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Bank Failure Prediction with Logistic Regression

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ABSTRACT: In recent years the economic and financial world is shaken by a wave of financial crisis and resulted in violent bank fairly huge losses. Several authors have focused on the study of the crises in order to develop an early warning model. It is in the same path that our work takes its inspiration. Indeed, we have tried to develop a predictive model of Tunisian bank failures with the contribution of the binary logistic regression method. The specificity of our prediction model is that it takes into account microeconomic indicators of bank failures. The results obtained using our provisional model show that a bank's ability to repay its debt, the coefficient of banking operations, bank profitability per employee and leverage financial ratio has a negative impact on the probability of failure.

Keywords: Bank Failures; Logit Model
JEL Classification: G33; C34; C35

1. Introduction

The two last decades are marked by notable banking and financial crises by their extent as well as their exorbitant financial costs. In fact, many developing countries witnessed serious disturbances to their banking systems manifesting the companies' insolvency, the disturbances of exchange flow, which went even to the bankruptcy of big companies. Today, banking and financial crises show a sharp persistence, since most countries affected by the 2008 crisis could not find a way out of it yet. Moreover, the current crisis requires a bigger attention than that paid to its predecessors since it bears a worldwide and banking character. This crisis touched mainly the banking systems having difficulties, knowing that they represent the heart of the economic activity and its financing. From now on, every malfunctioning of banking system will change the behaviour of economic agents; create a feeling of distrust of investors and depositors towards credit establishments, which results into serious disturbances to real economy.

The redundancy of these crises gives birth to a feeling of fear towards the installation of a cyclic and chronic phenomenon which exhausts all remedies without getting out of them. From now on, the establishment of an advanced alert model of banking and financial crises becomes more than necessary to better avert eventual financial jolts and seek even to avoid them.

Up to here, the majority of empirical writings about crises advanced detection are of macroeconomic order. A study of macroeconomic data is then used to develop an alert system which is able to detect several financial crises in advance. Moreover, this empirical step presents limits since it can't detect the banking weaknesses of microeconomic nature beforehand. Actually, we think that the integration of a microeconomic approach in the construction of a banking crises precocious alert model could enlarge its detection power.

This article is organised in the following way. In the section to come, we present a literature review on the microeconomic indicators of banking weaknesses. Section 3 methodology. In section 4, a data presentation and a selection of the model variables. We present our results of the estimation in section 5. Section 6 the conclusion of our work.

2. Brief Literature Reviews

Many authors are oriented towards the study of banking crises as destructive phenomena focalizing on the events which precede their happening. In particular, these studies aim at constructing statistic models that send an advanced early warning signal to banking bankruptcy "early warning system". This method is based upon the classification of banks into two groups discriminating the sound healthy banks from those that are in difficulties.

Authors like Santoso (1996), Gasbarro et al. (2002) searched to involve the determinants of Indonesian banks defects in their construction of an early warning system. Others like, Powo (2000) searched to construct a bankruptcy indicator panel in the Economic and Monetary Union of the West African countries for the construction of a logistic and conditional model in data of panel. In these descendents, the major empirical studies are subdivided into two categories of approaches: macroeconomic and microeconomic.

The big range of studies which treat the macroeconomic approach puts in advance the big influence of economic contractions on banks often materialized by the blind and brutal financial liberalization making banks more vulnerable to macroeconomic shocks. Particularly, the exaltation of public politics not adapted to the financial changes and the laxness of the supervision authorities, worsening strongly the banking weaknesses. Nevertheless, the application of high interest rates, the massive reflow of foreign financial flows, the increase of non performing credit rates and the decrease of currency stock amount are macroeconomic variables that influence the functioning of both systems; economic and financial. (Demirguc-Kunt and Detragiche (1998, 2002), Kaminsky and Reinhart (1999).

