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Financial Leading Indicators of Banking Distress: A Micro Prudential Approach - Evidence from Europe

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Abstract

Sovereign and Subprime crises have corrosive effects on European banking system. In this study, we aim to explain and predict the state of distress for 618 European banks for a five year period (2007-2011). For this purpose, we applied early warning systems using traditional and developed methods: discriminant analysis, logistic regression and the artificial intelligence. Those methods aim to predict bank distress up to a year (two years) before it actually happened. Our study seeks to compare between these three methods and to choose the most appropriate for prediction. The key finding of this study demonstrates that the neural network method outperforms the other models. This result is too much useful for banks and help policy makers to do a better job in terms of regulatory reforms.

Keywords: a microprudential approach, bank distress, non performing loans, financial soundness indicators

1. Introduction

Given the importance of predicting bank distress, this topic has been gaining a greater interest in the two last decades. In fact, the main objective of an early warning model is forecasting difficulties in financial institutions. These early warning systems have recently experienced a very rapid evolution, particularly in view of banking regulators who continually develop such models in order to identify the financial distress in banks and provide an advance alarm to distressed institutions, allowing them the sufficient time to avoid the emergence of potential crises. Then, banks could react and take the necessary corrective measures. Moreover, early warning models identify three types of crises: currency crises, debt crises, and also banking crises. The authorities implement macroprudential supervision standards that attempt to assess the soundness of the financial system and its vulnerability to potential shocks. The quantitative analysis used in macroprudential supervision complements the use of financial soundness indicators (FSIs) and also the implementation of stress tests. Financial soundness indicators (FSI) were established by the FMI in order to gauge the financial vulnerability in banks. The FSI were grouped into two main cores: the core set indicators and the encouraged indicators. The macroprudential supervision approach that uses a combination of qualitative and quantitative methods. The qualitative methods focus on the quality of the legal, regulatory framework and the governance mechanism in the financial sector.

An important part of the qualitative information is often collected and used by internationally recognized standards and codes of good practice. However, the quantitative methods include a combination of indicators and statistical techniques able to summarize the strength and the resilience of the financial system to vulnerabilities.

Thus, these various tools are mapping all the possible financial vulnerabilities that could appear in different economic industries. Mager and Shmeider (2009) argue that these financial soundness indicators are indeed used in order to test the soundness of the banks and the financial system as a whole using a micro stress testing framework (Qualiariello, 2009; Lelyveld, 2009). In this case, several techniques have been used to predict the distress of a credit institution and also to help regulators in taking the right preventive actions. Among these techniques, we could mention linear regression or discriminant analysis and logistic regression (logit or probit). Moreover, we should notice that in recent years, several studies have focused on techniques that use artificial intelligence such as the neural network method.

In fact, these studies have also demonstrated the effectiveness of the new artificial neural methods compared to other techniques. These new techniques are used in several areas. However, they are recently used in order to predict the failure of a financial system.

Our study aims to predict the difficulties faced by 618 European banks and also to determine the most relevant indicators of a bank distress. This paper is also based on three methods in order to compare the effectiveness of different methods. The purpose of our work is to find the best method to forecast bank distress in a microprudential framework. In addition, our study tries to decompose the relevant determinants of internal failure affecting especially the solvency of banks that could lead the regulator to act before a bank's distress.

First, the introduction has to be seen within the wider context of existing frameworks in this field. The remainder of this paper is organized as follows. Section two develops a brief review of different methods of forecasting difficulties faced by banks and methods integrating financial soundness indicators. Section three describes the research design. Section four analyzes and summarizes the empirical findings. Finally, section five presents the conclusion, limitations and future researches.

2. Related Studies

This study is related to a growing body of literature that analyses the banking distress. Financial soundness indicators were established by the International Monetary Fund to ensure the soundness of financial institutions and markets as well as companies (Kulthunga & Rehman 2012). Financial soundness indicators are summarized by CAMELS criteria (C: capital adequacy; A: asset quality; M: management quality; E: earnings ability; L: liquidity; S: Sensitivity to market..). In addition, according to some authors, other accounting measures do not contain additional information to those provided by CAMELS indicators (Akhter & Dali, 2009). In addition, according to the World Bank (2005), these indicators (CAMELS) are a complement to the existing macro-prudential tools. These tools used by international organizations (FMI, ECB, WB…) in order to assess the risk management. In other words, they are complementary to the early warning systems in predicting distress. The most important difference between these two methods: early warning systems detect distress for individual institutions when the macro stress tests seek distress for a banking system.

