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ORIGINAL PAPER

Modelling banks' credit ratings of international agencies

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Abstract The aim of this paper is to construct a reliable banks' rating model for the main international agencies based on public information for the potential practical use. The Bankscope database for the period from 1996 to 2011 was used in the research. The ordered probit models show that inclusion of macroeconomic variables as well as the regional dummies improve their explanatory power. Moreover, the significance of the time dummies allowed us to conclude that rating agencies do change their grade when an economy operates on the different business cycle stages. Furthermore, the conclusions of a conservative nature of Standard & Poor's ratings and overvalued Moody's grades compared to the rating agency Fitch were performed. The models were checked for the in-sample and out-of-sample fit including distributional comparisons across agencies. The obtained model was classified as practically useful, as it gave 31 % of precise results and up to 70 % forecasts with an error within one rating grade. Moreover, 62 % of rating classes of banks were predicted without an error and more than 95 % of rating classes' forecasts had an error within one rating class.

Keywords Bank · Credit rating · Ordered probit model · Rating agency

JEL classification G21 · G33

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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 government. Successful forecasting of a possible bankruptcy at an early stage allows a regulator to take adequate precautionary measures.

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 a company belongs based on the probability of nonfulfillment of its obligations. Ratings play a substantial part in the area of business-information because they create investment potentials, indicate promising opportunities to allocate financial resources, encourage business confidence levels, and help in choosing counteragents. Therefore, the assignment of a rating not only reflects its past financial characteristics but also has a significant indirect effect on the future activities of an institution, as each bank seeks to maintain and improve its rating. Thus, the effective functioning of a rating agency results not only in detection of problems, but also in their solution. In addition, ratings are becoming increasingly important with the introduction of the internal rating approach (IRB-approach), provided in the “Basel II” agreement, and the extensive usage of scoring models for internal control.

In this context, the paper is aimed at creating a reliable model of a rating’s forecast based on publicly available information. The relevance of this paper is determined by the solution of one of the most important issues of a rating’s business: the process of full assessment of a bank’s financial performance by a rating agency is costly and time-consuming and agencies may not react in time (Duff and Einig 2009; Bellotti et al. 2011). Moreover, the credibility of a rating agency, that is based on its fulfillment of the key principles of objectivity, transparency and independency of the rating process, has been repeatedly challenged (Altman and Rijken 2004; Amato and Furfine 2004). In addition, a large number of credit institutions remain uncovered by rating agencies. Therefore, the possibility of a quick and easy forecast of a bank’s rating grade with the help of the proposed model will be useful for all bank’s counterparties.

The novelty 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, including macroeconomic and institutional factors, that precisely predicts rating grades. Moreover, it should be noted that most of the authors in their research have evaluated the risks of deteriorating in financial performance of a bank (downgrade), while this work is focused on forecasting not only lowering but also raising a bank’s rating. Furthermore, most of previous studies tried to predict the class of a rating, while this paper evaluates both types (grade and class) of rating classification.

The paper is structured as follows. Section 2 represents the literature review, where a table of factors that have potential influence on a bank’s rating is constructed and the hypotheses of the research are formulated. Section 3 illustrates the analysis of empirical data used for the research, the problems encountered in the formation of a representative sample and the theoretical foundations of the econometric methodology. Section 4 deals with the construction of the models for forecasting a bank's rating, the check of goodness of fit of these models and the hypotheses testing. Finally, in Sect. 5, the results of econometric analysis are discussed and conclusions are formulated.

2 Review and comparative analysis of credit rating's models

2.1 Evaluation of a bank's rating according to methodologies of international rating agencies and academic literature

There are different types of credit ratings that can be classified on the basis of time horizon (long term, short term), currency (local currency, foreign currency), aspect of worthiness (overall credit rating, issuer rating characterizing ability to honor issued securities). Another classification divides ratings to the Bank Financial Strength Rating (BFSR) without external support (stand-alone) and the long-term deposit rating (DR). The latter method implies adding external factors that influence the performance of a bank, such as support factors, currency risks and sovereign rating. It was contemporaneously developed by the world's largest rating agencies: Moody's, Standard & Poor's and Fitch (Öğüt et al. 2012) and by academic researchers (Karminsky and Peresetsky 2007, 2008; Vasilyuk and Karminsky 2011). This research is based on a long term stand-alone rating forecast.

There are several methodologies to select relevant indicators for forecasting the financial health of a bank, among them are BFSR and CAMELS. In this research it was decided to use the first methodology since it is broader and is used by major rating agencies.

