TOWARDS A MODEL FOR PREDICTING THE FAILURE OF CORPORATES BORROWERS FROM COMMERCIAL BANKS WORKING IN CHLEF: CASE OF BNA, AGB , NATIXIS BANK

Nacereddine **KARA ACHIRA***
Abderezak **HABBAR****

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Corresponding authors: n.karaachira@univ-chlef.dz

ABSTRACT

The purpose of this research is to build a model for predicting the failure of borrowing corporations from commercial banks working in Chlef. The data used in this study is 16 financial ratio obtained from the financial statements of the sample of 35 corporates during the period of 2006-2015. The sampling is based on 12 failed companies and 23 non failed companies, by using the Discriminant Analysis model, we have estimated a proposed model for predicting failure consists of 13 variables, this model has made a correct prediction rate amounts to 86,2 %.

KEY WORDS : Credit Risk Management, Credit Risk Modeling, Prediction Failure Models, Discriminant Analysis, Financial Ratios.

JEL CLASSIFICATION : G11, G21, G33, C61

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*Doctorant en science économiques à l'université de Chlef.
**Maitre de conférences à l'université de Chlef, Email: a.habbar@univ-chlef.dz

نحو نموذج للتنبؤ بفشل الشركات المقترضة من البنوك التجارية العاملة في ولاية الشلف: حالة البنك الوطني الجزائري، بنك الجزائر الخليج، بنك نتيكسيس

ملخص

نهدف من خلال هذه الدراسة إلى بناء نموذج للتنبؤ بفشل الشركات المقترضة من البنوك التجارية العاملة في ولاية الشلف، اعتمدنا على 16نسبة مالية مشتقة من القوائم المالية لعينة من 35شركة مقترضة (23منها سليمة و12 فاشلة) خلال الفترة 2006-2015، وباستخدام نموذج التحليل التمييزي توصلنا إلى بناء نموذج يتكون من 13متغير حقق نسبة تنبؤ صحيح بلغت 86,2%.

كلمات المفتاحية : إدارة مخاطر الائتمان، نمذجة خطر الائتمان، نماذج التنبؤ بالتعثر، تحليل تمييزي، نسب مالية.

تصنيف جال: G11, G21, G33, C61

UN MODÈLE DE PRÉVISION DE LA FAILLITE DES ENTREPRISES EMPRUNTEUSES DES BANQUES COMMERCIALES À CHLEF : CAS DE BNA, AGB, NATIXIS BANK

RÉSUMÉ

L'objectif de cette recherche est de construire un modèle pour prédire l'échec des entreprises emprunteuses auprès des banques commerciales exerçant à Chlef. Les données utilisées sont 16 ratios financiers obtenus à partir des états financiers de l'échantillon de 35 sociétés au cours de la période 2006-2015. L'échantillonnage est basé sur 12 entreprises défaillantes et 23 entreprises non défaillantes. En utilisant le modèle d'analyse discriminante, nous avons estimé un modèle proposé pour prédire l'échec qui se compose de 13 variables et qui a atteint un taux de prévision correcte de 86,2%.

MOTS CLÉS: Gestion du risque de crédit, Modélisation du risque de crédit, Modèles de prédiction d'échec, Analyse Discriminante, Ratios financiers.

JEL CLASSIFICATION : G11, G21, G33, C61

INTRODUCTION

Since the beginning of the second half of the twentieth century, a new approach has emerged in the criteria on which banks rely on credit decision making. This approach promotes the use of mathematical and statistical models in the process of credit analysis. In addition to relying on financial analysis and financial ratios, banks also rely on more accurate models that permit to rationalize the credit granting decision. These models are called "Failure Prediction Models". Studies of W. Beaver (1966) and E. Altman (1968) were the first which found mathematical models to predict the failure of borrowing companies from banks, which led to many studies to find several models and using various statistical methods that aim to predict the failure of corporate borrowers from banks to rationalize the credit granting decision. In keeping with the innovations in the credit analysis process, commercial banks operating in Algeria must rely on such models to reduce the risk of credit default and increase returns. For this purpose, we will propose a model for predicting failure based on the data of borrowing companies. So the main question is :

How accurate are of the failure prediction models to predict the failure of corporate borrowers from commercial banks operating in Chlef?

In this study, we aim to build a model for predicting a feasible failure useable to rationalize the decision to grant credit in commercial banks operating in Algeria.

