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JEL Classification (separated by "-")	G21 - G24 - G32	

The Synergy of Rating Agencies' Efforts: Russian Experience

Alexander Karminsky

Abstract We examine the synergy of the credit rating agencies' efforts. This question is important not only for regulators, but also for commercial banks if the implementation of the internal ratings and the advanced Basel Approach are discussed. We consider Russian commercial banks as a good example where proposal methods might be used. Firstly, a literature overview was supplemented with an analysis of the activities of rating agencies in Russia. Secondly, we discussed the methods and algorithms of the comparison of rating scales. The optimization task was formulated and the system of rating maps onto the basic scale was obtained. As a result we obtained the possibility of a comparison of different agencies' ratings. We discussed not only the distance method, but also an econometric approach. The scheme of correspondence for Russian banks is presented and discussed. The third part of the paper presents the results of econometric modeling of the international agencies' ratings, as well as the probability of default models for Russian banks. The models were obtained from previous papers by the author, but complex discussion and synergy of their systematic exploration were this paper's achievement. We consider these problems using the example of financial institutions. We discuss the system of models and their implementation for practical applications towards risk management tasks, including those which are based on public information and a remote estimation of ratings. We expect the use of such a systemic approach to risk management in commercial banks as well as in regulatory borders.

Keywords Econometric model • Mapping • Rating • Rating scale • Risk management

JEL Classification G21, G24, G32

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1 Introduction

Ratings have been an essential tool for risk evaluation for more than a century and their range of use is still growing. Ratings transform a great volume of information into the rating agencies' opinion on the current financial stability and risk of an entity. They represent the result of a complex assessment of separate companies or single financial instruments (further named as entities). An increasing number of banks, especially those from emerging markets, have become a part of the rating systems in recent years, and the expectation that banks and other entities are going to be rated has become conventional. Rating costs are relatively low for both the issuers and the investors, but the percentage of all banks and companies with ratings is still not large. Moreover, there are no widely accepted instruments to compare rating estimations by different agencies.

Previous research has shown that ratings are *important for many reasons*, including: regulatory rules, as well as the Basel Accords, asset management and investors for portfolio allocations, government and market regulation covenants for investments and participation at financial tenders and auctions, information for fixed income and equity markets, and so on.

We should also mention that interest in resolving these issues is still increasing. The development of approaches based on internal ratings systems under the Basel II Accord (Basel 2004) has a practical interest for internal ratings and their models that would help to predict the credit ratings of banks using only freely accessible public information, especially for developing markets. The topic has received increased attention in connection with the global crisis that began in 2007 and the implementation of Basel III (Basel 2010). The regulation of rating agencies' activities was one of the main topics of the G20 meeting in Moscow in February 2013 (G20 2013).

The key goals of this research are to develop methods of comparison and to compare the bank ratings of the main rating agencies from different points of view. We focus on the synergy of the common use of the ratings of an entity estimated by different agencies, as well as cooperated internal ratings in this integration process. We also consider previous ratings and the probability of default models of different entities to extend the sphere of influence of rating methods for risk management.

For this purpose we executed an analysis of the connected literature, as well as the dynamics of the process of setting ratings to Russian banks (Sect. 2), considering different methods and algorithms for the comparison of ratings (see Sect. 3). Particular attention is devoted to the rating business in Russia and the comparative analysis of ratings of Russian banks that has been rapidly developing and redeveloping in recent years and has involved substantial efforts by the rating agencies.

Later on in Sects. 4 and 5 we discuss the rating model system, which has been obtained in previous papers from the synergy position. We briefly discuss the structure and parameters of the databases, the type of econometric models (order and binary choice), the financial and macroeconomic indicators for the models, and the comparison of the main international ratings connected with Russian financial institutions. Conclusions are provided in last section.

2 Comparison of the Ratings: Literature and Practice Overview

The process of rating assignment is similar for different international rating agencies. Frequently, agencies publish their methodologies. However, they do not include detailed information, but rather general directions for rating assessment.

The basic problem for using credit ratings by regulatory bodies and commercial banks is the comparability of the ratings from different agencies. From a practical point of view it is important to compare ratings. So the question is how a relationship between the rating scales can be found when different levels of defaults and expected losses are established.