According to the Moody's report (Moody's Investors Service 2011), methodology BFSR is formed from the five key groups of parameters: franchise value, risk positioning, regulatory environment, operational environment and financial fundamental. Each of these groups of parameters consists of the relevant factors that affect the rating of a bank. In order to take in account these factors in a model for each of them a suitable coefficient (ratio) should be found. A review of academic literature (Afonso 2002; Ayvazian et al. 2011; Karminsky et al. 2013; Karminsky and Kostrov 2014; Karminsky and Sosyurko 2010; Kostrov and Karminsky 2014; Lazarides and Drimpetas 2016) is summarized in Table 1. Note that the expected impact of each indicator (ratio) on a bank's rating is also indicated below: "+"—rating upgrades, "−"—rating downgrades, "±"—ambiguous influence.

The traditional models of banks' ratings focus on the financial performance, but in the current literature authors recommend using several additional factors, such as macro variables, dummy variables and institutional variables that should be discussed in details (Berger et al. 2000; Grunert et al. 2005).

Studies of banking activity in developed countries often show that the usage of market-based macroeconomic indicators significantly increases the predictive power of models (Bellotti et al. 2011; Gropp et al. 2006; Karminsky and Peresetsky

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 × (1-dividend–payout ratio)	+
Market share	1. Revenue market share (%) = 100*net interest revenue ($)/total (country) market interest revenue	1. +
	2. Individual bank's total assets/total assets of all banks in the country	2. +
	3. Size estimate = log of total assets	3. +
Market power or 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 = ratio of interbank deposits placed over interbank deposits purchased	+
Geographical diversification	1. Diversification of investment portfolio across different geographic regions	1. +
	2. Number of foreign countries where a bank operates	2. +
Earnings stability	Volatility of earnings = percentage from one standard deviation of the variability around the trend line fitted through 3–5 years of earnings' history with a scale ranging from 1 to 99	–
Earnings diversification	1. Other earning assets/total earning assets	1. +
	2. Loans to banks/total earning assets	2. +
	3. Income from derivatives, other securities/total earning assets	3. +
2. Risk position		
Corporate governance	1. Value of government bonds/total assets	1. +
	2. Value of shares by foreign shareholders/equity	2. +
	3. Equity/number of shareholders	3. +
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)—the ratio of the maximum possible amount of losses on loans to the volume of financial resources of a bank	–
3. Regulatory environment	1. Indicator of regulator's independency	1. +
	2. Availability of a deposit insurance	2. −
4. Operational environment		
Stability of the economy	1. Macroeconomic variables (listed below)	1. +
	2. Sovereign rating	2. +
	3. Economic freedom index	3. −
	4. Corruption perception index (transparency international methodology)	4. −
5. Financial fundamental		
Profitability	1. ROA, ROE	1. +
	2. Net interest margin = interest income−interest expenses	2. +
	3. Net interest revenues/average assets	3. +
	4. Income net of distribution/average equity	4. +
	5. (EBIT + loan loss provision)/risk weighted assets	5. +
	6. Dividend payout ratio	6. +

Table 1 continued

Factor	Potential indicator (ratio)	Expected sign
Efficiency	1. Cost to income ratio	1. −
	2. Operational expenses/operating income	2. −
Liquidity	1. Current ratio	3. +
	2. (Market funds−liquid assets)/total assets	4. −
	3. Deposits/equity	5. −
	4. Net assets/total deposits and other short term funding	6. +
	5. Liquid assets/total deposits and other short term funding	7. +
Capital adequacy	1. Tier 1 ratio	1. +
	2. Equity/total assets	2. +
	3. Capital/total assets	3. +
	4. Equity/debt (financial leverage)	4. ±
Asset quality	1. Impaired loans/gross loans	1. −
	2. Loan loss reserves/gross loans	2. −
	3. Impaired loans/(equity + loan loss reserves)	3. −
	4. Unreserved impaired loan/equity	4. −
Management quality	1. EBIT/total revenue	1. +
	2. EBIT/total assets	2. +
	3. Public deposits/total liabilities	3. +

2007; Teker et al. 2013). Among the used macroeconomic indicators are GDP per capita (+), real GDP growth (+), inflation (−), unemployment (−), CPI (−), government debt to GDP (−), current account balance (±), international reserves (+), dollar exchange rate (±), domestic savings to GDP (+). The expected sign of the influence of each indicator on a credit rating of a banking institution is provided in parenthesis. Alternatively, instead of using numerous macroeconomic variables, in the paper by Caporale et al. (2012) an overall country index, calculated according to the updated methodology, was introduced. This technique allows lowering the multicollinearity problem that arises due to the high correlations between the most of the macroeconomic indicators.

In addition, in many studies, for example in the paper by Distinguin et al. (2013) it was found that various qualitative factors such as regional affiliation of a bank and area of its activity have significant influence on its rating. In order to take in account these effects in the model, dummy variables should be used.

Another important factor that should be considered while modelling a bank's rating is institutional variables. Among them are the factors related to the control and regulation of a banking system as a whole and some economic relations, such as the level of corporate governance (Peresetsky and Karminsky 2008), quality of management and market position (Grunert et al. 2005). However, all of these variables are qualitative and hence require subjective evaluation of an expert in order to be transferred into a quantitative format.