Commercial banks are constantly developing their methods of credit analysis to ensure that they have access to more accurate decisions to avoid credit defaults, for this purpose, the trend towards modeling of credit granting decision in line with the various changes and rapid developments in the banking environment both at the level of borrowers and competitors domestically and internationally.

Mathematical models and quantitative methods helping to take a credit decision in commercial banks in Algeria have a limit use, in public banks, so it is important to address this issue because of its importance in reducing the risk of credit default.

In this study, we will rely on the deductive approach. We describe the literature review and the theoretical framework of the research and then analyze the available data from the financial statements of the companies to build the model of predicting failure.

1- LITERATURE REVIEW

1.1- Credit Risk: Definition and types

Credit risk includes credit default risk and credit spread risk. The former form of credit risk is the risk that an issuer of debt (obliger) is unable to meet its financial obligations resulting in an investor incurring a loss equal to the amount owed by the obliger less any recovery amount. Credit spread risk is the risk of financial loss or the underperformance of a portfolio resulting from changes in the level of credit spreads used in the marking-to-market of a product. Downgrade risk is a form of credit spread risk because the anticipating or actual downgrading of an issue or issuer will result in an increase in the credit spread (Frank J. Fabozzi et al, 2004).

1.2. Failure Definition

Failure is defined as the inability of a firm to pay its financial obligations as they mature. Operationally, a firm is said to have failed when any of the following events have occurred: bankruptcy, bond default, an overdrawn bank account, or non-payment of a preferred stock dividend (W. Beaver, 1966). And according to E. Altman, failure, in an economic sense, means that the realized rate of return on invested capital, with allowances for risk consideration, is significantly and continually lower than prevailing rates on similar investments. Somewhat different economic criteria have also been used, including insufficient revenues to cover costs and where the average return on investment is continually below the firm's cost of capital (E. Altman et al, 2019).

According to the Basel Committee on Banking Supervision, failure definition reflects many of these events: (Basel Committee on Banking Supervision, 2001)

a) It is determined that the obliger is unlikely to pay its debt obligations (principal, interest, or fees) in full;
b) A credit loss event associated with any obligation of the obligor, such as charge-off, specific provision, or distressed restructuring involving the forgiveness or postponement of principal, interest, or fees;
c) The obligor is past due more than 90 days on any credit obligation;
d) The obligor has filed for bankruptcy or similar from creditors.

1.3- The credit granting decision

The credit granting decision is one of the most important decisions within the bank. As there must be controls and criteria to be taken in a way that contributes to the achievement of its objective, because this decision may result after its implementation to credit risks such as default risk, downgrade risk, credit spread risk (Anson et al, 2004). In the Oxford Dictionary, the word "risk" is defined as the possibility of something undesirable happening in the future (Sally Wehmeier, 2000). The risks inherent to bank credits are considered as the main challenge for the operation of measuring and managing the risks since the last 1990. The past few decades have seen the emergence of several quantitative methods that have been developed to decide on granting credits, including credit scoring models (Liang, 2003).

1.4- Prior Research on Prediction Failure Models

Research on business failure traces back to the late 1800s when the establishment of commercial banks greatly increased the flow and spread of financial information, this availability financial data was the genesis of business failure studies. Early studies primarily focused on financial and accounting measures and subsequently the topic spread into economics, information systems, general management, sociology and entrepreneurship. And in the 1930s the great depression formed the catalyst that led to the study of business failure to begin in earnest (Grace S. Walsh et al, 2016).

We will present the original studies, then the most important later studies that have made additions especially in the model building methods. We will take into account the diversity in the date of publication, the method used, and the case study.