2.1 Rating Comparisons in the Literature

Among the first papers aimed to compare the ratings of different agencies was the one by Beattie and Searle (1992). Long-term credit ratings were gathered from 12 international credit rating agencies (CRA) that used similar scales. The sample of differences between the pairs of ratings for the same issuer was found. Around 20 % of the pairs in that sample involved differences in excess of two gradations. That may be explained by differing opinions about the financial stability of the issuers, as well as by different methodologies used by the rating agencies. But the average difference between ratings of the main international agencies S&P and Moody's was insignificant.

Cantor and Packer (1994) compared Moody's ratings of the international banks with the ratings of nine other rating agencies. It was found that the differences were greater on average than those discussed earlier. The average rating difference among the biggest international and three Japanese rating agencies was nearly three gradations.

The CRAs sometimes explain this effect in terms of a conservative approach when dealing with an unrequested rating because they do not have as much information about a company with which they have a rating contract, as they would with a company that has entered into a rating agreement. Poon (2003) empirically concluded that unrequested ratings were lower on average than the requested ratings, and found that the effect could be explained as self-selection.

The questions connected with the desire of issuers to use rating shopping to obtain the best ratings were developed to overcome the difficulties to apply ratings for regulatory aims (Cantor and Packer 1994; Karminsky and Peresetsky 2009).

A lot of studies have analyzed the reasons for differences in ratings from different agencies rather than constructing a mapping between the different scales. Liss and Fons (2006) compared the national rating scales supported by Moody's with its global rating scale.

Ratings have also been compared in Russia by some authors (Hainsworth et al. 2012), according to Russian bank ratings connected both national and international agencies. Matovnikov (2008) looked at the relationship between the gradations of rating scales and the total assets and capital of banks. Hainsworth used an iterative application of linear regressions to find mappings between the rating scales of all the credit rating agencies.

A wide array of literature on rating modeling uses econometric models; for example, for bank ratings (Caporale et al. 2010; Iannotta 2006; Peresetsky and Karminsky 2011). Typical explanatory variables from publicly available sources have been defined for models of ordered choice. Examining changes in rating gradation over time for a limited sample of international CRAs was fulfilled.

The selection of the explanatory variables is an important step for the elaboration of such models. Firstly, quantitative indicators that are employed by the rating agencies may be examined (see, for example, Moody's 2007), as well as non-confidential indicators that have previously been employed by other researchers. Typical informative indicators are connected with the CAMELS classification and include the size of the company, its profitability, stability, liquidity, and structure of the business, as expressed through companies' balance-sheet figures. In recent years, the use of such factors as state support for banks or companies, and support from the parent company or group of companies has also become more frequent.

Secondly, the use of macroeconomic indicators has become popular recently (Carling et al. 2007; Peresetsky and Karminsky 2011). Among the most common indicators there are inflation index, real GDP growth, industrial production growth and oil prices, and changes in the foreign exchange cross-rates of currencies for export-oriented countries. Because of the correlation between the majority of macroeconomic indicators they may be used mostly separately. Thirdly, the potential efficiency of market indicator exploration (Curry et al. 2008) for public companies should be mentioned. It should also be noted that alternate indicators may be informative for developing and developed markets.

At the Higher School of Economics and the New Economic School in Moscow there has been research on modeling the ratings of international credit rating agencies in Russia (Peresetsky et al. 2004; Karminsky et al. 2005; Peresetsky and Karminsky 2011). These studies have focused on finding economic and financial explanatory factors, that affect ratings, and on comparing the ratings of international agencies.

2.2 *Dynamic of the Rating Agencies Activities in Russia*

The growth of the number of Russian agencies ratings has been significant in recent years. Four Russian rating agencies achieved registration in the Russian Ministry of Finance as well as three international ones. Due to this fact, the question of the integration of these agencies' efforts and comparison of their rating scales is important. As for now we have nearly 700 ratings for banks only. We observed a threefold growth in 5 years (2006–2011). We also see that the number of ratings given by Russian agencies is roughly similar to the international agencies' ratings (Karminsky et al. 2011a, b).

Despite the comparative growth in the number of ratings, the rating methods are largely unclear, and expertise plays a significant role. This hinders the usage of ratings for risk evaluation and decision-making even at the state level. It is the reason for interest in the creation of internal ratings and model ratings.