In this study, we try to show that financial soundness indicators (FSI) assess and predict the financial sector vulnerability. Cihak (2007) argues that financial ratios are able enough to provide a summary Table of the soundness in a financial sector and in its different components. Cardarelli, Elekdag and Lall, (2011) discuss the reasons of the severe financial turbulence which could lead effectively to an economic slowdown. In addition to that, Authors identified the different phases of the financial turmoil in advanced economies using a financial stress index (FSI), and proposed an analytical framework able to assess the impact of financial stress on the real economy. They conclude that the financial turmoil characterized by bank distress is more likely to undergo a deep downturn. Several models have been developed in order to detect distress and weaknesses in financial institutions. As a matter of fact, these models are widely used to ensure financial system stability. In particular, developed models are respectively the early warning systems (EWS), the resilience tests (stress tests) and finally artificial intelligence models which were recently implemented. Indeed, some authors have emphasized the complementarity between stress tests and early warning systems.

Early warning systems include different ratios derived from financial statements which include variables related to the regulatory and institutional environment, they even use different macroeconomic variables with the aim to predict system's failures.

In addition to that, those monitoring systems are also used to provide useful indicators of the bank situation. These systems are used primarily to get prevented from bank problems. Banking system problems are often presented by a weak level of capitalization, liquidity and solvency… For this reason, often studies used several indicators relating to solvency, performance and liquidity to assess the risk profile of a banking group (Anderson, 2008; Giovanis, 2010; Wong, Wong, & Leung, 2010).

Based on the estimation of the default risk, in this case we can do a separation between banks seen as riskier and toward those seen as less risky. Researchers have tried then to ameliorate models able to predict the potential financial distress in different sectors and in different countries. They actually used several statistical methods to accomplish this objective. Among these methods we can notice:

Discriminant analysis (Sinkey, 1975; Altman, 1968; Lin, 2009; Giovanis, 2010; Kouki & Elkhaldi, 2011), logistic regression (Thomson, 1991; Gonzalez-Hermosillo, 1999; Godlewski, 2004; Montgomery, Hanh, Santoso, & Besar, 2005; Lin, 2009; Giovanis, 2010; Messai & Jouini, 2013a). We could also notice that the Probit regression is a multivariate statistical method that was used to predict bankruptcies for some ailing banks (Barr & Siems, 1994; Doganay, Ceylan, & Aktas, 2006; Lin, 2009; Wong et al., 2010).

2.1 Traditional Methods

Several researchers have tried also to expand their studies by using multiple methods, to choose the most appropriate and to show that one of them is most effective. Among the authors who used several prediction methods, we could mention Donganay et al. (2006) and Wong et al. (2010) studies.

Doganay et al. (2006) have developed an early warning system for predicting at least three years before the banking failure using three methods: Logit, Probit and discriminant analyses. These authors incorporated multivariate statistical regressions and used 27 ratios to predict the failure. The sample included distressed banks during the period 1997-2002. This sample is composed of 42 banks and 19 of them failed. The authors found that the most appropriate model for predicting bank distress is logit.

Similarly, Konstandina (2006) used logit analysis to predict the failure of Russian banks. She used 6 macroeconomic factors and 13 factors specific to banks as independent variables. She also used another proportional hazard model that identifies the factors influencing the time resistance of a bank during a financial crisis. She found that the increase in bad debts and also that holding treasury bills enhance the risk of the bank distress. On the other hand, Andersen (2008) used the logit method in order to identify the most relevant variables in detecting distress in Norwegian banks. He distinguished 23 of explanatory variables of bank distress. He determined six relevant variables inherent to the CAEL rating system presented as follows: capital adequacy, asset quality, earnings ability and liquidity. Mayes and Stremmel (2012) used also logit method and survival time analysis in order to predict banking failure. The models incorporate CAMELS indicators. These authors explain that the risk weighted capital adequacy and the adjusted leverage ratio are the most relevant indicators of a bank distress.