The empirical literature on financial failure prediction is large and varied, in terms of explanatory variables and methodological techniques (Ashraf S, 2019).The earliest study of the prediction failure models might be dated back to the 1930s. The first study was published by Fitzpatrick entitled "A comparison of the ratios of successful industrial enterprises with those of failed companies". He compared the values of financial ratios between the failed and non-failed firms and found that the failed firms usually had poorer variables (Fitzpatrick, 1932). In 1966, Beaver published a study entitled "Financial ratios as predictors of failure". He examined the predictive power of 30 ratios when applied five years prior to failure, for a sample contained a pair of 79 failed and non-failed firms during the period from 1954 to 1964. And using unvaried discriminant analysis, he reached a model of three variables, this model achieved a correct prediction rate estimated at 78% five years prior to failure and 87% one year prior to failure (Beaver, 1966). In 1968 E. Altman published a study entitled "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy" which aims to predict the failure five years before its occurrence for a sample contained a pair of 33 failed and non-failed firms during the period from 1946 to 1965. Using the multiple discriminant analysis he reached a model of five ratios selected from 22 ratios called "Z-Score model", this model is extremely accurate in classifying 95 % of the total sample correct (E. Altman, 1968). In 1974, Blum published a study entitled "The failing company doctrine" which aims to identify the variables that can be used to predict failure. He built a model by using accounting data and financial market data during the period from 1954 to 1968 for a paired sample of 115 failed and non-failed firms. And using discriminant analysis method ,he reached a model of five variables that achieved a correct prediction rate estimated between 93% and 95% one year prior to failure, and 80% two years prior to failure and 70% three years prior to failure (Blum, Marc P, 1974). In 1977, E. Altman et al presented a study entitled " ZETATM analysis A new model to identify bankruptcy risk of corporations" which aims to make a comparison between the method of linear discriminant analysis and the quadratic discriminant analysis, and to identify the variables that permit to predict the failure five years before its occurrence, for a sample of firms consisting of 53 bankrupt firms and 58 non-bankrupt entities during 1969-1975. He used the linear discriminant analysis and developed its previous model "Z –score" into a new model of seven ratios known as the ZETA Score, this model achieved a correct prediction rate estimated at 93% one year prior to failure and 70% five years prior to failure (E. Altman et al, 1977). In 1980, Ohlson published a study entitled "Financial ratios and the probabilistic prediction of bankruptcy" which aims to predict failure, the study was conducted on a sample consisting of 105 failed firms and 2058 non-failed firms during 1970-1976. Using the conditional Logit model, Ohlson reached a model of nine variables, this model achieved a correct prediction rate estimated at 96.12% a year prior to failure, 95.55% two year prior to failure. And he pointed out two points: First, the predictive power of any model depends upon when the information (financial report) is assumed to be available. Second, the predictive powers of linear transforms of a vector of ratios seem to be robust across (large sample) estimation procedures. Hence, more than anything else, significant improvement probably requires additional predictors (Ohlson, J. A, 1980). In 1994, Altman & all published a study entitled "Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience)" which aims to build a corporates distress prediction model and to analyze the comparison between traditional statistical methodologies for distress classification and prediction, i.e., linear discriminant or logic analyses, with an artificial intelligence algorithm known as neural networks. The study was conducted on a paired sample of 213 failed and non- failed firms during 1982-1992. Using linear discriminant analysis, the study achieved a correct prediction rate estimated at 86.4% for the failed firms and 90.3% for non- failed firms. And using neural networks, it achieved a correct predictive rate estimated at 97.7% for the non-failed firms and 97% for the failed firms (E. Altman et al, 1994). In 2008, Abdullah et al published a study entitled "Predicting corporate failure of Malaysia's listed companies: Comparing multiple discriminant analysis, logistic regression and the hazard model" which aims to compares three methodologies for identifying financially distressed companies, multiple discriminant analysis, logistic regression and hazard model. In a paired sample of 52 distressed and non-distressed companies during 1990-2000, the predictions of the hazard model were accurate in 94.9% of the cases examined. This was a higher accuracy rate than generated by the other two methodologies. However, when the holdout sample is included in the sample analyzed, MDA had the highest accuracy rate at 85% (Abdullah et al, 2008). In 2009 LIN, Tzong-Huei published a study entitled "A cross model study of corporate financial distress prediction in Taiwan: Multiple discriminant analysis, logit, probit and neural networks models" which aims to examine the predictive ability of the four most commonly used financial distress prediction models and thus constructed reliable failure prediction models for public industrial firms in Taiwan. Multiple discriminant analysis, logit, probit, and artificial neural networks methodology were employed to a dataset of matched sample of failed and non-failed Taiwan public industrial firms during 1998–2005. The results indicated that the probit, logit, and ANN models which were used in this study achieve higher prediction accuracy and possess the ability of generalization. The probit model possesses the best and stable performance. However, if the data does not satisfy the assumptions of the statistical approach, then the ANN approach would demonstrate its advantage and achieve higher prediction accuracy (LIN, Tzong-Huei, 2009). In 2010 Yazdipour, R. et al published a study entitled "Predicting firm failure: A behavioural finance perspective" which first argues that researchers in the area of financial distress and failure cannot ignore the human/managerial/decision-making side of the business and just focus on the business' operations side, then it discussed how psychological phenomena and principles, known as heuristics or mental shortcuts, could be utilized in building more powerful failure prediction models especially for small and medium-sized enterprises (Yazdipour, R. et al, 2010). In 2012 Alhassan Bunyaminu et al published a study entitled "Predicting corporate failure of UK's listed companies: Comparing multiple discriminant analysis and logistic regression" which aims to compares two corporate failure prediction models, namely; multiple discriminant analysis (MDA) and logistic regression in attempt to identify whether or not financial ratios can be used as indicators of failure in the UK, to identify financial ratios that are most important for detecting potential insolvency of UK's public listed companies and also which model is better in predicting corporate failure. The study employed financial information for a paired sample of 50 distressed and non-distressed UK listed companies during the period 2000–2010. The initial sample of 100 companies was divided into a 70% estimation (training) sample and a 30% holdout (test) sample. The Logit model achieved the highest overall classification results for year 2 and 3 and also for the cumulative three years prior to insolvency, with average classification of 71% and 81.9% respectively. Although the MDA model achieved a lower percentage of overall correct classification (average of 68.9% all three years and 80% for cumulative three years), it resulted in slightly higher overall percentage in the first year prior to failure (Alhassan Bunyaminu et al, 2012). In 2017 Ibrahim OnurQz et al published a study entitled "A Theoretical Approach to Financial Distress Prediction Modeling" which aims to examine a theoretical base for the financial distress prediction modeling over eight countries for a sample of 2,500 publicly listed non-financial firms for the period from 2000 to 2014. Using panel logistic regression, the overall full sample prediction accuracy of the model is 87.16% at T-1 and 85.37% at T-2. And using neural networks, the overall prediction accuracy at T−1 for the full sample is 89.88% and 88.31% at T-2 (Ibrahim OnurQz et al, 2017). In 2019 Robert N. Lussier et al published a study entitled"Success versus Failure Prediction Model for Small Businesses in Ghana" aims to test the validity of Lussier model in predicting success or failure of small business in Ghana, the study uses Logistic Regression to analyze a sample of 101 failed and 107 non-failed small businesses. The study support the model validity in Ghana and three variables (capital, economic timing, and marketing skills) were significant in predicting small businesses success or failure. The model achieved a correct predictive rate estimated at 86.5% (Robert N. Lussier et al, 2019)

