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Forecast of the credit risk of Moroccan companies

Prévision du risque de crédit des entreprises Marocaines

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Abstract

Among the problems faced by banks is the assessment of the creditworthiness of borrowers. In this context, the credit rating method has been developed with increasingly sophisticated tools to address their concerns. The purpose of this article is to present and apply the logistic regression method as a means of classifying the business failure problem based on the accounting data of a sample of Moroccan companies. The results of our study are based on a database of 2,030 credit files granted to Moroccan companies (SMEs and GE) in 2015 and 2016. The resulting regression equation allowed us to select 12 variables (financial ratios). and identifiers) as important in analyzing the probability of non-repayment. After the necessary statistical tests and validation simulations, we recorded a prediction rate of over 93% for our model.

Keywords: Credit risk, Literature Review, Classification, Methods of valuation, Logistic regression.

Résumé

Parmi les problèmes rencontrés par les banques, il y a l'évaluation de la solvabilité des emprunteurs. Dans ce contexte, la méthode de notation du crédit a été mise au point avec des outils de plus en plus sophistiqués pour répondre à leurs préoccupations.

Le but de cet article est de présenter et d'appliquer la méthode de régression logistique en tant que moyen de classification du problème de défaillance d'entreprise sur la base des données comptables d'un échantillon de sociétés marocaines. Les résultats de notre étude reposent sur une base de données de 2 030 dossiers de crédit octroyés à des entreprises marocaines (PME et GE) en 2015 et 2016. L'équation de régression qui en a résulté a permis de sélectionner 12 variables (ratios financiers et identifiantes) aussi importantes afin d'analyser la probabilité de non-remboursement. Après les tests statistiques nécessaires et les simulations de validation, nous avons enregistré un taux de prévision de plus de 93% pour notre modèle.

Mots clés : Risque de crédit, Revue de la littérature, Classification, Méthodes d'évaluation, Régression logistique.

Introduction

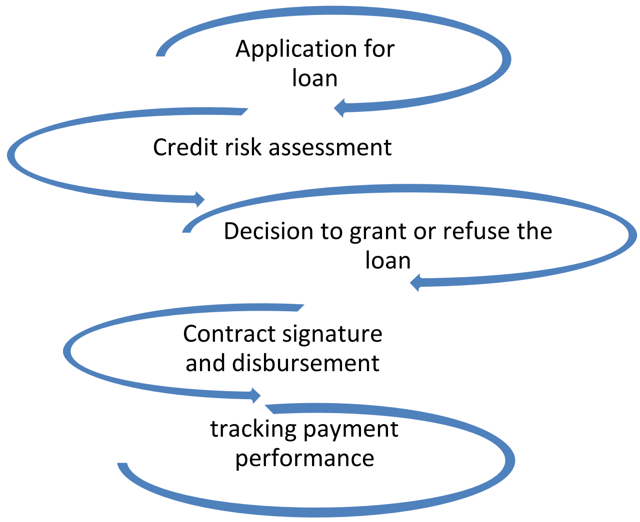
the bank may be subject to several types of risk: market risk, operational risk, currency risk, etc. Among these risks, there is the credit risk, also known as the risk of non-repayment, which has major consequences on the liquidity of the bank. Indeed, the control of this risk has become one of the major strategic axes of the management of the banking companies. The Basel Committee has put into practice prudential rules concerning the management of credit risk. Its first steps were defined in 1988 in order to regularize the regulatory framework governing the activity of all the banks of the signatory countries via the application of the ratio Cooke AND Mac Donough. The most recent example is the subprime financial crisis (2007) in the United States, which has become widespread in advanced economies and even emerging economies (Redoulès, 2008). In recent years, banks have been developing increasingly sophisticated models for assessing and managing their credit risk. This development has always allowed availability to easily obtain information and process data quickly. The prediction of credit risk has been analyzed through several techniques and several research studies, one of the most widely used methods being credit rating (Altman, 1968, Altman, Haldeman and Narayanan, 1977, Conan and Holder, 1979). This evaluation process is finalized by the engagement of a scoring function that facilitates decision-making regarding the granting of credit to borrowing companies. In this context of research and prevention of risks, which is part of our problematic, we wonder what is the contribution of the logistic regression method in the quantification of credit risk and to what extent the classification of quality borrowers in terms of credit repayment granted, does it prevent him to deal with it? Indeed, our article is structured as follows. As a first step, we present a review of the literature on credit risk and the methods of its valuation, namely rating techniques. Third, it is necessary to develop a default probability model to predict and classify healthy and failing firms according to their risk class. Finally, we present our conclusions.

