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Failure Prediction: Discriminant Analysis on a Sample of the Moroccan SMEs/Les

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Abstract:

In the current perpetual economic context, several companies have undergone economic and financial difficulties which can, in certain cases, lead to bankruptcy. Indeed, the factors explaining the failure of companies are multiple. The objective of our study is to classify companies in difficulty according to their degree of viability. We will refer to the statistical methods and more precisely the discriminant analysis, allowing to understand the most determining variables of the deterioration of their situation, through a sample of 669 Moroccan companies. This study has revealed that the bankruptcy of companies is partly linked to financial autonomy, Gearing, inventory turnover, activities and management, profitability of assets and net return on equity, the share of WCR in relation to turnover and indebtedness.

Keywords: Business failure, risk prediction, discriminant model, SME/LE

1. Introduction

Like the majority of countries, the Moroccan economic fabric shows that each year some companies disappear and others survive and among the latter, companies that encounter financial difficulties, while others continue to develop. The issue of business failure is still a challenge for players in the banking sector. Indeed, failure is not an exclusive domain of small and medium-sized companies, it can affect them all, regardless of their size, even those listed on the stock exchange. Blazy et al. (1993) define failure as "*the situation from which a recovery procedure is opened against a company*". Banking institutions have become a key player in the economy insofar as they are confronted with the problem of assessing the probability of individual defaults of their customers, are already experiencing a profound change in their regulatory environment. Since 1988, regulations drawn up by the Basel Committee aimed at guaranteeing the strength of the banking system, forces banks to cover the risks they take in their credit activity with bank equity.

However, estimating the risk of business failure remains one of the most raised issues by researchers and professionals in this field. Due to the scale and the negative consequences that the disappearance of companies can entail, banking institutions suffer a very high cost in the case of partial or total loss of the funds lent, but also a major risk for other creditors, who in this situation, may in turn become defective. Many studies have used techniques for predicting the probability of failure. These different works concern the use of linear discriminant analysis, intelligence techniques, Bayesian networks and probabilistic models. Among the works carried out in this field are the ones that have developed models that make it possible to predict the financial health of companies with more precision (Altman, 1968, 1984; Bardos, 1989; Ding et al. 2008; Li and Sun, 2009). The central question of this work is part of this perspective: **What are the financial and accounting determinants of the failure of the Moroccan companies?**

The answer to this question is the subject of this paper. We will successively present the state of the art devoted to business failure, the formulation of hypotheses, the highlighting of business failure forecasting models. Finally, we will reflect upon the methodological choice and the analysis of the different empirical results obtained from the discriminant model.

2. Literature review and hypotheses development

In recent years, the annual number of business failures has continued to grow and this trend is accentuated especially during crisis situations. According to Guilhot (2000): "*It is more important to predict bankruptcies than to seek their causes*". Thus, the large amount of debt, due to the bankruptcy of companies, is a strong reminder of the need to anticipate failure. Indeed, the modeling of the default probability of portfolios remains one of the subjects that interest researchers in management sciences. There are multiple approaches to modeling the probability of default of portfolios which must respect several constraints.

In this first part, we will present the context and the issues related to the modeling of the probability of default for a bank as well as the methods of estimating the risk of default which were of particular interest to us. Then, we will proceed with the development of research hypotheses following this literature review.

2.1. Univariate modeling approach

Beaver (1967) was one of the first to look into the problem of modeling the probability of default and then Altman (1968), these works seem to have been the real starting point and the reference in many studies. Thus, models for modeling the probability of default based on accounting information take into account explanatory variables grouped together in a one-dimensional dichotomous way.

The univariate approach consists of comparing the financial ratios of failing companies to those of healthy companies and then detecting the systematic differences that exist between the two groups in order to help users predict the failure (Fitzpatrick, 1932; Winakor and Smith, 1935; Merwin, 1942; Beaver, 1966). Five categories of ratios have been used to predict the probability of default: these are liquidity, profitability, debt, solvency and activity ratios.

Fitzpatrick's study (1932), was conducted on a sample of 19 healthy and 19 failing companies, based on the trend, in order to predict the risk of default three years before the failure, of the ratios used, namely the net profit to equity and equity to total debt.

