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STUDYING REPLICABILITY OF AGGREGATE EXTERNAL CREDIT ASSESSMENTS BY PUBLIC INFORMATION

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In this paper, we examine if the aggregate rating constructed as a consensus of individual credit ratings can be accurately predicted with publicly available non-rating information about company. Adopting approach from computational social choice we construct consensus of ratings assigned by seven credit rating agencies to Russian banks in national scale and compare it with several proxies based on publicly available characteristics of those banks. We measure how much aggregate (consensus) rating and proxies are agreed in terms of ordering banks by their credit quality and discriminatory power in predicting defaults over the one-year horizon. We show that aggregate (consensus) rating is comparable to financial-data-based econometric default model in term of discriminatory power, but as ordering the former have a fairly low agreement with the last. We also found that using models for predicting initial credit ratings allows for building a proxy that has practically high agreement with the original aggregate rating, but original aggregate rating outperforms proxy in terms of discriminatory power. It was also found that greater agreement between original aggregated rating and proxy can be achieved on the subsample of investment grade ratings.

JEL Classification: B23, G21, G24

Keywords: credit rating agency, credit ratings, rating aggregation, consensus ordering, logit model

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1 Introduction

Credit rating agencies (CRA) play a significant role in the modern financial market presenting professional opinions on the financial stability or creditworthiness of companies or other legal entities. Being an opinion, CRAs' credit assessments do not always match due to conceptual differences (different rating philosophy[5], analyzed factors, applied models, etc.) or due to such reasons as occasional calculation errors, delayed reaction or intentional misrepresentation.

Disagreements between CRAs' assessments can be significant. For example, it can happen that the same entity is rated by S&P as a BBB and Fitch as a BB, i.e. is assigned ratings implying significantly different credit quality. Indeed, the first CRA states that the entity "has adequate capacity to meet its financial commitments" (Standard&Poors, (2016), p.6), whereas second one says that the entity "indicates an elevated vulnerability to default risk" (see Fitch Ratings, (2014), p.9). Such situation frequently turns into opposite ordering of the same entity by different agencies with respect to entity's peers, therefore such CRAs' opinions can be considered as inconsistent and can hardly be seen as reliable indicator of relative risk of particular entity.

The natural question arises. Is it possible to construct a collective indicator of credit quality from two or more independent (may be partially contradicting) opinions and what properties this indicator should have to be meaningful, robust and useful? The process of constructing such indicator can be called aggregation. In context of credit ratings, the result of such aggregation can be called an **aggregate rating**.

There are three main reasons for studying aggregate credit ratings and the quality of aggregation.

1. **Reducing reliance on single external credit ratings**. In 2010, responding to the lessons learnt from the global financial crisis 2007-2008, the G20 Financial Stability Board issued a resolution encouraging to reduce reliance (especially mechanistic) on CRA ratings by banks in order to prevent negative consequences of inaccuracy of ratings and the «cliff effect». However, in emerging markets such as Russian one, CRA ratings play key role in providing information on companies' creditworthiness. Therefore, regulators and market participants can hardly abandon CRA ratings, at least for now.

   An aggregate rating would reduce the dependency of the financial ecosystem on any single CRA in the spirit proposed by the Financial Stability Board resolution. It can also be used by

[5] Point-in-time (PIT), through-the-cycle (TTC) or hybrid.

financial regulator as master (reference) scale in order to provide a mapping of external rating scales to regulatory scale thus creating a fair, level-field, and most importantly robust framework.

2. **Meaningful aggregation.** Banks use internal rating based models to assess the creditworthiness of their counterparties. These models routinely deal with heterogeneous information – external credit ratings, credit spreads, internal models, expert estimates, etc. Aggregating this heterogeneous information into one internal rating estimate is exactly what an aggregate credit rating does with CRA ratings. A meaningful internal aggregation model is very important for regulatory compliance, especially in a low-default environment, where models cannot be validated using statistical data on defaults (see also the next reason).
3. **More data of better quality for training other models**. In a default-rich environment, models for estimating credit quality are usually trained on samples of defaulted and not defaulted companies (with a suitable definition of default, usually including a time horizon). However, in low-default environments the defaulted set is almost empty, which makes training problematic. A usual solution to this problem is to train the model not to identify defaults from non-defaults, but rather to replicate an external credit quality proxy such as external credit ratings (BCBS (2005), p.96-102). However, the question of which external credit rating to choose immediately arises.

An aggregate credit rating is a natural candidate for such credit quality proxy. It is preferable to a single external credit rating, because:

a. It is more robust to any outliers in rating data. Quality input data allows to train credit quality models with more precision.
b. It encompasses more companies than any single external credit rating. More input data also increases training quality and possibilities. For some kinds of models, more data makes all the difference.
c. It eliminates the variability of the resulting model estimates. Training the same model to replicate different external credit ratings can and will result in different models, because the sets of rated companies differ for different external credit ratings, and also because some companies are rated differently by different CRAs.

However, the points 2, 3a, 3b and 3c above explicitly depend on the availability of independent studies of such aggregating methodologies.

This paper, while not intending to close this question, contributes to the topic by proposing methodology for studying quality and applicability limits of arbitrary aggregate rating relative to existing credit risk models in order to determine if such aggregate rating can be seen as suitable tool for issues described in point 3. The methodology is based on two-step algorithm which helps to determine, 1) if the aggregate rating performs as well as best-practice credit risk models on its own domain of rated companies, 2) if aggregate rating can be accurately modeled and, therefore, extrapolated to the non-rated companies without loss it competitiveness. We argue that aggregate rating that successfully pass these two steps suits as candidate for the point 3.

The various approaches to rating aggregation can be found in academic and practical literature. "Ad hoc" (rule of thumb) methods[6] are usually intuitive and easy to implement, but they typically lack for conceptual soundness. More comprehensive approaches can be roughly divided into two classes: model (generally parametric) and model-independent (generally normative and non-parametric) approaches. Model approaches are still understandable and tractable, but typically more complex than "ad hoc" and heavily dependent on assumptions about information they aggregate (e.g. ratings are assigned by rating agencies independently of each other and etc.). Elements of model-based aggregation of ratings can be found in Karminsky, Peresetsky (2008), Aivasyan et al. (2011), Hornik et al. (2010), Karminsky et al. (2013), Grun et al. (2013) to name a few. Implementation of model-independent approach is primarily based on interpretation of data and desirable properties of aggregate rating. Examples of such approaches are Eisl et al. (2013), Buzdalin et al. (2017). In particular, the paper Buzdalin et al. (2017) adopts the concept of consensus from social choice theory as basic principle of rating aggregation.

In this paper, we apply proposed methodology to studying the aggregate rating constructed in paper Buzdalin et al. (2017) as a consensus of individual credit ratings assigned to Russian banks by three international rating agencies (Fitch, Moody's and Standard&Poors) and four Russian national rating agencies (AKM, NRA, RA Expert and RUS Rating) from the third quarter of 2010 to the first quarter of 2016. As from now on, we use one particular method of aggregation, therefore, here and after, we will use terms **aggregate rating** and **consensus rating** as interchangeable. The original paper by Buzdalin et al. (2017) show that consensus rating demonstrates good discriminatory power and robustness, the method of its construction is computationally hard, so it is important to make sure that aggregate ratings provides information that is worth its complexity.

This paper has the following structure. Section 2 describes the methodology of the research.

[6] E.g. Russian information service company Interfax calculate and disseminates such aggregates.

Section 3 briefly describes used data and Section 4 presents and discusses results. Section 5 concludes.

2 Methodology

In fact, proposed methodology is a two-step algorithm.