Our long-term goal is to research the possibility of forecasting company ratings based solely on publicly available information, including indicators from international financial reports and market conditions on stock exchanges.

3 Comparison of Ratings: Methods and Algorithms

The rating process has some problems, such as

- A relatively small number of updated communicative ratings.
- Difficulties of comparison of estimation between different rating agencies.
- Absence of any integrative effect from available competitive estimations of independent agencies.
- A demand for extended usage on independent rating estimations primarily owing to modeling techniques.

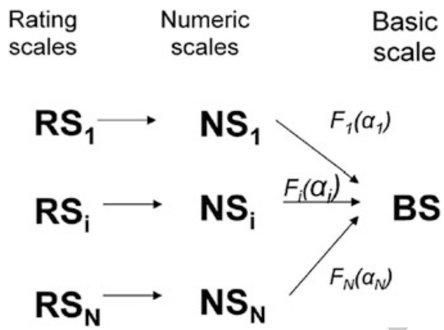
We aim to achieve a comparison capability of independent estimations of different ratings. In this way the elaboration and development of the approaches and methods are especially urgent because of synergy opportunities connected with the limitations mentioned above. For these aims the Joint Rating Environment (JRE) was introduced, and included a selection of basic rating scales, the building of a mapping system of external and internal ratings to a base scale, and the common usage of all rating estimations for every class of issuer or financial instrument.

We used statistical approaches to calculate the distance between different ratings for the same entities. Also we selected a basic scale, in which we proposed to measure the difference between ratings, and proposed to use mapping between rating scales, while our aim is to find functional approximations of such maps.

Econometric approaches were studied in the paper (Ayvazyan et al. 2011). In this method, firstly, the econometric order choice models for every CRA were determined. Then the correspondence between latent variables for the model for the basic CRA and every other CRA model in polynomial form was estimated. These gave an opportunity to determine the mapping of every CRA scale to the basic scale at last.

The main points of distance algorithm for the rating scales' comparison include not only the methodology of agency-scales mapping, principles and criteria for

Fig. 1 The system of scale mappings



comparison of rating scales, but also the choice of an optimization algorithm, the construction of a comparison scheme and a table, the principles of result auditing during that time and so on (Hainsworth et al. 2012).

In this paper Moody's rating scale is used as a basic scale, but the results must be practically invariant to the choice. The system of mapping, which was presented in Fig. 1, was established. In this figure the first group of mapping deals with the correspondence between the rating and numerical scales, which is reasonable because of the rating's orderliness. The mappings to the basic scale

$$F_i\ (\alpha_i) : \ NS_i \rightarrow BS$$

for every rating scale R_i were parameterized, and our aim is to find the vectors α_i for each scale i = 1, . . . , N, where N—the number of the scales.

We have considered some parameterization of mappings $F_i(\alpha_i) = a_{i1} * f_i(R_i) + a_{i2}$, using functions $f_i(R_i)$ from some classes and a vector of parameters of the map $\alpha_i = (a_{i1},\ a_{i2})$. At this step we have formulated the task of the parametric optimization problem. We used a square measurement between rating images in this research:

$$\min_{\{\alpha_i, i=1,\ldots N\}} \sum_{Q} \left(F_{i1}\left(R_{i1jt}, \alpha_{i1}\right) - F_{i2}\left(R_{i2jt}, \alpha_{i2}\right)\right)$$

Above we mean that

Q—the set of combinations of points over time
q = {quarter t, bank j, the rating of the basic agency R_{i1jt}, the rating of the other agency R_{i2jt}};
F_{i1} and F_{i2}—the maps for *i1* and *i2* scales as defined above.

During the research we compare linear, power and logarithmic function classes f_i, which were used for the evaluation of map dependences.

