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Russian bank credit ratings and bank license withdrawal 2012–2016

Anatoly Peresetsky
Aleksandra Zhivaikina

11 credit ratings of Russian banks, assigned by international and Russian rating agencies during 2012–2016.

Econometric models of these ratings designed on the public information reveal difference in the approach of the rating agencies to the Russian bank ratings.

We consider bank default as the bank license withdrawal by the Bank of Russia.

We found that the models of the international and domestic rating agencies have different attitudes/positions to the various reasons/grounds of the bank license withdrawal formulated in the Bank of Russia orders.

All rating agencies make public their rating assignment methodologies, develop those indicators of banks' financial soundness which they take into consideration. But they don't make public quantitative methods which they use when rating banks, and, consequently, these methods cannot be replicated (Balios, 2016).

A lot of studies are devoted to modelling ratings on the basis of publicly available information. Such models can be used for assigning "model" ratings to the banks that do not have ratings assigned by rating agencies.

Such "model" or "predictive" ratings can be used by a regulator for the purpose of banking supervision; they may also be used by commercial banks when looking for their business partners.

Central Bank of Russia

Crisis of 2008
Support of banks from CB RF. Demand for ratings. New RA.

Cleaning of the Russian banking system.
Elvira Nabiullina (head of CB RF since June 2013)
About 300 bank licenses were withdrawn since 2013.

New rules for the Credit Rating agencies accreditation at CB RF, 2016.

On 13.01.2017:
-- The Analytical Credit Rating Agency (ACRA) (5 banks)
-- Expert RA (~160 banks)

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Literature.
Ordered Logit models

These models were first used in the work (**Kaplan, Urwit, 1979**) for modelling ratings of obligation.

Morgan (2002) analyzes the differences in bank ratings assigned by two rating agencies (Moody's and Standard and Poor's).

(**Caporale, et al., 2012**) the ordered logit model was used to analyze bank ratings assigned by Fitch agency in the period from 2000 through 2007.

Like in (**Belotti and al., 2011**) they show a general tendency towards "deterioration" of ratings as time goes on. The accuracy of rating predictions, rather high up to 2007, becomes less accurate before the banking crisis of 2007-2008.

Literature.
Ordered Logit models

(**Iannotta et al., 2013**) the ordered logit models are used to analyze the ratings of European banks assigned by Standard and Poor', Fitch Rating and Moody's in the period from 2000 through 2009.
The study shows that state-owned banks get higher ratings than similar private banks which agrees with possibility to get state support.
However, with all other things being equal, their *individual* ratings, (that is, *financial stability*) is lower than that of similar private banks.

(**Gogas et al., 2014**) model ratings of the USA banks. They estimate model the long-term rating of Fitch USA banks for the period 2008-2011, and predict year 2012 ratings.
With grouping the ratings into 3 categories {(AA,A); (BBB); (BB,B,CCC)} the share of accurate predictions for the model with 8 regressors was 81.5%.

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Literature.
Russian banks

The first models of Russian bank ratings which used econometric ordered logit models were developed in

Soest et al., 2003
Peresetsky et al., 2004
Karminsky, Peresetsky, 2007
Peresetsky, 2009
Peresetsky, Karminsky, 2011
Vasilyuk, Karmisnsky, 2011

(**Peresetsky, 2012; Karminsky, 2015**) review of papers on modelling bank ratings.

