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Extended modeling of banks' credit ratings

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Abstract

The aim of this paper is to construct a reliable model based on public information for the practical usage of interested agents, regulators and banks themselves. During the work, a table of representative variables that have potential influence on ratings was constructed. The research is based on the Bankscope database that contains financial information about international banks for the period from 1996 to 2011. A Matlab code was created in order to fill in the gaps in a database. As a result, an ordered probit model provides the following conclusions. First, macro variables improve explanatory power of the model. Second, the regional affiliation effect is significant. Furthermore, rating grades are adjusted to economy's business cycle. Moreover, Standard&Poor's and Moody's are predicted to be the most and the least conservative rating agencies, respectively. The final model was classified as practically useful as predicting of rating grades gave 31% of precise results and up to 70% forecasts with an error within one rating grade, while predicting of rating classes resulted in 62% and 95% respectively.

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Keywords: Banks; credit ratings; ordered logit and probit models; rating agencies

1. Introduction

Economic growth and stability of any country depend on the financial environment of its banking system. Given the critical role of banks as financial intermediaries, the estimation of their financial stability is one of the main goals of regulators and a government. One of the commonly used ways of assessing the financial performance and controlling the level of risk of a bank is an evaluation of its rating. Rating determines the class to which the company belongs based on a probability of nonfulfillment of its obligations. Ratings are becoming increasingly important with the introduction of an internal rating approach (IRB - approach), provided by "Basel II" agreement, and an extensive usage of scoring models for the internal control.

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In this context, the paper is aimed to create a reliable model of rating forecasts based on publicly available information, which can be used as an early warning system. The research is based on the Bankscope database that contains information about banks from all over the world for the period from 1996 until 2011. Most of the authors in their research evaluated the risks of deterioration in financial performance of a bank, while this paper is focused on forecasting not only downgrades but also upgrades of banks' ratings.

The paper is structured as follows. In the literature review the table of factors that have potential influence on banks' ratings is constructed and hypotheses of the research are formulated. Then the analysis of empirical data used for the research is made and the problems of a representative sample formation are illustrated. The main part deals with the theoretical foundations of the econometric methodology and the forecast model of a bank's rating. Finally, the check for goodness of fit of the model is presented and conclusions are formulated.

2. Academic literature review and formulation of hypotheses

2.1. Factors of influence of bank's rating

There are several methodologies used for a selection of relevant indicators for forecasting the financial health of a bank. In this research it was decided to use Bank Financial Strength Rating (BFSR) methodology since it is used by major rating agencies. A list of indicators commonly used in academic literature [1-16] is summarized in Table 1.

Table 1. Potential indicators according to the five main groups of parameters of BFSR methodology

Factor	Potential indicator (ratio)	Expected sign
1.Franchise value		
Sustainability	Sustainable Growth Rate ROE x (1-dividend–payout ratio)	+
Market share	1. Revenue market share (%) = 100 * Net interest Revenue ($) / Total (country) Market interest revenue 2. Individual bank's total assets / Total assets of all banks in the country 3. Size estimate = log of total assets	+
Market power or market concentration	H-statistics Herfindahl-Hirschman Index (HHI)	+
Market structure	Log of the ratio of the number of banks to the population in a country	+ / –
Market discipline	Interbank ratio = Interbank deposits / Interbank deposits purchased	+
Geographical diversification	1. Diversification of investment portfolio across different geographic regions 2. Number of foreign countries where a bank operates	+
Earnings stability	Volatility of earnings – percentage from one standard deviation of the variability around the trend line fitted through 3 to 5 years of earnings' history with a scale ranging from 1 to 99	–
Earnings Diversification	1. Other earning assets / Total earning assets 2. Loans to banks / Total earning assets 3. Income from derivatives, other securities / Total earning assets	+
2. Risk position		
Corporate governance	Experts estimation	
Key-man risk	The amount of losses in the case of losing an important member of the team	–
Risk management	Risk ratio (credit, market, liquidity and interest rate risks) = Maximum possible amount of losses on loans / Volume of financial resources of a bank	–

