Dynamic Mapping of Probability of Default and Credit Ratings of Russian Banks

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Abstract

Investors are interested in a quantitative measure of banks' credit risk. This paper maps the credit ratings of Russian banks to default probabilities for different time horizons by constructing an empirical dynamic calibration scale. As such, we construct a dynamic scale of credit risk calibration to the probability of default (PD).

Our study is based on a random sample of 395 Russian banks (86 of which defaulted) for the period of 2007-2017. The scale proposed by this paper has three features which distinguish it from existing scales: dynamic nature (quarterly probability of default estimates), compatibility with all rating agencies (base scale credit ratings), and a focus on Russian banks.

Our results indicate that banks with high ratings are more stable just after the rating assignment, while a speculative bank's probability of default decreases over time. Hence, we conclude that investors should account for not only the current rating grade of a bank, but also how long ago it was assigned. As a result, a rising capital strategy was formulated: the better a bank's credit rating, the shorter the investment horizon should be and the closer the date of investment should be to the rating assignment date in order to minimise credit risk.

The scientific novelty of this paper arises from the process of calibration of a rating grade to dynamic PD in order to evaluate the optimal time horizon of investments into a bank in each rating class. In practical terms, investors may use this scale not only to obtain a desired credit rating, but also to identify quantitative measure of credit risk, which will help to plan investment strategies and to calculate expected losses.

Keywords: banks, credit ratings, probability of default, mapping, calibration

JEL classification: G21, G24, G33

Introduction

The sustainability of a country's financial system primarily depends on the performance of financial institutions. The key financial institutions are banks and credit organisations. The assessment of banks' credit risk is an important issue for governments, regulators and investors. All such economic agents are interested in having banks functioning well, as they serve as the main financial intermediaries on the market. The most commonly-used ways of assessing financial performance and controlling the level of credit risk of a bank are by evaluation of default probability and via credit rating. The probability of default (PD) is the likelihood of a bank failure over a fixed assessment horizon, and a credit rating (CR) determines the class to which a company belongs based on the PD.

CR is represented in symbolic form, which may lead to problems with the interpretation and quantitative assessment of potential losses of a bank's counteragent. However, a CR model itself usually has better forecasting power compared to a PD model with quantitative outcome. Therefore, the calibration scale of CR to PD will allow to obtain quantitative estimate of credit risk, based on a CR grade assigned by a rating agency (RA) or as forecast by a CR model.

The aim of this paper is to construct a dynamic scale of CR calibration to PD. Investors are interested in a quantitative measure of banks' credit risk. This goal is achieved with the help of default frequencies estimation for each group of credit rating grades. This scale is built on the basis of an extensive sample of Russian banks and can be used by both investors and internal management in credit risk assessment. The topic of this paper may be of particular importance in the current situation, which is critically close to a global economic crisis.

The topic of mapping CR to PD is frequently studied: many researchers and RAs propose their own calibration scales. However, the novelty of CR to PD calibration scale of this paper is supported by the following superior features. First, the scale has a high frequency dynamic nature that allows to estimate the change in PD of a particular CR class, with a quarterly periodicity after the rating assignment date. Second, this calibration scale provides a quantitative PD estimate for a CR assigned by any national or international rating agency, because it uses uniform CR scale in calibration. Third, this scale was constructed based on a data sample of Russian banks that accounts for the specific features of the country.

Additionally, while constructing the calibration scale, we notice several important patterns and try to explain their possible reasons and origins. A dynamic scale assessing the calibration of qualitative CR measures to quantitative PD measures showed that the better the credit rating of a bank, the higher the CAGR of PD is (PD increases in time at a faster rate in the better rating classes). As a result, the rising capital strategy was formulated. Investment in banks with a better credit rating is optimal right after the rating issue, and is efficient over a short term period. However, to achieve minimal credit risk for capital investment in banks with highly speculative rating grades, it is optimal to choose a long run investment 1-2 years after the rating assignment.

