Models for Moody's bank ratings

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2011

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Abstract

The paper presents an econometric study of the two bank ratings assigned by Moody's Investors Service. According to Moody's methodology, foreign-currency long-term deposit ratings are assigned on the basis of Bank Financial Strength Ratings (BFSR), taking into account "external bank support factors" (joint-default analysis, JDA). Models for the (unobserved) external support are presented, and we find that models based solely on public information can approximate the ratings reasonably well. It appears that the observed rating degradation can be explained by the growth of the banking system as a whole. Moody's has a special approach for banks in developing countries in general and for Russia in particular. The models help reveal the factors that are important for external bank support.

Keywords: Banks, Ratings, Rating model, Risk evaluation, Early Warning System
JEL Classification: G21, G32

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We are grateful to Selcuk Caner, Sergey Golovan, Mehmet Baha Karan, Pavel Katyshev, Iikka Korhonen and to participants in the Second International Credit Risk and Rating Conference (Ankara), Third Bachelier colloquium on mathematical finance and stochastic calculus (Metabief), 9th International scientific conference "Modernization of economy and globalization" (Moscow), and seminars at the New Economic School, CEMI RAS (Moscow), for discussions and to Andrey Miakonkih for research assistance.

1 – Introduction

The credit ratings of Moody's, Standard and Poor's, and Fitch play a key role in the pricing of credit risk. This role will be further expanded with the implementation of the Basel-2 Accord, which requires rating estimations of bank partners' credit risk.

These ratings are especially important for banks in developing countries, since economic agents there do not have long experience the market economy and so are not highly experienced in estimating risks. There are in fact few firms in these countries that have ratings by the international rating agencies. One of the reasons is that banks have to pay a lot to the agency for the rating procedure. For example, at the end of 2007, only 84 of 1135 Russian banks had Moody's ratings (about 120 had at least one rating by an international rating agency). Since Moody's rates more Russian banks than any other agency, we focus in this paper on Moody's ratings.

There are not enough observations on Moody's ratings of Russian banks for the purpose of econometric modelling, which is why we use a large sample of international banks (incl. Russian banks) in order to achieve model identification. The idea is that we can design a model based on a large international data set and tailor it to Russia with the relatively small data set that we have for Russia.

According to Moody's methodology [Moody's (2007a,b)], Foreign-currency long-term deposit ratings (DR) are assigned on the basis of Bank Financial Strength Ratings (BFSR), taking into account "external banks support factors" (joint-default analysis, JDA). We build models for both ratings.

Our paper contributes to the extant literature in two ways. First, we build econometric models of two Moody's bank ratings, including banks from developing countries (including Russia), using only publicly available information. We demonstrate that the goodness of fit of the models which use only public information is fairly good. Second, we use the models to study the "rating degradation" [Blume et al. (1998); Amato and Furfine (2004)], to demonstrate the special approach of Moody's to developing countries and to model the unobserved "external bank support factors" which Moody's experts take into account.

In practice, such models could be used by banks (in implementing the Basel-2 IRB approach) and by bank supervision authorities (as part of an Early Warning System, EWS), especially in developing countries, where there are still many banks without ratings.

There is a vast literature on econometric models of ratings. Altman and Saunders (1998) include a review of the approaches to modelling credit risk. The seminal paper by Altman and Rijken (2004) uses rating models to study the observed stability of ratings. Soest et al. (2003) were the first to model the ratings of Russian banks. Blume et al. (1998) use models to demonstrate "rating degradation" and find that rating standards have become more stringent in terms of the specific variables used in their study. By contrast, Amato and Furfine (2004) argue that this finding is overturned when account is taken of systematic changes in risk measures.

In 2007 Moody's introduced a new JDA (joint-default analysis) approach for assigning the Foreign-currency long-term deposit rating (DR) on the basis of Bank Financial Strength Ratings (BFSR), taking into account "external bank support factors" [Moody's, 2007a,b].

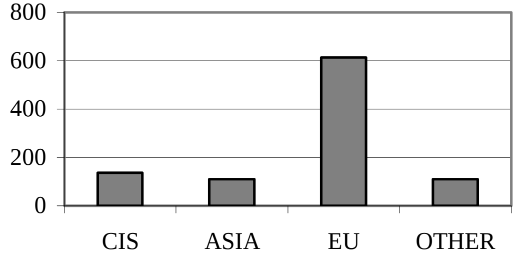
Moody's Bank Financial Strength Ratings (BFSR) represent Moody's opinion of a bank's intrinsic safety and soundness. Assigning a BFSR is the first step in Moody's bank credit rating process. BFSR is a measure of the likelihood that a bank will require assistance from third parties such as its owners, its industry group, or official institutions, in order to avoid a default. BFSR do not take into account the probability that the bank will receive such external support, nor do they address the external risk that sovereign actions may interfere with a bank's ability to honor its domestic or foreign currency obligations. DR (deposit rating) — as a view of relative credit risk — incorporates the Bank Financial Strength Rating as well as Moody's expert opinion of any external support.

We use our models to reveal which public information is helpful in forecasting "external bank support factors", i.e. we build a model for such (unobserved) "external bank support factors".

