans the neural networks outperform all the other scoring techniques and that the most statistically relevant financial ratios for predicting loan default for the Tunisian bank are linked to the investment policy, the importance of the debt service, the short term liquidities and the firm's competitiveness. We thus underline the whole reasoning process behind the screening of loan applications and stress that borrowers should pay attention to reduced number of financial ratios when managing their business.

JEL Classification: *B41, C14, D81, G21, P43*

Keywords: *Credit Scoring; Discriminant Analysis; Logistic Regression; Classification Trees; Neural Networks; Financial Ratios; Risk Assessment; Tunisian Banks*

[*] The authors would like to thank an anonymous referee and the Editor for very useful comments and suggestions as well as the scientific committee and the participants of the Global Finance Conference 2009 for interesting discussions and recommendations. The usual disclaimer applies.

I. INTRODUCTION

Over the last twenty years, financial liberalisation represented one major evolution in an important number of developing countries. Besides its positive effects[1], most of the time developing markets liberalisation was accompanied by a significant increase of risks in the banking industry. The number of corporate defaults significantly affected the banking activity in these countries, generating financial crises and contagion over the whole international financial system. Moreover, financial globalisation induced an increased competition between domestic banks and very sophisticated foreign banks along with stringent regulatory attention to risk management practices. The Tunisian economy represents a good example in this matter.

Since the deregulation and liberalization process in the mid 1980s, the Tunisian financial sector has become more market oriented, with huge importance for the economy. The Tunisian banking system is structured around the Central Bank of Tunisia (CBT) and consists of 14 commercial banks that collect deposits of any maturity, provide short and medium-term credit and may engage in long-term credit operations. More specifically, there are 6 development banks that finance investment projects over the medium and long term and participate in the capital of private firms, 8 offshore banks and 2 merchant banks. In spite of recent bank privatizations, government presence remains dominant in the banking sector. The government is the controlling shareholder in 11 of the 20 commercial and development banks. Out of the 14 commercial banks, 9 are under private ownership, and 5 under government majority ownership, following the privatization of two banks in 2002 and 2005. The estimated total assets of the country's five largest banks are about US $10 billion. Foreign participation in their capital has risen significantly and is now well over 20%.

The Tunisian banking system is considered generally sound and is improving as the Central Bank has begun to enforce adherence to international norms for reserves and debt. Recent measures include actions to strengthen the reliability of financial statements, enhance bank credit risk management, and improve creditors' rights. Revisions to banking laws tightened the rules on investments and bank licensing, and increased the minimum capital requirement. The required minimum risk-weighted capital/asset ratio has been raised to 8%, consistent with the Basel Committee capital adequacy recommendations. Thirteen of the country's fourteen banks conform to the ratio, compared with only two in 1993. Despite the strict new requirements, many banks still have substantial amounts of non-performing or delinquent debt in their portfolios. Thus, they are forced to implement and develop different techniques for evaluating and managing credit risk[2].

The ongoing global financial turmoil that threw economies all around the world into severe recessions renews the interest for implementing appropriate credit risk devices. More than never the necessity for banks to correctly predict the possibility of default of their potential counterparties becomes crucial.

The financial literature proposes different approaches for measuring credit risk[3]. Lending institutions typically use ratings and credit scoring methods to rank credit applicants based on their expected performance. Despite that they are often confused as they both assess the risk of an individual debtor, ratings and credit scoring employ rather different methodologies. While ratings are essentially based on a fundamental analysis of the debtor's riskiness, the credit scoring approach is illustrated by a discriminant analysis, i.e. statistical methodology to optimally classify a population of debtors into distinguishable groups, namely “good” and “bad”. Moreover, whereas ratings are used for big companies issuing large amounts of debt, credit scoring requires large, heterogeneous populations, generally composed by small debtors, for the statistical parameters to be reliable. Finally, while ratings are ordinal risk indicators of the debtors’ riskiness following the opinion of the rating provider, credit scores are actual estimates of default probabilities of debtors in a group. Hence, their reliability strongly relies upon the sample size, the proportions of good and bad debtors it contains and the different mathematical approaches used to distinguish between them.

The early work on scoring issues is introduced and developed by Bierman and Hausman (1970) and Dirickx and Wakeman (1976) followed by Srinivasan and Kim (1987). Thomas et al. (1996) and Hand (1997) provide extensive discussions on credit scoring problems, including the various approaches used in practice and the treatment for different applications, e.g. mortgage lending, credit card lending, small commercial lending, etc. An excellent overview of the different statistical methods in consumer credit scoring including an insightful analysis of evaluating scoring mechanisms, i.e. scoring the score, can be found in Hand and Henley (1997) and Hand (2001).

As stated previously, for Hand and Henley (1997) credit scoring describes the formal process of determining how likely applicants are to default on their debt service. The statistical models, also called score-cards or classifiers, use as inputs predictor variables extracted from application forms and other sources. Their output is an estimate of the probabilities of defaulting. The decision to accept or reject is taken by comparing the estimated default probability with a suitable threshold.

Credit scoring techniques constitute an empirical or statistical approach of loan default prediction. They allow detecting the relationship between the default and the characteristics of a firm directly from the data, and globally include the discriminant analysis, the logistic regression, the classification trees and the neural networks.

The present paper aims at empirically comparing the performance of the different scoring techniques in detecting corporate default on a portfolio composed by the corporate credits of 151 companies hold by one of the biggest banks in Tunisia. The extensive use of these techniques in developed countries went along with the academic literature emphasizing the benefits and methodological issues surrounding the different models (see for example the above quoted studies or Altman and Narayanan, 1997 among others). However, evidence regarding the credit scoring performances in developing countries is rather limited (see for example Altman et al., 1979 for Brazil; Bhatia, 1988 for India**;** Pascale, 1988 for Uruguay; Vigano, 1993 for Burkina Faso; Schreiner, 2004 for Bolivia; Dinh and Kleimeier, 2007 for Vietnam). In this context, our study is, to our knowledge, the first to provide such an extensive analysis of the corporate lending activities of a bank in Tunisia and, by extension, in the North African developing countries. Our objective is thus to identify the most performing internal credit scoring model for Tunisian banks which aim at improving their current predictive power of financial risk factors. In particular, we point out the most important corporate financial indicators a bank needs to collect and how these can be combined in a credit scoring model.