2- METHODOLOGY RESEARCH

2.1- Sample selection

According to the data , we could get the current study targeted a sample of 35 firms that got a credit at least from commercial banks working in Algeria (BNA, AGB, Natixis bank) during period from 2006 to 2015, this sample consists of 23 non- failed firms and 12 failed firms.

2.2- Variables and Multiple Discriminant Analysis

2.2.1. Variables Selection

Generally, there are five accounting ratio categories describing the main operating and financial aspects of a company's profile: liquidity, profitability, leverage, coverage and activity (Altman et al, 2018). All previous studies mentioned, regardless of the approach used, have one common impediment: they are not based on an economic theory in choosing the variables for distinguishing between failing and non failing firms. Instead, researchers selected financial ratios as predictor variables mainly because of their popularity and predictive success in previous research, and the choice of discriminating variables in the study was based on the major financial ratios that were found statistically significant in predicting failure in prior research (Evridiki Neophytou et al, 1999).These ratios are also examined in this study. In order to identify the statistically significant ratios.

The next step in the model building process is to identify a number of variables that could be helpful indicators of firm credit worthiness. Consistent with a large number of previous studies, we choose 16 accounting ratios extracted from the firms' financial statements according to their importance in assessing the credit worthiness, these ratios describe the main operating and financial aspects of a firm's profile; we present them in the following table:

Table 1. Original financial variables

Variables	Description
R1	Equity / Total debt
R2	Total debt / Total Assets
R3	Current assets / short term debt
R4	Working capital / Total Assets
R5	Net Income / Equity
R6	Short term debt / Total Assets
R7	(Current assets – inventory) / short term debt
R8	Non-crurent liabilities / Total Assets
R9	Cash / short term debt
R10	Sales / Total Assets
R11	Working capital / sales
R12	Current assets / sales
R13	Cash/ Sales
R14	Earnings before interest, tax, depreciation and amortization / Total Assets
R15	Total result before interest and taxes / Total Assets
R16	Inventory/sales

Source: Realized by consulting the previous studies

2.2.2. Multiple Discriminant Analysis (MDA)

R. A. Fisher published two studies in 1936 and 1938 respectively entitled "The use of multiple measurements in taxonomic problems" and "The statistical utilization of multiple measurements" (R. A. Fisher, 1938) which aims to develop the discriminant analysis model (R. A. Fisher, 1936), which can be used to determine the most significant ratios for firms' classification to failed or non- failed firm.