2 – Data

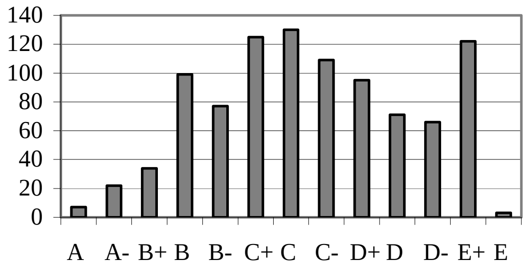
The dataset consists of financial indicators from the publicly available bank balance sheets of banks from 42 developed (DEV = 0) and developing (DEV = 1) countries for the period 2002–2005. Moody's bank ratings for these banks are available for the period 2003–2006. Overall there are about 1000 observations on some 380 banks. Fig. 1 presents the distribution of banks in the dataset which have BFSR over 4 regions. The distribution resembles that for all banks, except that North American banks are not included in the data.

Figure 1. Distribution of banks with BFSR over the dataset



The distribution of banks over BFSR rating categories is presented in Fig. 2. The two modes in the histogram can be explained by heterogeneous development of bank systems. Banks in developed countries generally have high ratings, the benefit of publishing low ratings being ambiguous. This contrasts with the situation in developing countries, where any rating by an international rating agency is a good sign. Due to country ceilings, most of banks from developing countries have BFSR ratings below D+.

Figure 2. Distribution of banks in dataset for BFSR rating categories



Correspondence between BFSR (E to A) and DR (B3 to Aaa) ratings in the world in January 2007 is presented in table 1. Each cell in the table gives the number of banks with the corresponding pair of ratings categories. Since most banks were concentrated along the diagonal, one is inclined to conclude that BFSR determines DR on the whole. However, some banks are concentrated above the diagonal, which means that some banks have DR ratings higher than BFSR ratings due to external bank support factors.

For model estimation, we use ordinal numerical scales for ratings from 12 to 0 for RFSR and from 15 to 0 for DR. Zero corresponds to the higher rating category.

Table 1. Correspondence between BFSR and DR ratings in the world, January 2007

	A	A–	B+	B	B–	C+	C	C–	D+	D	D–	E+	E
Aaa	**6**	1		1	2		3	2	1			1	
Aa1		**8**	2	4	2		3	3	2	1			
Aa2			**28**	16	2	2	6	2	1		1		
Aa3			2	**48**	18	15	11	9	8				
A1					**36**	15	13	11	16	1	1		
A2					2	**83**	23	19	16	6	7		
A3						1	**72**	15	17	10	10	2	
Baa1						1	4	**24**	13	6	5	1	
Baa2								**18**	10	14	12	11	
Baa3									**8**	5	4	3	1
Ba1									3	5	**6**	2	
Ba2								4	4	**11**	6	6	
Ba3						1	2	2	9	3	**24**	10	1
B1								1	9	7	5	**26**	3
B2										1	2	**39**	3
B3										1	3	**16**	

The financial indicators in the dataset and their descriptive statistics and correlations are presented in tables 5–7 in the Appendix. Financial indicators are grouped with respect to Moody's methodology [Moody's (2007a)]. The main groups are: size of the bank, capital adequacy, profitability, efficiency, and asset quality (table 6). For each group, the indicators are highly correlated, which is why it is not reasonable to include all of them in the models.

In addition to the bank financial indicators, the following variables are included in the models:

- Dummy variables: indicators of whether the bank belongs to the developing market (DEV = 1) and RUS = 1 if the bank is from Russia (therefore for bnk from Russia DEV = RUS = 1).
- Dummy variables for years D03–D05 for observations on financial indicators for 2003–2005
- Corruption perceptions index from Transparency International agency (2007), TI CPI

- Volatility of the country's economic growth; VOLAT has values from 1 to 5; the index is calculated according to Moody's methodology from the sample standard deviation of a country's nominal GDP growth for the last 20 years.

3 - Models

In this section, the two ratings (DR, BFSR) will be explained in terms of a small set of bank characteristics, time dummies and country-specific variables. Since a rating is a qualitative ordinal variable, the natural choice for ratings analysis is a model of ordered response (ordered logit). See [Kaplan and Urwitz (1979)] for the first application of this model to bond ratings. We use White-Huber standard errors to control for heteroscedasticity. In selecting a model, the main criteria are economic interpretation and certain statistical criteria: Akaike criterion, pseudo-R^2, and t-statistics.

Preliminary examination of the gaps between the time of actual rating observation and the time of observation of bank financial indicator reveals an "optimal" time gap of 18 months. (6, 12, 18, 24 months gaps are considered as candidates).

In table 2, two models for each of the two ratings are presented. The same set of regressors is selected for the two models, since in the next section these models are used for modelling external support. Bank financial performance indicators included in the models are presented in table 6 in the Appendix. As one can see from table 7, financial indicators for the same group are usually highly correlated, which is why only 1 or 2 of them are included in the model.

Models 1 and 2 are for DR rating. Model 1 uses the initial bank data and model 2 the quantile scales for bank financial indicators. To construct a quantile scale for the bank-specific variable x we use the share of banks in the sample for the given year t with values of variable x smaller than that of x_{it} for the given bank i. That is, in quantile scale regressions, we use $\tilde{x}_{it} = P(X < x_{it} \mid year = t)$ instead of x_{it}. Thus, in the regression in quantile scales, bank-specific variables reflect the relative position of the given bank in the banking system in the given year with respect to the corresponding variable.