1. Credit risk: Literature review

1.1. Credit risk: concepts and definition

Many authors have attempted to define the notion of credit risk, for FAYE (1993), credit risk is defined as the risk of losing all or part of the receivables in case the borrower no longer at maturity the will or the opportunity to honor its commitments. For Clement WONOU (2006), credit risk can be defined as the probability (large or small) that loans granted to one or more clients are not reimbursed. As for François DESMICHT (2004), he defines credit risk as the risk of loss in the event of default by the borrower. For SAMPSON, this is "the tension that inhabits bankers is inseparable from their business, they look after the economies of others and yet they make profits by lending them to others, which inevitably entails risks. A banker who does not take a risk is not one. " Indeed, Hamadi Matoussi et al. (2004), shows that the control of credit risk has become one of the major strategic axes of the management of banking institutions. The assessment of credit risk is a matter of concern for most financial institutions, mainly banks. Indeed, the assessment of this risk is mainly related to the regulation which imposes the use of the different techniques of measurement and evaluation of this risk. In the context of credit risk assessment, the analysis of the client's file is the most important phase. The figure below represents the credit decision-making steps:

Figure 1: Main phases of the decision to grant credit



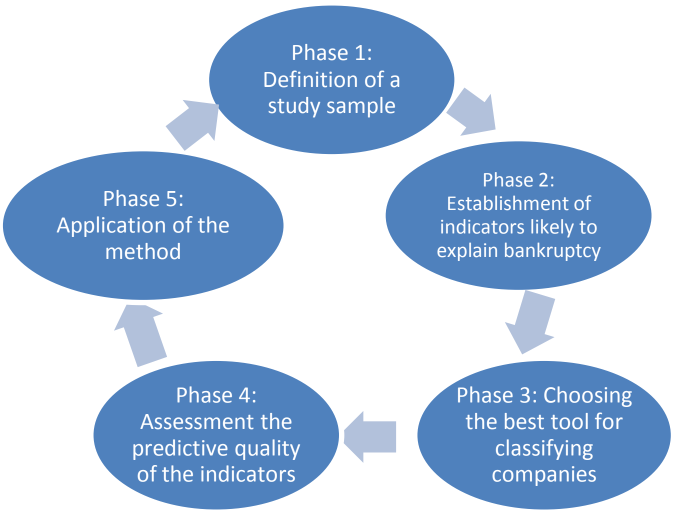
Source: Elaborated by the author

Monitoring credit performance comes in the last stage of the credit analysis process, it consists in constantly monitoring the ability to repay and intervene in case of deterioration in the quality of it.

1.2. The measure of credit risk

After the credit risk identification phase comes the stage of its evaluation, which is a process that is part of the use of different risk measurement methods. This is linked to the regulations in this area. Indeed, as long as the bank grants credit, it runs the risk of non-repayment of debts from a defaulting borrower something that has adverse effects on the financial situation of the credit institution. Indeed, the management and control of risks permanently improves the financial strength of banks and optimize the risks and performance of the loan. In its new reform, the Basel II Committee has allowed banks to operate their own internal risk assessment systems (Armstrong & Fink, 2006). In fact, the measure of credit risk is based on one of two approaches, namely the standard approach, which is an approach based on a classification of risks drawn from external ratings. This is the case for credit rating agencies. the approach by the internal ratings. According to the model of Conan and Holder, the classification allows a classification of the most risky companies, the latter takes place in 5 essential stages:

Figure 2: the different stages of the Conan and Holder model



Source : Joanna N.S. Julie Makany et Chantal Gabsoubo Yienezoune, 2013

2. Theoretical view on the different methods of evaluation on the risk of default

2.1. Identification of credit risk

Credit risk identification comes before the credit risk assessment stage, in fact, risk identification is a transaction or series of transactions that identify a risk, in describing it and stating its main features. The purpose of risk identification is to identify potential problems before they become real problems and to include this information in the assessment stage. The process of identifying the risk of default makes it possible to specify the degree of risk and to identify their contextual information. Its main purpose is to determine quantitative factors such as financial and qualitative ratios such as industry, market developments, and the quality of financial information.