MDA is used for modelling the value of a categorical dependent variable based on its relationship to more than one independent variable. In its most common form MDA tries to derive a linear combination of characteristics of these variables that best discriminates between the categories, based on the statistical decision rule of maximizing the between category variance while minimizing the within category variance among these variables. One advantage of

MDA is the reduction of the analysis space dimensionality, i.e. from the number of independent variables to ***k-1*** dimension(s), where k equals the number of original a priori categories. Since the financial distress prediction is concerned with only two categories of failed group and non-failed group, the analysis is transformed into its simplest one dimension and the discriminant function transforms the values of variables to a single discriminant score of Z, which is then used to classify and predict the financial performance of the original firms or/and out-of-the-sample ones. MDA can be described mathematically as follow:(Liang Qi, 2003)

Consider n firms in the model sample, and a set of p independent variables (financial ratios), $X_1, X_2, \ldots, X_p$, and a binary category variable Z referring to firm financial performance. The predicted categorical measure Z_u (discriminant score) for firm u may be represented as:

$$Z_u = b_0 + \sum_{i=1}^{p} b_i X_{iu} \ , \quad i = 1,2, \ldots , pu = 1,2, \ldots ,n$$

Where b_i is the discriminant coefficient and b_0 is the constant. MDA assigns firm u to the failed category of g if the posterior probability of membership of firm u in category g is greater than that in the non-failed category of g'. That is

$$P(g/X_u) > P(g' / X_u) \ , \qquad g \neq g'$$

Posterior probability is a likelihood of category membership conditioned on knowing X_u. Assuming that the independent variables follow multivariate normal distribution and the two category covariance matrices are equal, then the posterior probability of membership of firm u in category g is given as

$$P(\ g \ / \ X_u) = \frac{q_g \ . \exp \ (-\frac{1}{2} D_{ug}^2 \ )}{\sum_{g'=1}^{k} q_{g'} \ . \exp \ (-\frac{1}{2} D_{ug'}^2 \ )}$$

Where q_g and $q_{g'}$ denote respectively the prior probabilities of membership in category g and g', "prior" in the sense that is a probability of category membership before X_u is known.D_{ug} and D_{ug} 'are distance between the observation vector of firm u and the centroid of category g and g'.

3- RESULTS AND DISCUSSIONS

Through the SPSS23 software; we have conceived the failure prediction model using the MDA as a method to identify the discriminatory variables that could be helpful indicators of firm credit worthiness. We get the following variables (see appendix 01):

Table2: The discriminatory variables of the model and its coefficients

Variables	Coefficients	Variables	Coefficients
R1	-0.006	R10	-0.227
R2	-0.097	R11	-0.366
R4	0.153	R12	0.090
R5	5.462	R13	-0.715
R6	0.989	R14	-4.847
R8	4.380	R15	-0.142
R9	0.141	Cst	-1.446

Source: SPSS output (see appendix 01)

We note from table 1 that among 16 financial ratios, the MDA produced 13 of the most significant financial ratios for predicting the risk of failure. And three variables were considered to be unable of discrimination are : current assets / short term debt, (current assets – inventory) / short term debt, Inventory/sales (see appendix 02).

Through the previous table, we have the model's equation as follows:

$$\begin{aligned} Z = {} & -0.006\,R1 - 0.097\,R2 + 0.153\,R4 + 5.462\,R5 + 0.989\,R6 + 4.380\,R8 \\ & + 0.141\,R9 - 0.227\,R10 - 0.366\,R11 + 0.090\,R12 \\ & - 0.715\,R13 - 4.847\,R14 - 0.142\,R15 - 1.446 \end{aligned}$$

What can be seen from the proposed model is that the financial ratio that has the highest ability of discrimination is R5 (Net Income / Equity) which has the largest coefficient (in absolute terms), the positive sign of its coefficient reflects the positive relationship between it and the firm's distinctive point. The distinctive point value rises as R4 increases. Thus, the likelihood of this firm belonging to the non-failed firms group rises. And we can observe that R1 (Equity / Total debt) has the least ability of discrimination, the negative sign of its coefficient indicates an inverse relationship between it and the firm's distinctive point. The distinctive point value declines as R1 increases. Thus, the likelihood of this firm belonging to the failed firms group rises.