2.2 The Methods of Artificial Intelligence

The artificial neural networks have made their entry in management science as a quantitative prediction method since 1990 (Paquet, 1997).

This method has been improved after the emergence of new and sophisticated techniques. These models have been recently applied to finance and they are called Adaptive Neuro-Fuzzy inference system (ANFIS). Moreover, ANFIS model is considered very effective in predicting an event or a failure (Kiran & Rajput, 2011).

Boyacioglu, Kara, & Baykan (2009) consider that bank failure threaten the resilience of a system as a whole. Therefore, they categorize banks as distressed and non distressed ones. They try to test classification performances for various neural network techniques. They used 20 financial ratios based on CAMELS acronym. Four techniques are employed: multi-layer perceptron, learning vector quantization, competitive learning and self organizing map. The findings of this research show that learning vector quantization and the multi-layer perceptron are the most effective models for predicting failure. Fioramanti, (2009) highlights the flexibility of neural networks and their ability to approximate nonlinear relationships. The operation of the ANN method is similar to the human brain logic by using highly non-linear approximation functions.

Yildiz and Akkoc (2010) have developed neural networks based on a Neuro Fuzzy technique. The authors define it as a method that combines two approaches, namely neural networks and fuzzy logic. It looks like a hybrid artificial intelligence technique. This new method was also adopted to predict bankruptcies in the Turkish banking sector. In fact, they chose a sample of 55 Turkish banks: 19 fundamentally robust banks and 36 failed banks. The success of prediction was made after the use of Neuro Fuzzy model is 90.91%. The application of neural networks and multivariate discriminant analysis was done primarily to compare it with the Neuro-Fuzzy model. The performance of the first two methods is respectively 86.36% and 81.82%. Although there is no big difference between the performances of models, the authors concluded that this new Neuro-Fuzzy method was slightly more successful. Giovanis (2010) presents a suiTable model of early warning distress using logistic regression and ANFIS model panel (Adaptive Neuro-Fuzzy Inference System). To check if a company is distressed, Giovanis (2010) follows the logic applied by Gentry et al. (1985).

A firm that reduces the dividend is in a financial distress. With random effects logit model, the author has performed better forecasts than those found using a simple binary logistic regression. Using Neuro-fuzzy system (ANFIS), the author concluded that it is a more appropriate tool for financial risk managers and decision making in Central Banks. The sample is composed of 179 financial institutions in Taiwan Security Exchange (TSE) during 2002-2008. The author finally concluded that the neural model is useful in predicting bankruptcies (global and also national economic crises). He also noted that this model outperforms significantly the logit regression, indicating that it is actually the most appropriate tool for financial risk managers and economic policy makers in central banks and national statistical offices.

The author concluded also that the use of this technique is much better than previous methods. Furthermore, using data related to developing countries during periods of sovereign debt crises can lead to a progress by applying a less developed non-parametric method based on artificial neural networks (ANN) (Fioramanti, 2009; Boyacioglu, Kara, & Baykan, 2009).

Similarly, Sevim, Oztekim, Bali, Gumus, & Gursen (2014) develop an early warning system to predict currency crisis. These authors used three methods: logit regression, decision tree and artificial neural networks. The main finding consists that the Turkish economy is not expected to face a currency crisis. It resists until the end of 2012.

3. Sample, Variables and Methodology

The sample for this study encompasses 618 banks in 18 countries in Europe during 2007 to 2011. Financial data were retrieved from Bankscope database. Our work is based on financial variables representing financial soundness indicators.

Table 1. Presentation of sample

Countries	Code	Banks		Countries	Code	Banks	
		Number	Percent			Number	Percent
Austria	AT	10	1.62%	United kingdom	GB	60	9.71%
Belgium	BE	9	1.46%	Greece	GR	13	2.1%
Switzerland	CH	94	15.21%	Ireland	IE	9	1.46%
Germany	DE	12	1.94%	Italy	IT	89	14.4%
Denmark	DK	22	3.56%	Netherland	NL	14	2.26%
Spain	ES	33	5.34%	Norway	NO	75	12.14%
Finland	FI	5	0,81%	Portugal	PT	19	3.1%
France	FR	96	15.53%	Sweden	SE	58	9.38%

The distress of a bank is determined based on the non performing loans to gross Loans ratio (NPLGL). Several studies opted for this choice as Reinhart and Rogoff (2010) who consider non performing loans as a proxy for financial crises and state that the presence of these non performing loans is a signal of potential financial crisis. Similarly, Messai and Jouini (2013b) and Vogiazas and Nikolaidou (2011) confirm that the high percentage of non performing loans, both in developed and in emerging countries is often associated with bank distress and financial crises.

