A MODEL OF RATING OF EASTERN EUROPEAN BANKS

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Abstract
In this paper the authors apply a unique credit rating system on a sample of banks in Romania, Hungary, The Czech Republic and Poland, based on the CAMEL, PERLAS and Stickney models. The aggregate model correlates the results of these rating systems in an unique rating system according to ratings agencies Standard & Poor's, Moody's and Fitch scores. All these models are based on the financial ratios of performance, activity, capital adequacy, liquidity, equity and management. The results indicate that such evaluation is closed to the agencies' ratings as the final model aggregates the partial score of each model included.

Key words: credit rating agencies, capital adequacy, bank rating

JEL classification: G15, G21, G24, G32

1. The Importance of Ratings

There are many world rating agencies, but the most powerful are three US agencies, called "The Big Three": Standard & Poor's, Moody's Investor Services, and Fitch Ratings. The events that preceded the unfolding financial crisis and its after math showed that assessments of rating agencies did not always match the economic reality because the models didn't take into account the main causes and the consequences of the financial crisis. Although the regulations Basle I, Basle II and Basle III which attempted to shelter banks from the danger of bankruptcy, either through recapitalization which means either by strengthening prudential supervision of banking, failed to prevent the financial banking crisis and its consequences which are still felt in the

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economy at present. The bank rating models based on multiple discriminate analyses or on the rating systems in different countries reveal the reality of the banking world from country to country and may not be generalized. In this regard we think that in the rating model building that can be applied to different countries should consider related system models from the credit – scoring models and end with the supervisory banking rating system such as OPAR and SAABA in France, BAKIS in Germany, PATROL in Italy, RAST in Netherlands, RATE and TRAM in United Kingdom, CAMELS and SEER in the United Stated and CAAMPL in Romania, providing viable solutions to the banking sector on the global development banks. The most difficult problem is how to integrate different rating systems and models in a unique early warning system. Therefore we consider that this research can be considered a starting point in the building process of a unique early warning system for any bank in the world.

Credit rating agencies such as Moody's, Standard & Poor's, Fitch IBCA and Thomson Bank Watch bundle and process a set of data and they use information that has an extremely high strategic value. The data is taken from financial reports, forecasts, investment and international programs, mergers and acquisitions between companies, liquidations and bankruptcies, strategic investors and institutional pools etc. After processing they become brief, and gradual, the entire rating process being characterized by objectivity and complete confidentiality.

This credit rating products market, that on one hand and in our opinion it is concerning the degree of informing the general investors at the risk involved in the decision of investing in financial markets, on the other hand it is disputed by rating agencies. The financial investors, who are usually poorly informed regarding the degree of risk, need an independent, objective and competent data providing on the financial market products, on the quality of the primary market issues of securities as well as those that are offered on secondary market of stocks, bonds, etc. However, bank credit institutions already have information about investment risk that they can provide, on request, to the customers. Nevertheless the public is always attracted to the competitive environment even if there is a commission that has to be paid, therefore more attention will be given to information published by a prestigious rating agency, then to local information. In the globalized financial markets, when French, German or English, securities are quoted at the Japanese stock exchange, when European, Asian or Australian titles are quoted at the New York Stock Exchange (NYSE), when a Hong Kong investor wants to purchase securities in the Czech Republic while being in Chicago, it is difficult if not impossible even for the savvy investors to evaluate credit risks or quality securities of the companies willing to buy liquidities.

2. Literature Review

Many authors consider the rating as a bankruptcy measurement option in the bank activity. During the financial crisis many analysts tried to connect banks difficulties with their rating. They show that in the run-up to the financial crisis of 2007-2008, market participants relied heavily on the ratings that credit rating agencies assigned to financial instruments, including mortgage-backed securities, in order to determine creditworthy investment options. These firms sold their bond ratings to bond investors (White, 2009). Another paper studies the impact of the subprime crisis on the ratings issued by the rating agencies in evaluating the solvency of banks. The authors design a methodology to separate the observed change in ratings into two multiplicative components: one associated with the deterioration of the banks' solvency itself and another associated with the change in the agencies' valuation criteria (Salvador et al, 2014, p.13–31). Another paper investigates the relative opacity of banks using disagreement between the major bond-rating agencies (Moody's and Standard and Poor's [S&P]) as a proxy for uncertainty (Morgan, 2002,p. 874-888).