In addition, Beaver (1966) conducted a study on a sample of 79 failing and 79 healthy companies, to discriminate between companies and classify each one in one of the two groups on the basis of accounting ratios. To estimate the predictive value of each ratio, his study consisted of two phases: first, he uses a subgroup in which he classifies companies according to the value taken by a particular ratio and then he determines the critical threshold of each ratio. Afterwards, if the ratio is below a critical threshold, companies are considered to be in default, whereas those with a higher ratio are not. The critical threshold is determined in such a way as to maximize the rate of correct classifications in the first sub-sample. A classification of the companies of the second sub-sample is then carried out from the previously determined critical threshold and another rate of good classifications is calculated. Beaver selected among thirty ratios the ones with a strong forecasting capacity:

- Cash flow / Total debts;
- Net income / Total assets;
- Total debts / Total assets;
- Working Capital / Total Assets;
- Short-term debt ratio and no-credit interval.

The univariate statistical model of Beaver certainly has the advantage of its simplicity and the outcome of good results. However, Beaver does not take into consideration the joint effect and the strong interdependence of the ratios.

Therefore, one of the extensions of this univariate approach consists of the construction of a developed model based essentially on a statistical approach such as discriminant analysis, logistic regression, a neural approach, similar to neurons network, self-organizing maps and genetic algorithms.

2.2. Multivariate modeling approach

Afin Altam (1968) used multidimensional discriminant analysis to classify a company in the group of those who are failing or those who are healthy. A simple decision rule was used which was to assign it to the group it is closest to. The discriminant analysis led to the construction of a function

called score, a linear combination of the explanatory variables retained, of which the realization expresses the level of risk of the company. In the case of two groups N and D, the score of the company characterized by x is written:

$$f(x) = (m_N - m_D)W^{-1}(x - \frac{m_D + m_N}{2})$$

Altman chose 5 ratios that best separate the two groups of companies. Altman followed the following function: Z = α1X1 + α2X2+ ... + αNXN, the ratios (Xi) are weighted by αi values. In order to judge the financial situation of a company, the regression model takes into account (liquidity, solvency, profitability, activity and growth), which are the most relevant and essential ratios in the prediction of default of a company. According to Altman, the application of the discriminant procedure led to the emergence of the following optimal score function:

Z= 0,012 X1 + 0,014 X2 + 0,033 X3 + 0,006 X4 + 0,999 X5

With :

X1 = Working Capital / Total Assets;
X2 = Reserves / Total Assets;
X3 = Earnings Before Interest and Tax / Total Assets;
X4 = Market capitalization or FP / total debt;
X5 = Turnover / Total Assets.

According to Altman, the model revealed that all companies that scored 2.99 or higher were healthy. Those with a score below 1.81 were bankrupt. The score in the area between 1.81 and 2.99 showed an ambiguous signal: some companies were healthy while others were bankrupt.

Therefore, the use of a single threshold to classify companies is likely to lead to errors. Altman set the critical value of his score at Z = 2.675 to minimize these errors. Thus, a company that obtains a Z score < 2.675 will be classified as failing, or more precisely a Z score < 1.81 announces its failure within one year; and a Z score > 2.99 signifies that the company is in a good financial health.

The model of Altman (1968), aroused a particular interest insofar as they followed the same methodology using only the linear discriminant analysis and took again the same ratios as Altman (Atiya (2001), Grover and Lavin (2001)).

Like the study of Altman (1968), Shirata (1998), Bardos (1998) tried to determine the financial ratios which make it possible to predict a bankruptcy of the company, by adopting only the linear discriminant analysis.

The choice of discriminant analysis is justified by the fact that it is currently the most widely used method (Li et al., 2010). The score function, thanks to the study of the contribution of each ratio, is an aid to understanding bankruptcy. Moreover, thanks to its temporal robustness, it offers the best classification.

To summarize the ratios of our study, we present in this table all the financial indicators chosen. Some of these indicators are directly involved in the formulation and verification of our hypotheses, while others serve as contingency factors such as age and height.