The paper is structured as follows. First, we introduce the literature review on CR and PD mapping. Next, the detailed data description and the methodological issues are discussed. Empirical results are provided in the main part, and the paper ends with our conclusions.

Review of related academic literature and hypothesis development

There are several literature streams that study the non-linear dependence between credit ratings and other fundamental risk parameters (PD, LGD and EAD). For example, Volk [1] in his paper linked the forecasted values of firms' PDs with credit ratings and identified disparities in firms' creditworthiness when estimated by these methods. Papers [2] and [3] study the phenomenon whereby a higher credit rating may lead to a higher LGD. Another literature stream focuses on the calibration of PD and CR to the same scale. The paper cited at [4] compares a variety of calibration approaches and concludes that a 'scaled likelihood ratio' approach is superior to the standard 'scaled PDs' approach. Pomasanov and Vlasov [5] introduce the model of credit ratings calibration on PD for Russian banks. Alternatively, paper [6] offered models for credit ratings and PD calibration in samples with small number of bankrupt firms. The proposed method is based on the idea of benchmarking and genetic algorithms. Moreover, paper [7] provides a calibration scale that takes into account the forecasted PD and has a forward-looking nature. Different methods of comparing the credit ratings and PD were used in the academic papers cited at references [8; 9; 10]. For example, Godlewski [8] compared banks' CR and PD in emerging countries and proved a partial divergence of ratings with the use of a PD scoring model, by finding out that CR tends to aggregate banks' default risk information into intermediate-to-low ratings grades. Most of the articles mentioned above offer an econometric model, which can be used for interpreting CRs with the help of PD (see, e.g. [1; 4; 5; 7; 11; 12]). Moreover, the tables with credit ratings and implied PDs are provided by RAs themselves: S&P (Annual Corporate Default and Rating Transition Study), Moody's (Corporate Default and Recovery Rates) and Fitch (Transition and Default Studies). However, one faces several limitations while applying these scales to Russian banks:

- First, RAs do not provide the corresponding scales of credit rating conversion for different countries and for different geographic groups. The data used by the RAs to prepare these calculations mostly include their home country (the USA) and the countries of major shareholders (developed countries such as Canada and the UK). Russian banks are not representative in such databases;

- Second, the values of annual historical default frequencies (estimates of default probabilities) for various credit ratings are calculated by each RA empirically (based on default statistics of banks with credit ratings of a particular RA), which leads to an inadequate comparison of the level of creditworthiness for the same rating class in different time periods;
- Third, the scales provided by each RA are not dynamic in nature, i.e. they provide only annual frequencies. An investor may not evaluate the possible losses which can occur in the short run (in a month/quarter after the investment is made).

Based on this literature review, we aim to construct a uniform calibration scale that simultaneously includes the CR of different RAs and allows to estimate the probability of default in different time frames after credit rating assignment. Following a time frame analysis, the following hypothesis was formulated.

Hypothesis 1. Banks with high ratings are more stable just after the rating assignment, while a speculative bank's probability of default decreases over time.