In this research the model that forecasts a bank's rating using both financial and market indicators was established.

2.2 The formulation of hypotheses of the paper

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

2.2.1 Hypothesis 1: The usage of macro variables in a model of a bank's rating 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 government policies on the state-owned banks, and due to the interdependence of all banks, on the banking system as a whole.

2.2.2 Hypothesis 2: Regional affiliation of a banking organization 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. It is quite logical to suggest that banks from developed countries will have higher and less volatile rating grades than those from developing countries.

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

On the one hand, the rating of a bank should be fairly stable over time and obey «through-the-cycle» rule (Altman and Rijken 2004; Amato and Furfine 2004; Karminsky and Peresetsky 2007). However, on the other hand, the transition to another business cycle stage is often accompanied by the change not only in the macro parameters but also in a bank's financial stability. This is also worsened by the growth of uncertainty, as the duration of a business cycle may not be always predicted. In the case of rejection of this hypothesis the time lag of the influence of the transition to the other stage of a business cycle on a bank's rating should be analyzed.

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

Despite the fact that many rating agencies use similar letter designations, the approaches to financial analysis differ among them. In order to prove this hypothesis some significant and consistent difference between rating grades of different rating agencies should be found. In this case it will be also possible to judge about relative impulsiveness or conservatism of these agencies. In previous studies, it was observed that the rating agency Standard & Poor's is more cautious and conservative when evaluating the financial stability of banks, compared with its two largest competitors Fitch and Moody's. Also it was revealed that Moody's approach to the assessment of banking risks is the most liberal (Karminsky and Peresetsky 2007; Vasilyuk and Karminsky 2011). Moreover, this investigation will allow us to evaluate the quality of a bank in one more way, as according to Morgan (2002): the greater the difference between the scores of the various rating agencies, the lower the financial transparency of the bank.

3 Data and methodology

3.1 Formation of a representative sample from the empirical dataset

This research is based on the Bankscope database by Bureau van Dijk. The Bankscope provides quarterly financial data, general information about the banks, rating grades of the biggest rating agencies as well as institutional parameters and global macroeconomic indicators. There are more than thirty thousand banks in the Bankscope database and the data was extracted 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 the data about the last change of a bank's rating: the date of change, previous and current rating. This means that for each bank the rating is known only for one point in time at which there was a last change in rating. Therefore, the creation of a panel or time series sample is impossible, so the considered data is cross-sectional. Another feature of the data provided is its asymmetric distribution in the analyzed periods. The distribution of rating changes over time and between the agencies is illustrated on Fig. 1 below.

It can be seen from the graph that the largest proportion of the rating changes has been made during the most recent year of the sample. This is intuitively correct as large amount of banks' ratings are reconsidered annually or once in few years. Consequently, for most of the banks in the sample the rating was changed in the last 7 years of the analyzed time range.

3.2 Generation of depending and explanatory variables

Rating agencies assign their grades in a symbolic form. However, in order to obtain coefficient estimates in an econometric model these symbols should be transformed into numerical values. In this paper, two different types of numerical assignment of rating grades were considered. The first method (grade) implies ranging grades beginning from 1 that is given to banks with the best rating, and ending with the last biggest number for the worst rating. However, the difference between groups such as AA+ and AA may be too small to be properly modeled, for this reason less

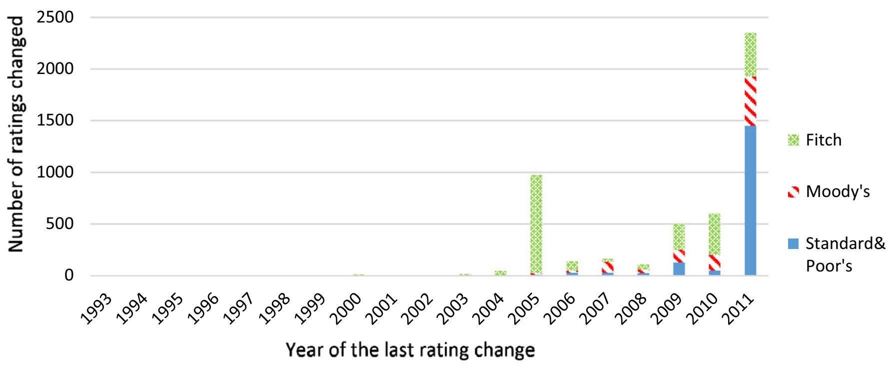

Fig. 1 Distribution of the last rating changes over time for Fitch, Moody's and Standard & Poor's (Source: author's calculations)

precise division of ratings into classes (class) should be also considered. Ranging grades by classes assigns the same numerical value to the group with the same number of letters, ignoring the signs "±" and the numbers "1, 2, 3" in the scale of Moody's. Two ways of transformation of a rating from symbolic to numeric form are summarized in Table 2 below. The more specific way is identified in the column headed "Grade numeration" and the other way in the column headed "Class numeration"