An additional analysis of the default statistics for Moody's and S&P gives us an opportunity to use a priority logarithmic approximation, which we use in this paper for empirical analysis. It must also be mentioned that for the previous problem we

Table 1 Table of parameters for bank scale mappings in a logarithmic model specification

AQ3
AQ4

Rating scale	a_{i1}	a_{i2}
Moody's (Russian scale)	0.254	2.202
Standard and poor's	0.916	0.146
Standard and poor's (Russian scale)	0.265	2.113
Fitch ratings	0.749	0.594
Fitch ratings (Russian scale)	0.213	2.162
AK&M	0.269	2.491
Expert RA	0.373	2.329
RusRating	0.674	1.016
National rating agency	0.163	2.474
Number of estimations	*3,432*	
Pseudo-R^2	*0.902*	

could have used econometric program packages such as eViews or STATA because of the use of the quadratic criteria (the experiments with other criteria showed the robustness of the comparison results).

We provided this analysis for both Russian and international data. For the Russian data we had a sample for a time span of 20 quarters (from 1Q 2006 till 4Q 2010), as well as the data for periods until 2012 in other examples. We have collected data from three international agencies (Moody's, S&P and Fitch) on both international and national scales, as well as from four Russian agencies (AK&M, NRA, RusRating and Expert RA). This sample has included 7,000+ pairs of ratings for 370 Russian banks with any rating during this time span.

The result of the optimization task decision is presented in Table 1.

The results derived from this can be presented both in scheme (Fig. 2) and table interpretations. At this point we have constructed a scale correspondence, which may be used in practice for regulatory and risk management purposes.

It should be mentioned that the correspondence between international agencies on traditional scales are not identical, and we can compare the difference between these agencies with the Russian banks.

It also should be noted that the results included in the scheme are stable. We have compared the results not only with a different base scale, but also with two different methods such as distance and econometric methods. The results obtained give us the opportunity to acquire comparable estimations of entities for both regulation and risk management aims.

For the international banks' models an accurate forecast was generated in nearly 40 % of cases. The forecasting power may be estimated by mistakes on the part of the models, which in the case of no more than two grades gave a probability of 1–2 %. These results were comparable with previous models, but extended to three international rating agencies simultaneously.

The signs for all the models were almost equal, and could be easily explained from a financial point of view. Coefficient sign analysis allowed us to make the following conclusions:

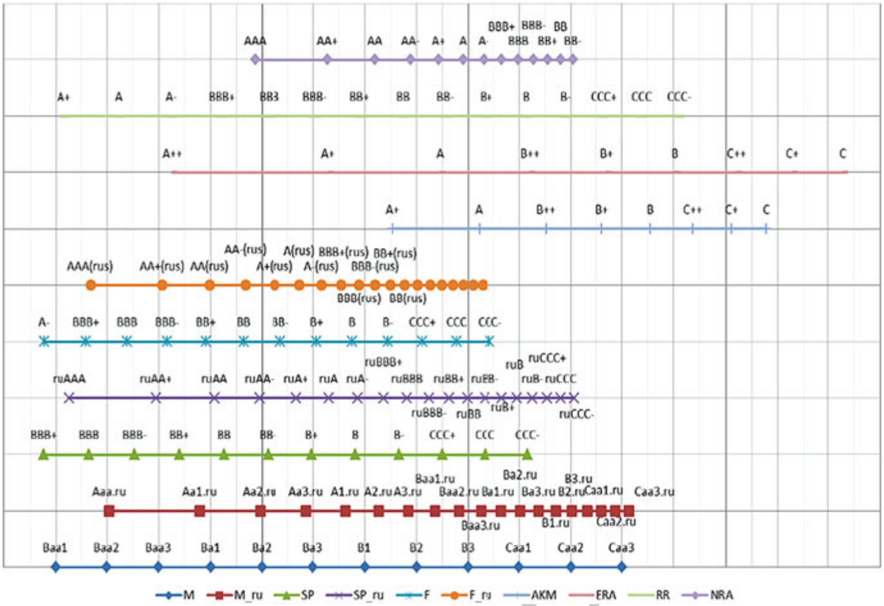


Fig. 2 Scheme of correspondence for CRA scales working in Russia

- The size of the bank is positive for a rating level increase, also as capital ratio and asset profitability as the retained earnings to total assets ratio.
- Such ratios as debt to asset and loan loss provision to total assets have a negative influence on the rating grade.
- Macro variables are also important for understanding the behavior of bank ratings, and are presented with a negative sign for the corruption index and inflation.

We also constructed models for Russian bank ratings using a Russian data base and have concluded that the influence of financial indicators is mainly the same (Vasilyuk et al. 2011).