2.2. Methods of measuring credit risk: Scoring methods

Regardless of the approach used by the bank, the key element in determining the weighting Basel II credit risk remains the counterparty's rating (company, individual, bank, sovereigns, etc.). The main purpose of this synthetic indicator is to measure the risk of default of the borrower (Tarik QUAMAR & Said LOTFI, 2018). Indeed, Models of credit risk management and evaluation have developed significantly in recent decades. This development allows easy access to information and speed in data processing. Indeed, several techniques are used to quantify the credit risk, the most used is the scoring method. The first work of credit scoring seems in the pioneering work of Beaver (1966) and Altman (1968) then it has developed over the past 30 years. We quote mainly the famous Z function of Altman (1968), and after the improvements of Altman, Haldeman and Narayanan (1977), this function becomes the ZETA function. According to (Cairo and Kossmann, 2003), Credit Scoring neither approves nor rejects a loan application, it can rather predict the probability of occurrence of poor performance (default), as defined by the lender. For (Edighoffer, 1993), this scoring method corresponds to a method of financial analysis that attempts to synthesize a set of ratios to arrive at a single indicator allowing to distinguish in advance healthy companies from failing companies. The figure below represents the credit scoring process.

Figure 3: Credit Scoring Process

Source: Yang Liu, (2001), New Issues in Credit Scoring Application, Work report N°16, Institut fûr Wirtschafts informatik

Several authors have applied the technique of credit scoring in their research work, through a study that focuses on the risk of non-repayment of credits. In general, we can distinguish two methods that can be used to develop a scoring model or statistical notation: linear and non-linear. It is noted that for the linear methods, one can distinguish the logistic regression method, the discriminant analysis as for the nonlinear or non-parametric methods, one finds the method of the networks of artificial neurons, the expert system.

3. Default risk modeling

3.1. Presentation of the econometric model

Among the methods used in predictive analysis, we find the technique of logistic regression that has been appreciated in the field of finance mainly in epistemological surveys and credit scoring. In this empirical part, we will propose an econometric model to assess the risk of default on a sample made up of SMEs and large Moroccan companies (GE), this sample consists of several quantitative and qualitative ratios.

Indeed, Logistic regression can be defined as a regression model when the variable to explain Y is qualitative. The independent variables selected were selected based on their ability to maximize the explanatory power of our default model of Moroccan companies.

In our model, we consider a variable to predict the default of a firm

Let Y = y1, y2 ... yk

And X=X1, X2, …Xj as predictors in the form of financial ratios.

3.2. Theoretical framework of logistic regression

Logistic regression is a statistical technique that aims, from an observation file, to produce a model to predict the values taken by a categorical variable, usually binary, from a series of variables. explanatory continuous and / or binary. The purpose of logistic regression is to model the behavior of an individual with respect to a given risk. For example, belonging to one of the categories "defaulting customer" or "non-defaulting customer" when applying for a credit, according to a certain number of explanatory variables. The model can be written in the form:

$$\mathbf{Z=X'.\,\beta+\varepsilon}$$

where:

ε : Null expectation error and variance σ2.

β : vecteur des paramètres associés aux variables explicatives.

X: vector of the parameters associated with the explanatory variables.

Z: unobservable variable that explains the membership of an individual to a specific class.

Our database consists of 2030 (mother population) credit files granted to Moroccan companies (small and medium-sized enterprises and large enterprises) in 2015, 2016. It is distributed as follows with 1821 healthy companies and 209 failing, namely that 0 is represented for a healthy company and 1 for a defaulter.

Table 1: Total sample distribution by default number

Default	Number of Default
0	1821
1	209
Grand total	**2030**

Source : Spss

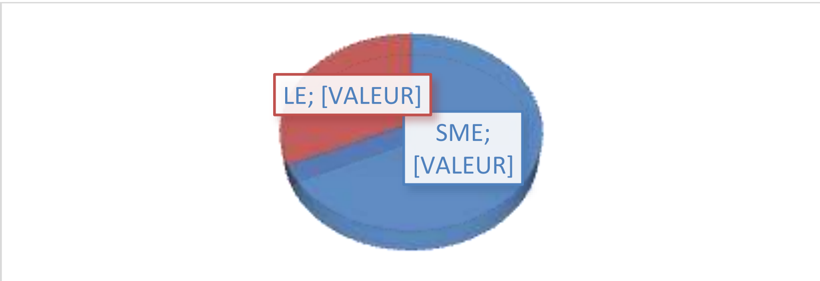
And the following table presents our initial sample of 32% of large firms and 68% of small and medium-sized enterprises.