Table *: Financial themes used in the study

Ratios		Formulas
R1	**Company age**	Rating Date -Creation Date
Structure / Solvency ratios		
R2	**Financial Autonomy ratio**	Equity capital / Permanent capital
R3	**Financial Equilibrium ratio**	Permanent capital / Net fixed assets
R4	**Gearing**	MLTD/Equity capital
R5	**Interest Coverage Ratio**	GOP/ financial charges
Activity and Management Ratios		
R6	**Inventory Turnover**	(Stocks /TO) *360 days
R7	**Duration of Customer Credit**	**4.1. (Trade receivables** / TO) * 360 days
R8	**Duration of Supplier Credit**	(Frs/ Purchases resold and consumed)*360 days
R9	**Asset Turnover**	TO / TOTAL ASSETS
Profitability Ratios		

R10	**Return on Assets**	Net income / total Assets
R11	**(Net) Return on Equity**	Net income / Equity capital
R12	**Ggross Profit Margin**	Earnings before tax / CAT
Liquidity ratios		
R13	**Current Ratio**	Current assets/ Current liabilities
R14	**Cash Ratio**	Cash assets / current liabilities
R15	**Quick Ratio**	(Cash + trade receivables) / current liabilities
R16	**Financial Equilibrium**	WC/WCR
R17	**WCR rate**	WCR/ TO
R18	**Financial Equilibrium**	Permanent financing / Fixed assets
Debt Ratios		
R19	**Cost of Debt**	Finance charges/ bank debt
R20	**Coverage of Financial Charges**	Finance charges/ TO

Source: Authors

From the table below, the factors which determine the prediction of failure, four hypotheses will be the focus of our study.

Hypothesis 1: Lack of profitability is an explanatory factor for business failure.
Hypothesis 2: the company's ability to repay and cover its financial charges is a key element in predicting company bankruptcy.
Hypothesis 3: Lack of liquidity is an explanatory factor for business failure.
Hypothesis 4: The greater the need for working capital, the greater the deterioration in the financial situation of companies.
Hypothesis 5: Factors related to the level of indebtedness have an impact on the financial situation of companies.

3. Method

Two methodological steps were followed, firstly, we selected our sample for the construction of our database and, secondly, we presented the choice of financial ratios used as analysis indicators, mainly accounting, which best differentiate failing companies from non-failing ones. The objective is to establish a stable statistical relationship between the explanatory variables of each of the two

groups (Refait, 2004). In order to achieve our objective, it was necessary to have a database, composed of two types of companies of which the only criterion that distinguishes them is the state of payment of their loans vis-à-vis the bank. Thus, the notion of failure used in the context of our research is:

• More than 90 days in arrears on debt payment;

• The transfer of the account to the collection service.

Through our sample, we used the existing database at a large local bank, both for the failing companies and for the healthy ones. The selection criteria which have been laid down are the exclusion of: Sectors of activity of a financial nature, companies with a very limited history (less than five years of existence) and those of which information is missing for at least two consecutive years. Thus, we ended up with a final representative sample, which is made up of 669 companies, for which we have accounting and financial information for two regular years.

4. Empirical results

4.2. Descriptive statistics

The sample size is made up of 669 different active companies with positive bank loans over the period from 2017 to 2018. Their turnover is strictly lower than 175 million dirhams for the SME category and higher than 175 million dirhams for the LE category.

Table: Distribution of the sample by enterprise size

	Frequency	%
SME (turnover less than 175 million MDH)	439	65,62%
LE (turnover higher than 175 million MDH)	230	34,38%
Total	669	100%

Source: Authors

The companies, in the portfolio used, constitute a sample made up of 669 companies, for which we have accounting and financial information for two regular years. Our sample consists of 65.62% represented by SMEs and 34.38% by the Large Enterprises. These results corroborate the SME

statistics in the Moroccan economy of INFORISK (2011) on the weight of the SME represents 99% of the national productive fabric.

4.3. Choice of variables

The choice of analysis ratios was made following a logical and methodological approach in order to constitute a list to meet the objectives and expectations of our research. We have selected a combination of six themes reflecting the independent variables explaining the prediction of the Moroccan companies in default of payment. Thus, the themes that we have adopted in our analysis are: structure, solvency, profitability, liquidity, indebtedness, and commercial management.

Table *: Financial themes used in the study

Ratios		Formulas
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R7	**Duration of Customer Credit**	**4.4.** (**Trade receivables** / TO) * 360 days
R8	**Duration of Supplier Credit**	(Frs/ Purchases resold and consumed)*360 days
R9	**Asset Turnover**	TO / TOTAL ASSETS
Profitability Ratios		
R10	**Return on Assets**	Net income / total Assets
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Debt Ratios		
R19	**Cost of Debt**	Finance charges/ bank debt
R20	**Coverage of Financial Charges**	Finance charges/ TO

Source: Authors

We applied the Altman model (1968) to classify companies according to their status (healthy or in default). It appears from the empirical results of our sample that the companies are divided into two subgroups according to their status (healthy or in default) and distributed in the table*.