Our results show that on our sample of Tunisian corporate loans the neural networks outperform all the other scoring techniques with an overall accuracy of 96.9%, followed by the classification trees (with an overall consistency in classification equal to 89.4%), the logistic regression (82.9%) and the discriminant analysis (81.2%) which is in line with previous literature using developed banking systems data. Moreover, though we start with a similar set of financial indicators as many credit scoring models applied on developed countries data, our analysis points out that the most statistically relevant financial ratios for predicting loan default for the Tunisian bank are the weight of fixed assets, the weight of financial expenses, the average maturity of payable accounts and accounts receivable, the return on capital employed and the return on activity. Hence, the investment policy, the importance of the debt service, the short term liquidities and the firm's competitiveness are the key factors that reflect its ability to avoid financial distress.

This paper is organized as follows. We start by briefly presenting our research methodology, namely the different credit scoring methods which also stress the theoretical background of our research question. The next section proposes a description of our sample on which we test the validity of the different scoring techniques. The last section concludes and proposes some potential extensions.

II. OVERVIEW OF CREDIT SCORING TECHNIQUES

The tremendous development of the credit market gave a high impetus for banks to develop tools and models to help standardize, automate and improve credit decisions. An efficient credit allocation allows directing resources toward their most productive applications, with a positive effect on productivity, output and growth. Furthermore, from the financial institution viewpoint, improving credit decisions may also provide a significant advantage in a highly competitive market, hence increasing profits and the probability of survival (see also Glennon et al., 2008). Finally, the significant heterogeneity among borrowers makes market prediction rather difficult. It is though primordial for banks to implement automated models that consistently classify credits by their overall credit quality. Credit scoring models are typically used for this purpose in order to predict expected performance over a fixed time horizon, based on borrowers past behaviour, current status and different risk factors that affect their ability to pay.

The basis for modern credit scoring techniques is provided by the early work of Fisher (1936) who implemented the statistical technique called discriminant analysis to differentiate groups in a population through measurable attributes, when the common characteristics of the group members are unobservable. Durant (1941) firstly recognized the possibility of using this statistical technique to discriminate between good and bad borrowers. The first consumer credit scoring systems were developed in the fifties, in the US and since then, the application of credit scoring systems hugely extended to include mortgage loans, credit cards sector, and even to detect high risk drivers, in marketing, for selecting addresses in a list for commercial purposes, etc. Eisenbeis (1996), Frame et al. (2001) and Berger and Frame (2007) provide very good discussions on the history and application of the credit scoring techniques on banks business portfolios.

Despite their advantages, i.e., coherent, explicit models allowing an improvement in credit valuation and pre-testing before use, credit scoring models also show some weaknesses. First of all they do not take into account qualitative elements linked both to the quality of the borrowing firm management and the particular features of the market on which the firm operates. Second, as any statistical model, they experience type two errors, i.e. placing the debtor in the bad group when it is actually good, and type one error, i.e. placing the debtor in the healthy group when it really belongs in the bad one. These errors induce costs for the user of such models, i.e. in the first case the loan would be rejected and the corresponding profit lost whereas in the second case a loan would be granted and some money would be lost if and when the default occurs. Third, credit scoring models have difficulties in taking into consideration changes that may modify the attitude of the different borrowers with respect to default. Finally, since all credit scoring models are based on financial ratios that may be subject to several limitations, especially window dressing, any decision solely using these different ratios should be taken with caution[4].

The empirical approach of loan default prediction globally includes linear and nonlinear models. The parametric econometric techniques such as linear discriminant analysis and logistic regressions are part of the first category of models, whereas the non parametric techniques based on classification trees and artificial intelligence techniques/expert systems, e.g. artificial neural networks, compose the nonlinear category of credit scoring models. A brief description of these four techniques is provided in the following paragraphs.

A. Linear Approaches of Bankruptcy Prediction

The early approach of credit scoring methodology is commonly structured along the lines of Altman's (1968) Z-score model. Altman's Z-score model is an application of multivariate discriminant analysis (MDA) in credit risk modelling. Historical financial ratios measuring liquidity, cumulative profitability, productivity, capital structure and efficiency used as inputs appeared to have significant discriminating power to separate the firm that fails to service its debt from the firms that do not. These ratios are weighted to produce a measure (credit risk score) that can be used as a metric to differentiate the bad firms from the set of good ones.

Once the model is estimated, it can then be applied to new applicants for whom the default probability is unknown. The result is a credit score for each new loan application with a high score indicating a better performance of the borrower and thus a lower probability of default. The obtained score has to be compared to a cut-off value to determine whether the application is accepted, rejected or needs further assessment.

The original Z-score model was revised and modified several times in order to find the scoring model more specific to a particular class of firm (for a detailed presentation of the different developments please refer to Altman and Narayan, 1997 and Altman, 2000).

The tremendous use of this classical linear discriminant analysis is explained by its numerous advantages, such as robustness, interpretability, simple utilization, easy maintenance (Bardos, 1998). Nevertheless, its major disadvantage comes from its underlying hypothesis, namely Gaussian distributed data, while credit data are often non normal.

One possibility to circumvent the non normality of data is to use an extension of the linear discriminant model that allows for different parametric distributions, namely a logistic regression also known as the logit model. Ohlson (1980) introduces the logistic regression model for bankruptcy prediction problems that can be summarized as follows. Given a vector of application characteristics x, the probability of default p is related to vector x by the following relationship

$$\log\left(\frac{p}{1-p}\right) = w_0 + \sum w_i x_i \tag{1}$$

The parameters w_i are then estimated by maximum likelihood techniques, which in turn require the use of a numerical optimization procedure. An important consideration is that there are many distributions that satisfy the logistic assumption besides the normal one, which should theoretically produce discriminant functions with better classification power. As the output is in between 0 and 1, the logistic regression has a nice probabilistic interpretation.