China's commercial banks are confronted with fierce competition from advanced big commercial banks abroad, and therefore the rating and ranking of China's commercial banks are (Ji, et al, 2012, p. 122-125). Using a comprehensive dataset of rating agencies and countries over the period 1989-1999, in another paper is demonstrated that artificial neural networks (ANN) represent a way to predict the sovereign ratings based on probit modeling (Bennell, et al, 2006, p. 415-425). Credit ratings information plays a crucial role in supporting sound financial decision-making processes. Most previous studies on credit rating modeling are based on accounting and market information (Lu, et al, 2012). In a recent paper other authors analyzed the effects of sovereign rating actions on the credit ratings of banks in emerging markets are analyzed using a sample from three global rating agencies across 54 countries for 1999–2009 and find that sovereign rating upgrades (downgrades) have strong effects on bank rating upgrades (downgrades)

(Gwion and Rasha, 2013, p. 563–577). Politicians often propose force strategies in fighting the underground economy in order to increase budget revenues: some advocate for trust-based strategies, some advocate for power-based strategies and others for an appropriate mixture of trust and power (Bătrâncea, et al, 2012, p.97-106; 2012, p.201-210; 2012, 378-383; 2015, p.5-22); (Kogler, et al, 2013, p.169-180)

Others investigate the rating channel for the transmission of changes in sovereign risk to the banking sector, analyzing data from Moody's, S&P and Fitch before and during the European debt crisis. Sovereign rating downgrades and negative watch signals have strong effects on bank rating downgrades in the crisis period. The impact is stronger for multiple-notch sovereign rating downgrades, and more pronounced in PIIGS countries. (Alsakka, et al, 2014, p. 235–257). In recent years, credit rating agencies have started rating firms who have not asked for a rating. Authors set out to examine these claims using a comprehensive and international sample of 1,060 bank ratings and develop a model to explain bank ratings based on the bank size, profitability, asset quality, liquidity, and sovereign credit risk (Poon and Firth, 2005, p. 1741–1771). In a statistical research other authors studied the impact of 18 factors balance sheet of banks have on the indicator ROE, and concluded that it can establish a multiple strong connections between these factors and ROE, based on univariate method (Bătrâncea et al, 2008, p. 164 – 178; Bătrâncea, 2006). In another paper the rating analysis is based on three key principles according with Basle II agreement: Clear rating responsibilities, the rigorous enforcement of the „four eyes” principle in the rating process and an independent rating authorization for the account management (Bătrâncea, et al, 2007, p. 80-83). “Credit scoring” method aims to provide predictive models for assessing risk of failure of an entity which based on statistical techniques of discriminate analysis of information provided by the transformation of economic and financial indicators in a score able to predict success or failure of a business (Bătrâncea, 2011, p. 44 – 54). Traditionally an institution's default risk was assessed by the indicators measuring the profitability, liquidity and solvency (Bătrâncea, et al, 2013, p. 18-30).

Using seven ratios representing seven facets of bank financial management practices a paper rates and ranks the 68 commercial banks operating in Gulf Cooperation Council countries using the logit regression technique to identify financial management practices of those banks which managed to remain in the top quartile both before and after the 2008 financial crisis (Sree, 2013). In the aftermath of the financial crisis, another study investigates which underlying determinants cause bank rating transitions and find that is a significant dependence of rating upgrade or rating downgrade transition hazards on rating-specific covariates and macro-economic covariates (Louis, et al, 2013, p.280–283). Another study aims to present an empirical model designed to forecast bank credit ratings using only quantitative and publicly available information from their financial statements. For this reason, the authors use the long-term ratings provided by Fitch in 2012 (Gogas, et al, 2014, p. 195-209).

Another paper explores a new approach to early warning systems for commercial banks where the analysis and logit estimation are used to measure the condition of individual institutions and to assign each of them a probability of being a problem bank. The model employs widely used financial ratios and information taken from bank examinations. The factors produced by the model for use in the logit estimation are very similar to the CAMEL rating system used by bank examiners. The empirical results show that the combination of factor analysis and logit estimation is a promising method of evaluating bank condition (West, 1985, p.253–266). Our paper we evaluate a sample of Eastern European banks ratings over 11 years, using CAMEL, PERLAS and Stickney models.