Table *: Breakdown of the portfolio of companies according to their status (healthy or in default)

Category	Total Sample	Defects %	Healthy %
PME	439	244	195
GE	230	124	106
Total	669	**368**	**301**

Source: Authors

4.5. Means equality tests

The analysis of the descriptive statistics and the test of equality of means revealed the following remarks (see appendix*):

- A variable has significantly different means when we consider the two types of companies: these are the following variables: (R2; R4; R6-R12; R14; R17 and R19; R20) of which difference is significant at the threshold of 5%. For the rest of the variables (Age; R5 and R3; R15 and R16), the difference in mean is not significant.

- As for the size variable (CA), it is significantly higher, at the 5% level, in both types of companies.

4.6. Fisher's discriminant analysis

In order to examine the discriminating power of each explanatory variable, we will conduct Wilks1

1.Wilks' Lambda is the ratio of within-group variation to total variation. The within-group variation is, for each group, the sum of the squares of the differences between the individual discriminant scores and the group centroid. The total variation is the sum of the squares of the differences between all the individual discriminant scores and the overall mean discriminant score. Wilks' Lambda is a statistic used by discriminant analysis to test whether multiple groups of multivariate observations have significantly different means.

test calculated on all the ratios of the two groups of companies (SME/LE). Thus, the significance of Fisher's statistics rejects the null hypothesis which states that, for a given ratio, there is discrimination between the two groups of companies.

Practically, we will carry out the methodology of Bardos and Zhu (1997) using Wilks' λ, which consists of choosing, each time, the variable which has the greatest discriminating power. Then, at each step the model is examined. If the variable of the model which contributes the least to its discriminating power, measured by Wilks' λ, is below the previously chosen significance threshold (in our case, we have chosen the significance threshold of 10%), the variable is removed.

Wilks' lambda statistical result should be as low as possible. Its value varies between 0 (absolute discriminating power between the two groups) and 1 (zero discriminating power, which means that no distinction is possible between the groups and therefore the discriminant function is of no interest). It is a question of focusing the analysis of the research, only, on the potential variables. These tests also contribute to improving the reliability of the model by eliminating other variables of less importance.

Table *: Means equality tests of groups

	Wilks' Lambda	F	ddl1	ddl2	Signification
Age_societe	1,000	,019	1	667	,891
R2	,724	254,263	1	667	,000
R3	,997	1,991	1	667	,159
R4	,974	17,966	1	667	,000
R5	,999	,804	1	667	,370
R6	,965	24,067	1	667	,000
R7	,946	38,354	1	667	,000
R8	,948	36,639	1	667	,000
R9	,932	48,897	1	667	,000
R10	,784	183,899	1	667	,000
R11	,971	20,083	1	667	,000
R12	,984	10,700	1	667	,001

R13	1,000	,062	1	667	,804
R14	,993	4,604	1	667	,032
R15	,999	1,000	1	667	,318
R16	1,000	,003	1	667	,958
R17	,993	5,002	1	667	,026
R18	,996	2,609	1	667	,107
R19	,973	18,218	1	667	,000
R20	,920	58,044	1	667	,000
LOGActifimmobilisé	,989	7,420	1	667	,007
LogCA	,996	2,647	1	667	,104
LogTotalBilan	,971	19,583	1	667	,000

Source: Authors

It appears from the table above that the Fisher test indicates, at the 5% threshold, that 14 variables are significant, that is to say, they have a discriminating power between the two groups of companies. This test confirms the results obtained by the correlation between the dependent variable and the explanatory variables. To this end, we can confirm that our initial hypotheses are validated and that the 12 categories of ratios used make it possible to discriminate between the two types of companies. Thus, we note respectively, that the ratios of: R2, R4, R6-R12, R19 and R20 are the most significant indicators of the financial situation of the Moroccan companies.

4.7. Tests of the discriminating power of the model

The tables below, respectively, present the Wilks Lambda test, the canonical correlation, the Box test and then the confusion matrix:

Table *: Global Correlation: Eigenvalues

Function	Eigenvalue	% of variance	%Cumulative	Canonical correlation
1	1,359[a]	100,0	100,0	,759
a. The first 1 canonical discriminant functions were used for the analysis.				