3.Regulatory environment	Indicator of regulator's independency	+
4.Operational environment		
Stability of the economy	1. Macroeconomic variables 2. Sovereign rating 3. Economic Freedom Index 4. Corruption Perception Index (Transparency International methodology)	 2. + 3. + 4. –
5.Financial fundamental		
Profitability	1. ROA, ROE 2. Net interest margin = Interest income – Interest expenses 3. Net interest revenues/ Average assets 4. Income net of distribution/ Average equity 5. (EBIT + Loan Loss provision) / Risk weighted assets 6. Dividend payout ratio	+
Efficiency	1. Cost to income ratio 2. Operational expenses / Operating income	–
Liquidity	1. Current ratio 2. (Market funds-Liquid assets) / Total assets 3. Deposits / Equity 4. Net assets / Total deposits and other short term funding 5. Liquid assets / Total deposits and other short term funding	1. + 2. – 3. – 4. + 5. +
Capital adequacy	1. Tier 1 ratio 2. Equity / Total assets 3. Capital / Total assets 4. Equity / Debt (financial leverage)	1. + 2. + 3. + 4. U
Asset quality	1. Impaired loans / Gross loans 2. Loan loss reserves / Gross loans 3. Impaired loans / (Equity + Loan loss reserves) 4. Unreserved impaired loan / Equity	-
Management quality	Expert estimation	

2.2. Hypotheses of the paper

Based on the analysis of previous academic literature and the database (described below) the following hypotheses were formulated:

Hypothesis 1: The usage of macro variables in a model of banks' ratings will improve its predictive power.

This hypothesis suggests that the financial and political situation in a country should significantly affect financial performance and, therefore, be an important determinant of a credit rating of a bank that is located in this country. This is justified by the influence of macroeconomic policies on the state-owned banks and on the banking system as a whole, due to interdependence of all banks.

Hypothesis 2: Regional affiliation of a bank has an influence on its rating.

Geographical regions differ in their market structure, laws and regulations. The easiest way to test this hypothesis is to compare ratings of banks in developed and developing countries. Previous research [1] suggests that banks from developed countries will have higher and less volatile rating grades than those from developing countries.

Hypothesis 3: Credit ratings are not changed in a short term (during the transition to another stage of a business cycle).

On the one hand, a rating of a bank should be fairly stable over time and obey «through-the-cycle» rule [2-4]. However, on the other hand, a transition to another business cycle stage is often accompanied by changes not only in the macro parameters but also in a banking financial stability.

Hypothesis 4: There are differences in determinants of credit ratings used by different rating agencies.

Rating agencies vary in their approaches and methodologies of forecasting banks' ratings. In order to prove this hypothesis, some significant and consistent differences between rating grades by different rating agencies should be found. In this case, it will be also possible compare these rating agencies and judge about their relative impulsiveness or conservatism.

3. Data and methodology

3.1. Generation of a representative sample from the empirical data

The paper is based on the Bankscope database by Bureau van Dijk. The quarterly data was extracted for the period from 1996 to 2011. In order to generate a representative sample, data filtration methods were applied. The focus of this paper is individual, profit maximizing banks, so all state-owned, worldwide and central banks were omitted. However, the main reduction of the sample size appeared due to the fact that only a small share of banks (3256 banks) was assigned a rating grade by at least one of the main rating agencies: Moody's, Standard&Poor's or Fitch. Moreover, the Bankscope database provides only data about the last change of a bank's rating: the date of change, previous and current rating. That means the creation of a panel or time series sample is impossible, so cross-sectional data was considered.

In this paper two different types of numerical assignment of rating grades were considered. The first method implies ranging specific grades beginning from 1 assigned to best rating. However, the difference between groups such as AA + and AA may be too small to be properly modeled, for this reason a less precise division of ratings into classes was considered. Ranging grades by classes implies assignment of the same numerical value to the group with the same number of letters, ignoring the signs "+/-" and the numbers "1,2,3" in the rating scale of Moody's.