Table 2. Models for DR and BFSR

		(1)	(2)	(3)	(4)
		DR	DR	BFSR	BFSR
		Natural	Quantile	Natural	Quantile
Year 2003	D03	0.586***	0.192	0.571***	0.005
		(0.153)	(0.154)	(0.158)	(0.156)
Year 2004	D04	0.660***	–0.011	0.869***	–0.059
		(0.151)	(0.145)	(0.162)	(0.151)
Year 2005	D05	1.332***	0.162	1.552***	0.133
		(0.320)	(0.319)	(0.321)	(0.364)
Developing market	DEV	–0.078	–0.342	2.058***	2.322***
		(0.263)	(0.277)	(0.350)	(0.312)
Russia	RUS	0.256	0.261	2.827***	2.176***
		(0.232)	(0.208)	(0.394)	(0.341)
Volatility of economic	VOLAT	–0.036	0.059	–0.034	–0.014
growth		(0.074)	(0.073)	(0.068)	(0.065)
Corruption index	TI CPI	–0.588***	–0.647***	–0.610***	–0.598***
		(0.045)	(0.046)	(0.047)	(0.047)
Logarithm of total	LTA	–0.734***	–4.576***	–1.159***	–7.419***
assets		(0.052)	(0.412)	(0.067)	(0.418)
Customer Deposits /	D_EQ	0.144***	3.094***	0.103***	1.419***
Shareholders' Equity		(0.015)	(0.295)	(0.016)	(0.329)
Shareholders' Equity	EQ_TA	0.088***	2.980***	0.031	0.255
(%) Total Assets		(0.022)	(0.455)	(0.023)	(0.473)
Problem Loans (%)	PL_GL	0.012	0.596*	0.087***	1.941***
Gross Loans		(0.010)	(0.313)	(0.025)	(0.336)
Personnel Expenses	PE_OI	1.451**	0.019	4.737***	1.159***
(%) Operation Income		(0.615)	(0.239)	(0.910)	(0.292)
Interest expense (%)	CIBL	0.386***	1.753***	0.407***	2.960***
Avg interest bearing		(0.074)	(0.622)	(0.101)	(0.788)
liabilities					
Interest Income (%)	YAEA	–0.035	–0.410	–0.119***	–1.657***
Avg Interest Earning		(0.037)	(0.518)	(0.038)	(0.639)
Assets					
Interest Expense (%)	IE_II	–0.0070	1.020**	0.0058	0.599
Interest Income		(0.0058)	(0.518)	(0.0088)	(0.590)
Pseudo-R^2		0.254	0.242	0.385	0.367

*,**, and *** — significant at 10%, 5%, and 1% level. Standard errors in brackets

Time dummies are positive and significantly different from zero in models 1 and 3 in natural scales. Moreover, the coefficient of the time dummy increases with time (e.g. 0.586, 0.660, and 1.332 for 2003, 2004 and 2005 in model 1). This means that if a bank keeps its financial indicators constant over time it gets a lower rating in 2005 than in 2002 (rating degradation). Consistent with the finding in [Karminsky and Peresetsky (2007)], the time dummies are insignificant in models 2 and 4 in the quantile scales. That is, if a bank keeps constant its relative position in the banking system, its rating does not change. This means that rating degradations observed in models 1 and 3 simply reflect the advancement of the banking system as whole. If a bank does not show "improvement" against a background of the general "improvement" of other banks, then its rating gets degraded. And if, for example, a bank grows in size at the same rate as the size of the banking system grows and the bank keeps its relative position in the system, its rating does not change.

However, the goodness of fit measure pseudo-R^2 is higher for models with natural scales (models 1 and 3) than for models with quantile scales (models 2 and 4), and therefore we use the models in natural variables below.

Both ratings are higher for large banks. Ratings are lower for banks with high ratios of customer deposits to shareholders' equity, since that ratio increases with risk. Poor quality of loans (problem loans as % of gross loans) also lowers the ratings. Inefficiency (high personnel expenses) lowers the ratings. Capitalization (equity-to-assets ratio) is significant only for the DR model, which might be explained by its being related to a bank's external support factors.

Given that all the other variables are fixed, the BFSR rating is lower for banks in developing markets and even lower for banks in Russia[1]. This means that political and structural risks are taken into account in BFSR ratings. The influence of those two factors (DEV, RUS) is less for DR; clearly, it is smoothed by external support, which is more pronounced in developing countries. This finding is in line with that of Somerville and Taffler (1995), who study *Institutional Investor* country credit ratings and frequency of arrears on external debt-service, and conclude that bankers are overly pessimistic about the creditworthiness of less-developed countries.

Banks in countries with high levels of corruption have on average lower ratings. (Recall that a low value of TI CPI means a high level of corruption).

Goodness of fit (pseudo-R^2) is higher for models of BFSR rating (0.36–0.38) than for DR rating models (0.24–0.25). This is to be expected, since DR includes by construction more expert opinions (e.g. external sup-

[1] We have also made that study for a few other developing countries: results are presented in table 8 in the Appendix.

port), and hence should be less suitable for modelling with publicly available data than BFSR ratings, which are stand-along ratings.

4 - Models for external bank support factors

According to Moody's methodology [Moody's (2007a,b)], a DR rating differs from a BFSR rating in terms of "external support" factors. One approach to determining which publicly available factors *q* are important for external support is to simply regress DR on BSFR and *q*. However, this procedure is made problematic by the fact that both DR and BFSR are discrete variables. We therefore resort to a more flexible procedure, as described below.