Furthermore, the microeconomic approach aims at questioning the institutional factor such as the principle factor of bank vulnerability. This study uses a matrix of accounts ratios gathered from individual balance sheets of target banks. These ratios reflect the individual and interior behaviour of banks, which allows us to construct an information panel about the level of difficulty of the latter.

In fact, most of banking crises were always preceded by bankruptcies, closing succession, fusion or repurchase by other financial institutions (Kaminsky and Reinhart, 1999). These bankruptcies are explained by Bell and Pain in (2000) by an unbalance of the assets level in favour of the liabilities. The increase of the liabilities volume is often explained by a high level of defect payment by borrowers causing a dry-up of assets and then of a huge loan credit. In addition, a sudden and maintained in time disturbances of assets prices on the market increase the risks in the market. Meanwhile, a financial institution is not protected from an eventual race running to wickets, a stealthy and brutal phenomenon where the factors responsible for it are always exterior and supplied by a strong information asymmetry. This situation can affect banks individually; they can also be spread from a country to another through a contagion phenomenon.

Minsky (1957), underlines the importance of the excess of credits in the come-up of financial crises. He explains that in a phase of economic growth and stability the banks' behaviours tends to develop into more laxness by providing more and more credit loans without having information about the debtors' ability to honour their commitments. In fact, the expansion of loans size is suspected when it exceeds the GDP in terms of growth. Thus, the credit growth will be associated to an excessive risk taking from the banks in their credit activity.

On the other hand, Miotti and Plihon (2001) show that a change in the financial agents' behaviour can cause a pure financial contagion without, causing an external shock. They explain this change by the preference of immediate interest and the taste pronounced by the banks to take risks. Banks have changed their behaviours of restriction and control and they moved towards much softness and flexibility through adapting the notion of speculation as a source of risky profitability.

The recent crises showed the disadvantages of preferring the immediate interest and the pronounced taste of banks for risk. They arose following a major increase of cash operations on the derived products to generate important revenues by bringing out risks of the assessment. This practice reduced the capital funds and the imposed taxes in risk taking (Randall, 2009).

3. Methodology

Our econometric analysis has to do with the estimation of model of qualitative answer, making contribution to the Binary Logistic Regression method. This econometric method was used in the work of Demirguc-Kunt and Detragiache (1998). Their study focused on 65 developed and developing countries along the period 1984-1994 on annual data using the model Logit of econometric estimation of the probability to a threatened economy which is undergoing a banking crisis.

Miotti and Plihon (2001), referring to the works of Kindleberger (1996), have used in their study about the Argentina crisis in 1995 and Korea in 1998 the Probit method while integrating microeconomic data relative to the taking of banks risks by means of speculation. It is in this same trend that our empirical and methodological reasoning takes its inspiration.

The binary logistic regression method that we adopt assumes that the fact that the explicative variables X_i should be financial ratios reflecting the microeconomic activities of banks. The couples $(X_1, Y_1)....(X_n, Y_n)$, are independent and identically distributed according to the normal law such as $X_i \in \Re^d$. The dependent variable Y_i allows a random law of Benoulli which takes the value of 1 when there is a banking defect or 0 otherwise.

Our aim through the use of the Logit method is to predict the probability of banking defect illustrated by $PD = P(Y_j = 1 | X_i \approx x)$. Meanwhile, since our regression is binomial we will use the method of generalized linear method (GLM) introduced by Nelder and Wedderburn (1972). The scores are calculated in a first step by $\beta_0 + \beta^T X$ that represents a linear combination of financial ratios. In the second step, the defect probability will be estimated by means of the function G:

$$PD = P(Y_j = 1 | X_i \approx x) = G(\beta_0 + \beta^T X) \qquad (1)$$

with:

G: $\Re \to [0,1]$ is a logistic function that takes values between 0 and 1:

$$G(s) = \gamma(s) = \frac{1}{e + e^{-s}} \qquad (2)$$

s : scores are given by the function log odds:

$$s = \ln\left(\frac{\gamma(s)}{1-\gamma(s)}\right) \qquad (3)$$

The estimation of parameters $\beta_0,.....,\beta_d$ is via the method of maximum likelihood procedure and function of the Lagrangian is written:

$$L(\beta_0,...,\beta_d) = \prod_{j=1}^{n} \left[Y_j \gamma(\beta_0 + \beta^T X_j) + (1-Y_j)\log(1-\gamma(\beta_0 + \beta^T X_j)\right] \qquad (4)$$

Y_j fluctuates between 0 and 1 so we can write our Lagrangian as follows:

$$\log L(\beta_0,...,\beta_d) = \sum_{j=1}^{n} \left[Y_j \log(\beta_0 + \beta^T X_j) + (1-Y_j)\log(1-\gamma(\beta_0 + \beta^T X_j)\right] \qquad (5)$$

To determine the estimators $(\hat{\beta}_0,.......\hat{\beta}_d)$ we Maximizes the function L or logL. At the end the maximum likelihood estimator of the probability of default (PD) is given by:

$$\psi(X) = \gamma(\hat{\beta}_0 + \hat{\beta}^T X) \qquad (6)$$

Furthermore, it is necessary to choose the most performing explicative variables to predict the banking defect. For the best model selection, we calculate the Akaike Information Criterion (AIC). First of all, we apply the step by step regression introducing all the explicative variables and in every step some variables will be removed. Then, these models are classified according to their AIC and the model having the weakest AIC will be selected. The AIC can be counted as follows:

AIC = -2logL+2p (7)

with:

L: maximum likelihood of the fitted model

p: the number of estimated parameters

In fact, the model that has the lowest deviation value-2logL is one who admits the best fit.

In a final step and after choosing the model with the weakest AIC value, we calculate the test chi-two to test the good data adjustment by the chosen logistic model. The value of chi-two is given by:

χ^2 = (deviation of the first model with the constant (intercept)-the latest model deviance)

ie :

$$\chi^2 = (-2\log L_N) - (-2\log L_F) \qquad (8)$$

4. Data and Variables

4.1 Data

The data used in this work are collected from the annual reports of the Central Bank of Tunisia and Tunisian association of banks and financial institutions. Our study is based on annual data spanning 8 years, from 2002 to 2010 for the 14 universal Tunisian banks. Banks are the Amen Bank (AB), Banque Nationale Agricole (BNA), La Société Tunisienne de Banque (STB), Banque de Tunisie (BT), Union Internationale des Banques (UIB), The Arab Tunisian Bank (ATB), Attijari Bank (Attijari Bank), La Banque de l'Habitat (BH), Banque Internationale Arabe de Tunisie (BIAT), La Banque Franco-Tunisienne (BFT), La Banque Tuniso-Kowitienne (BTK) , Banque Tuniso-Libienne (BTL) the Tunisian Qatari Bank (TQB), L'Union Bancaire pour le Commerce et l'Industrie (UBCI), La Banque de la Tunisie et des Emirats (BTE).

4.2 Selection of variables

4.2.1 The dependent variable

In literature, the majority of empirical studies of the banking defect or crisis build binary indicators to identify the crises episodes. In the present study, our variable of binary response answer is established through an index of banking weakness measure inspired by the works of Kibritcioglu (2002). This index is built through three indicators; the banking deposits, the private sector credits and the loans contracted by the banks. The index is then written:

$$FB_t = \frac{\dfrac{(D_t - \mu_d)}{\sigma_d} + \dfrac{(Cp_t - \mu_{cp})}{\sigma_{cp}} + \dfrac{(E_t - \mu_e)}{\sigma_e}}{3}$$

Where D_t represents the annual variation of banking deposits volume, Cp_t the annual variation of credits accorded to the private sector, E_t the annual variation of loans contracted by every bank. μ and σ are respectively the arithmetic and the standard deviation of variables.