Linear and logistic regressions became standard benchmarks in loan default prediction and have been compared exhaustively in practice. The empirical results obtained by applying both techniques to the same sample of data show that the two methods produce very comparable results. Nevertheless, in the case of the logistic regression the coefficients are obtained under much weaker assumptions. As the linear discriminant analysis, the logistic regression is also highly sensitive to correlations among explanatory variables; hence, one should ensure that there are no such variables left in the training set. Similarly, as with discriminant analysis, the logit approach is limited by a parametric form of the model. Finally, the logistic regression requires important samples in order to provide a good level of stability.

The logit model is used by Campbell and Dietrich (1983) to identify the main variables that are significant in explaining mortgage prepayments, delinquencies and defaults. Gardner and Mills (1989) employ the same technique to estimate the probability of default for currently delinquent loans, while recognizing that delinquent borrowers do not necessarily end up in default. Lawrence and Arshadi (1995) use the logit model in the analysis of problem loans and resolution choices using borrower and bank variables. Finally, Charitou et al. (2004) show that the logit method is superior to other methods in predicting defaults.

B. Non Linear Approaches of Bankruptcy Prediction

Financial literature points out different reasons why a nonlinear approach would be superior to a linear modelling in loan bankruptcy prediction problems. Atiya (2001) for example mentions saturation effects in the relationship between financial ratios and default prediction and multiplicative factors, i.e. the impact of negative cash flows on the default probability gets amplified if the firm has large liabilities. These considerations explain the development of more recent techniques in credit scoring modelling such as the classification trees and the neural networks.

The Classification and Regression Trees (CART) technique is introduced by Breiman et al. (1984). It is originally developed as an instrument for dealing with binary responses and, as such, it is suitable for use in credit scoring where default and non-default responses are contained in data. Observations are split at each node by a function of one characteristic to create subgroups in which a single feature mostly dominates. When no split can be found that increases the class specificity at a node, the tree has reached a leaf node. When all observations are in leaf nodes the tree stops growing. Each leaf can then be assigned a class and an error rate (not every observation in a leaf node is of the same class).

For example, consider a sample of credit applicants described by n characteristics $x_1, x_2, \ldots, x_n$. These applicants may be split into two classes, i.e. "good" and "bad" borrowers. The aim of any credit scoring model is to find a classifier that separates good borrowers from bad ones. In the classification tree system, one performs a set of sequential binary splits of the data. The algorithm starts from the root which contains both healthy and bad credits and then loops over all possible binary splits in order to find the characteristic x and the corresponding cut-off value c that best separates the side containing mostly good borrowers and the side containing mostly bad borrowers. If $x_i < c_i$ then the borrower is classified in the bad credit category while if $x_i \geq c_i$ then the borrower belongs to the good credit category. This recursive procedure is applied until a stopping criterion is satisfied (for more details, see also Bastos, 2008). Each node contains more homogeneous borrowers than the preceding ones. In principle, the tree could grow until all leafs contain only good borrowers or only bad borrowers. However, one does not look for the "maximal" tree, i.e. the most optimal one, which would be very time-consuming, but for an efficient rule of classification, i.e. statistically insignificant nodes can be eliminated[5].

The greatest strength of classification tree approach is its transparency and ease of deployment. The method does not stipulate any hypothesis on data distribution and any particular type of relationship between the predicted and the independent variables. However, the weaknesses of classification trees are that they need large amounts of data and can take large amounts of time for model building. Another major limitation of classification trees is their instability, i.e. small fluctuations in the data may result in large variations in the classifications.

Frydman et al. (1985) are the first to use the CART method in credit scoring and show that it outperforms linear discriminant analysis. Chandy and Duett (1990) compare classification trees, logit modelling and discriminant analysis on a sample of commercial papers and obtain comparable results for the three methods while Devaney (1994) shows that logit and CART methods differ substantially in selecting the financial ratios that are the best predictors of households default. Feldman and Gross (2005) use the CART method for mortgage defaults and underline the advantages and disadvantages of this method with respect to traditional models.

Finally, as underlined by Atyia (2001), neural networks are the most recent model in the credit scoring literature as their first use to the bankruptcy prediction problem appears only at the beginning of the 1990s. Odom and Sharda (1990) use Altman's financial ratios described above and compare the performance of the discriminant analysis with the one of the neural networks on a sample composed by 65 US defaulting companies and 64 American healthy firms between 1975 and 1982. They conclude that the neural networks provide better results with a higher percentage of loans correctly classified and that the results are robust with respect to the proportion of bankrupt/healthy firms in the training set. This superior performance of the neural networks with respect to other default prediction methods is confirmed by an important strand of literature that we will mention below.

Neural networks are non-parametric, non-linear regression approaches inspired by biological nervous systems. A neural network is an interconnected network between the input variables and the output, composed by numerous non-linear computation devices called neurons. A neuron receives several inputs and produces a non-linear (or linear) transformation of these inputs to give an output. The output of each neuron may serve as input to another neuron with a multiplying factor called weight. The final output is thus a complex, non-linear function of the inputs. The neural network is based on learning; the system designs the size and weights in the network for optimum classification on the data. It learns by itself the relations between the different variables, starting from the data set, by simulating human reasoning. The optimization takes place in two stages. In the first stage the weights are initialized with some small random number. In the second stage, the nonlinear optimization scheme is implemented. This stage is the learning stage. The objective consists in minimizing the prediction error of target variables, i.e. outputs.

As they allow nonlinear and complex interactions among predictor variables, neural networks perform better than parametric methods. For simpler relationships between these variables, they should at least perform as well as traditional methods. However, the lack of transparency of neural networks may provide an incentive to the use of traditional approaches in such situations. Finally, neural networks need important databases and are computationally intensive, i.e. need a large number of iterations.

There are a lot of empirical studies using the neural networks methodology in default prediction, well summarized by Atyia (2001) among others. For brevity reasons we will mention only a part of them. Tam and Kiang (1992) study the application of the neural network model to Texas bank-failure prediction for the period 1985-1987 and compare the neural networks prediction accuracy with that of the other scoring techniques. Their results suggest that the neural networks are the most accurate, followed by the linear discriminant analysis, the logistic regression and the decision trees. Altman et al. (1994) employ both linear discriminant analysis and a neural network to diagnose corporate financial distress for 1,000 Italian firms and conclude that neural networks are not clearly dominant compared to traditional statistical techniques in decision accuracy. Desay et al. (1996) indicate that customized neural networks may provide a very promising avenue if the measure of performance is the percentage of bad loans correctly classified. West (2000) investigates the credit-scoring accuracy of five various neural network models on both German and Australian credit data and benchmarks them against those obtained with more traditional methods. The results suggest that logistic regression is a good alternative to the neural models; for the average case which includes some inferior neural network training iterations, the logistic regression seems slightly more accurate than the neural network.