An ordered logit model is formulated as

$$y_i* = x_i'\beta + \varepsilon_i \ , \qquad (1)$$
$$P(rating_i = r) = P(c_{r-1} < y_i* < c_r) \ .$$

The forecast of the model "index" is $\hat{y}_i = x_i'\hat{\beta}$, which could be considered a latent variable, a continuous measure for the rating. Let $\hat{z}_i$ and $\hat{y}_i$ be estimated latent variables for the DR and BFSR ratings respectively. According to Moody's methodology, $\hat{z}_i$ contains information from $\hat{y}_i$ and additional information on external bank support factors. Thus we can regress $\hat{z}_i$ on a function of $\hat{y}_i$ and additional regressors (2). Then, if the additional regressors q_t are significant, they must be related to the external bank support factors:

$$\hat{z}_i = f(\hat{y}_i) + q_i'\gamma + \varepsilon_i \qquad (2)$$

Since the function is unknown, we calculate the Taylor expansion of that function of order k , the order being determined by the number of statistically significant powers of $\hat{y}_i$:

$$\hat{z}_i = \beta_0 + \beta_1\hat{y}_i + ... + \beta_k(\hat{y}_i)^k + q_i'\gamma + \varepsilon_i \qquad (3)$$

The results of regression (3) for $k = 5$ are presented in table 3 (β s are not shown); two regressions are presented: (0) without any factors *q*, and (1) with a set of factors *q* consisting of time and country-specific dummies. One can see that external support is lower in 2007 (recall that the dummy is related to the time of data observation and the rating is assigned 18 months later) and is higher for developing than for developed countries. In Russia, external support is even higher than the average support in developing markets. A high R^2 for regression (0) shows that BFSR largely determines RD (see table 1).

Table 3. Models for external support

	(0)	(1)
Year 2003	—	0.111** (0.058)
Year 2004	—	–0.021 (0.056)
Year 2005	—	0.462*** (0.154)
Developing market	—	–0.255** (0.114)
Russia	—	–0.873*** (0.105)
R^2	0.942	0.947
R^2 adjusted	0.941	0.946

*,**, and *** denote significance at 10%, 5%, and 1% levels.

We use model (1) from table 3 as a benchmark and add additional explanatory variables in the functional form $\gamma_1 q_i + \gamma_2 q_i^2$, assuming the possibility of a nonlinear impact of factor q. Then we test the null hypothesis of zero impact: $H_0 : \gamma_1 = \gamma_2 = 0$. Table 4 gives the results of such regressions, showing only the estimates for γ_1, γ_2, F-statistic and R^2. The factors are sorted in accordance with volume of impact on external support.

The last column indicates the direction of impact. Consider, for example, the interest income-to-earning assets ratio. The functional form is actually U-shaped, but the parabola vertex is at 48.8, which is much greater than the sample average of 6.8. Hence the larger the value of q (earning assets ratio), the larger the value of its impact $\gamma_1 q + \gamma_2 q^2$ and the lower the external support. We conclude that a high interest income-to-earning assets ratio indicates a low level of external support. Similar considerations imply that the relationship between bank size and the corruption index is U-shaped. External support is low for high and low values of the corruption index. A bank with bad loans needs external support, as do banks in countries with high volatility of economic growth.

Table 4. Models for external support

Factor	$\hat{\gamma}_1$	$\hat{\gamma}_2$	F-stat	R^2	Support
Interest Income (%)	0.194***	–0.0020***	396	0.971	–
Avg Interest Earning Assets	(0.011)	(0.0003)			
Problem Loans (%)	–0.069***	0.00001	278	0.966	+
Gross Loans	(0.005)	(0.00008)			
Corruption index	–1.088***	0.068***	180	0.961	∩
	(0.069)	(0.005)			
Interest expense (%)	0.107***	0.0028***	151	0.960	–
Avg interest bearing liabilities	(0.018)	(0.0010)			
Personnel Expenses (%)	0.186	–4.66***	75	0.954	+
Operation Income	(0.778)	(1.268)			
Shareholders' Equity (%)	0.022*	0.00098***	46.5	0.951	–
Total Assets	(0.012)	(0.00034)			
Volatility of economic growth	–0.284***	0.070***	30.5	0.950	+
	(0.104)	(0.016)			
Interest Expense (%)	–0.0003	–0.000067	17.7	0.949	
Interest Income	(0.0051)	(0.000043)			
Logarithm of total assets	–0.520***	0.029***	12.9	0.948	∩
	(0.112)	(0.006)			
Customer Deposits /	–0.011	0.0013*	6.5	0.947	
Shareholders' Equity	(0.015)	(0.0007)			

*,**, and *** denote significance at 10%, 5%, and 1% levels; standard errors in brackets.

5 - Forecasting performance

In this section we study the in-sample forecasting power of the four models for DR and BFSR ratings from table 2. It is not clear how best to forecast with an ordered logit model. One approach is the following. Given the values of the x_i indicators, calculate $x_i'\hat{\beta}$ and then estimate the probabilities $p_i(r) = P(rating_i = r)$; the forecast of the rating $\hat{r}_i$ is that which corresponds to the maximum probability: $\hat{r}_i = \arg\max p_i(r)$ — the ML-forecast.