However, while constructing a representative sample, several problems were revealed. First, there is a large number of gaps in the database. Second, financial data is not proportionally distributed across the quarters. These problems lead to a significant reduction in the sample size. In order to overcome this discrepancy, the Matlab code was created. It takes average values from the two nearest observations. Moreover, data on banks whose ratings were not changed for more than one year were used again as the new observations with the same rating grade as before, but with new financial indicators at the new moment of time. This approach has significantly increased number of observations and the predictive power of the model.

3.2. Empirical Methodology

The data specification in this study has a discrete form of the dependent variable (rating grade or rating class). Therefore, the usage of the traditional method of least squares is impossible. Since a rating is a qualitative and ordinal variable, the most appropriate methodology is an ordered multinomial model (ordered logit / probit model). The analyzed score is estimated as a linear function of independent variables and a set of boundary values. The probability of achieving the outcome i is represented by the probability that the sum of the estimated linear function and a random error will be located inside the boundary of estimated values:

$$\Pr(outcome_k = i) = \Pr(cut_{i-1} < x_k'\beta + \epsilon_k \leq cut_i) \quad (1)$$

In the Formula 1 i is a forecasted score, which describes the desired variable; $x_k{}'$ − vector of independent variables; β − vector of estimated regression coefficients; cut_1 , cut_2 … cut_{j-1} − boundary values estimated by the model; $cut_0 = -\infty$; $cut_j = +\infty$, j − number of values which the dependent variable can take; ϵ_k − random error that has logistic or standard normal distribution.

The probabilities are calculated using the function of the standard normal or logistic distribution. In ordered multinomial models coefficients are estimated by maximum likelihood and an indicator of a predictive power of the model is pseudo-R2. However, this technique is optimal only on infinite samples. That is why such a thorough work was made in order to increase the number of observations.

4. The model and its predictive power

4.1. Model's description

The model introduced in this paper allows interested agents to determine the probability of different long-term ratings for international banks, having at their disposal only public information. This model was constructed for each subsample of rating agencies Moody's, Standard&Poor's and Fitch and for the total sample. The results obtained by the ordered probit regressions are shown in Table 2.

From the table 2 it can be seen that the model forecasts ratings' specific grade worse than overall ratings' class, as regressions 1, 3, 5 have a lower explanatory power (Pseudo - R2) than regression 2, 4, 6, 7. That was expected, since the grade forecast is more detailed than the class one. However, the analysis of rating grades is crucial as most previous studies tried to predict only the class of a rating, while this paper evaluates both types of rating classification. Also, the results show that, in terms of statistical characteristics (Pseudo - R2), both models with different specifications of the dependent variable have greater explanatory power in a regression based on a sample of banks' ratings that were assigned by the agency Fitch (5, 6), compared with Moody's (1, 2) and Standard&Poor's (3, 4). This could be due to the large number of observations in this subsample. Indeed, it can be seen that Pseudo- R2 is directly proportional to the number of observations (the greatest value achieved in the total sample), which proves the consistency of the model on large volumes of data.

All signs of coefficients coincide with their expected impact on ratings for all regressions. Impact of the ratio of loan loss reserves to gross loans appeared to be significant and almost the same in all models: the high level of reserves indicates the presence of "bad" loans issued by bank and leads to a downgrade in its rating. The ratio of equity to debt, which shows the structure of the bank's capital, appeared significant only in models built on the total sample and on the sample of ratings by Moody's. In the model an increase in bank's debt, which means a decrease in the ratio of equity to debt, corresponds to a lower rating forecast as the sample is dominated by banks with a very large volume of debt financing. Another parameter, the ratio of operating expenses to revenues, adversely affects rating of a bank and is significant in all models. The logarithm of total assets shows the size of a bank and has a positive relationship with the bank's financial stability. However, its influence is most clearly revealed in the methodology of Moody's. The ratio of other earning assets to total earning assets shows the diversification of banking revenues and is significant only in the regressions for the total sample (7) and for the agency Standard&Poor's (3, 4). The interbank ratio shows the share of issued loans in overall received funds on interbank market. With the increase in this coefficient a bank becomes less dependent on interbank loans and therefore its rating is raised. This parameter is highly significant in the regressions constructed from the total sample, and according to Fitch, but it is not important in terms of methodology Standard&Poor's and only partially significant for Moody's. Also, the dividend payout ratio, showing the profitability and sustainability of the enterprise, has a positive and significant effect in all models. The current liquidity of a bank is also a very important factor in evaluating its rating. A higher level of current assets compared to current liabilities increases the forecast of a bank's rating.