1. The first step is to determine if aggregate rating performers better and comparatively as well as widely used credit risk models perform for rated companies. Relatively poor performance on the own domain makes the aggregate rating worthless and not deserving further studying.

2. If aggregate rating performs relatively well on its own domain, the replicability of the aggregate rating is examined on the second step of the algorithm. We call the rating replicable if 1) fairly accurate predictive model of such rating can be built, 2) the model can be used to extrapolate ratings to the universe of non-rated companies, 3) the performance of extrapolated ratings is still better or comparable to the performance of the best-practice credit risk models.

Assuming a robustness of aggregation method itself, a successful pass of these two steps means that considered aggregate rating is suitable, since it is determined for all companies, robust and performs at least as well as best-practice models. A successful pass only of the first step means that aggregate rating has limited applicability outside its own domain, but still can be used for credit risk analysis, for example for validation purposes.

In this paper the first step is carried out in the following order.

1. We construct the aggregated (consensus) rating (brief description see in Subsection 2.1 Consensus-based aggregation of ratings), which is defined for the companies assigned two or more ratings from different rating agencies (further bellow we refer to such data set as Consensus sample, see Section 3 Data).
2. We build a logit default model that is utilized individual (financial, business) characteristics of the company and calibrated to default data (brief description see in Subsection 2.2 Econometric default model). This model is defined for all companies in our data. The model is estimated and tested on Training and Test Samples respectively (see Section 3 Data).
3. Then we compare discriminatory powers of aggregate rating and the logit model to determine if aggregate rating provides as much information on credit quality of Russian banks as standard purely default-based econometric model. We measure discriminatory power with Accuracy Ration (AR) indicator (see brief description in

Subsection 2.4 Discriminatory power).

On the second step we build a series of predictive models for consensus rating to study if consensus rating can be replicated and extrapolated outside its domain.

1. First we try to map level of consensus rating directly to individual (financial, business) characteristics of the companies via ordered logit model (see description in Subsection 2.3 Rating models). We compare predicted consensus with a real one in terms of discriminatory power and degree of agreement (see brief description in Subsection 2.5 Degree of agreement) in order to determine if model fits real aggregate rating well and has comparable quality in and outside its domain.
2. Second, we try to build CRAs ratings as inputs for aggregation via ordered logit model (see description in Subsection 2.3 Rating models). Then we compare consensus of modeled ratings with a real one in terms of discriminatory power and degree of agreement, as it is done for predictive model of consensus in previous point. We also carry out this exercise. In order to ensure that result is robust and is not subject to heterogeneous data (different rating methodologies, diffidence in rating class), we carry out this exercise for different combinations of CRA's and ratings:
    a. all ratings of all seven CRAs;
    b. all ratings of Russian national rating agencies;
    c. investment grade ratings of all seven CRAs.

2.1 Consensus-based aggregation of ratings

The approach to aggregation that we study in this paper considers credit ratings as relative orders of entities according to CRAs' opinions about their relative credit quality. Such ratings interpretation allows applying some of the widely used concepts from social choice theory to rating aggregation problem. The paper adopts Kemeny median concept which formalizes a fair (consensus) aggregation of orders and has some natural from practical perspective properties (see Brandt et al. (2016)). Kemeny median is a solution of the following problem

$$R^{*} = arg \min_{R} \sum_{k=1}^{m} d(R, R_k) , \tag{1}$$

where R^* – Kemeny median, m – number of input orders, R_k – k-th individual (input) orders, $d(R', R'')$ – Kemeny-Snell distance metric between orders R' и R''.

Although the Kemeny median concept is relatively well studied and developed, its application to the ratings aggregation problem has some specific features, such as high dimensionality and partial input order, i.e. orders may be defined not for all objects (not each CRA rates each entity). Moreover, original Kemeny median generally provides set of aggregations rather than unique solution. Together these features make ratings aggregation problem computationally complex.

In order to obtain a single solution within practically acceptable time, original optimization problem is modified by adding supplementary criterion and setting it in spirit of Tikhonov regularization. Genetic optimization algorithm is adopted for numerical solution. Therefore, a consensus rating is:

$$R^{cons} = arg \min_{R} \sum_{k=1}^{m} \phi_k [\tilde{d}(R, R_k) + \lambda \delta^2 (R, R_k)] , \qquad (2)$$

where R^{cons} is aggregate (consensus) rating, m – number of input orders, R_k – individual (partial) order of entities according ratings assigned by k-th CRA; $\varphi_k > 0$, $\sum_{k=1}^{m} \varphi_k = 1$ – weight representing relative CRAs' credibility (if all agencies are equally credible, then $\varphi_k = 1/m$, for all k); $\tilde{d}(R', R'')$ – modified Kemeny-Snell distance metric; $\delta^2(R', R'')$ - supplementary criterion. Having λ fairly small, consensus rating is still optimal according to criterion $\tilde{d}(R', R'')$, but also the best one according to supplementary criterion $\delta^2(R', R'')$.

Such approach applied to a real rating data provides aggregate rating with good discriminatory power, therefore it can be considered as fair and robust benchmark in a multi-rating environment. For more details on method and its properties see Buzdalin et al. (2017).

2.2 Econometric default model

The econometric models (such as logit or probit models) are tools widely used in practice to build up a multi-variable scoring/rating system calibrated to default data. These models are fairly simple, easy to implement and recognized by the Basel Committee (see BCBS (2005), p.33, p.37). It also frequently used for research purposes: Campbell et al. (2008), Agarwal, Taffler (2008), Kavussanos, Tsouknidis (2016) to name a few. Authors of these papers use data from financial statements and qualitative (typically categorical) indicators as an input in those models in order to assess default probability of entities from financial and non-financial sectors.

In these models default event of i-th entity is modeled by binary variable Y_i depending on variable Y_i^* which represents entity's credit quality:

$$Y_i = \begin{cases} 1, \text{if } Y_i^* \geq 0 & \text{(default)} \\ 0, \text{else} & \text{(no default)} \end{cases}. \tag{3}$$

If Y_i^* in its turn linearly depends on some observable variables X (entities characteristic, macroeconomic factor etc.) and some unobservable random component ε with distribution F, the probability of default can be written as follows

$$P(Y_i = 1) = P(Y_i^* \geq 0) = P(X_i'\beta + \varepsilon \geq 0); \tag{4}$$

$$P(Y_i = 1) = 1 - F(X_i'\beta). \tag{5}$$

where F(z) is usually chosen to be a logistic cumulative distribution function and the model is call logit.[7]

In this paper, an order of entities according to logit regression is considered as independent alternative to consensus rating and used for benchmarking its discriminatory power.

2.3 Rating models

If the consensus rating and its independent (default based) alternative show low agreement, one can construct a proxy of consensus rating in a way close in spirit to the way the original consensus rating built. As the original consensus rating consists of two components - the data (ratings) and the method (algorithm) of aggregation, - it is reasonable to ask if close proxy can be obtained by altering these components. In particular, can the close proxy be constructed from non-rating data, for example, by predicted ratings?

One of the generally accepted tools for assessing and prediction ratings is the econometric models of ordered choice, for example, ordered logit model. A credit rating of i-th entity assigned by particular CRA is modeled by variable y_i depending on variable.

$$y_i = \begin{cases} 0, \text{if } y'_i \leq c_0 \\ 1, \text{ if } c_0 < y'_i \leq c_1 \\ \quad\dots \\ n, \text{ if } y'_i > c_{n-1} \end{cases}, \tag{6}$$

where y'_i represents entity's credit quality, c_j - endpoints of the observable rating categories in terms of y'_i values, n is number of observed rating categories

[7] A popular alternative to logit model is probit model, which applies normal distribution instead of logistic. Usually logit and probit models provide fairly close results.