4 Modeling of Ratings and the Probability of Default Forecast Models

A lot of research is devoted to the difference in the ratings of the main international CRAs. They provide adjustments of explanatory financial and macroeconomic variables on the new horizon analysis dependence of ratings on their affiliation to specific groups of countries, their degradation over time, lags between dependence and independence variables, etc.

Firstly, econometric rating modeling needs comprehensive and well-organized data. Secondly, the class of econometric models and principles of their verification should be selected. A modern risk management system based on best practice is the next important component. Finally, such a system needs domestic experience data that would take into account the specifics of a country.

In this section we systemize the practice of research of such models for banks, corporations and countries in Russian bank applications. Additionally we will discuss the opportunities of the probability of default models in the case of Russia. We use the existing experience of such research, which was obtained and published in previous works. In this paper we try to understand how this knowledge may be accumulated in the JRE system.

4.1 Models and Data for Bank Ratings

Here, and further in this section, ordered probit/logit econometric models were used to forecast rating grades (for example, see Peresetsky and Karminsky (2011)). Numeric scales for ratings were also used as a result of the mappings mentioned in Fig. 1. For the main international CRAs, nearly 18 corporate rating grades were used.

The original databases for different classes of entity were used. There were two different databases used separately for banks for both international and Russian ones. The first database was obtained from Bloomberg data during the period 1995–2009. The database includes 5,600+ estimations for 551 banks from 86 countries. The data contains the banks from different countries including more than 50 % from developed and 30 % from developing countries. Russian banks are also included in the sample and form nearly 4 %.

The second database was constructed from the data for Russian banks according to Russian financial reporting. It contains 2,600+ quarterly estimations from 2006 until 2010 for 370 Russian banks.

We carried out model choices from different points of view for three agencies simultaneously. We determined which financial explanatory variables were the most informative ones. Then we considered quadratic models, using macro, market and institutional variables, as well as dummies. We used a rating grade as a dependent variable where the lower numbers were associated with a better rating. So a positive sign in the coefficient related to a negative influence on the ratings, and vice versa.

AQ5 You can see the chosen models for international banks in Table 2 (Karminsky and Sosyurko 2011).

For the international bank models, an accurate forecast was generated in nearly 40 % of the cases. The forecasting power may be estimated by the mistakes of the models, which in the case of no more than two grades gave the probability of 1–2 %. These results were comparable with the previous models, but extended to three international rating agencies simultaneously.

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Table 2 Bank rating models: international banks

Variable	Influence	S&P—issuer credit	Fitch—issuer default	Moody's—bank deposits	Moody's—BFSR	
Ln (assets)	+	−0.523***	−0.561***	−0.545***	−0.383***	t5.1
Equity capital/total assets	+	−3.012***	−1.945***	−2.758***	−1.607***	t5.2
Loan loss provision/average assets	−	42.763***	37.284***	19.188***	12.245***	t5.3
Long-term debt/total assets	−	0.008*	0.017**	0.023***	0.020***	t5.4
Interest expenses/interest income	−	0.353***	0.277***	0.294***	0.171***	t5.5
Retained earnings/total assets	+	−9.841***	−5.063***	−1.404*	−2.345***	t5.6
Cash and near cash items/total liabilities	−	2.303***	1.814***	1.985***	1.917***	t5.7
Corruption index	−	−0.408***	−0.356***	−0.383***	−0.316***	t5.8
Annual rate of inflation	−	0.038***	0.020**	0.028***	−0.009*	t5.9
Exports/imports	+	−0.584***	−0.400***	−0.559***	−0.017	t5.10
GDP	+	−4.40***	−4.40***	−12.20***	−15.80***	t5.11
Pseudo R^2		*0.293*	*0.266*	*0.295*	*0.192*	t5.12
Number of estimations		1,804	1,985	1,787	1,897	t5.13

The signs for all the models were almost equal and could be easily explained from a financial point of view. Coefficient sign analysis allowed us to make the following conclusions:

- The size of the bank is positive for a rating level increase, as are capital ratio and asset profitability as the retained earnings to total assets ratio.
- Such ratios as debt to asset and loan loss provision to total assets have a negative influence on the rating grade.
- Macro variables are also important for understanding the behavior of bank ratings, and are presented with a negative sign for the corruption index and inflation.