Moreover, the ratings assigned by Moody's are higher than by Fitch, because the coefficient of the dummy variable for Moody’s is negative and significant in the regression 7. Standard&Poor's, on the contrary, understates the rating grades compared to the other two rating agencies. The degree of influence of these two tendencies is approximately the same. This trend refers to the forth hypothesis and is further discussed in the next section. The second hypothesis of the paper is not rejected as the dummy variable for developed countries has a positive significant effect on ratings in all samples. This variable has the greatest weight in the Moody's methodology, compared to the other agencies.

Table 2. The results of credit rating models for different rating agencies forecasting overall rating class or specific rating grade

Dependent var. Independent var.	1. Moody’s (grade)	2. Moody’s (class)	3. S&P (grade)	4. S&P (class)	5. Fitch (grade)	6. Fitch (class)	7.Total (class)
Loan loss res / Gross loans	0,128***	0,136***	0,128***	0,122***	0,129***	0,111***	0,128***
	(0,017)	(0,019)	(0,023)	(0,025)	(0,017)	(0,016)	(0,011)
Equity / Debt	-0,012***	-0,014***	-0,015*	-0,012	-0,006	-0,012*	-0,014***
	(0,008)	(0,004)	(0,009)	(0,009)	(0,006)	(0,006)	(0,003)
OPEX / Operating income	0,008***	0,012***	0,011***	0,011***	0,005***	0,006***	0,008***
	(0,002)	(0,002)	(0,003)	(0,003)	(0,001)	(0,002)	(0,001)
Log total assets	-0,962***	-0,911***	-0,411***	-0,341***	-0,517***	-0,524***	-0,445***
	(0,052)	(0,057)	(0,03)	(0,03)	(0,021)	(0,021)	(0,015)
Other earning assets / Total earning assets	-0,706***	-0,631**	-0,575**	-0,719**	-0,319	-0,377*	-0,477***
	(0,266)	(0,289)	(0,278)	(0,321)	(0,215)	(0,217)	(0,153)
Interbank ratio	-0,0005***	-0,0005***	-0,0003*	-0,00008	-0,0004***	-0,0005***	-0,0003***
	(0,0002)	(0,0002)	(0,0001)	(0,0002)	(0,0001)	(0,0001)	(0,0001)
Dividend payout ratio	-0,0016***	-0,0015**	-0,002***	-0,002***	-0,0005*	-0,0004	-0,0008**
	(0,0007)	(0,0007)	(0,0007)	(0,0007)	(0,0002)	(0,0004)	(0,0003)
Current ratio	-0,002*	-0,004**	-0,006***	-0,005***	-0,0014	0,0009	-0,002**
	(0,001)	(0,002)	(0,001)	(0,001)	(0,0013)	(0,0013)	(0,0008)
Moody’s	–	–	–	–	–	–	-0,302***
							(0,047)
S&P	–	–	–	–	–	–	0,291***
							(0,047)
Developed country	-0,775***	-0,655***	-0,155*	-0,12*	-0,285***	-0,244***	-0,551***
	(0,119)	(0,137)	(0,072)	(0,041)	(0,069)	(0,083)	(0,049)
Inflation	0,12***	0,126***	0,129***	0,141***	0,068***	0,093***	0,108***
	(0,012)	(0,012)	(0,016)	(0,016)	(0,006)	(0,007)	(0,006)
Trade balance	-0,026***	-0,025***	-0,023***	-0,022***	-0,017***	-0,011***	-0,019***
	(0,003)	(0,003)	(0,004)	(0,004)	(0,002)	(0,002)	(0,002)
GDP per capita	-0,00003***	-0,00003***	-0,00002***	-0,00002***	-0,00003***	-0,00003***	-0,00003***
	(0,000003)	(0,000003)	(0,000003)	(0,000003)	(0,000002)	(0,000002)	(0,000001)
Before crisis (1996-2007)	-0,471***	-0,521***	-0,449***	-0,611***	-0,548***	-0,661***	-0,551***
	(0,079)	(0,09)	(0,088)	(0,04)	(0,067)	(0,075)	(0,049)
Year 2008	-0,551***	-0,578***	-0,712***	-0,793***	-0,389***	-0,536***	-0,537***
	(0,118)	(0,132)	(0,134)	(0,151)	(0,097)	(0,115)	(0,073)
Year 2009	0,231**	0,191**	0,161*	0,089	0,042***	0,332***	0,213***
	(0,095)	(0,085)	(0,088)	(0,098)	(0,052)	(0,092)	(0,071)
Year 2011	0,196**	0,16*	0,087	0,064	0,026***	0,29***	0,178***
	(0,081)	(0,087)	(0,096)	(0,103)	(0,074)	(0,08)	(0,05)
Number of observations	1094	1094	832	832	1498	1498	3421
Pseudo-R^2	22,65%	34,02%	20,55%	30,49%	22,7%	34,9%	35,1%
AIC	4316,914	2247,154	3055,793	1533,042	5729,552	2978,392	6975,02
BIC	4476,837	2352,104	3206,955	1636,967	5888,909	3095,253	7122,324