Table. Rating grades

International scalee								National scale											
S&P		Moody's		Fitch		RusRAtingr		S&P		Moody's		Fitch		RusRating		Expert RA		NRA		AK&M	
sp		m		f		rra		sp_ru		m_ru		f_ru		rra_ru		era		nra		akm	
AAA	1	Aaa	1	AAA	1	AAA	1	ruAAA	**1**	Aaa.ru	**1**	AAA(rus)	**1**	AAA	**1**	A++	**1**	AAA	**1**	A++	1
AA+	2	Aa1	2	AA+	2	AA+	2	ruAA+	**2**	Aa1.ru	**2**	AA+(rus)	**2**	AA+	**2**	A+	**2**	AA+	**2**	A+	**2**
AA	3	Aa2	3	AA	3	AA	3	ruAA	**3**	Aa2.ru	**3**	AA(rus)	**3**	AA	**3**	A	**3**	AA	**3**	A	**3**
AA–	4	Aa3	4	AA–	4	AA–	4	ruAA–	**4**	Aa3.ru	**4**	AA–(rus)	**4**	AA–	**4**	B++	**4**	AA–	**4**	B++	**4**
A+	5	A1	5	A+	5	A+	**5**	ruA+	**5**	A1.ru	**5**	A+(rus)	**5**	A+	**5**	B+	**5**	A+	**5**	B+	**5**
A	6	A2	6	A	6	A	**6**	ruA	**6**	A2.ru	**6**	A(rus)	**6**	A	**6**	B	**6**	A	**6**	B	**6**
A–	7	A3	7	A–	7	A–	**7**	ruA–	**7**	A3.ru	**7**	A–(rus)	**7**	A–	**7**	C++	**7**	A–	**7**	C++	7
BBB+	8	Baa1	**8**	BBB+	**8**	BBB+	**8**	ruBBB+	**8**	Baa1.ru	**8**	BBB+(rus)	**8**	BBB+	**8**	C+	**8**	BBB+	**8**	C+	8
BBB	**9**	Baa2	**9**	BBB	**9**	BBB	**9**	ruBBB	**9**	Baa2.ru	**9**	BBB(rus)	**9**	BBB	**9**	C	9	BBB	**9**	C	9
BBB–	**10**	Baa3	**10**	BBB–	**10**	BBB–	**10**	ruBBB–	**10**	Baa3.ru	**10**	BBB–(rus)	**10**	BBB–	**10**			BBB–	**10**		
BB+	**11**	Ba1	**11**	BB+	**11**	BB+	**11**	ruBB+	**11**	Ba1.ru	**11**	BB+(rus)	**11**	BB+	**11**			BB+	**11**		
BB	**12**	Ba2	**12**	BB	**12**	BB	**12**	ruBB	**12**	Ba2.ru	**12**	BB(rus)	**12**	BB	**12**			BB	**12**		
BB–	**13**	Ba3	**13**	BB–	**13**	BB–	**13**	ruBB–	**13**	Ba3.ru	**13**	BB–(rus)	**13**	BB–	**13**			BB–	**13**		
B+	**14**	B1	**14**	B+	**14**	B+	**14**	ruB+	**14**	B1.ru	**14**	B+(rus)	**14**	B+	**14**			B+	**14**		
B	**15**	B2	**15**	B	**15**	B	**15**	ruB	**15**	B2.ru	**15**	B(rus)	**15**	B	**15**			B	15		
B–	**16**	B3	**16**	B–	**16**	B–	**16**	ruB–	**16**	B3.ru	**16**	B–(rus)	**16**	B–	**16**			B–	16		
CCC+	**17**	Caa1	**17**	CCC+	**17**	CCC+	**17**	ruCCC+	**17**	Caa1.ru	**17**	CCC(rus)	17	CCC+	**17**			CC+	17		
CCC	**18**	Caa2	**18**	CCC	18	CCC	**18**	ruCCC	**18**	Caa2.ru	**18**	CC(rus)	18	CCC	**18**			CC	18		
CCC–	**19**	Caa3	**19**	CCC–	19	CCC–	**19**	ruCCC–	**19**	Caa3.ru	**19**	C(rus)	19	CCC–	**19**			CC–	19		
CC	**20**	Ca	20	CC	20	CC	**20**	ruCC	**20**	Ca.ru	20	DDD(rus)	20	CC	**20**			C	20		
R	**21**	C	21	C	21	C	**21**	R	**21**	C.ru	21	DD(rus)	21	C	21			D	21		

Data

Table 1. List of Ratings

Rating agency symbol	Rating agency	Scale	Range of digitized values	Range of digitized values in the sample after combining categories (number of categories)
sp	Standard&Poor's	International	1–21	9–17 (9)
m	Moody's Investors Service	International	1–21	8–18 (11)
f	Fitch IBCA	International	1–21	8–17 (10)
rra	RusRating	International	1–21	5–15 (11)
sp_ru	Standard&Poor's	National	1–21	1–10 (10)
m_ru	Moody's Investors Service	National	1–21	1–14 (14)
f_ru	Fitch IBCA	National	1–21	1–14 (14)
rra_ru	RusRating	National	1–21	1–12 (12)
era	Expert RA	National	1–9	1–6 (6)
nra	National RA	National	1–21	1–11 (11)
akm	AK&M	National	1–9	1–5 (5)