We also constructed the models for Russian banks ratings using a Russian database, and have concluded that the influence of financial indicators is mainly the same (Vasilyuk et al. 2011).

4.2 *Models of Corporations and Sovereigns*

The sample of corporations included information from different industries (oil and gas, utilities, retail, telecom, etc.) and countries. We considered the rated companies from these industries which also had financial and market indicators. Financial explanatory variables included such group indicators as size of company, capitalization, assets, management, efficiency, and liquidity. Among the macro indicators it stands out on the corruption perception index by Transparency International. While among market indicators the volatility of the market prices stands out. We also added industry classification dummies, as well as such factors as groups of countries and a company's affiliation.

We used both the agencies' and Bloomberg data for this sample. Financial indicators were selected for 30+ countries during 2000–2009 for 211 corporations. Our database included nearly 1,800 estimations (non-balance panel) for three international rating agencies; S&P, Fitch and Moody's ratings.

Order probit model parameters are presented in Table 3. We do not have the opportunity to use all the explanatory variables. You can see the best models, which differed in profitability indicators (Karminsky 2010).

The signs for all three models are equal, and have a good explanation from a financial point of view. As for its interpretation, a positive sign of coefficient relates to a negative influence on rating, and vice versa, because of the fact that the scale mapping choice should be taken into account. From this model we can make the following conclusions:

- The size of the company, asset profitability and the EBITDA to interest expenses ratio have a positive influence on the rating level. A ratio such as LT Debt to Capital has a negative influence on the rating grade.

Table 3 Comparison of corporate rating models for international CRA

Variable	S&P	Fitch	Moody's
LN (market capital)	−0.692***	−0.806***	−0.691***
Sales/Cash	0.00004***	−0.00051	−0.00049
EBIT/interest expenses	−0.0017***	0.0006	−0.0054***
LT debt/capital	0.006***	0.011***	0.019***
Retained earnings/capital	−1.107***	−0.581**	−1.230***
Volatility (360d)	0.012***	0.013***	0.016***
Corruption perception index	−0.217***	−0.088***	−0.088
Chemicals	−0.235***	0.381***	−0.182
Metal and mining	0.322***	1.317***	0.947***
Pseudo-R^2	0.215	0.220	0.276
Number of observations	1,362	423	339
$\lvert\Delta\rvert = 0$	40.6 %	34.3 %	42.5 %
$\lvert\Delta\rvert \leq 1$	87.7 %	87.7 %	87.0 %

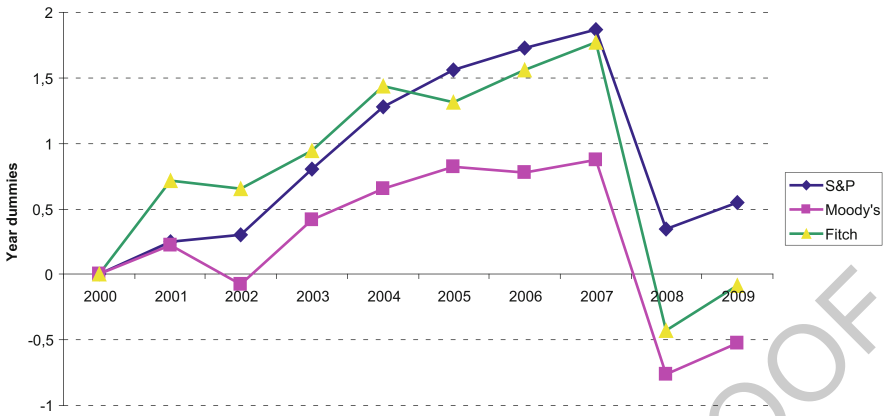

Fig. 3 Procyclicity of corporate ratings: year dummies dynamics

- Industry dummies are significant. We can see that companies from the utility and oil and gas industries have higher ratings.
- Market variables are also important for understanding the behavior of companies, for example, the corruption index has a negative influence.

Time has an important influence as well. We used a system of dummies during the years 2000–2009 to understand the impact of methodology and crisis. Most of the dummies are significant. We can see in Fig. 3 that all the agencies have the same procyclicity connected with the crisis of 1998 and 2008.