III. EMPIRICAL EVIDENCE ON A CORPORATE CREDITS PORTFOLIO

Our objective is to empirically compare the four different bankruptcy prediction approaches in order to identify the most performing internal credit scoring model for Tunisian banks which aim at improving their current predictive power of financial risk factors.

A. Data and Sample Description

The bank on which this study is done[6] is one of the most important banks in Tunisia, well rated by the different rating agencies, i.e. BBB by S&P and BBB+ by Fitch. The main part of its activities, i.e. 40%, is represented by the loans contracted by big size companies[7]. In a context where the access to information is not particularly fluid and in which standardized procedures are missing, this bank, characterized by an important portfolio of short, medium and long term credits, is working on implementing a system of financial diagnosis of companies simple to handle, based on scoring techniques, allowing to distinguish between good and bad borrowers. Hence, we managed to have access to a database containing a sample of companies operating in three distinct sectors, i.e. industry, trade and services[8]. After having studied the collected data and taken out all companies younger than three years as they record a higher default risk, we also left aside all companies for which we observed missing data. Finally we were left with a sample composed by 151 companies for which we collected the corporate accounting data over three financial years, i.e. 2003, 2004 and 2005. We then test the validity of our results for 2006 in order to check the stability of the scoring over time. At the end, companies were segregated into good (paid off loans) and bad (defaulted loans) categories. All our computations were done using the SPSS software.

Based on previous literature mainly inspired by Altman's (1968) early work, we considered financial ratios measuring solvency, liquidity, profitability, capital structure, return on capital employed, indebtness (see also Altman and Narayanan, 1997 or Allen et al., 2004). Atiya (2001) provides an interesting discussion on why the particular indicators summarizing different financial dimensions proposed by Altman (1968) and used in most other studies are relevant in bankruptcy prediction. The exact definition of the different financial ratios comes from the specificity of the Tunisian accounting system as introduced by the "Law defining the accounting system of corporations" number 96-112 on December 30, 1996. Meanwhile, we tried to minimize the correlations between the different ratios and decided to take into consideration twenty financial ratios which are the following:

Ratio	Interpretation
$R1 = \dfrac{\text{Net Turnover}}{\text{Total Assets}}$	Efficiency in the use of capital; a high speed in assets turnover generates a higher return
$R2 = \dfrac{\text{Fixed Assets}}{\text{Equity} + \text{Current \& LongTerm Liabilities}}$	Weight of fixed investments; if too high, could be difficult to sustain
$R3 = \dfrac{\text{Current Assets}}{\text{Short Term Debts}}$	General liquidity; should be higher than 1
$R4 = \dfrac{\text{Equity}}{\text{Equity} + \text{Long Term Debts}}$	Financial autonomy (N.B. Equity includes all shareholders funds, i.e. equity account, owner's equity); should be as high as possible
$R5 = \dfrac{\text{Equity}}{\text{Equity} + \text{Current \& LongTermLiabilities}}$	Capitalization level; as high as possible

$R6 = \frac{\text{Equity}}{\text{Total Debts}}$	Solvency ratio
$R7 = \frac{\text{Total Debts}}{\text{Equity} + \text{Current \& LongTermLiabilities}}$	Capital structure; a high ratio shows a higher default probability
$R8 = \frac{\text{Short Term Debts}}{\text{Total Debts}}$	Capital structure; stability of financing
$R9 = \frac{\text{Financial Expenses}}{\text{Short Term Debts}}$	Weight of financial expenses
$R10 = \frac{\text{Financial Expenses}}{\text{EBITDA}}$	Weight of financial expenses
$R11 = \frac{\text{Net Profit}}{\text{Equity}}$	Return on equity; if too low, difficult to attract new investors
$R12 = \frac{\text{Cash Flow}}{\text{Long \& Medium Term Debts}}$	Payback (reimbursement) capacity (N.B. Cash flow refers to cash flow from operating activity)
$R13 = \frac{\text{Short Term Bank Loans} + \text{Other Current Liabilities}}{\text{Change In Working Capital}}$	Bank participation in financing the working capital
$R14 = \frac{\text{Accounts Payable for Purchases \& Deliveries} \times 360}{\text{Purchases} + \text{Other Operating Expenses}}$	Average maturity of supplier credit
$R15 = \frac{\text{Accounts Receivable} \times 360}{\text{Gros Sales}}$	Average maturity of customer credit facilities; company should allow shorter term credit to its customers than the maturity of the credits allowed by its suppliers and hence finance purchases with sales
$R16 = \frac{\text{Quick Assets}}{\text{Short Term Debts}}$	Relative liquidity
$R17 = \frac{\text{Operating Profit}}{\text{Equity} + \text{Current \& LongTerm Liabilities}}$	Return on capital employed
$R18 = \frac{\text{Working Capital}}{\text{Change In Working Capital}}$	Coverage of the working capital
$R19 = \frac{\text{Net WorkingCapital}}{\text{TotalAssets}}$	Capacity of own capital to finance the assets
$R20 = \frac{\text{Operating Profit}}{\text{Economic Assets}}$	Return on activity (N.B. Economic assets include only productive assets)

B. Empirical Results with Different Scoring Techniques

1. Discriminant Analysis

We first use a step by step selection algorithm of the most pertinent financial ratios in order to build up a linear discriminant function that best allows discriminating between two categories of companies. These two categories are defined by the values of the financial difficulties indicators; group 0 contains companies that are in financial distress and group 1 contains companies that are financially healthy. After a pre-screening process, i.e. determine whether there are differences between the sub groups, one has to estimate the coefficients of the discriminant function and finally provide the classification results.

The pre-screening process is based on three indicators: mean or variance (standard deviation), Fisher test and Wilks' Lambda. This preliminary analysis points out the most discriminant variables between the two groups.