Data

Table 2. Share of banks with ratings

Quarter	obs.	*anyrat* %	sp %	m %	f %	rra %	sp_ru %	m_ru %	f_ru %	rra_ru %	era %	nra %	akm %
2012 q1	831	33	4.1	10.5	6.0	5.5	3.5	9.7	5.3	5.4	13.0	7.0	3.9
2012 q2	828	35	4.0	10.5	5.8	5.3	3.4	9.9	5.1	5.3	15.2	6.5	4.0
2012 q3	819	38	4.3	10.9	6.1	5.5	3.7	10.3	5.4	5.5	17.1	6.7	4.4
2012 q4	827	41	4.7	11.4	6.5	5.9	4.1	10.6	5.7	5.9	19.7	7.5	4.1
2013 q1	825	43	4.7	11.5	6.5	6.1	4.1	10.8	5.8	6.1	21.9	7.4	4.0
2013 q2	821	44	4.6	11.0	6.3	5.7	4.0	10.5	5.6	5.7	23.9	7.4	3.9
2013 q3	815	45	4.8	10.9	6.5	5.9	4.2	10.4	5.8	5.9	24.9	7.6	3.8
2013 q4	814	46	5.0	10.8	7.0	5.5	4.4	10.3	6.4	5.5	26.8	7.7	3.7
2014 q1	796	48	5.5	10.7	7.3	5.8	4.9	10.2	6.7	5.8	28.6	7.8	3.9
2014 q2	789	48	6.0	10.9	7.4	5.8	5.3	10.3	6.7	5.8	29.3	8.0	3.8
2014 q3	789	49	6.0	10.9	7.4	6.0	5.3	10.3	6.7	5.8	29.8	7.9	3.8
2014 q4	770	51	6.1	11.3	7.9	6.1	5.5	10.6	7.4	6.0	30.6	8.2	4.0
2015 q1	750	51	6.1	11.3	7.7	6.3	5.5	10.7	7.2	6.1	30.7	8.4	4.1
2015 q2	732	52	6.0	11.7	8.1	6.1	5.3	11.1	7.5	6.3	31.1	8.1	3.7
2015 q3	707	52	6.4	11.6	8.1	6.4	5.4	10.9	7.5	6.6	31.3	8.3	3.5
2015 q4	677	51	6.4	12.0	8.4	6.1	5.6	11.2	7.8	6.4	29.8	8.4	3.4
2016 q1	640	49	6.1	11.1	8.8	6.1	5.5	3.8	8.3	6.4	28.3	8.3	3.4

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obs — number of observations, ***anyrat*** — % of banks with at least 1 rating

Data

(Vernikov, 2015). ***state*12,** ***foreign***

State banks, group I. (68 obs.)

Sberbank, Rosselkhozbank, VTB, Gazprombank

State banks, group II. (566 obs.)

Banks with partial state ownership

Banks with foreign ownership

*state*12 (634 obs.) *foreign* (721 obs.)

sancbin – indicator of sanctions imposed on Russia (=1 since 2014q2)

Data

lnsk — bank size, logarithm of own capital;
dostkap — normative H1, capital adequacy;

Indicators of liquidity, bank's ability to quickly mobilize funds for fulfilling obligations:

lavb — share of liquid assets in balance currency and
dolgliq — normative H4, indicator of long-term liquidity.

Indicators of assets quality:

dkevb — share of long-term credits to economy in balance currency,
reske — bad debts reserves / total sum of credits extended to an economy;
pnaca — other non-performing assets / net assets;
ncbca — share of non-government securities in net assets.

mbkca — credits to other banks / net assets, indicator of activeness at the interbank market
snersk — non-residents' funds / own capital
bpca — balance profit /net assets, indicator of bank's profits
vdulca, vdflca, ke_fca — firms and households deposits for over 30 days and credits ofor households / net assets, indicators of the structure of assets and passives;
oksca — turnover on correspondent accounts / net assets
yy12,…,yy16 — dummy variables – indicators of the year of observations (a variant of accounting for macroeconomic situation)