The main explanatory variables for sovereign rating models may be classified into 6 groups of quantitative variables such as: bank characteristics, economic growth, international finance, monetary policy, and public finance and stock market characteristics. In our research 30+ parameters from all groups were analyzed.

We also used dummies for regions, financial crisis type and indicators of corruption (CPI index). Our sample included nearly 1,500 estimations for 100+ countries during the 1991–2010 periods. We dealt with Moody's bank ceiling ratings as a sovereign rating proxy. The models are presented in Karminsky et al. (2012).

We derived a strong association of sovereign ratings with economic growth, the public sector, monetary policy, the banking sector, the foreign sector, stock market variables and geographical regions. The forecast accuracy of the models is higher for investment-level grades than for speculative-level grades.

The majority of working explanatory variables for higher-investment ratings consists of the financial sector variables and GDP per capita. The majority of working explanatory variables for speculative-grade ratings includes budget deficit, inflation growth rate, export-to-import ratio and GDP per capita.

4.3 Probability of Default Models

Here, and later in the paper, the default is understood as one of the following signals for its registration:

- A bank's capital sufficiency level falls below 2 %.
- The value of a bank's internal resources drops lower than the minimum established at the date of registration.
- A bank fails to reconcile the size of the charter capital and the amount of internal resources.
- A bank is unable to satisfy the creditors' claims or make compulsory payments.
- A bank is subject to sanitation by the Deposit Insurance Agency or another bank.

We propose a forecast probability of default (PD) model, which is based on the relationship between banks' default rates and public information. We have constructed a quarterly bank-specific financial database on the basis of Mobile's information from 1998 to 2011: data in accordance with Russian Financial Reporting Standards, taken from bank Balance sheets and Profit and Loss statements.

During a 14-year period there were 467 defaults in compliance with our definition, as well as 37 bank sanitations. The quarterly database created has a good coverage of default events and the banking sector. We have applied a binary choice logistic model to forecast default probability. The maximum likelihood approach is used to estimate the model. The sample was split into two parts: "1998–2009"—to estimate models, and "2010–2011"—to test the predictive power of the models.

Financial ratios used as explanatory variables were determined from the literature review and common sense. They were tested on their separating power between bankrupt and healthy banks, as well as being divided into blocks according to the CAMELS methodology. We have also employed non-linearities in our model and found the optimal lag on financial ratios.

- Macroeconomic variables are highly correlated, and there were only two variables used in order to account for the effect of the macroeconomic environment on bank performance: quarterly GDP growth rates and the Consumer Price Index. We also controlled for the impact of the following on a bank's default probabilities:
- Monopoly power of a bank on the market (with the Lerner index).
- Its participation in a Deposit insurance system (with a dummy variable).
- The territorial location of the bank's operational activity (Moscow or regional)

Our key findings (Karminsky et al. 2012) were that:

- Banks with extremely high and low profitability have higher default rates due to their impact on the default probability of the profit-to-assets ratio (poor and risky banks).
- Banks with a higher proportion of corporate securities in assets carry a higher risk of a price crash on the market.

- Lower turnover on correspondent accounts in comparison with total assets increases the probability of default (a bank's potential inability to make payments).
- Banks with a considerable number of bad debts are less stable.

Additionally, a growing consumer price index increases a bank's default probability:

- Inflation reduces the real return on loans.
- Depositors are able to withdraw money and deposit it into the bank again at a higher interest rate or spend it.

We have also found that banks with a higher monopoly power are financially stable. Moscow-based banks have higher PDs on average.

We have found no evidence that a bank's participation in the Deposit insurance system influences its PD. The explanation is that the set of System participants is too diversified. The out-of-sample prediction performance of the model (for 2010–2011) is prominent: over 60 % of bank failures were correctly classified with a moderately sized risk group.

At the same time, the developed model underestimated the default probabilities for 2009. This result reveals some unrecorded channels that significantly increased the risks during the period of the recent financial crisis.

5 System of Models and Synergy of Rating Estimations

Previously we considered the capabilities which were given to us by rating mappings and models. Later we will discuss the synergy of these approaches as instruments of the Joint Rating Environment system (JRE-system). Such a system may be used for risk management in commercial banks; its main components for financial institutions are presented in Fig. 4.