If y'_i linearly depends on X (some observable entity's characteristic or macroeconomic factor), the probability of falling into some rating category can be written as follows

$$P(y'_i = 0) = F(c_0 - X_i'\beta),$$
$$P(y'_i = 1) = F(c_0 - X_i'\beta) - F(c_1 - X_i'\beta), \tag{7}$$
$$P(y'_i = n) = 1 - F(c_{n-1} - X_i'\beta).$$

One option to measure the goodness of a fitting of an ordered selection model is to measure the MacFadden's R^2 (Likelihood Ratio Index, LRI) which is the following:

$$\mathrm{LRI} = 1 - \frac{l_1}{l_0}, \tag{8}$$

where l_1 – log-likelihood function value for estimated regression, l_0 – log-likelihood function value if all coefficients except the "constant" are assumed to insignificant. As can be seen from the formula, it is almost a direct analogue of OLS R^2, and its meaning is the same. The larger LRI, the more accurately model predicts ratings. However, it is argued that integral goodness-of-fit measure should be considered along with more detailed indicator in order to provide more granular representation of fitting results (see, for example, Hosmer et al. (2013)). In this regard, we use classification table and present consolidated results of the accuracy of predictions by models to refine the results.

2.4 Discriminatory power

For the purpose of the study we need to measure of discriminatory power of scoring variables. Since a consensus rating in essence is a scoring variable and the discriminatory power is generally accepted indicator of rating quality, it is naturally to ask if the discriminatory power of consensus rating is comparable to discriminatory power of popular scoring default models calibrated to default data.

Generally, discriminatory power is represented by ROC (CAP)-curve[8] and measured by AUC (area under curve) and/or AR[9] (accuracy ratio) (for more information see Tasche (2010)). AUC ranges from 0 to 1, and the greater its value, the greater the discriminatory power of the model. For ROC-curve AR = 2 AUC-1 and ranges from 0 to 1. The quality for the scoring/rating model is also measured in terms of AR: the larger the AR, the better the model predicts defaults (see Pomazanov (2016), p.54 or Hosmer et al. (2013) p. 177). All these indicators have also been

[8] Receiver Operating Characteristic and Cumulative Accuracy Plot respectively. By their nature and function these two plots are close to Lorenz curve.
[9] In essence AR is a Gini coefficient.

recommended by the Basel Committee (see BCBS (2005), p.36-39) and have been used repeatedly in research.

2.5 Degree of agreement

For the purpose of the study we need to measure agreement between ratings (orders). In this paper, we do this using the modified Kendall correlation coefficient of τ_x (see Emond, Mason (2002)). There are few reasons of such choice. First, as Emond and Mason shown, τ_x is the unique rank correlation coefficient which is equivalent to the Kemeny-Snell distance metric which is the key component of consensus rating construction. Second, like any other concordance coefficient, it represents the degree of agreement between two orders, while it does not lend itself to an accurate quantitative estimate. Unlike the other concordance coefficients, the same dimension assessment scales are unnecessary. τ_x is calculated as follows:

$$\tau_x = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} r'_{ij} r''_{ij}}{n(n-1)}, \tag{9}$$

where r'_{ij} and r''_{ij} is the a sign reflecting the ratio of ratings R' and R'' for banks i and j, n is the total number of banks which has 2 ratings simultaneously.

The closer τ_x to a unit, the more agreed rating are. So if τ_x is close to 1, then consensus rating and its alternative/proxy are highly agreed; if τ_x is close to -1, then consensus rating and its alternative/proxy contradict each other. Values of τ_x close to 0 mean no/low correlation between ratings.

3 Data

We study if consensus rating of Russian banks is practically useful and can be fairly well replicated using information from financial statements and other publicly available characteristics of those banks. We consider data from 2010, when first regulation of credit rating industry was introduced by Russian Ministry of Finance, to 2016, when new industry regulation changed its landscape drastically (international agencies of BigThree left the market, ratings of most of national agencies were excluded from using as elements in financial regulations and one new agency entered the market).

Information on bank ratings is obtained from RU.Data.[10] Information on banks' financial indicators and defaults is obtained from Bank of Russia[11], mainly from bank's reports №101 (containing data on banks' key balance sheet items), №102 (income statement, published quarterly), №135 (containing data on capital requirements, liquidity requirements and others). All explanatory variables referred to in the next chapter is based on parameters from these forms. Variable meanings, correlation between variables and its descriptive statistics is in Appendix A, Appendix E and Appendix F respectively.

There are 134 Russian banks in our sample rated at least by two different agencies at some moment during the period. These banks and information on them we call Consensus Sample, since the real consensus is defined only for these banks. The statistic of banks from Consensus Sample can be seen in Figure 1. 17 of these banks defaulted during considered period.

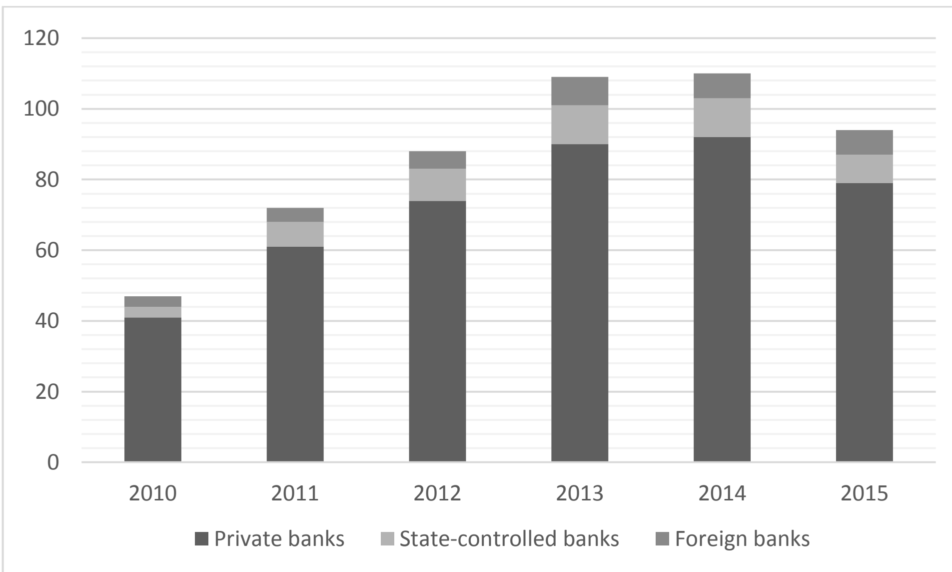

Figure1. Number of banks grouped by year and ownership.[12]
Source: authors' calculations.

The sample includes quarterly financial data and data on ratings assigned by seven CRA (Fitch, S&P, Moody's, RA Expert, AKM, NRA, RUS; see data on rating distributions in Appendix G) in national scale. Sample size is 1700 observations.

[10] http://www.ideal.ru/text.asp?Rbr=117
[11] https://www.cbr.ru/credit/
[12] State-controlled bank is defined as bank with 25% or more state ownership. Foreign bank is defined as bank with 25% or more foreign ownership, its ultimate owner is not a foreign government or any public-sector entity. Information on ownership structure has been verified by banks' and the Bank of Russia websites.

Consensus rating constructed as described in Subsection 2.1 categorizes 1700 observations into 314 categories. Each (consensus) category consists of observations where banks have exactly the same set of ratings. Observations are quite evenly distributed over consensus categories – generally each category contains from three to ten observations.

Since we intend to compare the consensus rating with the series of econometric models we also have utilize data on all bank system in considered period. This data is divided into two sample for model estimation and validation. In order to ensure homogeneity of Training and Test Sample respectively to Consensus Sample, we divide the entire data sample by time.