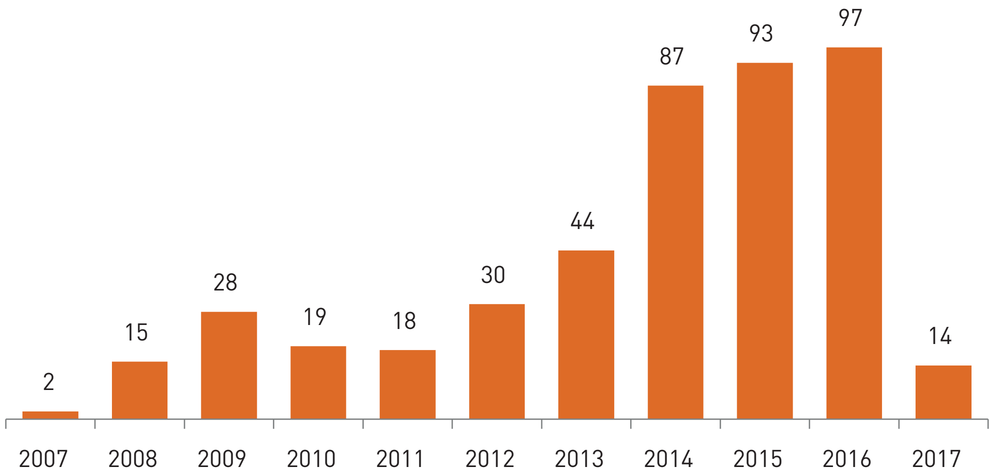
The intuition behind this hypothesis is that speculative banks that survive for a prolonged period are mainly small but stable, while banks with investment rating grades face huge competition and cannot fulfil regulatory requirements for a long period. Therefore, it is supposed that investors should account for not only the current rating grade of a bank, but also how long ago it was assigned.

Data sample description

The empirical research of this paper is based on the dataset that was consolidated with the help of Matlab code from two separate databases. The first is the "Banks and Finance" database provided by the informational agency "Mobile", while the second is the database of Central Bank of Russia, which consists of the RAS statements of all Russian licensed banks. The data was gathered with a quarterly periodicity that allowed us to obtain a panel dataset of Russian banks. Initially, information about 2071 banks was extracted for the period from 2004 to 2017.

Some data filtration methods were applied in order to generate a representative sample. First, all state-owned banks (according to the definition of Vernikov and Bobkov [13]) were omitted, as we consider standalone ratings. The main reduction of the sample size appeared due to the fact that only a small share of banks (395 banks) was assigned a CR grade. The historical data of CR changes was taken from on-line aggregators of banking statistics Cbonds.ru and Bankodrom.ru. The data included CR grades of national RAs (NRA, RAEX, AK&M, Rus-Rating, Ria-Rating) and international RAs (Standard & Poor's, Fitch, and Moody's). The data on banks' defaults were collected from Cbr.ru and Banki.ru. During the extraction period, 86 Russian banks that got a CR assessment defaulted at least once. See Figure 1 below for the historical distribution of all Russian banks (before any filtrations) for the period from 2007 to 2017.

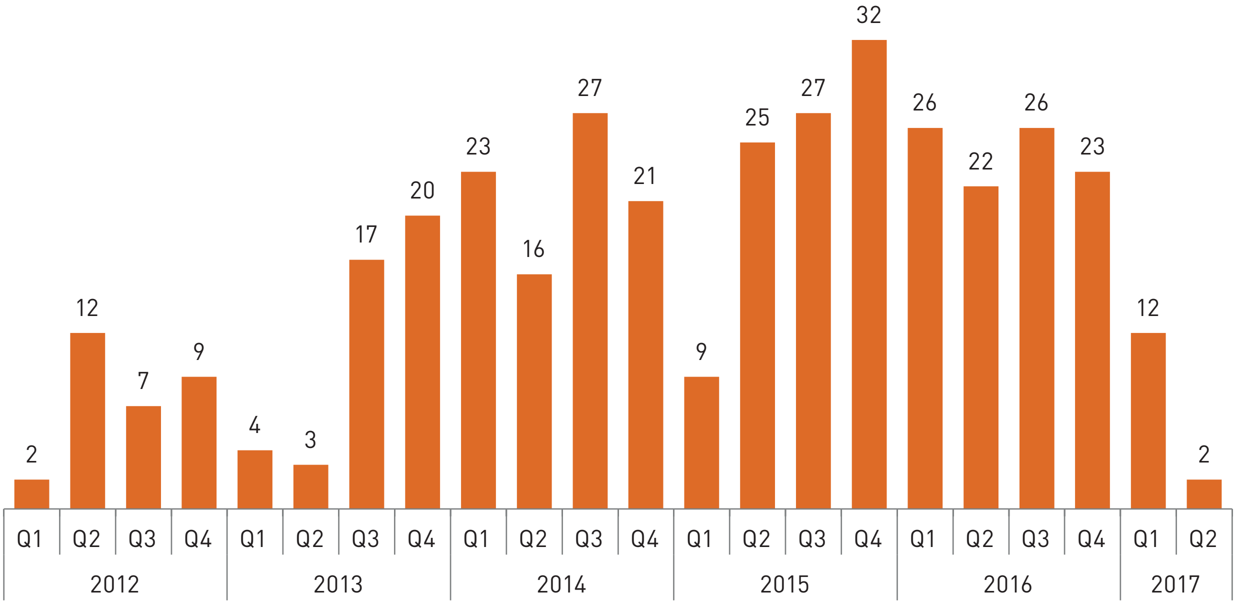
Figure 1. Historical annual distribution of defaults of Russian banks from 2007 to 2017