However, even for the binary logit model, this is not the best forecasting method. It leads to the choice of type 1 outcome if its estimated probability is greater than 0.5. If there is a small proportion of type 1 outcomes in the sample, this procedure will produce too many faulty forecasts. For this reason, some authors have recommended the use of another threshold (greater than 0.5) in this case.

Another natural forecasting procedure is to calculate $x_i'\hat{\beta}$ and then find the interval $[c_{r-1}, c_r]$ that contains it and use $\hat{r}_i = r$ as the forecast value (see equation (1)). We call this the interval-forecast.

As expected from the goodness of fit measure (pseudo-R^2), models 1 and 3 have slightly better predictive power than models 2 and 4, respectively; hence we show the results only for models 1 and 3.

Tables M1a and M1b present the figures for DR rating category forecasts for model 1 using the ML and interval-forecast methods. Cell entries are the numbers of forecasts. For example, 31 in column Aa3, row Aa2 means that 31 banks with rating Aa2 are classified as banks with rating Aa3 by the ML-forecast method. For the interval-forecast method, the number is 22 (table M1b).

Table M1a reveals the drawbacks of the ML-forecast method: rating categories Aaa, Aa1, A1, Baa1, Baa3, Ba1, Ba3 are never forecasted. In terms of econometrics, the reason is that the probabilities for the corresponding intervals $P(c_{r-1} < y_i^* < c_r)$ are too small relative to the other intervals. There are several underlying factors for this. The first is the relatively small number of sample observations with corresponding rating categories: 13 for Aaa, 22 for Aa1, 9 for Baa3, etc. (see table M1c). Hence, ML model estimation is "tuned" to other, more frequently observed, ratings. Another factor is that a triple-A rating is difficult to forecast because it is assigned only in exceptional circumstances, taking into account much informal information that is not accounted for in the model. Rating categories Baa3 and Ba1 are on the borderline between the investment and speculative rating classes. The difference between them is crucial for insurance companies and pension funds, which are allowed to invest only in firms with investment-level ratings. This is why there could be a psychological barrier for Moody's experts in assigning these ratings. Similar reasoning could be applied to the Aa1 (on the border between the top rating classes, Aaa and Aa), A1 (the border of the upper investment rating class), and Ba3 (the border between Ba and B rating classes) ratings.

Table M1b shows that the interval-forecast is almost free from that drawback. Only three rating categories (Aaa, Aa1 and Baa3) are never forecasted. The above explanations concerning qualitative borders between rating classes are also applicable here.

Table M1c gives figures for correct ($\Delta = 0$) and correct-within-one-rating category ($|\Delta| \le 1$) forecasts. For example, for the most common rating category in the sample, A2, the correct forecast percentages are 56.4% (ML-forecast) and 44.8% (interval-forecast); the respective correct-within-one-rating category forecast percentages are 64.9% and 84.2%.

The correct rating category forecast percentages are roughly the same for the two forecasting methods (ca 32%); for the correct-within-one-rating-category forecasts, the figures are 67-69%.

Table M1d presents the corresponding percentages for forecasts of DR rating classes: 61% for correct forecasts and 96% for correct-within-one-rating class forecasts.

Tables M3a, M3b, M3c, M3d present the BSFR rating forecasts for model 3, arranged as in tables M1a, M1b, M1c, M1d. Only two ratings categories, A and B-, involve the same problem of never being forecasted by the ML method. The percentages for correct rating categories forecasts are about 44%; for correct-within-one-rating category, 82%-83%. For the rating classes, the respective percentages are 74–75% and 99.6%.

On the whole, one can say that the predictive power of the BFSR rating model is higher than that of the DR rating model. As mentioned above, this is to be expected, since BFSR, by construction, reflects the bank's stand-alone position and includes less qualitative, informal factors than does the DR rating.

The interval-forecast method seems to outperform the ML-forecast method.

6 - Conclusions

Econometric models are constructed for two Moody's bank ratings: Foreign-currency long-term deposit rating (DR) and Bank Financial Strength Ratings (BFSR). The models use only public information and show a good prediction power. Therefore, such models could be used as part of early warning systems (EWS) by bank regulators and for risk evaluation within the IRB framework in the Basel-2 Accord.

The significant factors in regressions are the factors that are crucial for Moody's methodology: county-specific volatility of economic growth and the corruption index; bank-specific size (log of total assets), capital adequacy (customer deposits / shareholders' equity, shareholders' equity / total assets); assets quality (problem loans / gross loans) efficiency (personnel expenses / operation income), and profitability (interest expense / average interest bearing liabilities).

The best prediction power is achieved by models with 12-18 months lag between the time of observation of factors and the time of observation of ratings.

Given all the other factors, banks from developing countries get lower ratings and Russian banks get still lower ratings. It is quite possible that Moody's takes into account political risks in these countries.

It appears that the negative time trend disappears in models with quantile scales for bank-specific factors. This means that the rating agency actually relies not on absolute values of the bank's financial indicators, but on their relative values within the whole banking system. Hence the observed rating degradation for models with natural scales can be explained by the growth of the banking system as a whole.

A methodology for measuring external bank support factors was developed, and the most important factors for that support were found. It was demonstrated that banks in developing countries, and especially in Russia, have higher levels of external support than do banks in developing countries.

Models for FSFR rating have a higher predictive power than DR models. The interval-forecast method performs better than the ML forecast method for the constructed ordered logit models.