1. Training Sample consists of quarterly financial data on 946 Russian banks and their defaults from 01.07.2010 to 01.07.2014 years. The number of defaults equal 144. This sample is used as a training set to get scoring logit model.
2. Test Sample consists of data on 782 Russian banks from 01.10.2014 to 01.01.2016 years. The number of defaults equal 91. This sample is used as a test set in order to control overfitting of scoring logit model.

4 Results

Comparison with Logit model

Here we build a scoring logit model based on banks' public information and fit it directly to the banks' default data. Since logit model is derived from different data by different methodology we treat the ordering of the banks this model implies as an independent alternative for consensus rating (see Appendix C, model I and model II). [13]

In practice rating or scoring model is considered suitable under following conditions:

1. the model has a quality not lower than "good" (see Appendix B);
2. the quality of the model is stable on different samples.

Logit model has been trained and tested on Sample 1 and Sample 2 respectively. After final model is replicated on Consensus sample. Dataset is assigned to the three samples described in Section 3. The financial indicators used in final logit-model are presented in Table 1. Fitting results are presented in Table 2.[14]

Table 1. Explanatory variables description.

Variable	**Description**	**Sign of coefficient in model**

[13] Correlation matrix of models variables are in Appendix E.
[14] All variables are significant on 5% confidence level.

H3	normative indicator of current liquidity; ratio of liquid assets to demand deposits and other liabilities with 30 day to maturity(without min.balance)	Negative
H4	normative indicator of long-term liquidity; ratio of loans with 365 day maturity to sum of bank capital, liabilities with 365 day to maturity with min.balance	Negative
PA5 (H7)	indicator of large credit risks concentration; ratio of sum of loans with the highest credit risk(without reserves) to bank capital	Positive
PK3	indicator of capital quality assessment; ratio of supplementary capital to sum of share capital and disclosed reserves	Positive
SIZE	ln(total assets)	Positive
LN(DEP/ST_LOANS)	ln((total deposits)/(total short-term loans))	Positive
TOTAL LOAN	total loan, including interbank loan	Negative
E_F	(deposits of legal entities)/(total assets)	Negative
TR RATIO	(total reserves)/(total assets)	Positive

Source: authors' calculations.

Table 2. Summary of discriminatory power metrics.

	Logit model			**Consensus rating**
	Training Sample	Test Sample	Consensus Sample	Consensus Sample
AUC	80.70%	78.68%	84.70%	80.6%
AR	61.4%	57.36%	69.4%	61.2%

Source: authors' calculations.

Table 2 shows that logit model is not overfitted because AR of logit model on different set are comparable. Also AR of logit model and consensus rating are comparable. Recall that logit model is directly fitted to the default data, while consensus ranking is constructed from ex ante credit assessments, therefore the consensus rating may be considered as decent alternative to econometric default models from discriminatory power prospective.

However τ_x between logit model and consensus rating equals 33%. It means that according logit model banks are ordered significantly different in respect with their order in original consensus[15]. The reasons of observed disagreement may lay in both data and methodology. First, the consensus rating was constructed from credit ratings assigned by different CRAs. Each CRA has its own methodology and each methodology most likely requires its own set of explanatory factors, so more diverse set of financial indicators may be required. Second, the non-trivial algorithm for building consensus rating may create interdependences between inputs and result of aggregation that are difficult to detect for logit-model. Finally, the low default sample[16] (around 2.5% of all observations in Consensus Sample experienced default on one-year horizon) provides more options for shuffling observations without impact on discriminatory power.

Taking methodological nuance into account we study if consensus rating can be reproduced with a practical degree of precision by the same methodology but from alternative data. Also, this allows us to estimate how much information is needed to reproduce the consensus rating.

4.2 Comparison with consensus of modeled ratings

In this subsection a proxy for consensus rating is constructed from model estimates of CRAs' ratings (see Appendix C, model I and model IV).

The idea is to build a model for predicting CRA ratings observable characteristics of entities and use these estimates as inputs in consensus algorithm. We model credit ratings with ordered logit model as described in Section 2. As Table 4[17] shows, composition of independent variables is quite different in regressions models describing rating of different CRAs. Also, sign of coefficients in a few ratings' model is different. It could be explained different rating methodologies because coefficient sign is stable for different subsample (see Table 6). It should be noted that these models also take into account factors of state support and involvement of the bank in a foreign companies groups. Table 5 summaries rating models' accuracy measures.

[15] Obtained with a similar logit regression, where the independent variable is real consensus rating.
[16] Rated entities defaults less often that non-rated ones.
[17] Description of variables can be seen in Appendix A and correlation matrix in Appendix E.

However, τ_x between proxy and original consensus increases significantly and equals to 68.5%. Such rank correlation can be considered as practically high, since observed τ_x between CRA ratings ranges from 50% to 80% in our sample. Therefore the result indicates that using the same algorithm and the same data composition, but not the same data quality (ratings are only predicted value), is enough to construct the model rating, agreement degree with the consensus of which is a fairly good level.

Considering wide set of variables in rating models may provide more accurate ratings estimate and in its turn more accurate consensus replication. However, the example of international CRA shows that factors obtained on the basis of financial statement would not be enough for more precisely predicting ratings estimates.

Table 4. Explnataory factors for regression (by CRA).[18]

Factor	H1	H2	H3	H4	H7	H9.1	H12	H1_i	H2_g	H3_g	H3_i	PA3	PL5	PK3	Di	Size	e_f	T_L	L_s_t _g
AKM			+		+							+							
EXP	-		+	+		+	+					+	+				-	-	
FCH					+			-	-			+	+			-	-		
MDS	+	+			+	+					-				-	-	-		
NRA	-		-	-			-					+		+	-	-			
RUS												+		-		-	-	-	
SNP	+			-	+	+				-		+	-		-		-		+

Factor	Tr ratio	L_s_t	NonF	Res	D/L	CS	Tr ratio_g	Size_i	Di_g	Res_i	CS_g	Res_g	PK3_g	PL5_g	H10.1	e_f_i	e_f_g	F
AKM		+	+		-										-			
EXP	+	+		-							-		+		-		+	
FCH						+				-					+			
MDS				-			+	-						+	+			
NRA							+					-						
RUS		-																-
SNP	+			-		+			+						+	+		

"+" – positive sign of coefficient in model, "-" – negative sign of coefficient in model.
Source: authors' calculations.

[18] Explanation of the CRAs' abbreviation can be seen in Appendix D.

Table 5. Accuracy of ratings prediction (by CRA).

	AKM	EXP	FCH	MDS	NRA	RUS	SNP
MacFadden's R^2	68.53%	42.64%	33.21%	30%	47.20%	47.30%	31.95%
τ_x **of proxy and original**	78.54%	63.98%	66.79%	64.71%	73.69%	76.02%	62.06%
Share of exact matches	84.69%	67.64%	28.41%	37.45%	60.45%	52.44%	28.18%
Share of +Δ1 rang	6.70%	14.88%	15.11%	14.26%	16.91%	13.41%	24.07%
Share of -Δ1 rang	8.61%	15.34%	13.14%	13.99%	17.86%	15.04%	20.74%
Share of ±Δ2 rang	0.00%	1.99%	13.14%	14.44%	3.03%	6.91%	16.44%
Share of ±Δ3 rang	0.00%	0.15%	11.00%	9.12%	1.12%	12.20%	7.05%
Total quantity	209	652	609	1108	627	246	511

Source: authors' calculations.