* significant at 10%; ** significant at 5%; *** significant at 1%.

Moreover, macroeconomic variables such as inflation, trade balance and GDP per capita appeared to be significant even at 1% level and have approximately the same level of influence in all regressions (the first hypothesis is not rejected). Time indicators reveal a tendency for a sharp deterioration of credit ratings after the 2008 worldwide crisis. Before the crisis, and in its early stages in 2008, all three rating agencies assigned higher ratings. Then in 2009 the effects of the global crisis were reflected in credit ratings. That is confirmed by the positive sign of the coefficient. In addition, over time the negative effect of the crisis slowly diminishes as the positive coefficient in 2011 decreases for all tested samples. Therefore, the third hypothesis of the paper (credit ratings are not changed during the transition to another stage of the business cycle) should be rejected. This can be explained by the fact that global crisis is a longer-term phenomenon compared to a short-term downturn in a specific economy, and it can affect both: cyclical and potential indicators. The existence of a time lag proves that a rating agency does not change the assigned rating immediately, but only if there is sufficient information about the long-term impact of the changes.

4.2. Check of the predictive power of the model

First, in order to verify the predictive power of the models with different specification of the dependent variable their in-sample fit was analyzed. The results of models' in-sample fit for ratings' overall class forecasts are shown in Figure 1.

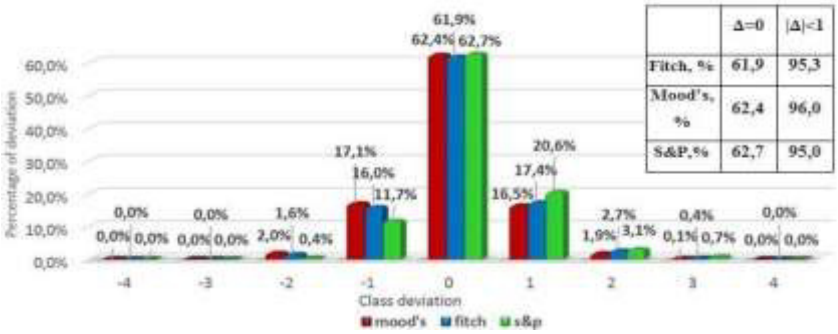

Fig. 1. Distribution of deviations of class forecasts of the models based on samples of Moody's, Standard&Poor's and Fitch (%)