Source: Authors' own calculations.

From the graph above we can conclude that after the 2008 crisis there was an increase in the number of defaults. Moreover, since 2014 the banking regulation proposed by the policy of Elvira Nabiullina in the Central Bank of Russia has become sharper. We can see that the growth rate of defaults reached 98% in 2014. In Figure 2 below, one can see a more detailed version of the historical distribution of defaults provided by quarters.

Figure 2. Historical quarter distribution of defaults of Russian banks from 2012 to 2017



Source: Authors' own calculations.

A disproportional distribution of defaults can be seen in quarterly periodicity of data (Figure 2). However, one can notice that usually the highest number of defaults appear at the end of the year (Q3 and Q4). This tendency can be explained by the fact that at the end of the year the fulfillment of annual normatives can be easily compared to the previous behaviour of the bank.

The last step of filtration was a manual check on outliers and unrealistic data. In the case of absence of some date (which rarely happened) we averaged the value with reference to the nearest periods. The overall amount of observations remaining was 11,627. Due to the intrinsically imbalanced nature of default data sets, the amount of default-periods were lower than non-default ones (223 of defaults compared to 11 404 of non-defaults).

Methodology description

Calibration of CR to the base scale

As the first step of dynamic CR to PD mapping scale construction, rating grades of national and international rating agencies were calibrated into a single scale. In order to construct a base rating scale, symbolic rating grades were transformed into numerical values and then calibrated into the common (base) scale, derived from the methodology of Karminsky and Sosurko [14] which is often used in research on this topic [15; 16].

It was concluded by Karminsky and Sosurko [14] that the best results of mapping scales are obtained by using the class of linear-logarithmic transformations. In this case, the parameterisation of mappings implies finding a pair of coefficients for mapping each of the scales into a basic one (free term and coefficient in front of the logarithm of the described rating scale). Moody's international scale was chosen as a dependent variable for the base scale construction. Therefore, the following regression was run in order to fulfill the mapping procedure:

$$LN(M) = \alpha LN(R_i) + b_i \qquad (1)$$

where M is a Moody's international scale and R_i is the scale of CR that should be calibrated to the base scale. In general, the specification of the model and the total values of the coefficients and characterise the function of converting the numerical values of ratings by the scales under consideration () to the base scale (). The estimated coefficients for international RAs like Standard & Poor's, Fitch, and Moody's (both international and national scales) and national RAs such as NRA, RAEX, AK&M, Rus-Rating, and Ria-Rating were calculated.

The results are summarised in Appendix 1.

The interpretation of this figure implies representation of symbolic CR into the numeric base scale, where smaller numbers are given to banks with the best CR, and the biggest numbers assigned to the worst of them. Therefore, in this paper 32 different grades of rating were considered.

Dynamic mapping of CR to PD

Taking into account all the above-mentioned limitations of the existing calibration scales, we aim to construct a uniform dynamic scale of the credit rating score conversion to PD. The credit rating scores used for calibration are calculated according to the base scale obtained after the credit rating mapping. Then, average default frequencies were taken as an empirical proxy of PD. Overall, to prepare a scale of credit rating score and PD compliance, the following steps were taken.