In addition to this variable, the empirical literature review demonstrates the existence of other proxies of distress such as provisions for loan losses and solvency ratio (equity to total assets). Sorge and Virolainen (2006) focus on credit risk and liquidity risk. The authors present a model for the relationship between the provisions for loan losses and relevant macroeconomic factors.

Banks with low non performing loans ratio compared to those with higher one would be classified as highly distressed. In fact, according to Lin (2010), the sample should be decomposed in quartile.

Also, a bank is considered in a serious trouble when the non performing loans ratio is greater than the third quartile (Q3 = 4.851%) for two successive years. Otherwise, the bank hasn't been distressed.

Our dependent variable will be presented by a binary variable: It is equal to 1 bank is in distress i.e. when non performing loans ratio is greater than 4.851% for two successive years. It is equal to 0 otherwise.

To explain the financial distress of banks, we choose 10 ratios that belong to the acronym CAMEL.

Table 2. Overview and definition of variables

Variables	**Definition**	**CAMEL**	**Expected sign**
EQTA	Equity / total assets	Capital Adequacy	-
EQNL	Equity /net loans	Capital Adequacy	-
LLPGL	LLP/gross loans	Asset quality	+
LLRNPL	LLR/NPL	Asset quality	-
CIR	Cost to income ratio	Management quality	+
ROEA	Return on equity average	Equity	+/-
ROAA	Return on assets average	Equity	+/-
LIQTA	Liquidity /total assets	Liquidity	-
LIQDEP	Liquidity /Customer & S. T. Funding	Liquidity	-
NLDEP	net loans/ deposit	Liquidity	+/-

Predicting difficulties faced by a bank can be carried out before one or two years, if a bank has a ratio higher than the third quartile (Q3) for two successive years (2009 and 2010), it is considered in distress for 2011.Our paper is based on three methods: discriminant analysis, logit, and neural network (ANN).

4. Analysis and Results Interpretation

Using the Pearson correlation matrix, we measured the correlation between the independent variables. We can then observe a strong correlation between certain variables such as equity to total assets ratio (EQTA) and equity to net loans ratio (EQNL). We reached the same conclusion for Return on equity average (ROEA) and Return on assets average (ROAA) and also for liquidity to total assets (LIQTA), liquidity to deposits (LIQDEP).

In fact, among 10 ratios, we only used 7 ratios whose correlation coefficient was less than 0.5. These variables will be the object of our analysis using these methods: discriminant analysis, logistic analysis and the artificial neural network.

In fuzzy logic we will consider only significant variables and the results obtained by other methods mentioned above. We follow also Giovanis's approach (2010).

4.1 Discriminant Analysis

The Discriminant analysis model was presented to predict business failure. In this model different information from multiple variables was combined with a single weighted score for each one (Ray, 2011). This score was calculated using the following general discriminant function:

$$Z_i = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_n x_n \quad (1)$$

Where Z is the score, xi is the independent variables, and αi, $\alpha_0$are the estimated coefficients.

The application of the discriminant analysis model using the method "step by step", allow us to select three ratios respectively loan loss provisions to gross loans (LLPGL), loan loss reserves to nonperforming loans ratio (LLRNPL) and equity to net loans ratio(EQNL).

The equation is designed as follows:

$$Z_i = -0.021 + 0.62LLPGL - 0.673LLRNPL \text{ (one year)}$$

The percentage classification model for discriminant analysis is equal to 77.7%. The Table below (Table2) shows the obtained results by the discriminant analysis model.

Table 3. Prevision results one year before the distress

			Expected classification		
		Distress	0	1	**Total**
Original	Effective	0	375	58	433
		1	80	105	185
	%	0	86.6	13.4	100.0
		1	43.2	56.8	100.0

The percentage of correct classification is equal to77.7%

The application of the method of discriminant analysis for two years provides the following Table:

$$Z_i = -0.019 + 0.467LLPGL - 0.649LLRNPL$$

The percentage in the discriminant analysis gives an overall ranking of 77.3%. The Table below (Table3) shows the results expected by the discriminant analysis model.