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Appendix

Table 5. Descriptive statistics

	VOLAT	TI CPI	LTA	TA	D_EQ	EQ_TA
Mean	3.07	5.82	9.414	263073	8.49	7.63
Maximum	5.00	9.70	14.239	16334506	26.12	50.51
Minimum	1.00	2.1	4.007	107.5	0.00	0.78
Std.Dev.	1.35	2.36	1.930	1097524.	4.87	4.81

	PL_GL	PE_OI	CIBL	YAEA	IE_II
Mean	4.63	0.30	3.92	6.92	55.29
Maximum	87.77	0.69	28.22	46.35	157.1
Minimum	0.00	0.00	0.01	1.29	0.144
Std.Dev.	7.21	0.10	2.56	4.36	18.3

Table 6. Financial indicators (highlighted ones included in models)

Indicator	Indicator	Indicator's group
TA	Total assets ($, mln)	Size
LTA	Logarithm of total assets	
EQ	Shareholders' Equity ($, mln)	
YAEA	Interest Income (%) Average Interest Earning Assets	Profitability
CIBL	Interest Expense (%) Average Interest Bearing Liabilities	
NIM	Net Interest Margin	
ROAA	Return on Average Assets (%)	
ROAE	Return on Average Equity (%)	
IE_II	Interest Expense (%) Interest Income	
CIR	Cost to Income Ratio (%)	Efficiency
PE_OI	Personnel Expenses (%) Operation Income	
PL_GL	Problem Loans (%) Gross Loans	Assets Quality
LLR_GL	Loan Loss Reserve (%) Gross Loans	
PL_EQ_LLR	Problem Loans (%) Shareholders' Equity + Loan Loss Reserve	
T1	Tier 1 ratio (%)	Capital adequacy
EQ_TA	Shareholders' Equity (%) Total Assets	
CAR	Capital Adequacy (%)	
D_EQ	Customer Deposits / Shareholders' Equity	

Table 7. Correlations

	LTA	EQ	YAEA	CIBL	NIM	ROA	ROE	IE_II	CIR
LTA	1	0.008	–0.364	–0.186	–0.370	–0.291	0.012	0.258	0.160
EQ	0.008	1	0.133	0.133	0.020	0.018	0.053	0.082	–0.053
YAEA	–0.364	0.133	1	0.730	0.687	0.451	0.160	–0.048	–0.165
CIBL	–0.186	0.133	0.730	1	0.240	0.120	0.013	0.496	–0.150
NIM	–0.370	0.020	0.687	0.240	1	0.763	0.162	–0.426	–0.214
ROA	–0.291	0.018	0.451	0.120	0.763	1	0.511	–0.334	–0.468
ROE	0.012	0.053	0.160	0.013	0.162	0.511	1	–0.123	–0.341
IE_II	0.258	0.082	–0.048	0.496	–0.426	–0.334	–0.123	1	0.060
CIR	0.160	–0.053	–0.165	–0.150	–0.214	–0.468	–0.341	0.060	1
PE_OI	0.296	–0.037	–0.248	–0.257	–0.153	–0.320	–0.232	–0.058	0.755
PL_GL	–0.107	0.150	0.026	–0.005	0.027	–0.083	–0.173	–0.016	0.074
PL_EQ_LLR	0.123	0.076	0.041	0.036	–0.022	–0.228	–0.253	–0.019	0.135
T1	–0.296	0.093	0.119	0.078	0.138	0.275	0.078	–0.050	–0.314
EQ_TA	–0.555	–0.019	0.317	0.055	0.443	0.525	0.082	–0.453	–0.287
D_EQ	0.248	0.111	–0.101	–0.049	–0.142	–0.237	–0.098	0.093	0.270

	PE_OI	PL_GL	PL_EQ_LLR	T1	EQ_TA	D_EQ
LTA	0.296	–0.107	0.123	–0.296	–0.555	0.248
SE	–0.037	0.150	0.076	0.093	–0.019	0.111
YAEA	–0.248	0.026	0.041	0.119	0.317	–0.101
CIBL	–0.257	–0.005	0.036	0.078	0.055	–0.049
NIM	–0.153	0.027	–0.022	0.138	0.443	–0.142
ROA	–0.320	–0.083	–0.228	0.275	0.525	–0.237
ROE	–0.232	–0.173	–0.253	0.078	0.082	–0.098
IE_II	–0.058	–0.016	–0.019	–0.050	–0.453	0.093
CIR	0.755	0.074	0.135	–0.314	–0.287	0.270
PE_OI	1	–0.063	0.131	–0.336	–0.265	0.309
PL_GL	–0.063	1	0.568	0.057	0.053	0.016
PL_EQ_LLR	0.131	0.568	1	–0.213	–0.166	0.215
T1	–0.336	0.057	–0.213	1	0.516	–0.310
EQ_TA	–0.265	0.053	–0.166	0.516	1	–0.434
D_EQ	0.309	0.016	0.215	–0.310	–0.434	1