Step 1: We calculate the matrix for each credit rating score which shows the default frequency for the banks which were assigned a particular credit rating in each of the available time periods. To estimate the default frequencies, we create R code (Appendix 4), which helps us to calculate the following matrices for each rating score. Each cell in a matrix represents the default frequency (DF) which is calculated as:

$$DF_{l,q}^{(r)} = \frac{Default_{l,q}^{(r)}}{Banks_l^{(r)}}, \quad (2)$$

where r is a rating score;

l is the time quarter of a credit rating assignment, l = (1, 2, …, 48);

q is the time quarter of a bank's default, q = (2, 3, …, 49).

Default is the number of bankrupt banks, $Default_{l,q}^{(r)}$ is the number of banks that got credit rating r in period l and defaulted in period q;

Banks is the total number of banks, $Banks_l^{(r)}$ is the total number of banks that got credit rating r in period l.

Consider Appendixes 2 and 3, which present the default frequencies for credit scores r =17.5 and r = 15.5 from the second quarter of 2012 to the second quarter of 2017. In the columns, the periods of ratings assignment are presented (l = 29, …, 48). In the rows, the periods of default with ratings r = 17.5 and r = 15.5 are shown (q = 30, …, 49).

Step 2: We do not fix the quarter when the credit rating *r* was assigned. We estimate the period after which a bank goes bankrupt starting from the moment of rating assignment over the entire time horizon. Thus, to estimate the PD, we take the average values of the cells diagonally. For example, the PD after one period is found as an average default frequency:

$$DF^{(r)}(k=1) = Average\left\{DF_{1,2}^{(r)}; DF_{2,3}^{(r)}; \ldots; DF_{48,49}^{(r)}\right\}, \quad (3)$$

where k is the number of quarters after which the bank went bankrupt.

Alternatively, the PD after two periods (quarters) is calculated as:

$$DF^{(r)}(k=2) = Average\left\{DF_{1,3}^{(r)}; DF_{2,4}^{(r)}; \ldots; DF_{47,49}^{(r)}\right\}. \quad (4)$$

Hence, the default frequencies after τ periods are found as:

$$DF^{(r)}(k=\tau) = \\ = Average\left\{DF_{1,\tau+1}^{(r)}; DF_{2,\tau+2}^{(r)}; \ldots; DF_{49-\tau,49}^{(r)}\right\} \quad .(5)$$

Step 3: We summarise the obtained results for each rating score r presented in the sample of Russian banks. The intermediate tables are constructed where we present the default frequencies which are used to estimate the PD in k time periods (quarters) of a bank with credit rating r.

Step 4: The estimated default frequencies for a set of rating grades are averaged for each rating class. This is done for a more logical representation of the obtained results and for keeping an approximately equal number of bank-periods in each class. We divide the rating scores on 5 rating classes: BBB [8-10], BB [12-13.5], B [14-15.5], CCC [16-17.5] and C [18.5-21] based on international scale. For example, the default frequency for a bank with credit rating from class CCC [16-17.5] after τ quarters is calculated as:

$$DF^{(CCC)}(k=\tau) = \\ = \frac{DF^{(16)} \times n^{(16)} + \ldots + DF^{(17.5)}(k=\tau) \times n^{(17.5)}}{n^{(16)} + n^{(17.5)}} \quad (6)$$

where $n^{(r)}$ is the total number of bank-periods with rating r.

As a result of the procedure described above, a dynamic transmission scale which relates a rating score to average default frequencies of Russian banks was summarised in table format for each rating class (Table 1 below).