The main part of such a system is the correspondence between rating scales, including the connection with internal ratings. They provide the opportunity to compare different ratings, as well as to use a comparable estimation of ratings received by several models. The synergy of such estimations gives a basic scale by independent risk weightings.

The system of models brings to the IRB Approach some possibilities, among which there may indications such as

- A basic scale established for the development and practical usage of econometric rating models within the IRB-approach for Russian and international rating agencies.
- Rating scale comparison methods defined for different agencies including external and internal rating reconciliation.
- Rating estimation forecasting approach and banking risk measurement dependent on internal and external factors.

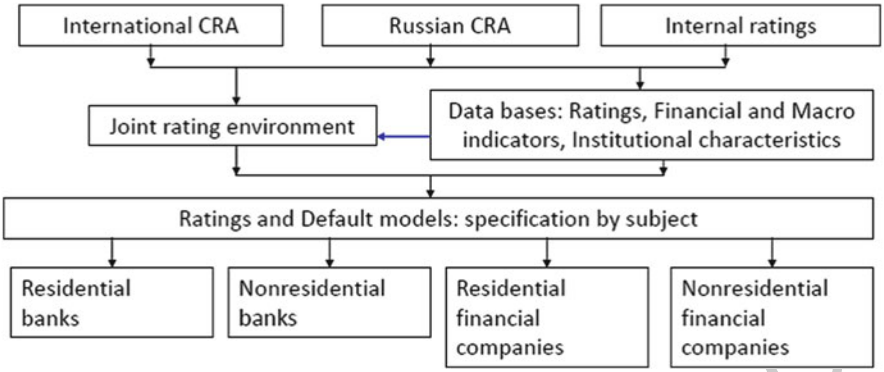

Fig. 4 Rating model system for financial institutions

- Rating forecasting for financial and non-financial companies which have no rating.
- Implementation of an econometric modeling system which requires:
  - Structured databases (data warehouse).
  - Support for all life cycle stages of models.
  - Monitoring, data gathering and the integration problem solution.

Of course such systems may be constructed for all types of entity, which were indicated at the specified risk management system according Basel II (Basel 2004). The details should be discussed for every bank or regulator separately. The discussion of these details is beyond the scope of this paper and may be done later.

Conclusion

We considered some methods of rating system construction, including a comparison of different rating estimates and modeling ratings for unrated entities.

The mapping of rating scales was introduced as the foundation for the comparison of rating scales using a distance method. We proposed this method for all the international and national agencies, which were recognized in Russia. This approach permits the synergy effect for rating agencies efforts as alternative opinions for risk management analysis. It may be combined with internal ratings for an increase in efficiency.

Moreover, the modeling and comparison of the main international rating agencies were discussed. Important factors were determined for such models as macro and market indicator influence etc. The remote assessment of econometric models should become a mandatory part of internal bank rating

(continued)

approaches. Data, monitoring and verification for econometric rating modeling were considered. The forecasting power of rating models was estimated, and it was quite high (up to 99 % with no more than a divergence of two grades).

Besides the bank rating models, the system should include corporate, sovereign and bond rating models. Some of them were presented in the paper, also as principles of their creations and main findings.

Bank and government financial regulators may be perspective users of the proposed methods. They can use such methods for the synergy of rating estimations.

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AUTHOR QUERIES

AQ1. Ref. “Karminsky et al. (2011)” has been changed to “Karminsky et al. (2011a, b)”. Please check, and correct if necessary.
AQ2. The citation “Ayvasyan et al. (2011)” (original) has been changed to “Ayvazyan et al. (2011)”. Please check if appropriate.
AQ3. The decimal comma has been changed to a decimal point in Tables 1, 2 and 3. Please check, and correct if necessary.
AQ4. Please provide the significance of “italics” in Tables 1 and 2.
AQ5. The citation “Karminsky and Sosyurko (2010)” (original) has been changed to “Karminsky and Sosyurko (2011)”. Please check if appropriate.
AQ6. Please provide the significance of “*, ** and ***” in Table 2.
AQ7. Please provide a definition for the significance of symbol “***” in Table 3.