Table 2: Total sample distribution by business segment

Categories	Total sample	%
Large Companies	646	32%
Small and Medium enterprises	1384	68%
Total	2030	100%

Source : Spss

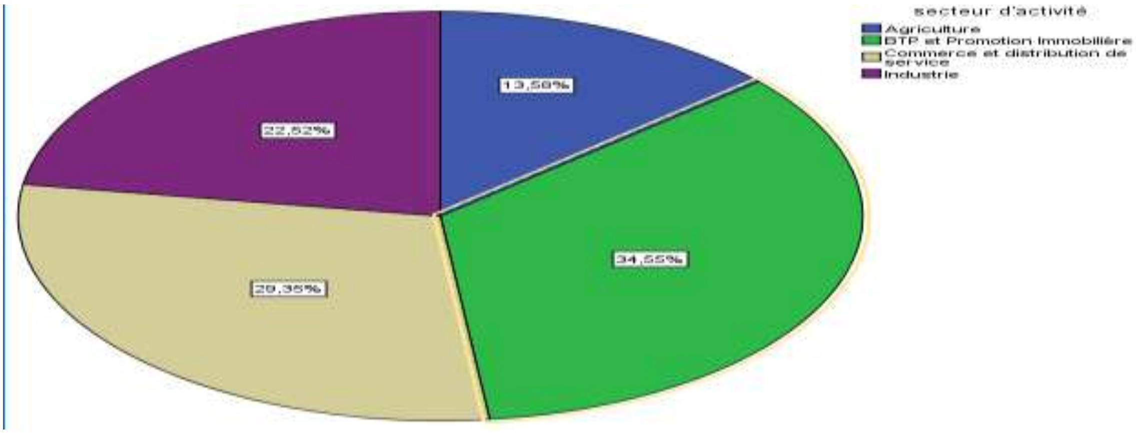
Figure 4: Distribution of small and medium enterprises (SME) and large enterprises (LE) in the sample



Source: Spss

According to the diagram below, we find that the business activity sector (SME and GE) in our sample is composed mainly of 34.55% of companies operating in the construction and real estate development sector, 29.35% in trade and distribution of service, 22.52% of industry and 13.58% in agriculture.

Graphic 1: Distribution of the activity sector in our sample



Source: Spss

For the elaboration of our development and test sample, we opted for a simple stratified sampling, this method makes it possible to represent the subgroups of a heterogeneous population. In fact, the distribution of the sample is proportional to the size of the subgroups and thus all individuals have the same chance of being selected as for the simple random sample, (Mamadou Saliou Diallo, 2006). In fact, the construction of a model requiring a validation step, the initial data file was split in two: the first sample is made up of 70% of the borrowing companies that will serve as a basic sample or learning, the second is called the test or validation sample, it is composed of the remaining 30%. The table below represents the distribution of observations between the development sample and the validation sample according to the number of defaults.

Table 3: Distribution of the total sample as a learning and test sample

Default	Sample of learning	Validation sample
0	**1275**	**546**
1	**146**	**63**
Grand total	**1421**	**609**

Source : Author

3.3. Choice of model ratios

For the prediction of the default risk of companies, we mainly based on the financial ratios since the majority of information on the company is taken from their financial statements (balance sheet and CPC), in our study we used 5 categories of ratios: ratios Size, ratios Indebtedness, Liquidity ratios, Structure ratios and Profitability ratios. The modeling was carried out on a development sample which constitutes 70% of the overall sample. The remaining 30% constituted a test sample. Our default risk modeling first consisted of univariate and then bivariate analysis. The latter consists of studying the link between the default variable that is defined by a gearing ratio, indeed a company is failing if the gearing ratio gearing ratio is greater than 0.8. The bivariate analysis was performed by referring to the Independence Chi 2 test which determines the individual discriminating power of each variable. In the end a Spearman correlation analysis was considered to eliminate the correlated variables and avoid biasing the model. The list of selected ratios is as follows:

Table 4: Retained Ratios

Explanatory variables	Categories	Explanations / Standards
Indebtedness	Indebtedness	The debt ratio measures the level of debt of a company
Turnover	Size	Turnover is the sum of the amounts of sales of products and services performed by a company during a financial year, it is considered as one of the witnesses of the size of a company.
Rotation of receivables	Liquidity	The average payment time granted by the company to its customers is set in advance according to the internal policy
Own funds in structure	Solvency	This ratio provides valuable insights into a company's balance sheet structure and measures the amount of assets that are funded by shareholders.
Cash ratio	Liquidity	It is a ratio that measures the liquidity of a company. The cash ratio, also known as repayment capacity or liquidity ratio
Financial expenses	indebtedness	The financial expenses thus include all the expenses paid by the company to its banks.
Asset Turnover	Activity	Measures the "productivity" of assets in terms of Dh of turnover generated by Dh of fixed and moving assets