Table 4. Result of a Ranking two years before the distress

			Expected classification		
		Distress	0	1	**Total**
Original	Effective	0	384	49	433
		1	91	94	185
	%	0	88.7	11.3	100.0
		1	49.2	50.8	100.0

The percentage of correct classification was equal to 77.3%

In this Table, we can notice that the model is able to correctly classify 375 robust banks of a total of 433. The precision model was equal to 86.6 %. This model can also classify correctly 105 distressed banks of a total of 185. Then, it can provide 56.8% precision for the group of distressed banks. Then the global percentage of a good ranking is equal to 77.7%. In the second case, we seek to predict distress before two years. This model was able to classify correctly, 384 of a total of 433 robust banks. The good ranking of healthy banks reaches 88.7%. In the case of the distressed banks, this model reached to classify correctly, 94 for a total of 185 distressed banks. The good ranking reached 50.81%. Then the global percentage of a good classification is equal to 77.3%.

4.2 Logit Method

The logistic regression method is characterized by a binary dependent variable.

For the bank (i) we have:

$$Y_i = \begin{cases} 0, \alpha_0 + \sum_{i=1}^{n} \beta_i x_i + \varepsilon_i \leq 0 \\ 1, \alpha_0 + \sum_{i=1}^{n} \beta_i x_i + \varepsilon_i > 0 \end{cases} \tag{2}$$

$$p_i = P(Y_i = 1) = P(\alpha_0 + \sum_{i=1}^{n} \beta_i x_i + \varepsilon_i > 0) = \frac{1}{1+e^{-\alpha_i - \sum \beta_i x_i}} \tag{3}$$

$$log \frac{p_i}{1-p_i} = \alpha_i + \sum \beta_i x_i \tag{4}$$

With $\frac{p_i}{1-p_i}$ is the relative probability of $Y_i = 1$

The use of logistic method one year before the distress shows that loan loss provision to gross loans (LLPGL) and loan loss reserves to non performing loans (LLRNPL) ratios are significant at a level of 1% while the ROEA ratio is significant at a level of 10%.

Table 5. Estimation result using logistic regression during a year of distress

Variables	Coefficients	t student
EQNL	2.092025	2.16**
LLPGL	0.9897102	6.18***
LLRNPL	-1.398115	-4.70***
CIR	-0.7391725	-1.17
ROEA	-0.2284727	-0.22
LIQTA	-0.1538859	-0.19
NLDEP	-0.0208422	-0.15
Cte	-0.485183	-0.90
LR chi2(7)	105.61	
R^2	0.14	

The percentage of correct classification was equal to 76.05%.

The use of the logit method two years before financial distress indicates that three ratios are significant. Those ratios are EQNL, LLPGL and LLRNPL. Equity to Net Loans ratio is considered as a buffer to absorb potential losses that can be faced by banks. A high percentage of capital implies lower risk of distress and helps to absorb potential losses (Mayes & Stremmel, 2012). This ratio is significant at a level of 5%. The other ratios are significant at a level of 1%. Our results improve the idea that a better profitability encourages banks to take excessive risks and increases the likelihood of distress. Equity to Net Loans ratio (EQNL) measures the efficiency with which institutions use their own funds. It can also provide information about the viability of their own funds. A high ratio could indicate high profitability and / or low capitalization. Loan loss reserves to Non performing loans (LLRNPL) is considered as a coverage ratio of non performing loans. As a consequence, there is a negative relationship between this ratio and bank distress.

Table 6. Estimation result using logistic regression for two years of distress

Variables	Coefficients	t student
EQNL	0.8917947	0.86
LLPGL	0.8427689	6.62***
LLRNPL	-1.465278	-4.21***
CIR	0.1465523	0.38
ROEA	-0.1563443	-0.20
LIQTA	-0.2673611	-0.32
NLDEP	0.1411453	0.97
Cte	-1.105471	-2.59***
LR chi2(7)	114.33	
R^2	0.1516	

Note. (***) significant at level 1%.

The percentage of correct classification was equal 77.02%.