3. Methods and Results

Problems with credit, liquidity, and fraud are the most common primary causes of bank failures, and combinations of these misfortunes are often seen. Capital inadequacy for the risks being run is by definition an almost universal secondary cause, the prelude of banking insolvency. Other important causes for banking insolvency are: assets quality, management, profitability and banking liquidity. This is why a rating system has been built for the banks in Eastern Europe in order to prevent banking insolvency prevision. The rating system used in banks represents an efficient tool for evaluating the credit institutions, to identify in due time those branches where a deterioration of the economic and prudence efficiency indicators might take place.

THE CAMEL RATING SYSTEM

CAMEL system is based on the evaluation of five components, reflecting in a uniform and thorough manner the performances of the credit corporation, according to the applicable legislation and regulations in force.

The specific analysis components of CAMEL system are: Capital adequacy(C); Assets quality (A); Management (M); Earnings (E) and Liquidity (L). Each of the five components are evaluated through a value scale between 1 and 5, where 1 represents the most performing level, while 5 represents the lowest. Four of the five components (C – capital adequacy, a – assets quality, E – earnings and L – liquidity) are analyzed according to several indicators, for which four intervals and four corresponding ratings are determined. In our case compound rating and quantitative rating were calculated as follows:

Compound rating = 20% * (M qualitative) Rating + 80% * (C, A, E, L quantitative) Rating

(CAEL quantitative) Rating = 25%* (C) Rating + 25%* (A) Rating + 25%* (E) Rating + 25%* (L) Rating

Table 1 The correlation between CAMEL ratings and the Risk Grade

Average Rating	Risk grade
1 – 1,5	A
1,51 – 2	B
1,99 – 2,5	C
2,51 – 3	D
>3	E

Source: Own evaluation

As a result of the analyses conducted on a sample of 20 banks, their rating is as follows:

Table 2 **The Evolution of CAMEL Rating System in the banking system**

CAMEL											
C. CAPITAL ADEQUACY											
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Capital adequacy = Equity/total loans	8,91%	7,77%	8,33%	9,76%	10,67%	1,52%	13,80%	12,73%	13,02%	14,57%	250,34%
Rating	**1**	**1**	**1**	**2**	**2**	**5**	**1**	**1**	**1**	**1**	**1**
A. ASSET QUALITY											
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Asset quality = Loan loss provisions/total loans	1,30%	1,46%	1,54%	2,31%	2,01%	1,20%	1,25%	1,28%	0,52%	4,75%	0,67%
Rating	**1**	**1**	**1**	**2**	**2**	**1**	**1**	**1**	**1**	**2**	**1**
M. MANAGEMENT											
TOTAL MANAGEMENT COMPOUND RISK	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	
E. EARNINGS											
Earnings ability = Pre-tax profit/total assets	1,22%	0,72%	1,66%	0,59%	0,77%	1,09%	0,15%	1,66%	1,27%	-0,16%	1,79%
Rating	**4**	**4**	**4**	**5**	**4**	**4**	**5**	**4**	**4**	**5**	**4**
L. LIQUIDITY											
Liquidity position = Deposits/total assets	66,23%	63,77%	62,78%	61,30%	56,75%	49,65%	59,67%	68,37%	68,69%	67,55%	72,71%
Rating	1	1	1	1	1	1	1	1	1	1	1
COMPOUND RATING	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	
TOTAL Score	**1,60**	**1,60**	**1,60**	**2,20**	**2,00**	**2,40**	**1,80**	**1,60**	**1,60**	**2,00**	**1,60**
CAMEL Risk grade	**B**	**B**	**B**	**C**	**B**	**B**	**B**	**B**	**B**	**B**	**B**

Source: Own calculus based on financial statements

By the CAMEL method the analyzed bank got the same risk grade excepting the state of the financial banking crisis.