Means and standard deviations are provided in Table 1 whereas the F test results and the Wilks' Lambda are shown in Table 2. Whereas from Table 1 almost all variables seem to discriminate between the two categories of credits, the F test results reduce the number of such discriminant variables to fifteen ratios out of the twenty that we computed. Finally, following the Wilks's Lambda test, we are left with only 2 such ratios, i.e. R9 (weight of financial expenses) and R17 (return on capital employed), that best discriminate between the two credit classes.

Table 1
Group statistics

	Defaulted Firms		**Healthy Firms**	
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**
R1	0.828	0.899	1.460	1.069
R2	0.372	0.258	0.251	0.230
R3	0.980	0.491	1.694	2.224
R4	0.750	0.602	0.881	0.214
R5	0.212	0.235	0.354	0.221
R6	0.529	0.662	1.240	2.556
R7	0.663	0.246	0.589	0.231
R8	0.838	0.189	0.911	0.168
R9	0.064	0.053	0.022	0.021
R10	0.522	3.075	0.254	0.367
R11	0.097	1.325	0.270	0.602
R12	1.242	7.512	3.967	23.626
R13	-0.914	41.439	1.254	23.414
R14	271.252	422.854	148.602	141.202
R15	143.402	123.680	95.030	67.292
R16	0.074	0.299	0.203	0.545
R17	0.024	0.136	0.124	0.131
R18	1.114	30.613	0.544	9.725
R19	0.013	0.361	0.159	0.230
R20	-0.024	1.383	0.278	0.552

Table 2
Equality tests of group means

	Wilks' Lambda	Fisher Test	P-Value
R1	0.912	42.914	0.000*
R2	0.943	26.668	0.000*
R3	0.960	18.412	0.000*
R4	0.977	10.544	0.001*
R5	0.914	41.934	0.000*
R6	0.970	13.640	0.000*
R7	0.976	10.743	0.001*
R8	0.961	17.952	0.000*
R9	0.768	133.468	0.000*
R10	0.996	1.964	0.162
R11	0.992	3.447	0.064
R12	0.995	2.295	0.131
R13	0.999	0.492	0.484
R14	0.959	18.924	0.000*
R15	0.940	28.096	0.000*
R16	0.982	7.996	0.005*
R17	0.880	60.547	0.000*
R18	1.000	0.079	0.779
R19	0.942	27.303	0.000*
R20	0.978	10.174	0.002*

* Significant at 5% level

Table 3
Stepwise statistics

Step	Variables Entered*	Variables Removed	Wilks' Lambda	P-Value
1	R9		0.768	0.000**
2	R17		0.728	0.000**
3	R14		0.709	0.000**
4	R20		0.695	0.000**
5	R5		0.682	0.000**
6	R2		0.664	0.000**
7	R15		0.657	0.000**
8	R7		0.651	0.000**
9		R5	0.652	0.000**

* At each step, the variable that minimizes the overall Wilks' Lambda is entered. The maximum number of steps is 40. ** Significant at 5% level

Finally, we choose the discriminant variables following a stepwise minimization process. At each stage, the characteristics that were not already incorporated in the discriminant function are evaluated and those that significantly improve the prediction power of the model are added. The selection criterion is based on Wilks's Lambda minimisation[9]. Results are provided in Table 3. For example, the R5 ratio (capitalization level) that was introduced during step number five is finally eliminated during the last step of the selection process as it can be rebuilt thanks to a linear combination of the ratios incorporated during the previous steps. Hence, we are left with seven discriminant variables.

The overall validity of our discriminant analysis is also shown by the results in Table 3 (last line). Based on these results, we can reject the null hypothesis of mean equality between the two groups, i.e. good and bad credits. Therefore, we can say that the discriminant analysis points out that the average scores of the two credit categories are significantly different.

Then, the scoring function that we obtain with the selected seven discriminant variables is the following:

$$\begin{aligned}\text{Score} = & -2.614+2.202\times R2+1.896\times R7+14.993\times R9+0.001\times R14+0.002\times R15 \\ & -1.836\times R17-0.272\times R20\end{aligned} \tag{2}$$

The prior probabilities for the two groups, i.e. default P(S=0) and no default P(S=1), are provided in Table 4. We notice that more than 50% of the credits are initially considered as belonging to the good credit category.

Table 4
Prior probabilities for groups

Situation	Prior	Cases Used in the Analysis
P(S=0)	0.416	185
P(S=1)	0.584	260
Total	**1.000**	**445**

The classification results are provided in Table 5 that summarizes well classified debtors and badly classified ones. In our case, the overall accuracy of the classification provided by the discriminant analysis is equal to 81.2%, i.e. 145 observations of group 0 and 222 observations of group 1 are correctly classified out of a total of 452 observations.

Table 5
Classification results provided by the discriminant analysis

Observed	**Predicted Group Membership**		
	0	**1**	**Percent Correct**
0	**145**	43	77.1%*
1	42	**222**	84.1%**
Overall Percentage			**81.2%*** **

* 77.1% corresponds to the percentage of defaulted firms that are correctly classified
** 84.1% corresponds to the percentage of healthy firms that are correctly classified
*** 81.2% corresponds to the percentage of all firms that are correctly classified

2. Logistic Regression

The results obtained with the logistic regression confirm the initial discrimination into two groups. The overall consistency of the classification provided by the logistic regression equals 82.9% (see Table 7) and the most discriminant ratios are R2, R5, R9, R14, R15, R17 and R20. The estimated coefficients of the logistic regression are provided by Table 6.