After formulation of the proposed prediction model, we can calculate the cut point Z^* on which to classify the borrowing firms in the future. We can calculate Z^*according to the following equation :

$$\boldsymbol{Z^*} = \frac{\boldsymbol{N_1 Z_1 + N_2 Z_2}}{\boldsymbol{N_1 + N_2}}$$

Where N_1 and N_2 are the sample size of failed and non-failed firms respectively, Z_1 and Z_2 are average discriminatory values for failed and non-failed firms respectively. If the distinctive point of the new borrowing firm is greater than or equal to the cut point, it is classified as a non-failed firm, if less, it is classified as a failed firm.

We found the cut point value equal to : $Z^* = 0.000344828$.

The following table shows the sample prediction results of prediction failure model:

Table 3: Results of prediction failure model

	The classification's results		Total
	1	0	
Number of failed firms	2	8	10
Number of no failed firms	17	2	19
Rate of failed firms	20%	80 %	100%
Rate of no failed firms	89.5%	10.5%	100%

Source: Prepared according to the outcomes of SPSS23 software (see appendix 04)

We note that MDN eliminated six firms in building the model because of their missing values. Through the results shown in table2, we notice that among 10 really failed firms, the proposed model found that there are only 02 failed firms and 08 non-failed firms, that means the model achieved a correct prediction rate of the failed firms estimated at 80%. And among 19 non-failed firms, the model found a 17non-failed firms and only 02 failed firms, that means the model achieved a correct prediction rate for the non-failed firms estimated at 89.5%. Therefore, the overall correct prediction rate of the proposed model is 86.2%.

The accuracy of the prediction failure model is also evaluated on the basis of Type I and Type II errors. The Type I error measures the percentage of failed firms that are classified as non-failed and Type II error measures those firms classified as failed but which didn't fail. The results in table3 shows that the Type I error of discriminant analysis model proves to be 20% while the Type II error is better at 10.5%. The average of the two types is lower than the assumed rate at the beginning of this study, and this is a good indicator of the quality of the proposed model.

CONCLUSION

Our main question in this study was: **How accurate are the failure prediction models to predict the failure of corporate borrowers from**

commercial banks operating in Algeria? We hypothesized that the proposed prediction failure model achieves an acceptable level of accuracy in prediction estimated at more than 80%.

Through this study, we have built a predicting failure model of 13 variables, chosen from 16 variables according to their importance in assessing the credit worthiness. These variables represent financial ratios extracted from the firms' financial statements of a sample of 35 firms that borrowed from commercial banks (BNA - AGB - NATEXIS) during the period from 2006 to 2015. And by using the MDA, we found that the model achieved a total correct predicting rate of 86.2% which is an acceptable rate.

Varying results were achieved in terms of the predictive power of the models that have been built, therefore it is changing by changing time and place, and still hasn't been reached a model that could generalized, and in this study we have reached a corresponding results compared to the previous studies results which used MDA.

At the level of the banking sector, relying on failure prediction models helps to avoid bank failures problems and achieves bank security by reducing the risk of credit portfolios of lender banks and stabilizing their revenues, thus contributing to improving their performance.

In the future, we will use new models such as Logit&Probit, Hazard model, and neural networks, to compare its results with the current study result, and we will as we will try to apply to a larger sample of the current sample. And we recommend future studies to rely on new variables such as corporate governance principles and behavioral variables

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APPENDIX

Appendix 01 : Discriminant Function Coefficients

		Function
		1
Equity / Total debt		-,006
Total debt / Total Assets		-,097
Working capital / Total Assets		,153
Net Income / Equity		5,462
Short term debt / Total Assets		,989
Non-current liabilities / Total Assets		4,380
Cash / short term debt		,141
Sales / Total Assets		-,227
Working capital / sales		-,366
Current assets / sales		,090
Cash/ Sales		-,715
Earnings before interest, tax, depreciation and amortization / Total Assets		-4,847
Inventory/sales		-,142
	(Constant)	-1,446

Appendix 02 : Variables Failing Tolerance Test[a]

	Within-Groups Variance	Tolerance	Minimum Tolerance

Current assets / short term debt	1623103,368	,000	,000
(Current assets – inventory) / short term debt	1349280,825	,000	,000
Inventory/sales	368,378	,000	,000

All variables passing the tolerance criteria are entered simultaneously.

a. Minimum tolerance level is ,001.

Appendix 03 : Classification Results[a]

		Etatd'entreprise	Predicted Group Membership		Total
			Failed	Non failed	
Original	Count	Failed	8	2	10
		Non failed	2	17	19
	%	failed	80,0	20,0	100,0
		Non failed	10,5	89,5	100,0

a. 86,2% of original grouped cases correctly classified.