Although τ_x is fairly high, consensus of modeled ratings have much lower discriminatory power (22.8%) than consensus of real ratings. It happens, because econometric models of the rating significantly overestimate some observations experienced default. As a result positions of those observations in proxy consensus are much higher than in original one. As those observations correspond to low (speculative grade) real ratings, it is worth to validate obtained result on subsample of banks having investment grade ratings.

We also observe moderate accuracy of econometric models for international CRA (see Table 5), so it is reasonable to examine agreement of consensus of modeled and real ratings on subsamples of national CRAs.

4.2.1 Investment grade subsample

Here we check whether CRAs' investment grade ratings are more accurately predicted by financial data and therefore consensus of their modeled values is more agreed with consensus of their real values (see Appendix C, model I and model V).

The ratings investment grade is ratings, which reflect the high level of financial sustainability of company, sovereign or securities. CRA publish usually their definition of investment grade class for international scales. However, this is not general rule for national ratings. For example, NRA divides its rating by three classes: investment, tolerable, speculative; other CRAs have no investment\speculative classification for national scales. Therefore, we carry out this classification based on the similarity of the interpretations of the rating categories included in investment grade of international agencies (Fitch and Moody's) and national agencies.

Thus, the first two ratings of the AK&M, the first three ratings of the RA "Expert", the first six ratings of the RusRating, the first seven ratings of NRA, S&P, Fitch, Moody's were taken. In result in "investment" sample 1100 observation is observed. The consensus rating is also reconstructed, as narrower sample is used.

As it can be seen from Table 6, regressions' independent variable of some CRA have changed – number of explanatory variables decreased. Moreover, share of exact matches and matches within ± 1 rating grade significantly increase (see Table 7 and Table 8). A particularly significant increase in predictions accuracy has occurred in international CRA[19].

Therefore, the ratings of investment grade and speculative should be assessed separately. In addition, the consensus rating constructed on these estimates has a high agreement degree with original consensus rating: τ_x equals 73%.

Such result may indicate that the investment grade ratings bring fewer contradictions into the proxy consensus rating than the speculative grade ratings. Ideally, to test this assumption, it would be worthwhile to construct proxy consensus rating only for NCRA investment grades. But this is not yet possible because of the lack of data on the NCRA ratings. Nevertheless, the models can be further improved in terms of predictive power. Improvement of this can be facilitated by using more suitable financial or non-financial indicators of the bank. This is especially important in forecasting international CRA ratings.

[19] However, it is worth noting that the consideration of state or foreign support factors could introduce distortions between real and model estimates.

Table 6. Explanatory factors for regression (by CRA, investment grades).

Factor	H1	H2	H3	H4	H7	H9.1	H10.1	H12	H1_i	H2_g	H3_g	H3_i	PA3	PL5	PK3	Di	Size	e_f
AKM							-						+					
EXP	-		+	+		+	-	+					+	+				-
FCH					+				-	-			+				-	
MDS	+	+			+	+						-				-	-	-
NRA	-							-					+		+	-	-	-
RUS															-		-	
SNP	+			-	+	+					x		+	-		-		-

Factor	Tr ratio	L_s_t	Non f	Res	D/L	CS	F	T_L	Tr ratio_g	S_i	Di_g	Res_i	CS_g	Res_g	PK3_g	PL5_g
AKM		+	+		-											
EXP	+	+		-				-					+		+	
FCH						+						-				
MDS										-						+
NRA				-					+					-		
RUS		-					-	-								
SNP	+			-		+					+					

"+" – positive sign of coefficient in model, "-" – negative sign of coefficient in model.
Source: author's calculations.

Table 7. Accuracy of ratings prediction (by CRA, investment grades)

	AKM	EXP	FCH	MDS	NRA	RUS	SNP
MacFadden's R^2	78.80%	44.09%	36.93%	29%	50.15%	46.83%	40.96%
Share of exact matches	95.32%	70.64%	51.00%	45.05%	63.47%	63.54%	49.63%
Share of +Δ1 rang	1.17%	14.44%	16.70%	13.66%	16.69%	11.46%	20.84%
Share of -Δ1 rang	3.51%	14.44%	17.37%	13.34%	17.52%	5.21%	19.60%
Share of ±Δ2 rang	0.00%	0.47%	10.02%	15.38%	2.31%	8.33%	7.20%
Share of ±Δ3 rang	0.00%	0.00%	4.23%	9.58%	0.00%	11.46%	2.73%
Total quantity	171	637	449	637	605	192	403

Source: author's calculations.

Table 8. Difference in the accuracy of predictions[20].

	AKM	EXP	FCH	MDS	NRA	RUS	SNP
Consensus Sample	100.00%	97.86%	56.66%	65.70%	95.22%	80.89%	72.99%
Investment Grade Subsample	100.00%	99.52%	85.07%	72.05%	97.68%	80.21%	90.07%
Δ precision	0.00%	1.66%	28.41%	6.35%	2.46%	-0.68%	17.08%

Source: author's calculations.

4.2 National CRAs subsample

It is reasonable to assume that more precise ratings estimates will allow obtaining proxy consensus rating which is more similar to consensus rating in terms of agreement. That is to say, the proxy is constructed from model estimates of national CRAs' ratings (see Appendix C, model I and model VI).

The same observations as in previous part were used to predict NCRA ratings. Note, that consensus rating is determined for banks with at least two ratings for from different CRAs. Therefore, only 394 observations were involved in comparison of proxy and original consensus rating based on ratings from NCRA.

[20] Comparison of share of exact matches plus share of ±Δ1 rang of two samples.

Table 9. Explanatory factors for regression (by National CRA).

Factor	H1	H3	H4	H7	H9.1	H10.1	H12	PA3	PL5	PK3	Di	Size	e_f
AKM		+		+		-		+					
RUS								+		+		-	-
EXP	-	+	+		+	+	+	+	+				-
NRA	+	-	+				-	+		+	-	-	-

Factor	Tr ratio	L_S_T	NonF	Res	F	T_L	Tr ratio_g	CS_g	Res_g	Or	State	PK3_g
AKM	+	+	+									
RUS	-	-			-	-				+	+	
EXP	+	+		-		-		-				-
NRA				-			+		-			

"+" – positive sign of coefficient in model, "-" – negative sign of coefficient in model.
Source: authors' calculations.

In this sample τ_x between proxy and original consensus equals 62.2%. Note that this value is slightly smaller than values for previous samples, despite the fact that ratings predictions accuracy on this subsample is higher than on Consensus Sample (Table 10.2 and Table 10.1 respectively).

Table 10.1 Accuracy of ratings prediction (by National CRA, full sample).

	AKM	EXP	NRA	RUS
MacFadden's R^2	68.53%	42.64%	47.20%	47.30%
Share of exact matches	84.69%	67.64%	60.45%	52.44%
Share of +Δ1 rang	6.70%	14.88%	16.91%	13.41%
Share of -Δ1 rang	8.61%	15.34%	17.86%	15.04%
Share of ±Δ2 rang	0.00%	1.99%	3.03%	6.91%
Share of ±Δ3 rang	0.00%	0.15%	1.12%	12.20%
Total quantity	209	652	627	246

Source: author's calculations.

Table 10.2 Accuracy of ratings prediction (by National CRA, paired ratings).

	AKM	EXP	NRA	RUS
Share of exact matches	92.12%	84.67%	76.54%	83.33%
Share of +Δ1 rang	7.88%	14.67%	22.22%	12.28%
Share of -Δ1 rang	0.00%	0.00%	0.00%	0.00%
Share of ±Δ2 rang	0.00%	0.67%	1.23%	1.75%
Share of ±Δ3 rang	0.00%	0.00%	0.00%	2.63%
Total quantity	165	300	243	114

Source: author's calculations.