Table 6
Parameter estimates of the logistic regression

Situation	Parameter	β*	Standard Deviation	P-Value
1	**Intercept**	1.791	0.409	0.000**
	R2	-2.896	0.652	0.000**
	R5	2.766	0.832	0.000**
	R9	-26.827	4.944	0.000**
	R14	-0.001	0.001	0.095
	R15	-0.005	0.002	0.014**
	R17	7.320	1.685	0.000**
	R20	0.634	0.142	0.000**

* Estimated coefficients of the score function ** Significant at 5% level

Table 7
Classification results provided by the logistic regression

Observed	Predicted Group Membership		
	0	**1**	**Percent Correct**
0	**137**	48	74.1%*
1	28	**232**	89.2%**
Overall Percentage			**82.9%*** **

* 74.1% corresponds to the percentage of defaulted loans that are correctly classified
** 89.2% corresponds to the percentage of healthy loans that are correctly classified
*** 82.9% corresponds to the percentage of all loans that are correctly classified

The estimated coefficient of R2 (ratio of fixed assets) is negative, as expected, i.e. a high level of fixed assets would be difficult to sustain, negatively affecting the financial health of the company. For R5 (capitalization level), the estimated coefficient is positive, which corresponds to our intuition, i.e. a higher R5 ratio increases the probability for the company to be considered healthy. The sign of the R9 (weight of financial expenses) coefficient is negative, which also matches our expectations, as we may conclude that a high percentage of financial expenses increases the risk that the firm experiences financial difficulties. R14 (average maturity of supplier credit) appears with a negative sign, which means that using a long delay for the payable accounts negatively affects the financial situation of the firm. This may indeed create situations in which the firm badly manages these liquidities, such as using them for longer term investments. As expected, R15 (average maturity of consumer credit facilities) appears with a negative sign too for the group of healthy companies; the longer the time spent to cash its deliveries is, the worst the financial situation of the firm may become. The estimated coefficients of the two last ratios R17 (return on capital employed) and R20 (return on activity) are both positive, which perfectly corresponds to our financial intuition, i.e. a higher return positively affects the financial status of the company. Finally, the scoring function provided by the logistic regression is:

$$\begin{aligned}\text{Score} = {} & 1.791 - 2.896 \times R2 + 2.766 \times R5 - 26.827 \times R9 - 0.001 \times R14 \\ & - 0.005 \times R15 + 7.320 \times R17 + 0.634 \times R20 \end{aligned} \tag{3}$$

3. Classification Trees

Our objective is to identify the variables that best explain credit risk. To do so, we first define a root and then perform a set of sequential binary splits of the data. The algorithm loops over all possible binary splits in order to find the characteristic and the corresponding cut-off value that best separates the side containing mostly good borrowers and the side containing mostly bad borrowers.

Twenty independent variables, i.e. financial ratios, were specified, but only eight were included in the final model. The other variables did not make a significant contribution to the model, so they were automatically dropped. Using the CHAID model the return on activity (R20) is the best predictor of credit quality. Most of the observations of the group having a R20 ratio lower than 9.94% are considered as defaulting whereas those for which the R20 ratio is higher than this cut-off value show a high probability for being considered in the good credit category. Then, the next best predictor is the R9 ratio (weight of financial expenses). On the left side of the tree, the best split is now based on two ratios, R17 and R19. We notice that for the companies with a percentage of financial expenses lower than 3% the next best predictor is the R17 ratio (return on capital employed), while those recording a R9 ratio higher than 3% are better classified based on the R19 ratio (auto financing capacity). We continue the same analysis on each side of the tree; the algorithm stops when all leafs contain only good borrowers or only bad borrowers. For example, for companies having a return on activity lower than 9.94%, a weight of financial expenses lower than 3% but a return on capital employed lower than -0.89%, the return on capital employed (R17) is the only significant predictor. Of the credits in this category, more than 90% are in default. Since there are no child nodes below, this is considered as a terminal node. For companies having a return on activity lower than 9.94%, a weight of financial expenses lower than 3% but a return on capital employed higher than -0.89% , the model includes one more predictor, R16 (relative liquidity) and so on. At each step, the algorithm also provides the improvement rate of the classification with respect to the previous one. The detailed figure of the obtained classification tree is available for any interested reader upon request from authors.

In order to measure the tree's predictive accuracy, we use the risk estimate and its standard error (Table 8). This risk estimate is the proportion of cases incorrectly classified after adjustment for prior probabilities and misclassification costs. In our case, the risk estimate equals 0.106 which indicates that the category predicted by the model (good or bad credit) is wrong for 10.6% of the classes. So the risk of misclassifying a credit is approximately 11%. The results in the classification table (Table 9) are consistent with the risk estimate. Table 9 shows that the model classifies approximately 89.4% of the credits correctly which is higher than what we obtained by using both the discriminant analysis and the logistic regression. For the bad credits, the model predicts a bad quality for 83.10% of them, which means that only 17.9% are inaccurately classified with the "good" credits, which is a fairly good classification.

Table 8
Risk estimate

Estimate	Standard Error
.106	.014

Table 9
Classification results provided by the classification tree

Observed	Predicted Group Membership		
	0	1	Percent Correct
0	**157**	32	83.1%*
1	16	**248**	93.9%**
Overall Percentage			**89.4%*** **

* 83.1% corresponds to the percentage of defaulted firms that are correctly classified
** 93.9% corresponds to the percentage of healthy firms that are correctly classified
*** 89.4% corresponds to the percentage of all firms that are correctly classified

4. Neural Networks

The network structure that we implemented in our study is known as a feed forward architecture because the correlations in the network flow forward from the input layer to the output one without any feedback loops. The input layer contains the predictors and the output layer contains the responses. Hence, the input layer contains twenty units representing the twenty financial ratios and a bias unit whereas the output layer contains two units, i.e. situation 0 which means financial difficulties and situation 1 which states for good credit.

There are also two hidden layers in our structure. A hidden layer contains unobservable nodes, or units. The value of each hidden unit is some function of the weighted sum of the inputs. The function is called activation function and the weights are determined by the estimation algorithm. The exact form of the activation function depends in part upon the network type and in part upon user-controllable specifications. The activation function that we used here is the hyperbolic tangent. Each unit of the second hidden layer is a function of the weighted sum of the units in the first hidden layer. The same activation function is used in both layers. Our structure contains nine units and a bias unit in the first hidden layer and seven plus a bias unit in the second hidden layer. Each response is a function of the units in the second hidden layer. The activation function that we used here is again the hyperbolic tangent. The description of our neural architecture is available for any interested reader upon request from authors.

To asses the performance of the network, we use the sum-of-squares error criteria. This is the error function (sum of squares of the differences between the observed dependent variables and those obtained via the predicted model) that the network tries to minimize. The minimum sum-of-squares error that we obtained equals 17.373 with a percentage of incorrect predictions of 3.1%. This is consistent with the results shown in the classification table (Table 10), i.e. the model classifies approximately 96.9% of the credits correctly which is higher than what we obtained with the three preceding methods. Hence, the neural networks approach provides the best classification of the credits in our sample.