Ordered logit

$$\begin{cases} P(y_{it}=1)=P(y_{it}^{*}\le c_1)=F(c_1-x_{it}'\beta), \\ P(y_{it}=2)=P(c_1<y_{it}^{*}\le c_2)=F(c_2-x_{it}'\beta)-F(c_1-x_{it}'\beta), \\ \dots \\ P(y_{it}=m-1)=P(c_{m-2}<y_{it}^{*}\le c_{m-1})=F(c_{m-1}-x_{it}'\beta)-F(c_{m-2}-x_{it}'\beta), \\ P(y_{it}=m)=P(y_{it}^{*}>c_{m-1})=1-F(c_{m-1}-x_{it}'\beta). \end{cases} \quad (1)$$

$y_{it}^{*}=x_{it}'\beta$ is latent variable, "*continuous rating*"

Ratings	International				National						
Regressors	sp	m	f	rra	sp_ru	m_ru	f_ru	rra_ru	era	nra	akm
lnsk	–1.729***	–1.538***	–1.052***	–2.198***	–2.343***	–1.250***	–1.349***	–2.246***	–1.387***	–3.150***	–7.406***
dostkap	–0.0399***	0.0228*	–0.0282***	0.143***	0.00534	0.0280**	–0.0189*	0.135***	0.0106**	0.114***	0.168***
lavb	1.086	–3.064***	4.304***	0.273	–0.252	–2.191***	1.932	0.108	–6.797***	–2.198***	–4.292*
dolgliq	–0.0114***	–0.00483**	0.00505	0.0200***	–0.00764**	–0.000756	0.0114***	0.0260***	–0.000333	–0.00807***	–0.000107
dkevb	–2.759**	–2.738***	–8.431***	–2.513**	–2.462**	–4.540***	–11.08***	–2.694**	–1.895***	–4.359***	–12.86***
reske	4.065***	0.114	3.529***	8.163***	3.784***	–0.472	2.836***	7.721***	0.649**	–3.591***	3.583
pnaca	–0.703***	–0.449***	0.0816**	0.301	–0.283	–0.551***	–0.585**	0.502*	–0.287***	–0.346**	0.0680
ncbca	7.415***	–0.445	1.332	2.813**	7.016***	0.166	–0.941	2.535**	1.290***	–2.399***	–13.37***
mbkca	–9.093***	–5.306***	–8.268***	–0.672	–3.504**	–5.201***	–8.453***	–2.719***	–0.191	–5.521***	2.736
snersk	–0.337**	–0.364***	–0.229***	0.459**	0.171	–0.372***	–0.375***	0.214	–0.305***	0.125	2.571***
bpca	6.300	–22.04***	–10.86**	–9.451	10.67	–29.92***	–20.04***	0.0407	–2.132	–5.527	–7.906
vdulca	8.757***	4.178***	4.063***	7.024***	5.196***	5.252***	4.849***	7.143***	–0.190	–2.240**	–3.145
vdflca	9.793***	4.940***	3.628***	–0.538	9.517***	5.555***	2.166***	–0.432	0.997***	0.516	3.389**
ke_fca	–3.615***	–4.684***	–0.00864	0.964	–4.392***	–3.528***	–0.981*	1.124*	–2.382***	–0.385	6.239**
oksca	–0.259***	–0.314***	–0.201***	–0.174***	–0.114	–0.299***	–0.502***	–0.0593	–0.0589***	–0.0340***	–0.589***
*state*12	–3.488***	–1.825***	–1.167***	–2.139***	–4.065***	–1.488***	–1.279***	–1.849***	–1.561***	0.585*	–4.697***
foreign	–2.930***	–0.413*	–1.934***	–7.417***	–10.56***	–0.0677	–2.781***	–6.980***	–0.295	–1.610**	–0.952
sancbin	0.648*	–0.110	–0.0275	0.0823	0.572	–0.131	–0.447	0.166	0.133	–0.0274	0.416
*yy*13	–0.252	0.523***	–0.0151	0.222	–0.130	0.445***	0.0116	0.198	–0.524***	0.399**	0.339
*yy*14	–0.201	0.745***	0.0968	0.326	0.00340	0.571**	0.227	0.220	–0.850***	0.293	0.520
*yy*15	0.133	0.989***	0.150	0.730*	1.008**	0.501*	–0.373	0.596	–0.142	–0.0835	1.333
*yy*16	0.565	0.897**	0.0696	0.728	1.417**	1.274***	–0.670	0.694	0.427*	0.173	1.897*
Observations	700	1468	940	777	614	1342	854	780	3327	1017	511
Pseudo–R^2	0.468	0.344	0.325	0.400	0.445	0.257	0.343	0.371	0.244	0.407	0.729
lnL	–717.0	–1881	–1355	–955.4	–749.5	–2279	–1224	–1113	–2917	–1294	–145.1
Categories	9	11	10	11	10	14	14	12	6	11	4