Table 8. Regression results for BSFR models for other countries

			(1)	(2)	(3)	(4)
			separate natural	joint natural	separate quantile	joint quantile
Country	Obs.	banks	Coeff.	Coeff.	Coeff.	Coeff.
Russia	94	45	2.848***	4.068***	2.178***	3.144***
			(0.395)	(0.634)	(0.342)	(0.445)
Kazakhstan	35	13	0.400	2.476***	0.062	1.911***
			(0.429)	(0.628)	(0.305)	(0.466)
Ukraine	26	13	–0.282	2.103***	–0.031	1.876***
			(0.487)	(0.773)	(0.483)	(0.660)
Turkey	35	15	–0.843*	1.170*	–0.264	1.059
			(0.487)	(0.698)	(0.628)	(0.708)
India	39	11	0.368	0.910**	0.496	0.782**
			(0.302)	(0.382)	(0.330)	(0.367)
Egypt	20	6	–1.499***	–1.490***	–2.094	–1.857
			(0.563)	(0.541)	(1.354)	(1.263)
Poland	20	8	0.902**	0.779**	0.755*	0.561
			(0.372)	(0.381)	(0.451)	(0.507)
Hungary	22	8	–2.117***	–1.759***	–2.710***	–2.061***
			(0.502)	(0.605)	(0.462)	(0.497)

From table 2 we conclude that Russia has lower ratings than the other developing countries, given the other factors. To study whether Russia is an exception, we ran regressions for BFSR rating, similar to models 3 and 4 from table 2, substituting the Russia dummy with dummies for one of the seven other developing countries. The results are presented at table 8. Column (1) shows the results for eight separate regressions in natural scales and column (3) those for the same eight regressions in quantile scales. Only the coefficients of country dummies and corresponding standard errors in brackets are shown. Columns (2) and (4) present results for the two regressions when all eight country dummies are included.

One notes underestimating results for the Kazakhstan and Ukraine ratings, as is the case for Russia. Coefficients for those countries are significant and positive, albeit lower in value than the coefficient for Russia. The same effect, but even less pronounced, is observed for India and Poland. Turkey does not differ from the other developing countries, but Egypt, and especially Hungary, show the opposite effect (ratings are better than average for developing countries, given the other factors). It appears that the rating agency experts estimate the political and structural risks in post-Soviet countries to be higher than the average risks for developing countries.

Table M1a. DR model 1, ML forecast

		Forecasted rating category															
		Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3
Actual rating	Aaa	**0**	0	3	10	0	0	0	0	0	0	0	0	0	0	0	0
	Aa1	0	**0**	13	9	0	0	0	0	0	0	0	0	0	0	0	0
	Aa2	0	0	**7**	31	0	14	1	0	0	0	0	0	0	0	0	0
	Aa3	0	0	12	**62**	0	36	3	0	1	0	0	0	0	0	0	0
	A1	0	0	1	40	**0**	45	12	0	2	0	0	3	0	0	0	0
	A2	0	0	2	21	0	**97**	25	0	16	0	0	11	0	0	0	0
	A3	0	0	0	6	0	78	**37**	0	6	0	0	3	0	0	0	0
	Baa1	0	0	0	1	0	12	30	**0**	1	0	0	0	0	0	0	0
	Baa2	0	0	0	0	0	16	10	0	**14**	0	0	17	0	2	1	0
	Baa3	0	0	0	0	0	2	7	0	0	**0**	0	0	0	0	0	0
	Ba1	0	0	0	0	0	0	0	0	3	0	**0**	14	0	1	2	0
	Ba2	0	0	0	0	0	1	5	0	8	0	0	**48**	0	5	0	0
	Ba3	0	0	0	0	0	3	3	0	2	0	0	10	**0**	6	8	0
	B1	0	0	0	0	0	0	0	0	2	0	0	16	0	**17**	17	2
	B2	0	0	0	0	0	0	0	0	1	0	0	16	0	7	**25**	2
	B3	0	0	0	0	0	0	0	0	0	0	0	11	0	1	2	**2**

Table M1b. DR model 1, interval forecast

		Forecasted rating category															
		Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3
Actual rating category	Aaa	**0**	0	7	3	3	0	0	0	0	0	0	0	0	0	0	0
	Aa1	0	**0**	14	3	5	0	0	0	0	0	0	0	0	0	0	0
	Aa2	0	1	**8**	22	13	8	1	0	0	0	0	0	0	0	0	0
	Aa3	0	0	18	**33**	45	12	4	1	1	0	0	0	0	0	0	0
	A1	0	0	1	18	**41**	23	13	2	5	0	0	0	0	0	0	0
	A2	0	0	2	7	29	**77**	18	11	18	0	2	8	0	0	0	0
	A3	0	0	0	3	16	52	**41**	7	9	0	1	1	0	0	0	0
	Baa1	0	0	0	1	0	10	25	**7**	1	0	0	0	0	0	0	0
	Baa2	0	0	0	0	1	12	11	1	**18**	2	5	7	0	3	0	0
	Baa3	0	0	0	0	0	1	4	4	0	**0**	0	0	0	0	0	0
	Ba1	0	0	0	0	0	0	0	0	3	1	**1**	12	1	0	2	0
	Ba2	0	0	0	0	0	1	0	3	12	2	9	**34**	6	0	0	0
	Ba3	0	0	0	0	0	2	2	2	2	0	0	7	**6**	6	5	0
	B1	0	0	0	0	0	0	0	0	3	2	2	7	8	**20**	12	0
	B2	0	0	0	0	0	0	0	0	1	1	4	10	2	15	**16**	2
	B3	0	0	0	0	0	0	0	0	1	0	0	9	2	0	2	**2**