First, the decrease of agreement between proxy and original consensus rating can be explained by shrinking of sample (less observations and CRAs). The less observations or CRAs in a sample, the more sensitive to a single mismatch consensus rating becomes. Moreover, national CRAs are less agreed on ordering banks according to their credit quality, so it is more likely to face the problem described above in subsection on consensus of financial indicators.

Second, disagreement is aggravated by the presence of speculative class ratings. Empirical calculations in articles Karminsky, Peresetsky (2008), Hung, Cheng (2013) confirm these considerations: the greatest errors in the accuracy of predictions are observed in the speculative group of ratings and 1 ratings grades in front of them. To evaluate this group of ratings, it may be worthwhile to apply a separate model to avoid contradict pairs number growth.

However, the obtained level of agreement is still fairly high from practical point of view.

5 Conclusion

In this paper, we propose a two-step methodology for studying 1) if the aggregate rating performs as well as best-practice credit risk models on its own domain of rated companies, 2) if aggregate rating can be accurately modeled and, therefore, extrapolated to the non-rated companies without loss it competitiveness. We argue that aggregate rating that successfully pass these two steps suits credit analysis purposes and can be used in credit model building and validation.

We apply this methodology to the aggregated rating of Russian banks constructed as a consensus of ratings assigned by different rating agencies. We examine if the aggregate rating constructed as a consensus of individual credit ratings can be accurately predicted by publicly available non-rating information.

We show that aggregate (consensus) rating is comparable to financial-data-based econometric default model in term of discriminatory power; however, corresponding orderings have a fairly low agreement. We also found that using models for predicting initial credit ratings allows for building a proxy that has practically high agreement with the original aggregate rating, but original aggregate rating outperforms proxy in terms of discriminatory power. It was also found that greater agreement between original aggregated rating and proxy can be achieved on the subsample of investment grade ratings. Nonetheless, it does not mean that a consensus is more suitable for investment grade ratings than for speculative.

Therefore, our approach shows that consensus rating performs well on its own domain and can be used on it as a factor for credit risk analysis and validation of internal model. However, we couldn't replicate the consensus rating with available information and econometric models well enough for extrapolation outside its domain and using it as a universal credit risk indicator.

Our approach can be applied to arbitrary aggregate rating constructed with any rating inputs and aggregation methodology. Authors intend to exploit in further research.

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Appendix A. Variables description.

Variable	**Interpretation**
"Variable name"_index	A variable created by multiplying a financial indicator by a dummy variable State(index g) or Foreign(index i)
Cash	Cash
CS	(Bank capital/Total assets)
D/L	ln(Total deposits/Long term loans)
Da	Deposits of legal entitiess
Db	Interbank deposit
Dc	Deposits with the Bank of Russia
Df	Deposits of foreign entities
Dg	State bodies deposits
Dh	Retail deposits
Di	Deposit of financial companies
Di	Deposit of financial companies
e_f	(Deposits of legal entities)/(Bank capital)
F	Dummy, foreign bank
H1	Capital adequacy ratio
H10.1	Ratio of sum of loan to bank insiders to bank capital
H12	Ratio of sum of investments in shares of other legal entities
H2	Instant liquidity ratio
H3	Normative indicator of current liquidity
H4	Normative indicator of long-term liquidity
H9.1	Ratio of sum of loans to the bank owners to bank capital
L_short_tot (L_S_T)	Total short-term loans
La	Legal entities loans

Lb	Interbank credit
Lc	Loans issued by the Bank of Russia
Lf	Loans to foreign entities
Lg	State bodies credits
Lh	Retail loan
Li	Loans to financial companies
ln(dep/st_loans) D_S	ln(Total deposits/Total Short-term loans)
NonF	Ratio of nonfinancial entities loans to total loans
Or	Borrowed reserves
PA3	Indicator ofoverdue loans share
PA5 (H7)	Maximum size of major credit risks
PK3	Indicator of capital quality assessment
PL5	(Interbank deposits- Inrebank Loans)/(Total deposits)
Res	Excess reserves
Secur	Purchased securities
State	Dummy, state-controlled bank
Total loans (T_L)	Bank account loans
tr ratio (T_R)	(Total reserves)/(Bank capital)

Appendix B. Model quality in terms of discriminatory power.

AR interval, 1 years risk horizon	Model quality	Significance for risk-management
80% and more	Advanced	The rating system allows to automate decision-making process for credit transactions, loan reserves and capital allocation
60-80%	Very good	
40-60%	Good	The rating result should be of great weight in decision-making process for credit transactions
20-40%	Medium	Rating can only be regarded as informative (referential). Reservation and allocation of capital should be implemented with standardized criteria (Bank of Russia or Standardized Approach of Basel II)
20% and less	Insufficient	The rating result have not be taken into account in decision-making process for credit transactions Reservation and allocation of capital must be implemented with standardized criteria (Bank of Russia or Standardized Approach of Basel II)

Source: Pomazanov (2016), p.54

Appendix C. Components of consensus ratings and its alternative.

№ model	**Estimated parameter**	**Basic data**	**Method**
I	Consensus	Ratings	Algorithm
II	Scoring logit model	Public information	Logit model
III	Consensus of financial indicators	Financial indicators	Algorithm + logit model
IV	Consensus of modeled rating (a)	Public information, ratings	Algorithm + ordered logit model
V	Consensus of modeled rating (b)	Public information, investment class ratings	Algorithm + ordered logit model
VI	Consensus of modeled rating (c)	Public information, NCRA ratings	Algorithm + ordered logit model

Appendix D. Explanation of the CRAs' abbreviation.

AKM	Rating Agency AK&M
EXP	Rating Agency RAEX («Expert RA»)
FCH	FitchRatings
MDS	Moody's Analytics
NRA	«National Rating Agency»
RUS	RusRating
SNP	Standard&Poor's

Appendix E. Correlation matrix for models variable.

In research studies on the credit ratings aggregation, the VIF (variance inflation factor) or the correlation matrix of explanatory variables is used to measure multicollinearity, if the question of testing multicollinearity is discussed. All are unanimous that the VIF values are 10 or more, the correlation coefficient is 0.75 in modulus and more precisely indicates that the use of a such pair of variables simultaneously leads to multicollinearity. In this paper, the authors hold the same opinion on the correlations.

Model II

	h3	h4	pa5	pk3	size	D_S	T_L	e_f	Tr_ratio
h3	1.000								
h4	-0.158	1.000							
pa5	-0.281	0.032	1.000						
pk3	0.074	-0.039	-0.149	1.000					
size	-0.010	0.230	-0.230	0.275	1.000				
D_S	-0.068	0.265	0.015	0.040	0.449	1.000			
T_L	-0.028	0.127	-0.093	0.249	0.505	0.263	1.000		
e_f	0.044	0.041	-0.066	-0.168	0.072	0.046	0.018	1.000	
Tr_ratio	0.049	-0.114	-0.078	-0.158	-0.325	-0.184	-0.115	-0.009	1.000

Source: authors' calculations.

Model IV

AKM

	h10.1	h3	h7	L_S_T	nonf	pa3	D/L	orcha
h10.1	1.000							
h3	-0.003	1.000						
h7	0.062	-0.280	1.000					
L_S_T	-0.127	0.103	-0.190	1.000				
nonf	0.148	-0.372	0.365	-0.354	1.000			
pa3	-0.074	0.167	-0.322	0.102	-0.155	1.000		
D/L	-0.203	0.012	-0.221	0.209	-0.149	0.045	1.000	
orcha	0.060	0.044	-0.077	0.036	-0.031	0.182	-0.295	1.000

Source: authors' calculations.