The first step of generation of the explanatory variables is choosing the optimal indicators (ratios) for all factors of a bank's rating considered in literature review. Then, the maximum correlation between the chosen parameters was set at 35 % in order to avoid multicollinearity. After forming a list of all possible parameters the most informative (those that have the biggest number of observations) of them were selected. After selecting the required parameters, we proceeded to the formation of the explanatory variables of the model. To do this, the values of the non-macro based indicators were taken with 6 months lag before the last rating change date. This time lag was chosen due to the fact that the process of assigning a rating by the rating agency takes some time to complete all the necessary procedures. The macroeconomic indicators are given on an annual basis, so the closest related year to the date of rating change was taken.

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 led to a significant reduction in the sample size. In order to overcome this discrepancy, the Matlab code that fills in the gaps by stepwise averaging was created. 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.

Table 2 Correspondence between symbolic and numeric forms of banks' ratings according to the grades of Moody's, Standard & Poor's and Fitch

Risk characteristic	Moody's	Fitch	S&P	Class numeration	Grade numeration
Prime	Aaa	AAA	AAA	1	1
High grade	Aa1	AA+	AA+	2	2
	Aa2	AA	AA	2	3
	Aa3	AA–	AA−	2	4
Upper medium grade	Al	A+	A+	3	5
	A2	A	A	3	6
	A3	A−	A−	3	7
Lower medium grade	Baal	BBB+	BBB+	4	8
	Baa2	BBB	BBB	4	9
	Baa3	BBB–	BBB−	4	10
Non-investment speculative grade	Bal	BB+	BB+	5	11
	Ba2	BB	BB	5	12
	Ba3	BB−	BB−	5	13
Highly speculative	Bl	B+	B+	6	14
	B2	B	B	6	15
	B3	B−	B−	6	16
Substantial risks	Caal	CCC	CCC+	7	17
Extremely speculative	Caa2	CC	CCC	7	18
	Caa3	C	CCC−	7	19
In default with little prosperct for recovery	Ca	–	–	8	20
In default	C	D	D	10	21

Source: author's calculations

3.3 Empirical methodology

The modelling of credit ratings may be performed by various methods. All of them may be subdivided into artificial intelligence methods and statistical methods. The latter includes linear probability models, discriminant analysis and multinomial choice models (Altman and Saunders 1998).

As the chosen data specification in this study has a discrete form of the dependent variable (rating), multinomial choice models are superior to both linear probability models and models of multiple discriminant analysis (Hájek and Olej 2010; Karminsky and Peresetsky 2007). As for the artificial intelligence (AI) methods, they are widely used during the last decade in academic research (Cao et al. 2006; Kumar and Bhattacharya 2006; Bellotti et al. 2011). However, Zan et al. (2004) and Lee (2007) in their papers showed that the predictions of AI models are not superior than the standard ordered multinomial models.

Since rating is a qualitative and ordinal variable, the most appropriate methodology is an ordered multinomial model (ordered logit/probit model). It should be noted that this method is different from the binary logit/probit models as the dependent variable takes more than two different values, and the models of multiple-choice (mlogit/mprobit) as the rating variable has significant inflexible order. 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 the random error will be located inside the estimated boundary values:

$$\Pr(outcome_k = i) = \Pr\left(cut_{i-1} < x_k'\beta + \varepsilon_k \leq cut_i\right), \text{where}$$

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

Thus, the probabilities are calculated using the following formulas:

$$\Pr(outcome_k = i) = \Pr\left(cut_{i-1} - x_k'\beta < \varepsilon_k \leq cut_i - x_k'\beta\right)$$

$$\Pr(outcome_k = 1) = \Phi\left(cut_1 - x_k'\beta\right) - \Phi\left(cut_0 - x_k'\beta\right) = \Phi\left(cut_1 - x_k'\beta\right)$$

$$\Pr(outcome_k = 2) = \Phi\left(cut_2 - x_k'\beta\right) - \Phi\left(cut_1 - x_k'\beta\right)$$

$$\ldots$$

$$\begin{aligned}\Pr(outcome_k = j) &= \Phi\left(cut_j - x_k'\beta\right) - \Phi\left(cut_{j-1} - x_k'\beta\right)\\ &= 1 - \Phi\left(cut_{j-1} - x_k'\beta\right), \text{where}\end{aligned}$$

Φ a function of the standard normal (probit) or logistic distribution.

In ordered multinomial models, coefficients are estimated by maximum likelihood and the indicator of a predictive power of the model is pseudo-R^2. Furthermore, in order to interpret the influence of an explanatory variable on the probability of one of the states of the dependent variable, marginal effects should be computed by the formula:

$$\frac{\partial \Pr(outcome_k = i)}{\partial x} = \varphi\left(cut_i - x_k'\beta\right) * \beta$$

However, it should be noted that this technique is optimal only on infinite samples. That is why such a thorough work was introduced in order to increase the number of observations.