Source: Author

3.4. Model Results

In order to assess the default risk of companies through exhaustive lists of ratios, we opted for the logistic regression method. This method has demonstrated its high discriminating power compared to other modeling methods including discriminant analysis and neural networks since it is more used by credit institutions. The path of logistic regression is initially concerned with the calculation of the marginal contributions that constitute the weight of each variable in the prediction of the defect. Then a validation of the robustness of the model retained through the coefficients of determination and the ROC curve. The modeling results are as follows:

Table 5: Calculation of marginal effects of study variables

Category of variables or ratios	Explanatory variables	Coefficient B	Marginal contribution	Weight
Signal Variables	Legal form	-,025	0,02491566	20%
	Activity area	,002	0,001550511	1%
	Region	-,004	0,004034625	3%
Size	Turnover	,017	0,017125153	14%
indebtedness	Indebtedness	-,003	0,003408292	3%
Liquidity	Rotation Accounts receivable	,013	0,012879715	10%
Structure	Own funds in structure	-,003	0,003355382	3%
Liquidity	Rolling Needs / Turnover	,005	0,004759032	4%
Indebtedness	Equity / own debt Medium and Long term	-,024	0,024194076	20%
Indebtedness	Financial expenses / Turnover	,004	0,003803625	3%
Rentabilité	Cash ratio	-,007	0,007199971	6%
Liquidity	Asset turnover	-,015	0,015498618	13%
Total			0,122724658	100%

Source : Author

We have retained the following model:

Z-Score=0.2***Legal form** +0.01***Activity area** +0.03*** Region** +0.14*** Turnover** +0.03*** Indebtedness**+0.1*** Rotation Accounts receivable** +0.03***Own funds in structure** +0.04*

Rolling Needs / Turnover +0.2* **Equity / own debt Medium and Long term** +0.03***Financial expenses / Turnover**+0.06* **Cashratio**+0.13* **Asset turnover**

According to the calculation of the marginal effects, the values of the coefficient B show that the indicators which act positively on the defect are the Sector of activity, the Turnover, the Rotation Receivables Customers, BFR / CA, Financial expenses / CA As for the variables that negatively influence are the legal form, the region, the indebtedness, the equity in the structure, the own funds / own ML debts, the cash ratio and asset turnover.

4. Evaluation of the discriminating power of the model on the modeling sample

4.1. Evaluation of the significance of the model by Fisher's test

Fisher's test is used to test the statistical relevance of any linear restriction on the coefficients of the regression. The Fisher test is the generalization of the χ^2 test, used to test the independence of variables or populations. The principle of this test is based on the frequencies (or even occurrences or proportions) obtained in each cell of the crosstab (categorical variables have no mean or variance as a reference). In our model, the Fisher test is presented in the table below:

Table 6 : ANOVA

ANOVA[a]						
Model		**Sum of squares**	**ddl**	**Middle square**	**F**	**Sig.**
1	**Regression**	**9,099**	**12**	**0,758**	**8,825**	**,000[b]**
	Residues	**84,887**	**988**	**0,086**		
	Total	**93,986**	**1000**			

Source : Spss

From the results of the Fisher statistic, which is significant, it can be concluded that the model is able to discriminate the target variable which is the default.

4.2. Evaluation of the significance of the model the pseudo R2

In a logistic regression, there is no real value of R2 as in a linear regression, and the analog of R2 is the pseudo R2 also called McFadden R2, which is calculated as follows:

$$R^2 = 1 - \frac{\ln L(\hat{\beta})}{\ln L(\hat{\beta}_0)}$$

With:

- $\ln L(\hat{\beta})$ **:** log-likelihood of the free model

- $\ln L(\hat{\beta}_0)$ **:** log-likelihood of the null model, only with the constant (constrained model).

The ratio above is formed of two negative or zero terms, the numerator being inferior in absolute value to the denominator (the log-likelihood of a constrained model is always lower than that of the free model). The pseudo R^2statistic is therefore well between 0 and 1. The two extreme cases are:

- If the constrained model is correct, $\ln L(\hat{\beta}) = \ln L(\hat{\beta}_0)$ and the statistic is 0 (the variations of Yi are not explained by the Xi).
- If the uncompressed model fits the data perfectly, $\ln L(\hat{\beta}_0)$ **= 0** and the pseudo R2 is 1.

Table 7: Summary of the chosen model

Summary of models

Model	R	R^2	R-two adjusted	Standard error of the estimate	Modifier les statistiques				
					Variation of R-two	Variation of F	ddl1	ddl2	Sig. Variation of F
1	,844[a]	,713	,632	,093	,713	8,825	12	988	,000

Source: Spss

The table above presents a summary of the logistic regression model used, including the coefficient of determination R^2estimated at 71% which concludes that the model has good discriminating power.