- Large banks have higher ratings (*lnsk* coefficient is negative)
- Signs of coefficients in the models of international ratings S&P, Moody's, Fitch, RusRating in most cases are same as signs of coefficients in the models of national ratings of the same agencies. Obviously, the agencies use similar approaches to developing international and national rating scales.
- sanctions indicator *sancbin* which is significant (at 10% level) for the international rating assigned by S&P.
- For the international rating Moody's and national ratings S&P and Moody's coefficients of years indicators *yy15, yy16* are greater (differ significantly) from *yy13*, i.e. with all other things equal banks get lower ratings at the end of the period. This may be a consequence of toughening requirements for the banks on the part of these rating agencies in the period from 2012 through 2016. (Deterioration of rating with time)
- Increase of long-term liquidity *dolgliq* (normative N4) improves ratings assigned by S&P, Moody's and has a reverse impact on ratings assigned by RusRating.

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Precision of the S&P international rating prediction

	BBB	BBB–	BB+	BB	BB–	B+	B	B–	CCC+	Exact matches %	± 1 grade matches %	Obs. In the rating grade
BBB	**39**	11	3	0	0	0	0	0	0	74	94	53
BBB–	10	**24**	7	1	3	0	0	0	0	53	91	45
BB+	5	13	**17**	5	3	0	0	0	0	40	81	43
BB	0	0	6	**8**	11	0	0	0	0	32	100	25
BB–	0	0	0	1	**55**	18	14	0	0	63	84	88
B+	0	0	0	5	25	**27**	50	0	0	25	95	107
B	0	0	0	0	0	6	**182**	27	0	85	100	215
B–	0	0	0	0	1	1	46	**67**	0	58	98	115
CCC+	0	0	0	0	0	0	3	6	**0**	0	67	9

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Prediction of accuracy of rating categories and rating classes

Rating	Exact rating grade matches, %	± 1 rating grade matches, %	Exact rating class matches, %	grades	classes
International scale					
S&P	60	94	85	9	4
Moody's	53	84	80	11	4
Fitch	41	79	79	10	4
RusRating	49	92	83	11	4
National scale					
S&P	50	81	74	10	4
Moody's	45	65	69	14	6
Fitch	52	67	64	14	6
RusRating	42	74	74	12	5
Expert RA	65	97	–	6	–
National RA	59	92	80	11	5
AK&M	90	100	–	4	–

Spearman's correlation of actual ratings with predicted ratings and continuous ratings (%).

	sp	m	f	rra	sp_ru	m_ru	f_ru	rra_ru	era	nra	akm
Predicted rating	89	83	86	87	90	77	88	85	54	87	89
Continuous rating	90	85	87	88	92	80	89	89	59	88	87

Low are
Moody's with 85% и 80% for international and national scales and Expert RA with 59%.

Almost all the values are in the range of 87% - 90%

High correlations allow to apply model ratings to banks that have no rating.

It seems that rating agencies' opinions differ less than when they rate large banks. (Probably, large banks are more transparent or are subject to a more thorough/precise analysis).

Bank default models

Classification of license withdrawal reasons

Name	Reasons	Observations
default	= 1, if the banks' license has been withdrawn in this quarter; = 0, otherwise.	229
laundry	= 1, if there is the term "*money laundering*" in the decree; = 0, otherwise.	75
volunt	= 1, if there is the term "*voluntary*" in the decree; = 0, otherwise.	25
econom	= 1, if there is the term "*economic failure*" in the decree, but **not** the term "*money laundering*" = 0, otherwise.	93
law_v	= 1, if there is the term "*violation of laws*" in the decree, but **not** the term "*money laundering*", and **not** the term "*economic failure*"; = 0, otherwise.	36