FCH

	h101	h7	size	pl5	pa3	CS	e_f	res_i	h1_i	size_i	h2_g
h101	1.000										
h7	0.067	1.000									
size	-0.188	-0.216	1.000								
pl5	-0.073	0.096	-0.078	1.000							
pa3	-0.074	-0.321	0.065	-0.019	1.000						
CS	-0.117	-0.156	0.076	-0.028	0.094	1.000					
e_f	-0.106	-0.076	0.062	0.017	-0.100	-0.062	1.000				
res_i	-0.202	-0.322	0.232	-0.027	0.080	0.105	0.161	1.000			
h1_i	-0.135	-0.190	0.128	-0.019	0.021	0.110	0.079	0.572	1.000		

size_i	-0.202	-0.326	0.229	-0.024	0.078	0.106	0.166	0.499	0.580	1.000	
h2g	-0.065	-0.016	0.349	-0.024	0.050	-0.146	0.070	-0.079	-0.046	-0.079	1.000

Source: authors' calculations.

RUS

	L_S_T	size	T_L	pa3	pk3	e_f	T_R	F
L_S_T	1.000							
size	0.040	1.000						
T_L	-0.022	0.500	1.000					
pa3	0.094	0.065	-0.036	1.000				
pk3	0.117	0.042	0.095	-0.006	1.000			
e_f	0.093	0.062	0.019	-0.100	0.052	1.000		
T_R	0.035	-0.339	-0.115	0.182	0.002	-0.023	1.000	
F	0.056	0.216	0.006	0.079	0.025	0.178	-0.080	1.000

Source: authors' calculations.

	h1	h101	h12	h3	h4	h91	L_S_T	pl5	T_L	pa3	res	e_f	T_R	pk3_g	CS_g	e_f_g
h1	1.00															
h101	-0.03	1.00														
h12	0.08	-0.09	1.00													
h3	0.18	-0.01	-0.01	1.00												
h4	-0.09	0.15	-0.02	-0.15	1.00											
h91	0.01	0.13	0.04	0.00	0.01	1.00										
L_S_T	0.00	-0.14	-0.03	0.11	-0.28	-0.01	1.00									
pl5	-0.05	-0.07	-0.01	-0.12	-0.04	-0.08	-0.22	1.00								
T_L	0.04	-0.05	0.17	-0.03	0.13	-0.02	-0.02	-0.02	1.00							
pa3	0.04	-0.07	0.00	0.17	0.02	0.00	0.09	-0.02	-0.04	1.00						
res	0.09	-0.14	0.28	0.04	0.19	-0.03	0.07	-0.03	0.42	0.24	1.00					
e_f	-0.10	-0.11	0.02	0.03	0.05	0.00	0.09	0.02	0.02	-0.10	0.04	1.00				
T_R	0.03	0.06	-0.05	0.04	-0.15	0.04	0.04	0.00	-0.12	0.18	0.01	-0.02	1.00			
pk3_g	0.06	-0.02	0.17	-0.01	0.07	-0.02	-0.01	-0.05	0.74	-0.02	0.26	-0.03	-0.08	1.00		
CS_g	0.01	-0.10	0.33	-0.04	0.15	-0.03	-0.05	-0.01	0.40	0.04	0.34	0.04	-0.10	0.59	1.00	
e_f_g	-0.04	-0.07	0.30	-0.04	0.16	-0.04	-0.06	0.04	0.25	0.04	0.33	0.21	-0.06	0.25	0.73	1.00

Source: authors' calculations.

	h1	h10.1	h2	h7	h9.1	di	size	res	e_f	pl5_g	h3_i	size_i	T_R_g
h1	1.000												
h10.1	-0.029	1.000											
h2	0.084	-0.012	1.000										
h7	-0.103	0.067	-0.289	1.000									
h9.1	0.012	0.125	0.000	0.052	1.000								
di	0.043	-0.104	-0.028	-0.098	-0.014	1.000							
size	0.065	-0.188	-0.021	-0.216	-0.060	0.649	1.000						
res	0.048	-0.091	-0.015	-0.117	-0.021	0.711	0.616	1.000					
e_f	-0.095	-0.106	0.026	-0.076	0.003	0.131	0.062	0.041	1.000				
pl5_g	0.005	-0.123	-0.019	0.110	0.001	0.161	0.101	0.127	0.092	1.000			
h3_i	0.064	-0.094	0.147	-0.257	-0.032	-0.006	0.105	0.004	0.218	-0.010	1.000		
size_i	0.047	-0.202	0.007	-0.326	-0.044	0.036	0.229	0.054	0.166	-0.015	0.658	1.000	
T_R_g	-0.037	-0.041	-0.049	0.048	-0.040	0.326	0.168	0.215	0.064	-0.011	-0.050	-0.074	1.000

Source: authors' calculations.

	h1	h101	h4	h7	h91	di	pl5	pa3	CS	res	e_f	T_R	h3_g	LST_g	Di_g	e_f_i
h1	1.00															
h101	-0.03	1.00														
h4	-0.09	0.15	1.00													
h7	-0.10	0.07	0.04	1.00												
h91	0.01	0.13	0.01	0.05	1.00											
di	0.04	-0.10	0.17	-0.10	-0.01	1.00										
pl5	-0.05	-0.07	-0.04	0.10	-0.08	0.01	1.00									
pa3	0.04	-0.07	0.02	-0.32	0.00	0.01	-0.02	1.00								
CS	0.27	-0.12	-0.13	-0.16	-0.01	-0.08	-0.03	0.09	1.00							
res	0.09	-0.14	0.19	-0.31	-0.03	0.57	-0.03	0.24	0.11	1.00						
e_f	-0.10	-0.11	0.05	-0.08	0.00	0.13	0.02	-0.10	-0.06	0.04	1.00					
T_R	0.03	0.06	-0.15	-0.08	0.04	-0.17	0.00	0.18	-0.01	0.01	-0.02	1.00				
h3_g	-0.01	-0.08	0.16	0.00	-0.04	0.54	-0.03	0.08	-0.14	0.31	0.06	-0.06	1.00			
LST_g	0.01	-0.02	0.05	0.03	-0.03	0.33	-0.06	0.03	-0.08	0.16	0.03	0.02	0.68	1.00		
di_g	0.03	-0.04	0.12	-0.10	-0.03	0.88	0.01	0.02	-0.07	0.41	0.10	-0.12	0.64	0.40	1.00	
e_f_i	0.03	-0.16	0.11	-0.29	-0.03	0.00	-0.01	-0.01	0.09	0.14	0.35	-0.07	-0.07	-0.04	-0.05	1.00

Source: authors' calculations.

	h1	h12	h3	h4	di	size	pa3	res	pk3	e_f	res_g	T_R_g
h1	1.000											
h12	0.079	1.000										
h3	0.177	-0.006	1.000									
h4	-0.091	-0.024	-0.155	1.000								
di	0.043	0.333	-0.041	0.168	1.000							
size	0.065	0.292	-0.004	0.259	0.550	1.000						
pa3	0.039	-0.001	0.167	0.019	0.009	0.065	1.000					
res	0.092	0.276	0.041	0.192	0.569	0.570	0.236	1.000				
pk3	0.105	0.000	0.088	-0.026	-0.015	0.042	-0.006	0.076	1.000			
e_f	-0.095	0.018	0.030	0.049	0.130	0.062	-0.100	0.038	0.052	1.000		
res_g	-0.025	0.297	-0.053	0.196	0.512	0.416	0.048	0.375	-0.075	0.071	1.000	
T_R_g	-0.037	0.155	-0.027	0.147	0.326	0.168	0.074	0.194	-0.059	0.064	0.615	1.000

Source: authors' calculations.