4.3. Rating Scale

The culmination of a business credit risk model is the construction of a rating scale that ranks firms according to their probability of default. This behavior is adopted not only by credit institutions but also by rating agencies such as Moody's and standard and Poor's. The statistical method that allows a rating scale consists of the application of this approach allowed to have the following distribution.

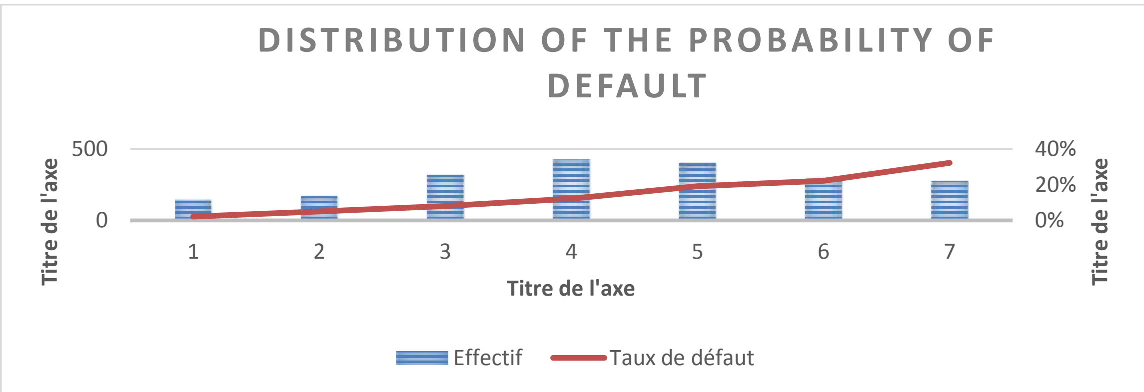
Table 8: Rating matrix

Slice	Effective	Percentage	Number of Healthy compagnies	Number of Defaulting Companies	Default rate	Classes
Between 0% and 0.04%	145	7%	140	5	2%	1
Between 0.04% and 0.47%	170	8%	160	10	5%	2
Between 0.47% and 1.63%	318	16%	301	17	8%	3
Between 1.66% and 6.81%	425	21%	400	25	12%	4
Between 6.81% and 26.89%	400	20%	360	40	19%	5
Between 26.93% and 50.22%	296	15%	250	46	22%	6
Between 50.31% and 100.00%	276	14%	210	66	32%	7
Total	2030	100%	1821	209	100%	

Source : Author

The graphical presentation of our observations (figure below) follows a normal distribution with a concentration of observations around the median classes and a smoothing of few observations between the beginning and the end and increasing average defect rates. The graph below illustrates the default profile and sample distribution.

Figure 5: Distribution of the default profile

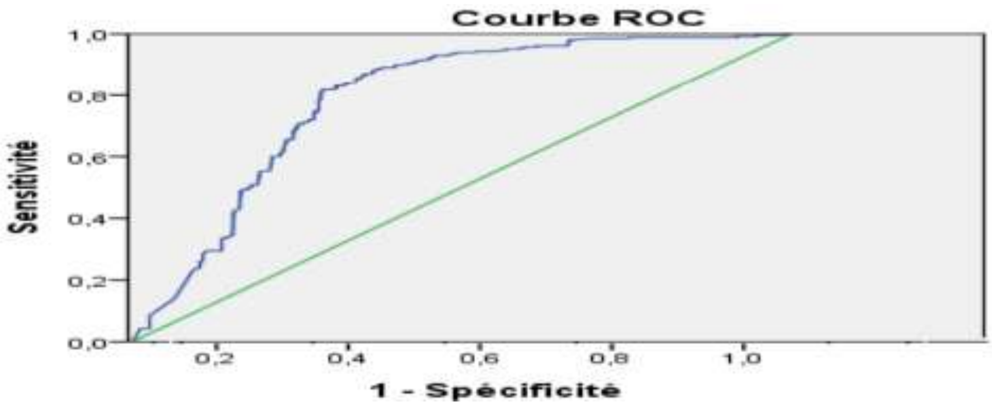


Source: Author

4.4. Validation test on the test sample

With respect to credit risk, it is the ability of a valuation variable or model to distinguish between healthy companies and those in financial difficulty. This ability to distinguish between defects and non-defects is a key requirement for the accuracy of an estimation model in general. Among the most widely used methods are the efficiency characteristics curve, referred to as Receiver Operating Characteristic (ROC). The Receiver Operating Characteristic (ROC) curve is used to study variations in specificity and sensitivity for different discrimination threshold values.