THE PERLAS RATING SYSTEM

Numerous financial indicators have been promoted worldwide as well as fixed rules for financial institutions, but few of them were gathered in an evaluation program capable of measuring both individual components and the system as a whole. Since 1990, the World Council of Credit Unions (WOCCU) uses a set of financial indicators called "PERLAS" or "PEARLS". Each letter of the word PERLAS measures key areas of credit union operations as follows: Safety, Effective financial structure, Rate of cost and revenue, Liquidity, Assets and their quality and Signs of growth. The system helps bankers to find the core solutions to the serious shortcomings of their institutions.

Introducing the PERLAS evaluation system may change the role of inspectors from the supervisory institution to verifying the financial information used to calculate the indicators. If errors are found, these are relatively easy to correct and often give the management team the opportunity to make an analysis of the operations of the institution. PERLAS system is a unique and different to other monitoring systems. It was initially designed as a *management tool* and then became an effective *supervision mechanism*.

Table 3 Correlation between PERLAS ratings and Risk Grade

Average Rating	Risk grade
22 – 24	A
19 - 21	B
16 – 18	C
13 - 15	D
<13	E

Source: Own evaluation

In the present study the situation is as follows if we take into account 8 performance criteria for the analyzed banks ratings using the PERLAS system:

Table 4 PERLAS ratings in the banking system

PERLAS	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
P6. Solvency	11,72%	11,85%	15,68%	28,70%	35,61%	40,96%	32,98%	38,90%	39,84%	25,89%	28,45%
P6 Rating	0	0	0	0	0	0	0	0	0	0	0
E1 Net loans balance / total assets	78,31%	76,80%	71,91%	58,51%	54,14%	52,26%	52,94%	51,69%	48,76%	54,18%	47,86%
E1 Rating	3	3	3	1	1	1	1	1	0	1	1
E5 Social fund balance / total assets	2,78%	2,50%	2,81%	2,09%	2,42%	2,29%	4,87%	5,71%	5,48%	5,65%	5,41%
E5 Rating	0	0	0	0	0	0	0	0	0	0	0
E8 Institutional Capital / Total Assets	16,72%	17,41%	22,06%	35,77%	41,05%	44,49%	41,74%	45,73%	46,61%	29,80%	30,58%
E8 Rating	3	3	3	3	3	3	3	3	3	3	0

A2 Unproductive assets / total assets	2,62%	2,53%	2,49%	2,51%	2,52%	2,35%	3,69%	4,67%	4,34%	3,95%	3,73%
A2 Rating	3	3	3	3	3	3	3	3	3	3	3
R9 Operating Expenses / Total Assets Average	10,16%	10,71%	11,72%	14,15%	15,09%	23,32%	25,28%	21,56%	22,45%	25,21%	25,21%
R9 Rating	2	2	2	1	0	0	0	0	0	0	0
L1 Liquid Assets - Current Liabilities / Social Fund	1963,73%	2001,44%	1794,08%	2296,53%	2158,89%	2425,47%	1112,02%	1005,99%	1143,18%	1133,58%	1500,58%
L1 Rating	3	3	3	3	3	3	3	3	3	3	3
S11 Increase in total assets	100,00%	111,14%	112,59%	134,51%	95,91%	105,41%	90,11%	85,30%	104,19%	96,87%	104,58%
S11 Rating	3	3	3	3	3	3	3	3	3	3	3
Total points	11,72%	11,85%	15,68%	28,70%	35,61%	40,96%	32,98%	38,90%	39,84%	25,89%	28,45%
Rating	0	0	0	0	0	0	0	0	0	0	0
Total points	17	17	17	14	13	13	13	13	12	13	10
PERLAS Risk Grade	C	C	C	C	C	D	D	D	E	D	E

Source: Own calculus based on financial statements

THE STICKNEY MODEL

Bankruptcy prediction models are known as methods for hazard assessment of financial entities, and financial theory there are three types of evaluation of this issue, namely univariate analysis, multivariate and logit. In the period 1980-1990 was logit methods used multiple discriminate analysis detrimental, and more recently logit analysis was considered more advanced analytical tools like neural analysis. Between logit models we considered the model developed by Claude Stickney. Stickney model involves the application of four stages: the first involves the calculation of seven financial indicators according with their coefficients established by the model. Based on these rates the Y score is calculated such as:

$$\mathbf{Y = +0,\ 23883 + \sum Partial\ Coefficient_{i} * Financial\ ratio_{i}}$$