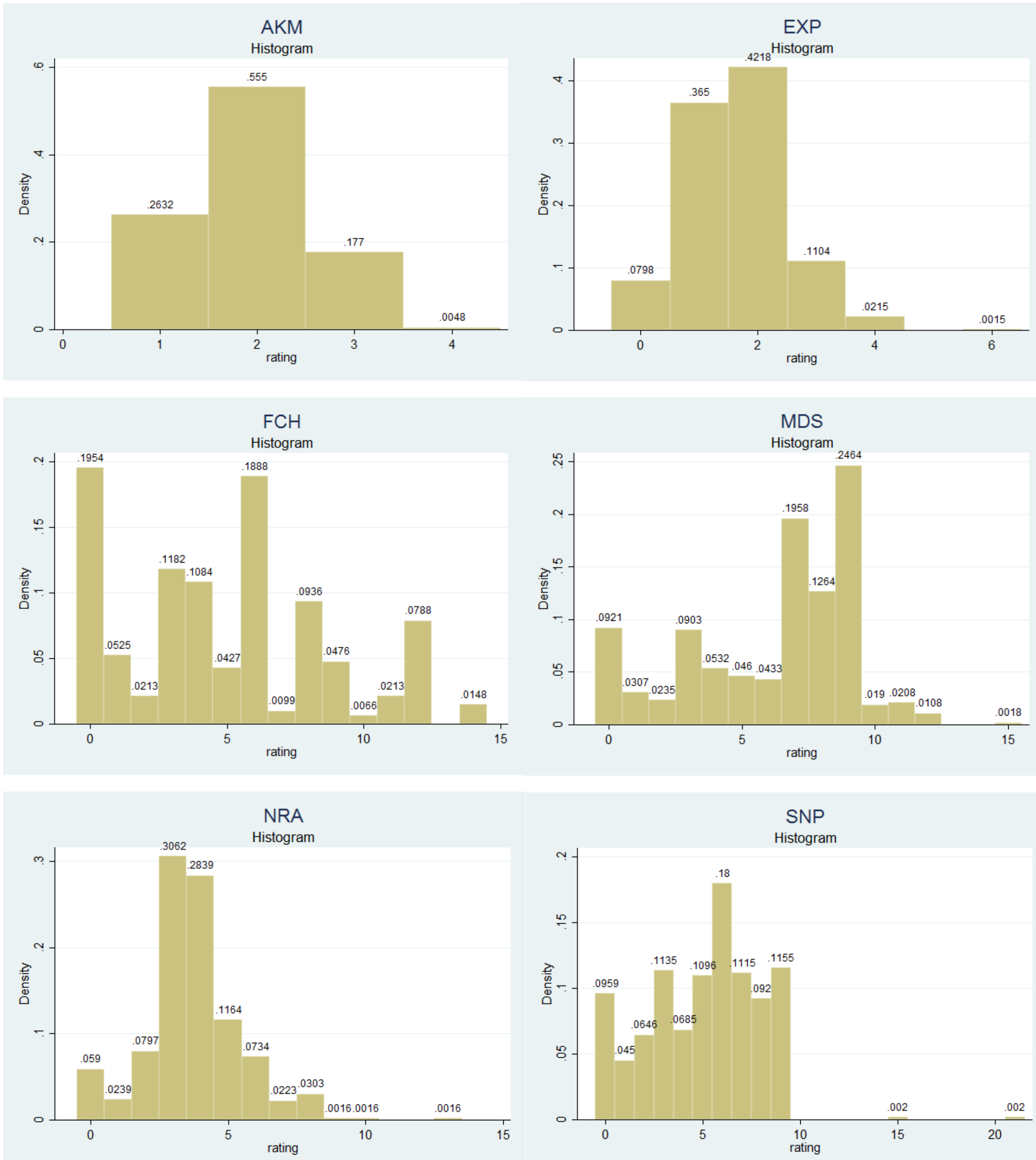
Appendix F. Descriptive statistics of explanatory variables.

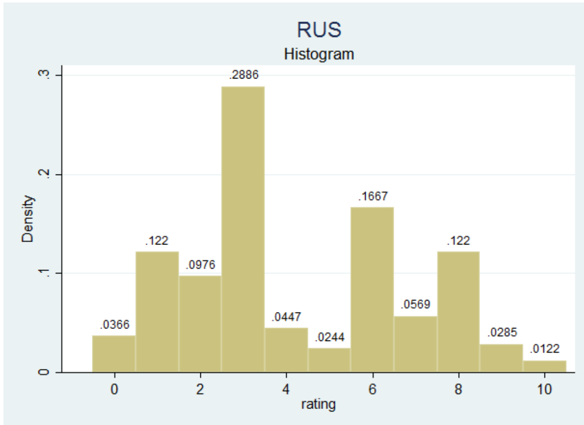
Variable	Obs	Mean	Std. Dev.	Min	Max
cs	1,700	0.29721	0.137209	0.00986	0.800349
cs_g	1,700	0.021651	0.074974	0	0.543285
D/L	1,700	17.79716	1.514874	12.88666	23.50904
D_S	1,700	21.45275	2.388049	14.88388	32.77662
di	1,700	8839488	2.43E+07	0	2.36E+08
di_g	1,700	4734544	2.23E+07	0	2.36E+08
e_f	1,700	0.092	0.065688	0.000756	0.466124
e_f_g	1,700	0.009814	0.036305	0	0.246516
e_f_i	1,700	0.009027	0.041216	0	0.466124
f	1,700	0.066471	0.249176	0	1
h1	1,700	7.551924	11.70625	0	77.21
h1_i	1,700	0.638847	4.127527	0	44.61
h101	1,700	0.928959	0.726141	0	6.93
h12	1,700	1.799224	4.395179	0	24.91
h2	1,700	71.89571	61.07142	10.84	898.6
h2g	1,700	5.618647	18.87149	0	168.86
h3	1,700	101.1857	63.59263	18.44	1014.37
h3_g	1,700	8.535929	27.94024	0	200.37
h3_i	1,700	8.725247	48.66564	0	926.75
h4	1,700	69.06213	27.90633	0	130.98
h7	1,700	279.3108	151.2251	0	866.14
h91	1,700	2.085876	9.917066	0	368.71
L_S_T	1,700	0.06672	0.121433	0	0.934414
LST_g	1,700	0.00398	0.019688	0	0.281264
nonf	1,700	0.825172	0.197842	0	1
or	1,700	2444386	1.14E+07	7474	1.59E+08
pa3	1,700	0.047723	0.046182	0	0.412712
pa5	1,700	279.3108	151.2251	0	866.14
pk3	1,700	4.975535	6.181481	-0.79566	67.44503
pk3g	1,700	0.348523	2.549823	-0.35753	67.44503
pl5	1,700	0.012728	0.050668	-0.45693	0.409203
pl5_g	1,700	0.000952	0.01689	-0.1744	0.134035
re_i	1,700	0.97307	3.663599	0	16.25949
res	1,700	13.15813	1.698182	7.885705	18.50355
res_g	1,700	1.401982	4.391423	0	18.50355
size	1,700	18.62496	1.550322	14.9372	25.45365
size_i	1,700	1.321562	4.96404	0	22.5007
state	1,700	0.094118	0.292078	0	1

T_R	1,700	0.011994	0.007954	0.001833	0.090487
T_R_g	1,700	0.000937	0.003393	0	0.034361
Total loan	1,700	2.33E+08	1.14E+09	426211	1.75E+10

Source: authors' calculations.

Appendix G. Ratings' histograms.





Source: authors' calculations.

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