$$default \equiv laundry + volunt + econom + law_v$$

Default models

regresors	***default***	***law_v***	***econom***	***laundry***	***volunt***
*ln**equity***	**–0.441*** **	**–0.787*** **	**–0.251** **	**–1.033*** **	0.114
dostkap	–0.000119	–0.00513	**–0.0465*** **	0.00947	–0.00100
lavb	**–6.977*** **	**–4.194** **	**–6.926*** **	**–6.429*** **	–1.305
dolgliq	–0.0136***	–0.0190**	–0.0133***	–0.0124**	0.00387
dkevb	–1.125*	–1.362	0.0211	–3.049***	–2.952
reske	0.369***	0.467	**0.321**	**0.321*** **	–0.327
snersk	–0.169	0.532**	–0.723*	0.175	–1.932*
bpca	–6.907***	–2.672	**–16.93*** **	**2.201**	4.092
mbkca	–0.467	–11.79*	–3.779	–1.422	4.261***
vdulca	–0.370	–1.178	–0.688	–1.289	0.278
vdflca	1.709***	2.479**	1.396**	0.843	0.687
ncbca	–1.256	–0.810	–4.216***	–0.615	0.585
oksca	–0.0248	–0.387**	–0.225**	0.0172	–0.177*
ke_fca	–1.578**	–1.891	–4.061***	0.152	1.161
pnaca	0.0325	–0.277	–0.118	–0.0709	0.246***
yy13	**0.693** **	1.005	–0.254	0.327	1.982**
yy14	**1.218*** **	**1.567***	0.214	0.932**	0.734
yy15	**1.321*** **	**2.303** **	0.464	0.620	1.004
yy16	**1.401*** **	**2.813*** **	0.641	–	–
sancbin	0.150	–0.782	0.142	**1.380*** **	0.708
constant	2.967***	6.153*	1.989	9.086***	–8.800***
Obs.	13230	13230	13230	13230	13230
Pseudo-R^2	0.150	0.181	**0.231**	0.178	**0.102**

Differences between models.
Time dummy are significant (Nabiullina, since 23.06.2013)

Are rating models and default models related ?

= Let $\hat{p}$ be the predicted probability of bank default
(the license withdrawal)
= Surprisingly, $\hat{p}$ is not significant in the default models!

Note: CB RF plans additional screening of accredited rating agencies, *RBC: December 14, 2016.*

Spearman's correlations of continuous ratings and indicators of license withdrawal prediction

	sp	*m*	*f*	*sp_ru*	*m_ru*	*f_ru*	*rra*	*rra_ru*	*era*	*nra*	*akm*
default	0.51	0.63	0.36	0.52	0.58	0.33	0.20	0.19	0.55	0.24	0.32
law_v	**0.69**	**0.79**	**0.56**	**0.62**	**0.76**	**0.60**	0.23	0.22	0.57	0.31	0.38
economy	0.55	0.54	0.38	0.37	0.54	0.39	–0.16	–0.17	0.33	-0.09	–0.02
laundry	0.47	0.64	0.42	**0.63**	0.56	0.39	**0.55**	**0.55**	**0.71**	**0.60**	**0.66**
volunt	0.18	0.14	0.13	0.12	0.15	0.11	–0.08	–0.09	–0.03	–0.13	–0.09

= Generally, the correlations are low.
= for international ratings of "the big three" agencies the greatest correlations correspond to license withdrawal due to "*violation of laws*".
= Fitch has lower correlation, probably, that Fitch takes into account more long-term factors
= The ratings of Russian agencies are considerably different from the international ones; the greatest correlation is observed with license withdrawal due to *money laundering*.
The same situation is with the national S&P rating,

Conclusions

- Presented models of 11 most popular Russian banks credit ratings
- Using the same model as a template allow to reveal differences between RA methodologies
- Spearman's pairwise correlation of actual and model ratings is quite high (80-90%) which gives grounds to applying model ratings to all banks. Such model ratings may be used as "vector" model ratings for estimating creditworthiness of banks that have no actual ratings.
- Designed the models of the probability of license withdrawals due to 4 reasons.
- The models reveal low correlation between rating and license withdrawals.
- International and domestic RAs take into account different reasons of the bank license withdrawals.
- "Vector rating" (11+5 dimensions)

= tbr. ….

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Thank you!