The predicting process using the logit regression shows that only two ratios were significant at a level of 1% namely: loan losses provisions to gross loans (LLPGL) and loan losses reserves to non performing loans ratio (LLRNPL). That improves the idea that prevision can be more efficient one year before the distress.

Confusion matrix in Table 7 indicates that percentages of classifications one year before the distress are as follows: in fact, that matrix indicates good ranking of distressed banks equal to 31.81 % and a good ranking of solid banks equal to 95,38%. Two years before the distress, this matrix indicates a good ranking of healthy banks which is equal to 97.4% then a good ranking of distressed banks equal to 29.19%.

Table 7. The Confusion matrix

	Before one year			**Before two years**		
	True			True		
Classified	1	0	Total	1	0	Total
1	57	20	77	54	11	65
0	128	413	541	131	422	553
Total	185	433	618	185	433	618

This matrix indicates the percentages of classification one and two years before the distress. In fact, the better ranking of solid banks was equal to 95.38% and the good ranking for distressed banks was equal to 30.81%. In The case of two years, confusion matrix indicates that good ranking of solid and distressed banks was respectively equal to 97.46 and 29.19 %.

4.3 Artificial Intelligence Method

The application of neural techniques to the same data allows us to take into account the non-linearity of variables. We refer to Boyacioglu, et al. (2009) research' and we used the Multi-Layer Perceptron (MLP) and we should also note that this network includes one or more hidden layers neurons. The connections between these layers are direct and total.

Our overall sample is divided into three sub-samples: the construction sample (70%), the test sample (15%) and the validation sample (15%).

The neural network has the following features:

- An input layer consists of 7 neurons corresponding to independent variables xi.

- A hidden layer consists of N neurons, only after several tests on the sample, the number which represents an optimum value of learning and generalization will be achieved.

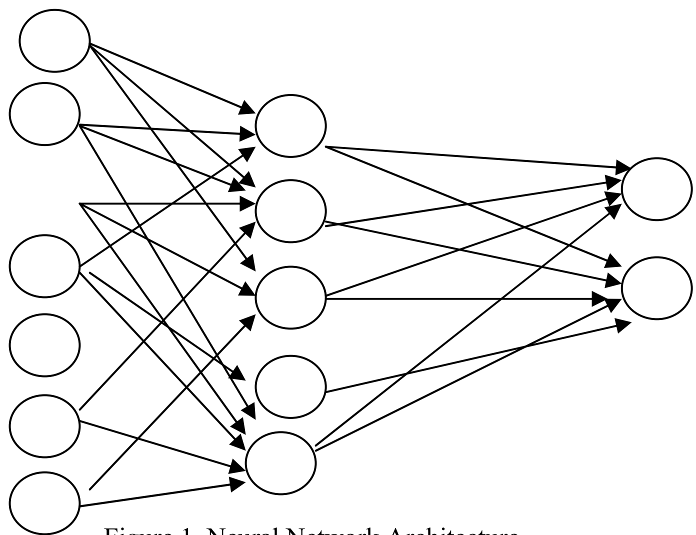

Figure 1. Neural Network Architecture

Two activation functions were used as below:

-The sigmoid function for the output layer

$$f(x) = \frac{1}{e^{x}+e^{-x}} \tag{5}$$

- The hyperbolic tangent function for the hidden layer

$$g(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{6}$$

The neurons of the hidden layer are determined based on the transfer function or activation of g (x):

$$y_i = g(x) = \sum_{i=1}^{n} w_{ij}x_i + w_{oj} \tag{7}$$

The activation function f (k, x) determines the output layers:

$$O_k = f(k,x) = \sum_{j=1}^{p} w_{jk} \cdot g\left(\sum_{i=1}^{n} w_{ij}x_i + w_{oj}\right) + w_{0k} \tag{8}$$

With i: the number of input variables i = 1…..n

x_{i} : neurons of the hidden layer

y_{j} : neurons of the hidden layer

j : number of hidden layer j=1……..p

O_k : The neurons of the output layer

The learning of such a network is monitored and the algorithm uses the back propagation of the error. This algorithm is used in the feed forward type networks. Each network of neurons has an input layer, an output layer, and at least one hidden layer.