4 The model and its predictive power

4.1 The basic model of ratings of international banks

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. The optimal set of indicators was selected on the basis of the most significant parameters, overall significance of the model (Pseudo-R2) and the smallest Akaike and Schwartz Information Criteria (AIC & BIC). Also the predictive power of the model (in-sample fit) and the coincidence with the expected sign of the coefficients were considered. During the comparative analysis of logit and probit regressions, the decision, based on the minimization of the AIC & BIC and the greatest number of significant coefficients, was made in favor of the probit model. The model was applied to each subsample of rating agencies Moody's, Standard & Poor's and Fitch and to the total sample. The results obtained by the ordered probit base regressions, which contain only parameters of bank's financial performance are shown in Table 3.

Since the grade forecast is more detailed than the class one, regressions 1, 3, 5 have a lower explanatory power (Pseudo-R^2) than regressions 2, 4, 6, 7. However, the results are still convincing, as most previous studies did not even try to predict the specific grade of a rating, while this paper evaluates both types of rating classification. In addition, the results show that Pseudo-R^2 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.

In order to interpret the signs of the estimated coefficients correctly one should remember that higher ratings correspond to lower values of the dependent variable as in Table 2. Keeping this in mind, we can conclude that 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 a bank and leads to a downgrade in its rating. The ratio of equity to debt, which shows the structure of a bank's capital, appeared significant only in models built on the total sample and on the sample of ratings by Moody's. This ratio is inversely proportional to the financial leverage. According to Modigliani–Miller's theorem in a world of perfect financial markets, without taxes and bankruptcy costs, the capital structure should not affect the value of the enterprise and, therefore, its rating. However, in the real world with an increase in debt financing one should balance the present value of tax shield (PVTS) with an increase in potential bankruptcy costs. Consequently, a slight increase in the debt obligation should have a positive impact on a rating, while massive debt financing should lower it. 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 a 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 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

Table 3 The results of a base credit rating model for different rating agencies forecasting rating class or rating grade

Dependent variable/independent variables	Estimated coefficients of the models						
	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 reserves/gross loans	0.159***	0.171***	0.148***	0.146***	0.169****	0.154***	0.162***
	(0.014)	(0.017)	(0.026)	(0.247)	(0.017)	(0.016)	(0.011)
Equity/debt	−0.011***	−0.01***	−0.006	−0.0004	−0.003	−0.006	−0.011***
	(0.003)	(0.003)	(0.008)	(0.008)	(0.006)	(0.006)	(0.003)
Operational expenses/operating income	0.009***	0.012***	0.009***	0.009***	0.007***	0.007***	0.007***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)
Log total assets	−0.909***	−0.861***	−0.398***	−0.333***	−0.477***	−0.482***	−0.42***
	(0.047)	(0.052)	(0.028)	(0.03)	(0.019)	(0.019)	(0.013)
Other earning assets/total earning assets	−0.261	−0.182	−0.748**	−0.908***	−0.135	−0.22	−0.41***
	(0.233)	(0.252)	(0.321)	(0.333)	(0.207)	(0.204)	(0.144)
Interbank ratio	−0.0004**	−0.00007	−0.0003	−0.0001	−0.001***	−0.001***	−0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Dividend payout ratio	−0.0025***	−0.003***	−0.002***	−0.002***	−0.001**	−0.0009**	−0.001***
	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0003)	(0.0003)	(0.0003)
Current ratio	−0.004***	−0.005***	−0.004***	−0.003***	−0.004***	−0.002	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0007)
Moody's	–	–	–	–	–	–	−0.237***
							(0.046)
S&P	–	–	–	–	–	–	0.203***
							(0.045)

Table 3 continued

Dependent variable/independent variables	Estimated coefficients of the models						
	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
Number of observations	1109	1109	836	836	1501	1501	3443
Pseudo-R2	0.149	0.228	0.149	0.207	0.169	0.252	0.253
AIC	4779.704	2647.724	3265.498	1732.345	6137.76	3410.339	8040.946
BIC	4909.996	2722.892	3388.443	1808.003	6265.294	3495.361	8157.684

Source: author's calculations

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

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. In addition, 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 (Topaloglou 2015). 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. These dummy variables showed significant results at 1 % level in all structural and functional specifications of the model.

4.2 The model with macro variables and time dummies

At the second stage, the basic model was extended by the inclusion of macroeconomic explanatory variables and dummy variables that reflect time characteristics (the year in which the rating was assigned and pre/post-crisis affiliation). The results of the ordered probit regressions are presented in Table 4.