Source: Authors

Table *: Wilks Lambda

Test Functions	Wilks Lambda	chi-square	ddl	Signification
1	,424	562,493	23	,000

Source: Authors

It emerges from the table above that the significance of the global Wilks Lambda tends towards '0', all the more, so as the Wilks lambda is low and the model is good. This reveals that the discriminant function is useful in explaining the differences observed between the groups of companies. Overall, we can conclude that the difference in the means of the groups of companies is significant.

We also noted that the "canonical correlation" column has a value of 0.759 or 75.9%. This strong correlation testifies the great usefulness of the discriminant function and confirms its fairly significant discriminating power.

4.8. The classification of companies

The application of the discrimination function, using the SPSS, makes it possible to develop a classification matrix in order to assess the performance of the model and to explain the errors of type 1 and 2. The results of this classification matrix are listed in the following table:

Table *: Classification Results

Classification Results[a,c]					
		LGD_1	Classe(s) of intended assignment(s)		Total
			Healthy Entreprises	Failing Entreprises	
Original	Effective	Healthy Entreprises	283	18	301
		Failing Entreprises	46	322	368
	%	Healthy Entreprises	94,0	6,0	100,0
		Failing Entreprises	12,5	87,5	100,0
Cross-validated[b]	Effective	Healthy Entreprises	282	19	301
		Failing Entreprises	50	318	368
	%	Healthy Entreprises	93,7	6,3	100,0
		Failing Entreprises	13,6	86,4	100,0
a. 90,4% original observations classified correctly.					
b. Cross-validation is only performed for observations in the analysis. In cross-validation, each observation is ranked by the derived functions of all other observations.					
c. 89,7% correctly classified cross-validated observations.					

Source: Authors

We note that the discriminant function allows the classification of 90.4% of companies correctly, that is, an error rate (misclassified enterprises) of only 9.6%. In addition, we note that 94% of class '0' enterprises (group of healthy enterprises) are well ranked, and 87.5% of class '1' (failing enterprises) are also well ranked. The type 1 error involves the wrongly classified healthy enterprises among the failing ones. The classification rate linked to this group is 6%. Type 2 error involves the wrongly classified failing enterprises among the healthy ones. The classification rate linked to this group is 12.5%.

4.9. The empirical discriminant model

Before moving on to the estimation phase, it is important to remind the reader of the econometric model of our study which tackles the analysis of bankruptcy prediction, thanks to selected accounting ratios, to classify any company with one of the two groups of companies. Hence, we have independent variables (the financial and accounting ratios) and a dependent variable (the bankruptcy prediction), which is a dichotomous variable. It takes the value:

- ‘**0**’: for a healthy company and,

- ‘**1**’: for a failing company.

To test this effect, we consider the following basic model:

$$\mathbf{Zi} = \alpha_0 + \sum_{K=1}^{J} \beta_K \mathbf{R}_{it}^{K} + \varepsilon_t$$

<u>**With :**</u>

- Rit: represents the value taken by the ratios of the enterprise;
- βk: the coefficient associated with the indicator Rk;
- Zi: the score of an enterprise;
- ε: is an error term.

It is the value of Zi in relation to the critical value Z* which determines the classification of enterprises in the group of healthy enterprises or that of failing enterprises.

The most correlated ratios between them should not appear in the same function, thus we eliminated, among the 22 most significant variables, those which are strongly correlated, while we opted for those having the greatest discriminating power. We opted for 11 ratios from which we extracted, through the SPSS, the coefficients of the score function.

The discriminant function is obtained after the step (see appendix, p *). We retained the explanatory variables shown in the following table.

Table *: Variables retained from the discriminant function

Step		Tolerance	F to eliminate	Wilks Lambda
	R2	,643	271,600	,612
	R10	,885	88,955	,491
	R11	,853	22,995	,448
	LOGActifimmobilisé	,371	5,228	,436
	LogCA	,084	135,915	,522
	LogTotalBilan	,068	111,138	,506
	R6	,471	34,081	,455
	R4	,789	9,759	,439
	R17	,820	16,223	,443
	R9	,600	13,280	,442
	R19	,833	7,597	,438

Source: SPSS Results

The average discriminating scores, for the two groups, allow each company to be assigned to its category are as follows:

Table *: Functions at the barycenters of groups

LGD_1	Function
	1
Healthy Entreprises	1,287
Failing Entreprises	-1,053
Non-standardized canonical discriminant functions evaluated at group means.	