The retro-propagation is based on presenting to the network an input vector, then, it calculates the output. It starts from the input layer, and it goes through the other layers until the output layer. This output is compared to the desired output, an error is then obtained. This error, is calculated from the output layer towards the input layer (retro propagation). This allows modification of the network weights and the learning process. It is essential to perform a normalization of all input data. Otherwise the quality of results is negatively affected. In other words, if the inputs have very different sizes, small ones will have no influence on the learning process (Boyacioglu, Kara, & Baykan, 2009).

Rescaling is the most commonly used normalization method. It is based on subtracting the minimum and dividing the result by the interval (x-min) / (max-min). The normalized values are between 0 and 1.

The number of neurons is selected by the lowest RMSE (Root Mean Square Error) coefficient.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{9}$$

The RMSE application offered a "check out" system by which the number of neurons could be verified. As a criterion for determining the number of neurons, RMSE allowed us to have five hidden layers neurons (see Table 8).

Table 8. Determination of the number of neurons in the hidden layer

	2010			2009		
Layer	Iteration	RMSE		Iteration	RMSE	
		Training	Testing		training	testing
1	12	0.44537625	0.38310573	22	0.458692708	0.444330958
2	29	0.43528382	0.45536798	11	0.434833301	0.459964129
3	27	0.4168345	0.41148147	18	0.44964208	0.465382638
4	51	0.40807107	0.40895232	18	0.425323406	0.447752164
5	**65**	**0.39410785**	**0.38097769**	**56**	**0.4035889**	**0.401105971**
6	23	0.42228071	0.39107928	3	0.542200148	0.528742849
7	21	0.40161922	0.43032081	9	0.451464284	0.462893076
8	48	0.39817458	0.39244235	17	0.450967848	0.471924782
9	19	0.4315449	0.42194549	28	0.416659333	0.4181758
10	19	0.44705257	0.4253716	30	0.453688219	0.458991285
11	24	0.39761288	0.39829637	14	0.441430629	0.476223687
12	13	0.4756238	0.4494619	10	0.469316524	0.449780391
13	28	0.39597348	0.39647194	3	0.537913562	0.497297698
14	12	0.40634468	0.43537915	23	0.416661733	0.414518998
15	12	0.45415856	0.42618541	30	0.456678224	0.434164715

The application of ANN method demonstrates that the most important variables in predicting distress (one year before the distress) are loan loss provisions to gross loans ratio (LLPGL), loan loss reserves to non performing loans (LLRNPL) and return on equity average (ROEA), respectively, with importance rate 100%, 57% and 27%. Regarding two years before the distress, the most important ratios for predicting bank distress are loan loss provisions to gross loans ratio (LLPGL), loan loss reserves to non performing loans (LLRNPL) and cost to income ratio (CIR), respectively, with importance rate 100%, 61.4% and 45.1%.

The Table 9 reveals the percentage of the most appropriate ratio to prevent bank distress. The result demonstrates the significant role given to loan loss provisions to gross loans ratio (LLPGL). This variable would be able to predict distress at the right moment. Indeed, banks must make provisions for loan losses in case of emergence of non-performing loans (Messai & Jouini, 2013b).

Table 9. Importance of independent variables

	Before one year		Before two years	
	Importance	Percent	Importance	Percent
EQ/TL	0.060	14.5%	0.067	21.4%
LLP/GL	0.413	100.0%	0.312	100.0%
LLR/NPL	0.235	57.0%	0.192	61.4%
CIR	0.068	16.5%	0.141	45.1%
ROEA	0.111	27.0%	0.102	32.6%
LIQ/TA	0.039	9.4%	0.081	25.9%
NL/DEP	0.074	18.0%	0.106	34.0%

Table 10 shows that the method of neural network is the best to predict distress. This method has a global performance equal to 80.6 % and 79.8 %, respectively one year and two years before the distress.

The prediction has been made a couple of times: one and two years before the distress. The prediction before one year indicates that prevision performance in the discriminant analysis, logic method and neural networks are respectively 77. 7%, 76.02%, and 80.6%. Then, the prevision before two years indicates that the prevision's performance in the discriminant analysis, logistic method and neural networks are respectively 77.3%, 77.02 % and 79.6%. This improves another time that the neural network method outperforms the two others (logit and discriminant analysis). These results confirm those obtained by Giovanis, (2010) and would be contrary to the result reached by Doganay, (2006) according to which logit is the best model to predict bank distress.