The new specification of the model significantly improved Pseudo-R^2 indicator and reduced AIC & BIC. In regressions that forecast the rating grade, Pseudo-R^2 increased by 6–8 percentage points, while the rating class analysis improved by 10–12 percentage points. In addition, all newly added variables were significant and in line with the expected interpretation, at the same time not worsening the significance of the variables of financial performance. In Tables 3 and 4 coefficients of some variables like interbank ratio, dividend payout ratio, current ratio, ratio of operational expenses to income, equity to debt ratio and gdp per capita are small (<0.01). However, these coefficients are not only statistically, but also economically significant. That conclusion was made by estimating standardized coefficients (coefficients divided by corresponding standard deviation). The change in probability for one instant change in any of these variables was at least 3 percentage points and all of the marginal effects were significant.

The interpretation of financial indicators in this model coincides with the base one. The dummy variable for membership of developed countries, which was not previously used in the base model, has a positive effect on a rating and is significant at 10 % level in all samples. This variable has the greatest weight in the Moody's methodology. Macro variables such as inflation, trade balance and GDP per capita (measured in dollars for all countries) were significant at 1 % level and have approximately the same level of influence in all regressions. While an increase in the level of GDP per capita, which is the main indicator of economic development of a country, increases the rating of a bank, an increase in inflation negatively affects it. The trade surplus has an ambiguous effect on the rating. It indicates the export orientation of the economy that is inherent mainly to developing countries with low sovereign rating. However, a sustainable current account deficit results in a high proportion of borrowing from the international market. If a negative trade

Table 4 The results of an extended credit rating model for different rating agencies forecasting rating class or rating grade

Dependent variable/independent variables	Estimated coefficients of the models						
	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 reserves/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)
Operational expenses/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)

Table 4 continued

Dependent variable/independent variables	Estimated coefficients of the models						
	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
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-R2	0.227	0.341	0.206	0.305	0.227	0.349	0.351
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

Source: author's calculations

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

balance is worsened by the poor quality of public administration, aimed at obtaining short-term gains, its negative impact on the macro-economic welfare of the country is only strengthened. In the model, the positive effect of increasing the trade balance on the level of the predicted rating is dominant. Regarding the newly added time indicators, in all samples there is a tendency for a sharp deterioration of credit ratings in 2009, which was due to the 2008 crisis. Before the crisis, and in its early stages, 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 a positive coefficient in 2011 decreases for all samples.

4.3 Hypotheses testing

The first hypothesis that the use of macro variables in the model will improve its predictive power was not rejected. This conclusion is based on the fact that all the added macroeconomic indicators were significant at 1 % level and Pseudo-R^2, together with the in-sample fit of the model, rose compared to the base one.

The second hypothesis (impact of the regional affiliation of banking institution on its rating) was not also rejected, as the dummy variable for developed countries was significant. A bank's rating is higher if it is located in a developed country.

The third hypothesis that the ratings are not changed during the transition to the other business cycle stage was rejected. Almost all regressions' coefficients of the time dummies within the extended model were highly significant and had stable signs. These parameters illustrate a significant tendency for a sharp deterioration of credit ratings in 2009, which was due to the 2008 crisis. 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.

The fourth hypothesis is aimed to verify the existence of differences in the rating's determinants used by different rating agencies. The model has shown that the given specification describes the Moody's methodology better than the methodologies of the other rating agencies. This conclusion can be drawn from the fact that all coefficients in the regressions 1 and 2 appeared to be significant at least at 10 % level. However, when the regressions were conducted based on rating assignments of Standard & Poor's or Fitch, some variables became insignificant. This fact illustrates the difference in methodologies of these rating agencies. In addition, from the total sample regression analysis, it can be concluded that Standard & Poor's understates banks' ratings and Moody's overstates them relative to Fitch. This trend is further discussed in the next section.

4.4 Checking the predictive power of the models

First, we analyzed the in-sample fit of the base and extended models constructed from the total sample of all three agencies in order to find out whether the

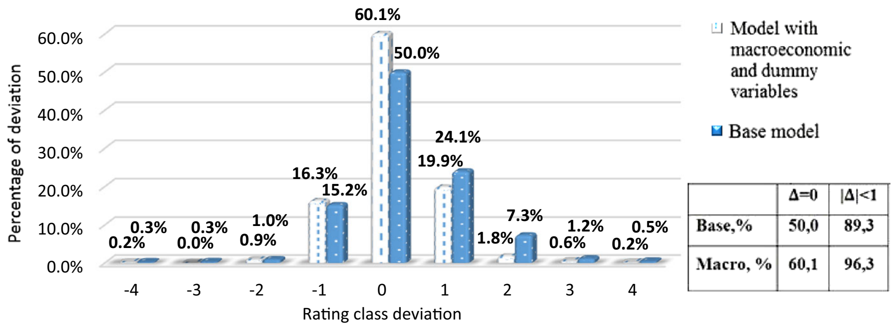

Fig. 2 Distribution of deviations of class forecasts of the base model and the model with macroeconomic variables (%) (Source: author's calculations)

macroeconomic parameters and the new dummy variables had improved the predictive power of the model. The results are shown on Fig. 2.