Figure 6: The ROC curve for the test sample



Source: SPSS

Table 9: ROC curve timeout for the test sample

Zoned under the curve

Zoned	Std error.	Sig. Asymptotic	Confidence interval 95% asymptotic	
			Lower bound	Upper bollard
0,786	0,011	0	0,765	0,808

Source: SPSS

Note that this curve moves away from the bisector more we can say that the latter has a satisfactory predictive power since for the test sample the curve of OCR, which is a powerful indicator, is close to the corner of the square.

Conclusion

No one can deny that the prediction of credit risk is a complex act and the robustness of a model can only be validated in practice. As soon as the banker grants a loan, he incurs the risk of it, that's why the bank must anticipate the occurrence of repayment difficulties and put in place the best methods of its evaluation. Indeed, the assessment of credit risk is considered as a basic necessity for bankers because it allows them to measure the degree of risk that can be incurred by its customers as well, the measurement of this risk remains necessary and thanks to specific techniques and methods for calculating the probability of default in order to classify or distinguish good from bad customers. Future research can include other qualitative indicators such as strategy, structure and management. Our study can be improved by using other classification methods to overcome the shortcomings of the methods studied and improve the forecast of credit risk.

References

1. Journal articles

- Adya, M., Collopy, F. (1998). How Effective are Neural Networks at Forecasting and Prediction? A Review and Evaluation, Journal of Forecasting, vol. 17, pp. 481-497
- AKERLOFF G. (1970). « Market for 'Lemons: Qualitative Uncertainty and the Market Mecanism », Quarterly Journal of Economics, vol. 89, août, pp. 448-500
- Altman E.I. (2002). Corporate distress prediction models in a turbulent economic and Basel II environment", Document de travail.
- Altman, E.I., MARCO, G., VARETTO, F. (1994). Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis and Neural Network – The Italian Experience, Journal of Banking and Finance, vol. 18, n° 3, pp. 505-529.
- Altman, E.I. (1980). Commercial bank lending: Process, credit scoring and costs of errors in lending », Journal of Financial and Quantitative Analysis 15, p. 813-832.
- Anderson, R. (2007). The Credit Scoring Toolkit: Theory and Practice for Retail Credit Risk Management and Decision Automation. New York: Oxford University Press.
- Aubier, M. (2007). Impact de Bâle II sur l'offre de crédit aux PME. Economie & prévision 2/2007 (n° 178-179), p. 141-148. Pour plus de détail consulter : URL : www.cairn.info/revue-economie-et-prevision.

- Barth, J., G. Caprio et R. Levine. (2004). Bank Regulation and Supervision: What Works Best? Journal of Financial Intermediation, vol. 13, n° 2, pp. 205-248
- Bailey, M. (2001). Credit scoring: the principles and practicalities. Kingswood, Bristol: White Box Publishing.
- BEAVER, W. H. (1966). Financial Ratios as Predictors of Failure, Empirical Research in Accounting, Selected Studies, Journal of Accounting Research, Supplement, vol. 4, pp. 71-111.
- Catherine Refait-Alexandre. (2004). La prévision de la faillite fondée sur l'analyse financière de l'entreprise : un état des lieux. La Documentation française. « Revue Economie & prévision »2004/1
- Comité de Bâle sur le contrôle bancaire. (2006). Convergence internationale de la mesure et des normes de fonds propres, dispositif révisé.
- Cramer, J. S. (2004). Scoring bank loans that may go wrong: A case study. Statistica Neerlandica, 58 (3): 365-380.
- Dagobert Ngongang. (2015). Asymétrie d'information et rationnement du crédit bancaire dans les P.M.E. camerounaises. P : 11 Revue Congolaise de Gestion 2015/1 (Numéro 20), pages 11 à 54
- Dewatripont M., Tirole. (1993). La réglementation prudentielle des banques », Edition Payot Lausanne.
- Eric Tordjman et Naji Freiha. (2003). La validation des systèmes de notation interne dans le cadre de Bâle II .
- Frydman, H.E, Altman, E.I. et Kao, D.L. (1985). Introducing recursive partioning for financial classification: The case of financial distress. Journal of Finance, p. 269-291.
- Hamadi Matoussi. (2010). La prévention du risque de défaut dans les banques Tunisiennes : Analyse comparative entre les méthodes linéaires classiques et les méthodes de l'intelligence artificielle : les réseaux de neurones artificiels. P : 10 et 13.
- Hand, D. J., Henley, W. E. (1997). Statistical Classification Methods in Consumer Credit Scoring: A Review. Journal of the Royal Statistical Society: Series A (Statistics in Society) 160 (3): 523-541.
- Jean Bouyer. (2012). Régression logistique - Modélisation des variables quantitatives.
- Jeanne Lazarus. (2012). Prévoir la défaillance de crédit : l'ambition du scoring. Raisons politiques 2012/4 (n° 48), p. 103-118.