Thus, there is an episode of a weakness average when the value of FB index varies between 0 and -0.5 and the high banking weakness when the FB value equates or is inferior to -0.5.

$$\begin{cases} 0 > FB > -0.5 & \text{low fragility} \\ FB \le -0.5 & \text{strength fragility} \end{cases}$$

In addition, we carry out the transformation of values taken by the index FB as binary response as follows:

$$\begin{cases} if\ FB_t \le -0.5 & Y\ take 1 \\ if\ FB_t \le -0.5 & Y\ take 0 \end{cases}$$

Finally, our ratio of banking weakness is established and converted into binary responses adapted to our variable to explain our sample of 14 Tunisian banks during the period (2000-2010).

4.2.2 The explanatory variables

In our study, we maintain 18 ratios associated to different dimensions of financial analysis that represent the different indicators of banking vulnerability measure. These ratios are regrouped into five groups, liquidity, management, activity, profitability and vulnerability shown in Table 1. The descriptive statistics are given in Table 2.

Table 1. The financials ratios

Ratio No.	Definition	Ratio	Category
x1	TD/TA	Total Deposit/ Total Assets	Liquidity
x2	TD/TP	Total Deposit/Total liabilities	Liquidity
x3	TC/TD	Total Credit/ Total Deposit	Liquidity
x4	TC/E	Total Credit/Loans	Liquidity
x5	E/TA	Debt / Total Assets	Liquidity
x6	ChB/TA	Charges/Total Assets	Management
x7	PB/TA	banking product/Total Assets	Management
x8	ChB/PB	bank charges/Net income	Management
x9	PnB/Nemp	banking product/Number of Employees	Management
x10	TC/TA	Total Credit/Total Assets	Activity

x11	TC/TP	Total Credit/Total liabilities	Activity
x12	TC/CP	Total Credit/Working Capital	Activity
x13	PnB/TA	banking product/Total Assets	Profitability
x14	E/(K+R)	Loans/(Capital+Reserve)	vulnerability
x15	TC/(TD+E)	Total Credit/Total Deposit+ Loans	vulnerability
x16	CCP/TP	Loans from Central bank/Total liabilities	vulnerability
x17	CP/TP	Working Capital/Total liabilities	vulnerability
x18	TD/M2	Total Deposit/M2	vulnerability

Table 2. Descriptive Statistics

Ratio No.	Min	Median	Max	kurtosis	Sta.Dev
x1	0.00	0.79	6.25	80.51	0.04
x2	0.00	0.87	1.01	5.07	0.02
x3	0.00	1.06	12.08	43.59	0.10
x4	0.00	12.24	6146.41	104.99	43.94
x5	0.00	0.05	1.71	70.53	0.01
x6	-0.08	0.03	0.28	59.47	0.00
x7	0.00	0.07	0.65	97.53	0.00
x8	-0.49	0.40	0.99	7.80	0.02
x9	0.00	72.81	287.58	5.02	3.17
x10	0.00	0.83	8.43	115.51	0.05
x11	0.00	0.92	2.10	7.15	0.02
x12	-1.16	8.77	82.11	21.66	0.83
x13	0.00	0.04	0.38	72.64	0.00
x14	0.00	0.55	3.19	0.59	0.07
x15	0.00	0.98	2.13	7.28	0.02
x16	0.00	0.00	0.12	13.31	0.00
x17	-0.34	0.10	1.53	19.48	0.02
x18	0.00	72.69	1504.09	19.48	18.29

The use of the step by step procedure in the choice of the most discriminating variables shows a criterion of the weakest AIC information of 71.05 for the model that regroups the variables x5, x6, x8, x9, x12, x13 and x14 which are presented by Table 3.