Table 10
Classification results provided by the neural networks

Observed	**Predicted Group Membership**		
	0	**1**	**Percent Correct**
0	**177**	8	95.7%*
1	6	**254**	97.7%**
Overall Percentage			**96.9%*** **

* 95.7% corresponds to the percentage of defaulted loans that are correctly classified
** 97.7% corresponds to the percentage of healthy loans that are correctly classified
*** 96.9% corresponds to the percentage of all loans that are correctly classified

C. Cross Validation of the Different Techniques

The stability of the scoring over time is checked based on a holdout sample containing accounting data for the same companies for 2006. The results are summarized in Table 11.

Table 11
Summary results

	Overall consistency		**Consistency in Classification of Previous Defaulters**	
	Training set	**Holdout set**	**Training set**	**Holdout set**
Discriminant Analysis	81.2%	81.5%	77.1%	61.9%
Logistic Regression	82.9%	81.9%	74.1%	73.8%
Classification Tree	89.4%	82.1%	83.1%	76.2%
Neural Networks	96.9%	85.2%	95.7%	78.7%

The neural networks provide the best consistency in classification; overall, 96.9% of the training cases are classified correctly and 95.7% of the defaulters in the training set are classified correctly. Classifications based upon the cases used to create the model tend to be too optimistic in the sense that the classification rate is inflated. However, the holdout sample helps to validate the model; here, overall, 85.2% of the cases were correctly classified by the model (78.7% for the defaulters). This suggests that, overall, the model is correct more than three out of four times.

The classification trees allow 89.4% of the overall training cases and 83.1% of the defaulters in the training set to be correctly classified. These percentages are slightly lower for the holdout samples, i.e. 82.1% and 76.2% respectively. The model still works reasonably well.

Concerning the logistic regression, 82.9% of the observations in the training set and 74.1% of the defaulters in this set are correctly classified. Again, these percentages are lower for the holdout sets, i.e. 81.9% and 73.8% respectively. A better model should correctly identify a higher percentage of the cases. Finally, the worst performer is the linear discriminant analysis, with an overall accuracy in the training set of 81.2% and of 77.1% for the defaulters of this set whereas the consistency on the holdout sample is even lower, 81.9% and only 61.9%.

To conclude, the neural networks outperform the three other techniques, on both the training and holdout samples. Indeed, the neural architecture allows considering all the possible interactions between the different ratios all along the network. However, the major disadvantage of this approach is the lack of economic and financial intuition of the different links in the network.

In order to perform a final cross check of our results, we consider a holdout sample composed by four companies, i.e. two firms in good financial health and two experiencing financial difficulties. For these four companies, we applied the different decision rules dictated by the four techniques discussed above. The holdout sample contains the four companies' accounts for 2007.

The results obtained with the discriminant analysis and the logistic regression are summarized in Table 12. For company number 1, i.e. good financial health, the logistic regression provides a better classification in the "good" credit category, i.e. 83.19% with respect to the discriminant analysis, i.e. 78.53%. For the second company in our sample, i.e. in financial distress, the discriminant analysis does not provide a clear-cut result; the company is almost equally classified as bad and good debtor, however with a slightly higher percentage for the bad credits class, i.e. 55.64% versus 44.36%. However, the logistic regression allows a clear decision regarding this company, i.e. experiencing financial difficulties, with a consistency of 94.21%. For the last two companies, both the discriminant analysis and the logistic regression, provide quite reliable classification results (see Table 13).

Neural networks are based on learning, which means that these systems learn by themselves the relationship between the different variables, based on a data sample. Therefore, we included our four new companies in the original sample and thanks to the learning process we were able to classify these companies as shown in Table 13. The neural architecture provides a correct classification of the four companies. Moreover, the consistency of the classification is much better than those provided by both the discriminant analysis and the logistic regression.

Table 12
Results of discriminant analysis and logistic regression on four companies over 2007

		Company 1 Healthy	Company 2 In distress	Company 3 In distress	Company 4 Healthy
Discriminant Analysis	1	78.53%	44.36%	0.01%	98.64%
	0	21.47%	55.64%	99.99%	1.36%
Logistic Regression	1	83.19%	5.79%	0.17%	99.24%
	0	16.81%	94.21%	99.83%	0.76%

Table 13
Results of the neural networks model on four companies over 2007

Company	Observed	Predicted value	Probability of being in 0	Probability of being in 1
1	1	1	6.04%	93.96%
2	0	0	98.85%	1.15%
3	0	0	91.45%	8.55%
4	1	1	5.29%	94.71%

Finally, when applying the decision rules derived with the classification trees approach, the results are summarized up in Table 14. More precisely, company number one is situated in the terminal node number 24, composed by healthy companies, company number two is included in the terminal node number 7 of companies in financial distress, which is the same for company number three, whereas company number four ends up, as company number one, in the terminal node number 24. So, the classification tree allows a correct classification of the four companies in our sample.

All in all, the holdout sample helps to validate the results obtained with the different models and confirms the superiority of the neural networks in separating between good and bad credits. Moreover, though we start with a similar set of financial indicators as many credit scoring models applied on developed countries data, our analysis points out that the most statistically relevant financial ratios for predicting loan default for the Tunisian bank are the weight of fixed assets, the weight of financial expenses, the average maturity of payable accounts and accounts receivable, the return on capital employed and the return on activity. Hence, the investment policy, the importance of the debt service, the short term liquidities and the firm’s competitiveness are the key factors that reflect its ability to avoid financial distress. The indicator linked to the investment policy shows the extent of a firm’s investment in non-liquid and often over-valued fixed assets; if this ratio is too high it may reflect possible over investment and important annual depreciation charges deducted from the income statement. The indicators linked to leverage point out the firm’s ability to sustain its financial debt service and are thus a direct image on its creditworthiness. The two ratios based on short term liabilities and customer credit facilities reflect the timing between cash inflows and outflows; an important gap between the two may result in liquidity shortage and even default on some payments. Finally, the two indicators that measure return are proxies for the firm’s competitiveness and, at the end, for its survival.