Figure 2 shows a clear improvement of the model's predictive power with the use of macro variables. The share of correct rating forecasts ($\Delta = 0$) has increased by 10 percentage points and was 60 % in the extended model. In addition, the percentage of forecasts with a deviation of not more than one rating class from the actual rating ($|\Delta| < 1$) also increased from 89.3 to 96.3 %. The base model had the property of overestimating the rating predictions, as can be seen from the disproportional distribution of forecasted errors illustrated above. Figure 2 shows that in the base model the positive prediction error dominates the negative one, which means that the actual numeric ratings exceed their forecasts in this model. However, the decreasing numerical values assigned to ratings relative to their symbolic grades (Table 2) means this tendency implies the reverse: the ratings forecasted by the base model are overstated. This is less of a problem in the extended model, since the distribution of its forecasted errors is much more symmetric with respect to zero. On the basis of this research, it was decided to use only the extended specification of the model in all further analysis.

The next step was a comparative analysis of the predictive power of the models, depending on the specification of their dependent variable and on the data samples on which these models were constructed. First of all the model that forecasts the rating class was compared for the sub samples of Moody's, Standard & Poor's and Fitch's rating grades. The results of its in-sample fit are illustrated on Fig. 3.

The results show that the model has high in-sample fit for all three rating agencies. The share of exact rating forecasts 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 the ratings assigned by Standard & Poor's were predicted to be one rating class higher by the model. This result indicates that Standard & Poor's is the most cautious in assigning high ratings compared to Moody's and Fitch. The distribution of forecast errors for this company is asymmetric and is dominated by positive deviations of actual numerical ratings from the estimated values, which means the actual ratings in this case are lower than forecast. At the same time, the distributions built for Moody's and Fitch have a more

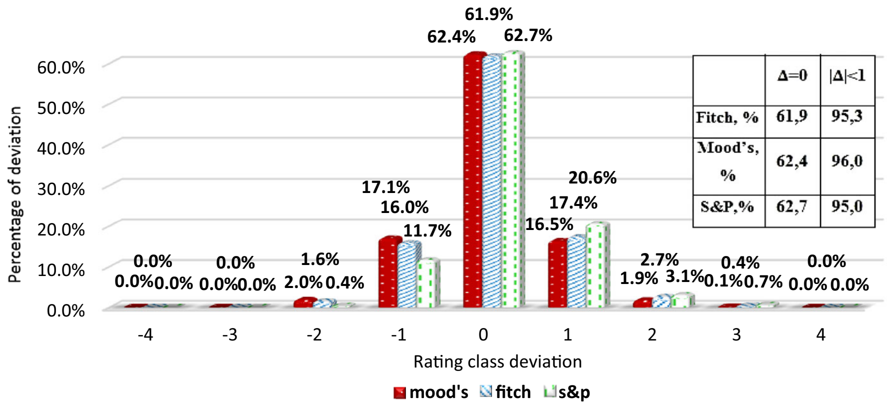

Fig. 3 Distribution of deviations of class forecasts of the models based on samples of Moody's, Standard & Poor's and Fitch (%) (Source: author's calculations)

or less symmetric shape with respect to zero, although Moody's has a slight tendency to overstating relative to the model forecasts (proportion of negative deviations prevails). This tendency is mitigated by the fact that the model itself tends to overestimate the rating.

From this analysis we can conclude that the rating agency Standard & Poor's is the most conservative in assigning ratings, while Moody's agency is the most liberal. This result coincides with the conclusion drawn from the analysis of the coefficients of the dummy variables. For a more detailed analysis of the forecasted errors, Table 5 was constructed.

Similar tables were constructed for Standard & Poor's and Fitch and some general tendencies of rating forecasts can be found. For example, 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 sample of data. 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 ratings. Moreover, a general trend of decline in the predictive power of the model for the transition class (from investment to speculative rating) "Baa" can be found from the data above. These findings confirm previous studies (Karminsky and Peresetsky 2007; Amato and Furfine 2004).

The next stage is the check of the in-sample fit of the precise model that predicts rating grades. The results are presented on Fig. 4.