` Then is calculated the probability of bankruptcy of banks following the algorithm:

$$\mathbf{P = 1/\ (1+e^{y})}$$

We also correlate the average rating with the risk grade, as follows:

Table 5 The correlation between Stickney ratings and Risk Grade

Average Rating	Risk grade

1	A
2 – 6	B
7	C
8	D
<8	E

Source: Own evaluation

The ratings obtained by this method are given in line with those developed by agencies Moody's and Standard & Poor's. Rating notations are partially standardized as in the evaluation process, analysts argued the need for a more pronounced differences in risk.

Table 6 The evolution of rating and probability of bankruptcy by Stickney method

Fiscal period	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
R1	15,05	15,61	13,99	16,39	12,13	10,82	10,33	9,44	7,64	7,06	6,84
K1	0,108	0,108	0,108	0,108	0,108	0,108	0,108	0,108	0,108	0,108	0,108
Score 1	1,6254	1,6859	1,5109	1,7701	1,3100	1,1686	1,1156	1,0195	0,8251	0,7625	0,7387
R2	4,33	4,02	3,05	1,72	1,36	1,27	1,39	1,34	1,11	1,37	1,06
K 2	1,583	1,583	1,583	1,583	1,583	1,583	1,583	1,583	1,583	1,583	1,583
Score 2	6,8544	6,3637	4,8282	2,7228	2,1529	2,0104	2,2004	2,1212	1,7571	2,1687	1,6780
R3	0,07	0,07	0,07	0,04	0,05	0,04	0,06	0,03	0,06	0,17	0,22
K 3	10,7800	10,7800	10,7800	10,7800	10,7800	10,7800	10,7800	10,7800	10,7800	10,7800	10,7800
Score 3	0,7546	0,7546	0,7546	0,4312	0,5390	0,4312	0,6468	0,3234	0,6468	1,8326	2,3716
R4	2,27	2,65	2,91	2,82	2,72	1,95	1,81	1,62	1,54	1,64	1,29
K 4	3,0740	3,0740	3,0740	3,0740	3,0740	3,0740	3,0740	3,0740	3,0740	3,0740	3,0740
Score 4	6,9780	8,1461	8,9453	8,6687	8,3613	5,9943	5,5639	4,9799	4,7340	5,0414	3,9655
R5	0,02	0,01	0,02	0,01	0,01	0,01	0,00	0,02	0,01	-0,01	0,03
K 5	0,4860	0,4860	0,4860	0,4860	0,4860	0,4860	0,4860	0,4860	0,4860	0,4860	0,4860
Score 5	0,0097	0,0049	0,0097	0,0049	0,0049	0,0049	0,0000	0,0097	0,0049	-0,0049	0,0146
R6	0,84	0,87	0,88	0,91	0,90	0,93	0,88	0,86	0,86	0,81	0,77
K 6	4,3500	4,3500	4,3500	4,3500	4,3500	4,3500	4,3500	4,3500	4,3500	4,3500	4,3500
Score 6	3,6540	3,7845	3,8280	3,9585	3,9150	4,0455	3,8280	3,7410	3,7410	3,5235	3,3495

R7	0,08	0,07	0,07	0,05	0,06	0,07	0,08	0,08	0,10	0,14	0,15
K 7	0,1100	0,1100	0,1100	0,1100	0,1100	0,1100	0,1100	0,1100	0,1100	0,1100	0,1100
Score 7	0,0088	0,0077	0,0077	0,0055	0,0066	0,0077	0,0088	0,0088	0,0110	0,0154	0,0165
R= 0.23883 – R1* 0.108 – R2*1.583-R3*10.78 + R4*3.074 + R5* 0.4860 – R6* 4.35 + R7* 0.11											
TOTAL SCORE	-5,6531	-4,1912	-1,7202	0,0353	0,6947	-1,4100	-1,9793	-1,9679	-1,9813	-2,9966	-3,9024
Bankruptcy probability	0,98762	0,96257	0,79128	0,49316	0,3686	0,74882	0,8225	0,82121	0,82273	0,91064	0,95361
Rating	**4**	**4**	**4**	**3**	**3**	**4**	**4**	**4**	**4**	**4**	**4**
Stickney Risk Grade	**B**	**B**	**B**	**B**	**B**	**B**	**B**	**B**	**B**	**B**	**B**