This study allowed us to conclude that the positive predictive value have correctly presaged a classification percentage of distressed banks. This percentage is greater than 50% for two models, namely discriminant analysis and neural networks.

Table 10. Classification one and two years before the distress

Sample		Previsions					
		Before one year			Before two years		
		0	1	Correct percentage	0	1	Correct percentage
Training	0	277	21	93.0%	276	23	92.3%
	1	64	65	50.4%	62	64	50.8%
	Global percentage	79.9%	20.1%	80.1%	79.5%	20.5%	80.0%
Testing	0	124	11	91.9%	126	8	94.0%
	1	26	30	53.6%	31	28	47.5%
	Global percentage	78.5%	21.5%	80.6%	81.3%	18.7%	79.8%

An error type I corresponds to a classification of a failed bank as robust and an error Type II is a classification of a healthy bank as distressed. Concerning error percentages, we notice that the lowest error is obtained after using the neural network model. As for the most important error, it was observed after using the logit model (23.96%). The error type II was largely observed after the use of the discriminant analysis method (35.58%). For the purpose, this confirms the results we have achieved (see Table 11).

Table 11. Summary table

Method	**Discriminant analysis**		**Logit**		**Neural networks (training)**		**Neural networks (testing)**	
1 or 2 years before distress	1	2	1	2	1	2	1	2
Positive predictive value (%)	56.75	50.81	30.81	29.19	53.57	47.46	50.39	50.79
Negative predictive value (%)	86.6	88.68	95.38	97.46	91.85	94.03	92.95	92.31
Error type I (%)	17.58	19.16	23.66	23.69	17.33	19.74	18.76	18.34
Error type II (%)	35.58	34.27	25.97	16.923	28.21	21.05	24.42	26.44
Global performance (%)	77.7	77.3	76.05	77.02	80.1	80	80.6	79.8

Note. Errors type I and type II: provide false alarm.

Finally, we consider that neural network is the best method to predict distress. On the one hand it has the best percentage of prediction. On the other hand it appears that the percentage of the error type I (false positive) is equal to 17.33% and is the lowest compared with percentage provided by the two other methods.

5. Conclusion

During the two last decades, several authors have focused on methods of forecasting the bank distress. The aim of this study is to determine the most relevant indicators of financial distress in European countries in order to avoid potential crises. The prevision was carried out one and two years before that distress would occur**.** In this study, we have opted for the ratio non performing loans to gross loans as predictor of bank distress. We have also opted for three methods in order to choose the most appropriate one**.** This comparison aims to highlight the usefulness of these different methods and to decide about the effectiveness of each method in a microprudential framework. We observe that influence of internal factors on the non performing loans to gross loans ratio (NPLGL) was very significant. Therefore, we concluded that distress could be explained by a high percentage of non-performing loans by banks in expansion periods, because during these periods banks undertake more risks such as excessive lending activities without considering the quality of each loan. We recall the example, in the

Japanese crisis in the 1980s, when banks continued heavily the granting of loans without checking if there are legal certainties over ownership building lands. The same thing happened during the subprime crisis. So, in this study, we want to determine the best distress indicators. Our results suggest also that CAMEL indicators remain the only rating system to put the most relevant and important ratios to predict distress. The dependent variable, then, can be expressed by internal factors inherent to banks, which are presented by CAMEL criteria. The best percentage of prediction is obtained when we use the method of neural networks. The performance achieved by this model before one and two years was respectively equal to 80.6% and 79.8%. As a consequence, using internal financial soundness indicators is too important to predict distress in individual banks. However, our study has a number of limitations. The distress prediction need to be used in both macro and micro prudential approaches. These two approaches are very complementary and related. Future research on distress prediction may be extended as follows: First, variables relating to a macroeconomic environment should be encompassed in order to define relevant factors which could explain distress in a macroeconomic approach (stress testing framework). Second, extending the methods of prediction and add survive analysis in order to predict difficulties. Finally, using several financial variables as well as macroeconomic variables in order to choose the most relevant leading indicators of distress and in order to enhance the robustness of the results in a stress testing framework (Anderson, 2008; Lelyveld, 2009; Quagliariello, 2009).

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