Table 14
Results of the classification trees model on four companies over 2007

	Company 1	Company 2	Company 3	Company 4
R1	1.6717	0.1653	0.1723	5.8461
R2	0.3782	0.0708	0.9643	0.0769
R3	1.1146	2.9250	0.0913	4.0000
R4	1.0000	1.0000	0.4440	1.0000
R5	0.4500	0.6850	0.2740	0.7690
R6	0.8181	2.1750	0.3774	3.3333
R7	0.5500	0.3149	0.7260	0.2307
R8	1.0000	1.0000	0.4717	1.0000
R9	0.0290	0.0000	0.2120	0.0000
R10	0.1620	0.0000	2.9010	0.0000
R11	0.2030	-0.1490	-0.1920	0.2000
R12	0.0000	0.0000	-0.0695	0.0000
R13	2.7500	0.0000	-0.9284	0.2000
R14	273.8589	153.9923	208.4147	4.7720
R15	60.0000	249.0000	31.6998	30.1435
R16	0.0988	2.1000	0.0084	1.3333
R17	0.1130	-0.1023	-0.0158	0.1538
R18	7.2500	-11.0000	1.5360	1.8000
R19	0.0630	0.6062	-0.3484	0.6923
R20	0.2921	-6.5000	-0.0217	0.3333

IV. CONCLUSION

Despite the tremendous development of banking activities, lending to corporate and private borrowers still represents the core of profit for commercial banks and other lending institutions in both developed and emerging countries. An increase in the amount of credit indeed contributes to an increase in profitability but it also exacerbates the risks in the banking industry, namely the number of defaulted loans. This phenomenon is even more present in developing countries, where the number of corporate defaults significantly affects the banking activity, generating financial crises and contagion over the whole international financial system. The Tunisian banking system is not better prepared than other developing markets in this matter. Therefore, over the last years, banks employ considerable efforts to develop tools and models to help standardize, automate and improve credit decisions. Such tools are provided by credit scoring methods that allow differentiating between good and bad debtors.

In this context, our paper was inspired by the current financial crisis and the necessity to well assess and manage the bank credit risk especially for developing countries. Our study is, to our knowledge, the first to provide such an extensive analysis of the corporate lending activities of a bank in Tunisia and, by extension, in the North African developing countries. Our objective is thus to identify the most performing internal credit scoring model for Tunisian banks which aim at improving their current predictive power of financial risk factors. In particular, we point out the most important corporate financial indicators a bank needs to collect and how these can be combined in a credit scoring model.

We compare the performance of four different scoring techniques, i.e. linear discriminant analysis, logistic regression, classification trees and neural networks, in detecting corporate default on a portfolio composed by the corporate credits of 151 companies allocated by one of the leading banks in Tunisia.

First of all, the linear discriminant analysis and the logistic regression help isolating the most statistically relevant financial ratios for predicting loan default. In the particular case of the Tunisian companies, these ratios are the weight of fixed assets (called R2), the weight of financial expenses (R9 and R10), the average maturity of payable accounts and accounts receivable (R14 and R15), the return on capital employed (R17) and the return on activity (R20). Then, the two methods provide very similar results in terms of predictive ability. Our results show that globally, both methods manage to correctly predict the classification in the two categories, i.e. good and bad loans, with an overall accuracy higher than 80% (81.2% and 82.9% respectively). However, the logistic regression is easier to handle and the predicted values of the dependent variable are always situated in a range between 0 and 1 which allows their interpretation as probabilities. This is not always the case for the discriminant analysis, which also requires other stringent assumptions among which the normality of the dependent variables.

The classification trees improve the results of the two traditional credit scoring techniques discussed previously, with an overall accuracy of prediction equal to 89.4%. The main advantage of this approach is the facility of interpreting the obtained results and the fact that it can provide prediction rules for each observation.

Finally, the neural networks appear as the best performing technique for preventive detection of corporate default. They provided an overall classification accuracy of 96.9%. However, they are sometimes criticised for a certain lack of transparency, namely the lack of information concerning their internal functioning.

In terms of the performance of the different scoring models, our results go in line with previous literature using developed banking systems data. Moreover, though we start with a similar set of financial indicators as many credit scoring models applied on developed countries data, our analysis points out that the most statistically relevant financial ratios for predicting loan default for the Tunisian bank are the weight of fixed assets, the weight of financial expenses, the average maturity of payable accounts and accounts receivable, the return on capital employed and the return on activity. Hence, the investment policy, the importance of the debt service, the short term liquidities and the firm’s competitiveness are the key factors that reflect its ability to avoid financial distress.

In the banking and financial turmoil that characterise today’s financial environment, managing credit risk becomes a crucial task for lending institutions. Hence, our methodology, besides pointing out the main techniques that can be used by lenders to improve their ability of making good loan decisions, shows borrowers in a developing country like Tunisia, the whole reasoning process behind the screening of loan applications. Moreover, borrowers can use this information and pay attention to a reduced number of financial ratios when managing their business.

ENDNOTES

1. In theory, liberalisation significantly contributes to emerging market integration with the global capital markets. As such, potential diversification domestic stocks see their prices bidding up by foreign investors while inefficient sectors are penalized by all investors. By consequent, the cost of equity capital goes down hence increasing investment and finally economic welfare.
2. The Government has established debt recovery entities to buy the non- or under-performing debt of commercial banks. There is no information available on the success of this measure.
3. Basically the literature distinguishes between actuarial and market price based credit risk methods. Ratings and scores are then included in the first category whereas the second one is represented by the Merton (1973) model and its developments on one side and the bond market prices and spreads approach on the other side.
4. We thank an anonymous Referee for pointing out this issue.
5. Several classification tree methods have emerged over the years besides the CART method, namely, Advanced CHAID and QUEST.
6. Unfortunately, for confidentiality reasons, we cannot provide the name of this bank.
7. This category includes trading companies with a turnover higher than Tunisian Dinars 30 billion, industrial firms with a turnover higher than Tunisian Dinars 20 billion, holdings and groups with a turnover higher than Tunisian Dinars 60 billion, institutional investors, all the companies operating in the tourism sector.
8. We thank the bank for this opportunity and for providing us the necessary data and are very grateful to Ayachi Imene for excellent research assistance.

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