Source: Own calculus

Table 7 The correlation between Stickney Ratings and the Risk Grade

Rating	Bankruptcy probability	Local county government rating	
		Moody's	Standard&Poor's
1	0,0-0,15	A3	A-
2	0,15-0.3	Baa1/Baa2	BBB+/BBB
3	0,3-0,6	Baa2/Baa3	BBB/BBB-
4	0,6-1,2	Ba1/Ba2	BB+/BB/BB-
5	1,2-2,5	Ba3	B+/B
6	2.5-5	B1	B-
7	5-10	B2/B3	CCC
8	Over 10	CaaCa/C	CC/C

Source: Adaptation E. Cade, Managing Banking Risks Woodhead Publishing, 1997, p. 115

The next step is to establish the ratings during the period. For this reason we built a scale of values between bank rating and the final score based on these methods.

Table 8 The Banks Ratings

Bank Rating	Score
AAA	12
AA+	11

AA	10
AA-	9
A+	8,5
A	8
A-	7,5
BBB+	7
BBB	6,5
BBB-	6
BB+	5,5
BB	5
BB-	4,5
B+	4
B	3,5
B-	3
CCC+	2,5
CCC	2
D(Default)	1,5

Source: Own estimation

For each risk grade we establish a rank as follows:

Table 9 The scale of values

Rank	Risk grade
4	A
3	B
2	C
1	D
0,5	E

Source: Own estimation

Based on these models we finally establish the ratings accordingly with the given banks ratings.

Table 10 The Banks Ratings

Fiscal period	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
CAMEL	**B**	**B**	**B**	**C**	**B**	**B**	**B**	**B**	**B**	**B**	**B**

Rating											
Score	3	3	3	2	3	3	3	3	3	3	3
PERLAS Rating	C	C	C	C	C	D	D	D	E	D	E
Score	**2**	**2**	**2**	**2**	**2**	**1**	**1**	**1**	**0,5**	**1**	**0,5**
Stickney Rating	**B**	**B**	**B**	**B**	**B**	**B**	**B**	**B**	**B**	**B**	**B**
Score	**3**	**2**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**
Final Rank	8	7	8	7	8	7	7	7	6,5	7	6,5
The Ratings	A	BBB+	A	BBB+	A	BBB+	BBB+	BBB+	BBB	BBB+	BBB

Source: Own calculus

Analyzing rating banks in the sample by the three methods above, for a period of 11 years, it is observed that while the results obtained using CAMEL are constant throughout the period which means that the banks are stable from the financial point of view. By the PERLAS model point of view these banks had major financial problems during the financial crisis and after crisis of course. Looking at the Stickney model we observe that rank is constant with a higher level of the probability of bankruptcy. Correlating these three rankings with the banks ratings we can see that until the financial crisis the banks had a good rating between A and BBB. During the crisis and post-crisis the banks had same difficulties with the deposits and with the loans, the ratings decreasing from BBB+ to BBB ratings.

4. Conclusions

The basic objective of prudential supervision is the early identification of banks considered inefficient in terms of indicators and evaluation criteria used in this rating system used different rating systems. Rating systems do not anticipate financial situations compared to early warning systems. The CAMELS rating system is based on six components aimed at assessing the coverage uniformly and vast performance of a credit institution under the regulations. By the Stickney considering the risk of bank failure and that is a complex issue involving both social issues and economic issues and even political issues given the fact that the bank is a financial institution whose main tasks is the management of depositors, work what should be done with a high degree of caution. Calculating the probability of bankruptcy involves several steps including, of course, the calculation of a series of economic and financial indicators. The PERLAS model help the bankers to better understand the consequences of their decisions.

Finally we think that by these the methods the credit institutions have an important tool to increase the performance to reduce the risks and to increase the bank market share. We may understand that our rating model is more optimistic than the rating agencies Moody's, Standard & Poor's or Fitch. Finally we consider that each estimation, based on criteria and models better establish the rating of the bank.

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