Source: SPSS Results

After calculating the function related to discrimination, we came to the following conclusion:

- If Z < - 1,053: the enterprise is considered to be in default.
- If Z > 1,287: it is considered healthy.
- If -1,053 < Z < 1,287: the enterprise is in an area of uncertainty which is located between the two centers of gravity of the two groups. We cannot conclude whether the company is failing or healthy. Evidently, we need to do further research. This is a zone of caution for the enterprise.

Table *: Coefficients of standardized canonical discriminant functions

	Coefficient	% of discrimination	Ranking
R2	,895	31,07%	1
R4	,181	6,28%	7
R6	,429	14,89%	3
R9	-,241	8,37%	5
R10	,487	16,90%	2
R11	,264	9,16%	4
R17	-,228	7,91%	6
R19	,156	5,41%	8

Source: SPSS Results

The table shows the following standardized discriminant function "Z":

$$Z=,895R2+,895R4+,895R6-,895R9+,487R10+,264R11-,228R17+,156R19$$

The function of Z score is, therefore, able to distinguish between the two groups of companies. Through the table above, 8 discriminating ratios among the 22 retained for this study play a capital role in the discrimination between the two groups. We found that the R2, R6, and R10 ratios possess the highest power explained in average of more than 60% of the total power of discrimination, since companies rarely file for bankruptcy as long as they have cash. However, the R2 ratio is ranked first with a capacity of 31%, which indicates that the share of equity that finances fixed

assets has a key role in differentiating between the two categories of companies. Similarly, the R10 and R6 ratios discriminate respectively between the two groups of companies with a capacity of 16.9% and 14.89%.

The ratios R2, R4, R6, R10, R11 and R19 have been selected with a positive weighting. Indeed, the higher the level of solvency, profitability, activity and management, the higher the discrimination function and the lower is the probability of going bankrupt. The results obtained agree with those of Keasy and Mc Guinnes (1990), Pompe and Belderbeek (2004) and Hamza and Bagdadi (2008). The latter believe that there is a causal relationship between the probability of failure and the profitability of companies.

The R19 ratio relating to indebtedness is selected from among the most discriminating ratios with a low power of discrimination between healthy companies and failing companies, as indicated by the work of Altman (1984), Charlambous et al. (2002), Liu and Smith (2007).

However, the coefficient attributed to the ratios R9 and R17 has a negative sign. These ratios respectively measure asset turnover and the traditional benchmark for assessing working capital requirements. Indeed, the greater the time lag is between receipts and disbursements, the more the company is in an unfavorable situation. This result supports the work of Yim and Mitchell (2002) and Pompe and Belderbeek (2004).

Finally, we can claim that business failure is partly linked to the cumulative effects of the financial autonomy, Gearing (i.e. structure and solvency H1), inventory turnover, asset turnover (i.e. activity and management H2), return on assets and net return on equity (H3), the share of working capital in relation to turnover (i.e., liquidity H4) and indebtedness (H5). These results are consistent with the previous findings and the various previous works in the literature.

5. Conclusion

This study has focused on the identification of the factors explaining the distrust of the Moroccan enterprises. This preventive management approach allows a better understanding of the risks and of the financial signals predicting the failure. The objective of this study is to propose a failure

prediction model. The results obtained are relatively satisfactory since the enterprises classification rate is 90.4% for the two years preceding the failure. This study shows a significant difference between the failing enterprises and the healthy ones according to the state of their profitability and their degree of liquidity.

However, the results obtained from this study indicated that the failure of an enterprise is partly related to the cumulative effects of the financial autonomy, Gearing, inventory turnover, activity and management, the return on assets and the net return on equity, the share of WCR in relation to turnover and indebtedness. These results confirm those of Ohlson (1980), Zmijewski (1984), Taffler (1983), Titman and Opler (1994), Refait (2004), Smith and Graves (2005), Altman (2006), Liou and Smith (2007).), Hamza and Baghdadi (2008).

Nonetheless, this study presents a certain number of theoretical and empirical limits: From a theoretical point of view, we state the more precise forecasting model including the multivariate discriminant analysis quantitative explanatory variables, more particularly, accounting and financial. However, the failure factors are numerous and heterogeneous. From an empirical point of view, Zmijewski (1984) shows that the results obtained by discriminant analysis are based on restrictive assumptions that may not be verified for financial data. Due to these constraints, some authors have resorted to parametric techniques which assume a different distribution of accounting variables: Economic techniques on qualitative variables such as the Logit model and the Probit model.

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