The fall in the in-sample fit of the model is due to the more detailed classification of the ratings. The share of exact predictions of a rating grade is on average 31 % among the 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 Standard & Poor's sample. Figure 4 shows that Standard & Poor's underestimates the rating grades according to this model

Table 5 Classification of deviations of the class of the predicted rating from the actual rating assigned by Moody's (%)

Moody's		Rating forecast, %							N
		Aaa (%)	Aa (%)	A (%)	Baa (%)	Ba (%)	B (%)	Caa (%)	
	Aaa (%)	**0**	100	0	0	0	0	0	6
Actual rating, %	Aa (%)	1	**42**	57	0	0	0	0	189
	A (%)	0	3	**85**	8	4	0	0	440
	Baa (%)	0	0	48	**41**	13	11	0	170
	Ba (%)	0	0	2	3	**85**	9	1	219
	B (%)	0	0	2	0	51	**20**	27	47
	Caa (%)	0	0	0	0	87	0	**13**	23

Source: author's calculations

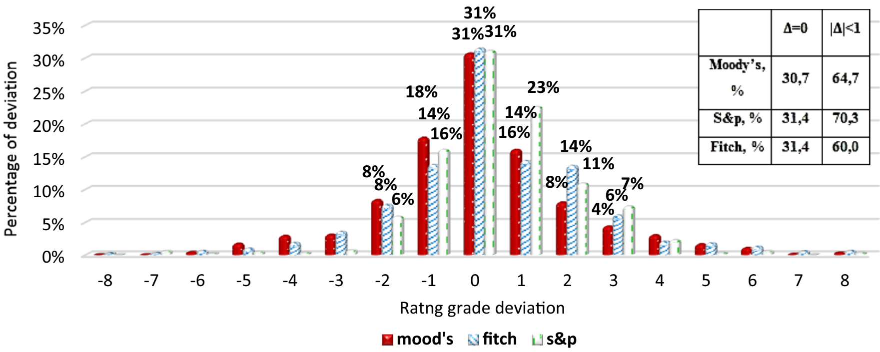

Fig. 4 Distribution of deviations of grade forecasts of the models based on samples of Moody's, Standard&Poor's and Fitch (%) (Source: author's calculations)

(green distribution is skewed to the right) and Moody's on the contrary assigns higher ratings (red distribution is skewed to the left).

The second part of this section is devoted to the analysis of the out-of-sample predictive power of the model. In order to accomplish this task, the data was limited to the observations from 1996 to 2010. Based on the new coefficients of the model, the forecast for the year 2011 was made. In order to calculate the predicted ratings, 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:

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

The rating grade with the highest predicted probability was selected as the model's forecast. Then the predicted rating was compared with the actual one

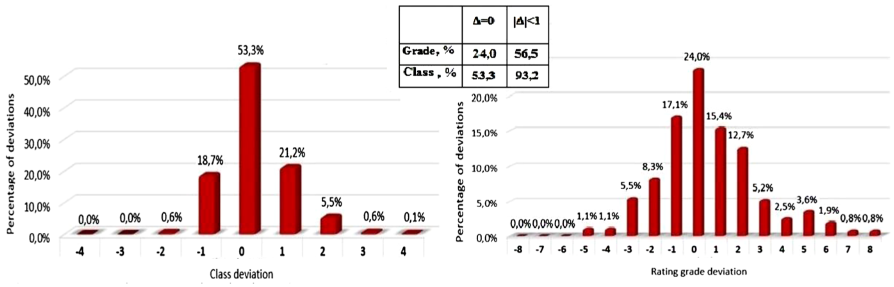

Fig. 5 and 6 Distribution of deviations of class (the *graph* on the *left*) and grade (the *graph* on the *right*) forecasts for the year 2011 (%) (Source: author's calculations)

assigned to a bank in the year 2011, and the distributions of forecast errors, illustrated on Figs. 5 and 6, were composed for both types of rating models (class and grade).

The results show a slight expected deterioration in the predictive power of the model 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 out-of-sample power of the model shows that in 93.2 % of the 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

This paper is devoted to the topic of current importance of constructing models for predicting credit ratings of international banks. The paper uses ordered probit models to predict international banks' ratings as assigned by the three main rating agencies (Fitch Ratings, Moody's and Standard and Poor's), using publically available data from 2006 to 2011. The determinants' analysis reflects the different assignment methodologies employed by the rating agencies. Thus, it was shown that Standard & Poor's is the most conservative, while Moody's assigns a higher rating than its competitors do. It is further found that inclusion of macroeconomic determinants improves the predictive performance of the models, that the regional location (in terms of developing or developed country) significantly influences a bank's rating as does the timing of the rating during the cycle (as assessed by the time period dummy variables). The models are checked for the in-sample and out-of-sample predictive fit including distributional comparisons across agencies. The obtained model is practically 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 class resulted in 62 and 95 % respectively.

In order to improve the quality of the research some more qualitative variables such as the quality of corporate governance (measured by indices like G-index and E-index), risk assessment of the loss of key employees, the organizational complexity can be used. Moreover, the separate modelling and further usage of corruption index, market power, and factors of external support should significantly increase predictive power of the model. Furthermore, some non-parametric methods like Decision Tree or ANN can be used in further research and the results should be compared with the probit model. The main advantage of these innovative methods is that they not only tell which variables are significant but also illustrates which variable is most significant, providing a ranking of them.

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