- Jean-Marc Daigle. (2002). L'utilisation des courbes ROC dans l'évaluation des tests diagnostiques de laboratoire clinique : Application à l'étude de la pneumonie d'hypersensibilité.
- Jean-Paul Betbeze et al. (2012) .Quelles leçons de la crise pour les banques centrales. La documentation française.
- Joanna N.S. Julie Makany et Chantal Gabsoubo Yienezoune. (2013). L'évaluation du risque de crédit des entreprises: cas de la banque congolaise de l'habitat. Revue Congolaise de Gestion 2013/1 (Numéro 17), pages 87 à 130.
- Mamadou Saliou Diallo. (2006). L'approche prédictive dans la théorie de l'échantillonnage.
- Monique Le Guen. (2008). La boîte à moustaches de TUKEY un outil pour initier à la Statistique.
- SAMPSON A. (1982). Les banques dans un monde dangereux. R. Laffont, 1982. p.38
- SAUNDERS A. (1999). Credit risk measurement – New approaches to value at risk and other paradigms. New York, Wiley, 226 p.
- Tarik QUAMAR, Said LOTFI, (2018). Les systèmes internes de notation : Architecture et enjeux sur la relation banque-PME marocaines. Revue du contrôle de la comptabilité et de l'audit Numéro 6 : Septembre 2018. ISSN: 2550-469X.
- Véronique Rougès. (2003) .Gestion bancaire du risque de non-remboursement des crédits aux entreprises : une revue de la littérature. 17 p
- Yoser Gadhoum et al. (2007). La décision de crédit. Procédure et comparaison de la performance de quatre modèles de prévision d'insolvabilité. La Revue des Sciences de Gestion 2007/2 (n°224-225), p. 177-183.
- Younes BOUJELBENE, Sihem KHEMAKHEM. (2013). Prévision du risque de crédit : Une étude comparative entre l'Analyse Discriminante et l'Approche Neuronale. P : 1-20.

2. Books

- Armstrong, John et Gary Fink. (2006). Les premiers à adopter l'accord de Bâle II seront les premiers à en tirer profit, Accenture (en ligne). Réf. du 31 mars 2006.
- Arnaud de Servigny. (2003), Le Risque de Crédit : Nouveaux Enjeux Bancaires. 2édi, Dunod.
- D. Dupré et M. El Babsiri. (1997), ALM : Techniques pour la gestion Actif-Passif. Eska
- F. DESMICHT (2004), Pratique de l'activité bancaire, édition DUNOD, Paris
- Jean-François FAYE (1993), Comment gérer les risques financiers. 156 p

- J. Bessis. (1995), Gestion des risques et gestion actif-passif des banques. Dalloz.
- J. Darmon. (1998), Stratégies bancaires et gestion de bilan. Economica.
- M. Dubernet. (1997), Gestion actif-passif et Tarification des Services Bancaires. Economica.
- Michel Dietsch, Valérie Golitin Boubakari. (2002), L'évolution des relations banques-entreprises dans les années 1990, Bulletin de la commission bancaire. N° 27– Novembre 2002 P : 41.
- Michel DIETSCH, Joël PETEY. (2003), Mesure et gestion du risque de crédit dans les institutions financières. Revue Banque.
- Olivier Redoulès. (2008), L'économie mondiale en 2008 : du ralentissement à la récession. Division Synthèse conjoncturelle, INSEE
- Oussama MARGHENI, Mohamed BENREJEB. (2011), Sur le crédit scoring par les réseaux de neurones artificiels. P : 1.
- Philippe Du Jardin. (2007), Prévision de la défaillance et réseaux de neurones : l'apport des méthodes numériques de sélection de variables. P : 47 ;48.
- Thierry Kenel. (2000), L'évaluation du risque de défaillance des entreprises : réseau de neurones ou analyse discriminante multivariée. P :154

3. THESIS

- FEKIH Nassima. (2014) : « L'apport des réseaux de neurones artificiels appliqués au management des risques comme outil de l'audit ». Thèse de doctorat. Université Abou Baker Belkaid Tlemcen.
- HEEM G. (2000) : « Le contrôle interne du risque de crédit bancaire », thèse de doctorat, Université de Nice – Sophia Antipolis