The results show that the model has a high internal predictive power for rating forecasts by all three rating agencies. The share of exact rating forecasts (Δ=0) on average was about 62%, while over 95% of the predictions of these models had a deviation of not more than one rating class from the actual rating. Moreover, up to 20% of ratings assigned by Standard&Poor's were predicted to be one rating class higher by the model (|Δ|<1). This is partly due to the overall insufficient significance of the variables used in the model. But also this result indicates that Standard&Poor's is the most cautious in assigning high ratings. The distribution of forecast errors for this company is asymmetric and is dominated by positive deviations of actual numerical ratings from what the model predicts which means the actual ratings in this case are lower than the forecast. At the same time, the similar distributions built for Moody's and Fitch have a more or less symmetric shape with respect to zero, although Moody's has a slight tendency to overstate ratings relative to the model forecasts (proportion of negative deviations prevails). This tendency is underestimated due to the model's general previously identified trend of overestimating the ratings forecasts.

From this analysis we can conclude that the rating agency Standard&Poor's is the most conservative in assigning ratings, while Moody's is the most liberal. This result coincides with the conclusion drawn from the analysis of the coefficients of the dummy variables for a rating belonging of to a specific rating agency.

The analysis implies some general tendencies of rating forecasts. First, in all rating agencies the largest proportion of the forecast deviation occurs when evaluating the best and worst banks. This may be due to the lowest number of observations for these credit organizations in the data sample. Another possible explanation is a significant degree of influence of qualitative non-financial parameters (which cannot be fully incorporated in the model) for the banks with the highest and lowest rating. Second, a general trend of decline in the predictive power of forecasting a bank's rating that relate to the transition class from investment to speculative rating (Baa) can be found from the data above. The model consistently overestimates the actual rating in the following situation. Previous studies (Karminsky and Peresetsky 2007; Amato and Furfine 2004) confirm our findings in both of these tendencies.

The next stage is the check of the in-sample fit of the model that predicts specific rating grades. The results are presented in Figure 2.

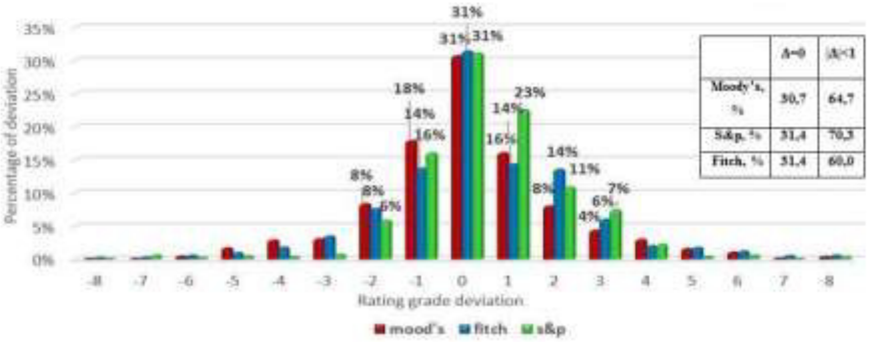

Fig. 2. Distribution of deviations of grade forecasts of the models based on samples of Moody's, Standard&Poor's and Fitch (%)

The fall in the internal predictive power of the model is due to the more detailed classification of the ratings. Using the model one can forecast not only the class of a bank's rating (e.g. AAA or AA), but also the rating grade itself (e.g. AA+ or AA-). However, such a detailed classification leads to more variation in forecast error. Thus, the share of exact predictions of a rating grade is on average 31% among models for different rating agencies. Moreover, the maximum share of the predictions within a deviation of one grade from the actual rating level is 70% and is achieved in the model, based on a sample of data from Standard&Poor's. With more detailed predictions all the tendencies described above for the class forecasts remain present and can be seen even more clearly. Figure 2 shows that Standard&Poor's underestimates the rating grades according to this model (green distribution is skewed to the right) and Moody's on the contrary assigns higher ratings (red distribution is skewed to the left). Analyzing the distribution of the forecast errors of Fitch, we can conclude that it is the most symmetric with respect to zero, but the general trend of overstatement ratings predicted by the model is still present (there are some positive outliers in the blue distribution).