Table M1c. DR model 1, correct forecast ratio for each rating category

		Actual rating category									
		Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3
Obs. in category		13	22	53	114	103	172	130	44	60	9
ML, %	Δ=0	0.0	0.0	13.2	54.4	0.0	56.4	28.5	0.0	23.3	0.0
Interval, %		0.0	0.0	15.1	28.9	39.8	44.8	31.5	15.9	30.0	0.0
ML, %	|Δ|≤1	0.0	59.1	71.7	64.9	82.5	70.9	88.5	70.5	23.3	0.0
Interval, %		0.0	63.6	58.5	84.2	79.6	72.1	76.9	75.0	35.0	0.0

		Actual rating category						
		Ba1	Ba2	Ba3	B1	B2	B3	total
Obs. in category		20	67	32	54	51	16	960
ML, %	Δ=0	0.0	71.6	0.0	31.5	49.0	12.5	32.2
Interval, %		5.0	50.7	18.8	37.0	31.4	12.5	31.7
ML, %	|Δ|≤1	71.6	71.6	50.0	63.0	62.7	25.0	66.9
Interval, %		73.1	73.1	59.4	74.1	64.7	25.0	68.8

Table M1d. DR model 1, correct forecast ratio for each rating class

		Actual rating class						
		Aaa	Aa	A	Baa	Ba	B	total
Obs. in class		13	189	405	113	119	121	960
ML, %	Δ=0	0.0	70.9	72.6	13.3	60.5	62.0	61.5
Interval, %		0.0	52.4	76.5	29.2	63.9	57.0	61.1
ML, %	|Δ|≤1	100.0	99.5	95.8	96.5	89.9	97.5	96.1
Interval, %		76.9	98.9	97.0	96.5	95.8	93.4	96.5

Table M3a. BFSR model 3, ML forecast

		Forecasted rating category												
		A	A–	B+	B	B–	C+	C	C–	D+	D	D–	E+	E
Actual rating category	A	**0**	2	1	4	0	0	0	0	0	0	0	0	0
	A–	0	**10**	4	8	0	0	0	0	0	0	0	0	0
	B+	0	2	**3**	26	0	3	0	0	0	0	0	0	0
	B	0	0	5	**56**	0	38	0	0	0	0	0	0	0
	B–	0	0	0	37	**0**	34	4	2	0	0	0	0	0
	C+	0	0	0	15	0	**77**	21	12	0	0	0	0	0
	C	0	0	0	4	0	43	**49**	27	6	0	1	0	0
	C–	0	0	0	6	0	11	29	**40**	20	1	0	2	0
	D+	0	0	0	2	0	8	4	14	**43**	17	4	3	0
	D	0	0	0	0	0	1	1	2	18	**32**	11	6	0
	D–	0	0	0	0	0	0	0	0	11	17	**14**	24	0
	E+	0	0	0	0	0	0	0	0	4	9	11	**98**	0
	E	0	0	0	0	0	0	0	0	1	1	0	1	**0**

Table M3b. BFSR model 3, Interval forecast

		Forecasted rating category												
		A	A–	B+	B	B–	C+	C	C–	D+	D	D–	E+	E
Actual rating category	A	**0**	0	7	0	0	0	0	0	0	0	0	0	0
	A–	0	**6**	9	7	0	0	0	0	0	0	0	0	0
	B+	0	0	**8**	20	4	2	0	0	0	0	0	0	0
	B	0	0	7	**40**	29	23	0	0	0	0	0	0	0
	B–	0	0	2	19	**26**	24	4	2	0	0	0	0	0
	C+	0	0	0	13	8	**72**	21	11	0	0	0	0	0
	C	0	0	0	3	4	41	**49**	26	6	0	1	0	0
	C–	0	0	0	4	3	11	31	**37**	20	1	0	2	0
	D+	0	0	0	2	0	8	5	13	**37**	23	5	2	0
	D	0	0	0	0	0	1	1	2	11	**40**	15	1	0
	D–	0	0	0	0	0	0	0	0	7	22	**22**	15	0
	E+	0	0	0	0	0	0	0	0	3	10	23	**86**	0
	E	0	0	0	0	0	0	0	0	1	1	1	0	**0**

Table M3c. BFSR model 3, correct forecast ratio for each rating category

		Actual rating category													
		A	A–	B+	B	B–	C+	C	C–	D+	D	D–	E+	E	total
Obs. in category		7	22	34	99	77	125	130	109	95	71	66	122	3	960
ML, %	Δ=0	0	45	9	57	0	62	38	37	45	45	21	80	0	44.0
Interval, %		0	27	24	40	34	58	38	34	39	56	33	70	0	44.1
ML, %	|Δ|≤1	29	64	91	62	92	78	92	82	78	86	83	89	33	81.8
Interval, %		0	68	82	77	90	81	89	81	77	93	89	89	0	83.3

Table M3d. BFSR model 3, correct forecast ratio for each rating class

		Actual rating class					
		A	B	C	D	E	total
Obs. in class		29	210	364	232	125	960
ML, %	Δ=0	41.4	60.5	84.9	72.0	79.2	74.4
Interval, %		20.7	73.8	82.1	78.4	68.8	75.8
ML, %	|Δ|≤1	100.0	100.0	99.5	99.1	100.0	99.6
Interval, %		100.0	100.0	99.5	99.1	100.0	99.6