Table 3. Selected variables according to the criterion of the lowest AIC information

Ratio No.	Definition	Ratio	Category
x5	E/TA	Debt / Total Assets	Liquidity
x6	ChB/TA	Load Banking / Total Assets	Management
x8	ChB/PB	Load Bank / Banking Product	Management
x9	PnB/Nemp	Net banking / Number of employees	Management
x12	TC/CP	Total Credit / Equity	Activity
x13	PnB/TA	Net banking income / Total Assets	Profitability
x14	E/(K+R)	Borrowing / (Capital + Reserve)	vulnerability

5. Empirical Results

According to the Table 4 we notice that all the variables are statistically significant to the threshold of 5 % except for the ratios x9 and x13 that are significant to 1 %. In the other hand, our model is globally significant to 1 % with a Chi2 statistic of 34.08966.

The ratios x5, x8, x9 and x12 are negatively significant. The estimation reveals that the variable which measures the ability of banks to repay their debts (x5) decreases in quite a significant way the probability of defect for the Tunisian banks. Also, the variable x8, x9 and x12 that are respectively the banking exploitation coefficient, the defect banking probability, the banking profitability per employee and the ratio of financial shift, negatively influence the defect probability. In the other hand, the ratios x6, x13 and x14 that represent the ratio of exploitation costs, the banking profitability and the ability of the bank to refund pay back its debts, save the positive significance and then to increase respectively the probability of banking defect.

Table 4. Results of logit regression

	Coefficient	*Erreur Std*	*z*	*p. critique*	
Constante	0.141982	0.823611	0.1724	0.86313	
x5	-52.5969	22.9047	-2.2963	0.02166	**
x6	167.726	85.2452	1.9676	0.04912	**
x8	-12.62	6.16244	-2.0479	0.04057	**
x9	-0.0732672	0.0254852	-2.8749	0.00404	***
x12	-0.297681	0.137488	-2.1651	0.03038	**
x13	114.552	44.4356	2.5779	0.00994	***
x14	3.1964	1.50566	2.1229	0.03376	**
Loglikelihood	-27.52638				
-2 Loglikelihood (Deviance)	55.05277	Chisquare	34.08966	P-value	0.00002

The odds ratio study given in Table 5 shows that the banking profitability x 13 records a very high ratio which is largely superior to 1, this means that the defect response is strongly probable. In fact, when a bank displays quite a low profitability rate means imperatively that it exists in a financial difficulty to cover its charges or to honor its engagements and then the increase of bankruptcy risk. Also, the probability of defect response is strong for the ratio of exploitation costs x6. Undeniably, the increase of banking exploitation costs engenders a considerable decrease of the profitability and then an imbalance of assets liabilities, which puts the banks in difficulty.

Table 5. Odds Ratio

	Odds Ratios
Intercept	1.15256
x5	0
x6	6.96E+72
x8	0
x9	0.92935
x12	0.74254
x13	5.62E+49
x14	24.44436

The ratio x14 that measures the ability of a bank to pay back its debts, records quite a high ratio and consequently the defect response is also high. It is evident that, if the size of bank debt is so imposing compared to savings and banking capital, the bank is then found unable to honor its commitment towards their lenders. In fact, the inability of repayment pushes banks into difficulties to resort to fish-out service of the lender as last resort otherwise bankruptcy and judiciary liquidation.
The response absence of defect is evident to an X= x5 and X=x8 with a null odds ratio. Hence, the defect response is of 0.92, 0.74 times respectively for an X=x9 and X=x12.

6. Conclusion

The objective of this study is to establish the microeconomic indicators which are able to predict the banking defect. The use of collected financial ratios from the Tunisian banks balance sheets shapes our battery of indicators inspired by the CAMEL typology, from which we wanted to select the ratios that have a strong predictive power to construct a prevision model of bank defect from it.

The use of a vector of ratios selected from advance by a stepwise regression, like a vector of explanatory variables in our logistic model have provided us with satisfactory results with expected signs and significations. Likewise, the most pertinent ratios in the explanation of banking defect at the Tunisian banks are the decrease of banking profitability and the ability of banks to repay their debts which appear to be a high odd ratio.

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