The second part of this section is devoted to the analysis of the external predictive power of the model. In order to accomplish this task, the data was limited to observations from the time period of 1996-2010. Based on the new coefficients of the model the forecast for the year 2011 was made. To calculate the predicted ratings by a multinomial ordered probit model the predicted probabilities of each rating grade were calculated as the difference between the values of the standard normal distribution (Φ) at two points that were calculated using the estimated boundary values (cut_j) and the product of vectors of estimated coefficients (β) and the values of explanatory variables for the year 2011 (x'_k) according to the formula:

$$\Pr(outcome_k = j) = \Phi(cut_j - x'_k\beta) - \Phi(cut_{j-1} - x'_k\beta) \tag{2}$$

After composing a panel table of the predicted probabilities of banks ratings, the rating grade with the highest probability was selected as the model's forecast. Then the predicted rating was compared with the actual one assigned to a bank in the year 2011, and the distributions of forecast errors, illustrated on Figure 3, were composed for both types of the rating models.

	Δ=0	|Δ|≤1
Grade, %	24.0	56.5
Class, %	53.3	93.2

Fig. 3. Distribution of deviations of class (the graph on the left) and grade (the graph on the right) forecasts for the year 2011 (%)

The results show a slight expected deterioration in the predictive power under the out-of-sample fit check. Nevertheless, the model can accurately predict the grade of the expected rating with a probability of 24% and its class with a probability of 53.3%. In addition, the analysis of the external power of the model shows that in 93.2% of cases, the prediction error of the expected rating of a bank will not exceed one rating class and a maximum deviation in one gradation will be observed in 57 cases out of 100. Based on this analysis we can conclude that this model can have a practical use for predicting the ratings of international credit organizations.

5. Conclusion

In this paper banks' credit ratings models of international agencies were constructed. The study can be useful for banks themselves, regulators and banks' counteragents for an early forecast of deterioration in banks' financial stability. The practical significance of this study is conditioned by the introduction of the obligatory estimation of the internal ratings of banks and by the easy and fast way of evaluating a bank's financial performance based only on publicly available information.

During the research the following conclusions were made (All findings are based on the sample from Bankscope database for the period from 1996 until 2011 that was obtained by means of a special program in Matlab):

1. The significant financial variables that affect banks' credit ratings were: ratio of loan loss reserves to gross loans, ratio of equity to liability, cost to income ratio, log of total assets, interbank ratio, ratio of other earning assets to total earning assets, dividend payout ratio, current ratio.

2. The explanatory and predictive power of the model is increased by the additional use of macro variables, such as inflation, the trade balance and the level of GDP per capita, which supports the first hypothesis of this study.

3. The usage of the dummy variable for affiliation to developed countries allows us to take into account the significant regional impact on the rating of a bank.

4. Whether the rating was assigned before / after the crisis is also a significant factor of ratings change so the third hypothesis of this study about the absence of the effect of the business cycle stage on rating was rejected. The existence of a time lag in rating assignments led to results showing that the impact of the global crisis that began in 2008, was reflected in bank ratings only in 2009 and gradually decreased until 2011.

5. The model based on the total sample of all rating agencies showed the significant differences in their methodologies which supported the fourth hypothesis of this paper. Thus, it was shown that Standard&Poor's is the most conservative, while Moody's assigns a higher rating than its competitors.

6. The final model is useful for predicting rating grades, as it gave 31% of precise results and up to 70% forecasts with an error within one rating grade, while predicting of rating classes resulted in 62% and 95% respectively.

The fundamental contribution of this paper is the study of a new source of extensive empirical data, the formation of a new approach in dealing with incomplete and asymmetric data and in construction of a model with a unique set of indicators that precisely predicts rating grades. In order to improve the quality of the model, some more qualitative variables such as the quality of corporate governance, risk assessment of the loss of key employees, the organizational complexity of the credit institution could be used. Moreover, the separate modeling and further use of the corruption index, market power, and factors of external support as explanatory variables in a rating model should increase its predictive power.

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