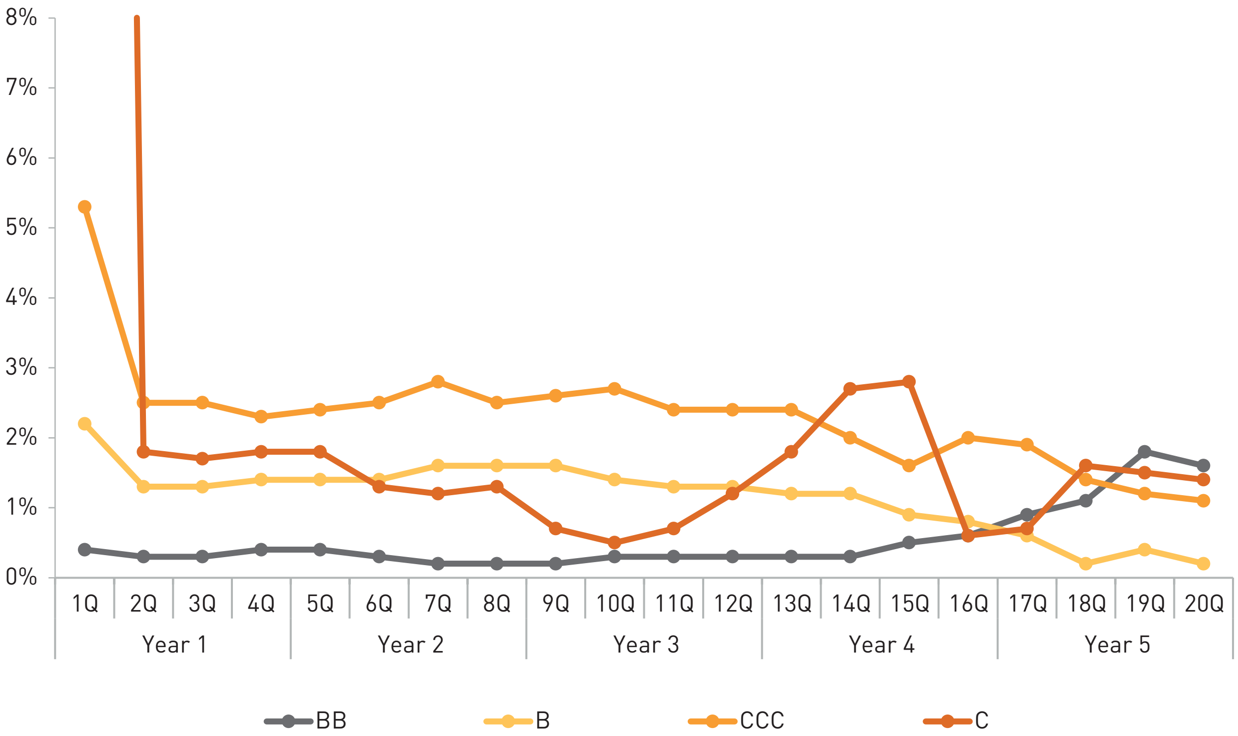
Table 1. Dynamic transmission scale of credit ratings and DF (%)

	BBB [8-10]	BB [12-13.5]	B [14-15.5]	CCC [16-17.5]	C [18.5-21]
1 quarter		0.40	2.20	5.30	56.10
2 quarters		0.30	1.30	2.50	1.80
3 quarters		0.30	1.30	2.50	1.70
4 quarter		0.40	1.40	2.30	1.80
Cum. DF in 1 year	-	1.30	6.30	12.60	61.40
5 quarters		0.40	1.40	2.40	1.80
6 quarters		0.30	1.40	2.50	1.30
7 quarters		0.20	1.60	2.80	1.20
8 quarters		0.20	1.60	2.50	1.30

	BBB [8-10]	BB [12-13.5]	B [14-15.5]	CCC [16-17.5]	C [18.5-21]
Cum. DF in 2 years	-	2.40	12.30	22.90	67.00
9 quarters		0.20	1.60	2.60	0.70
10 quarters		0.30	1.40	2.70	0.50
11 quarters		0.30	1.30	2.40	0.70
12 quarters		0.30	1.30	2.40	1.20
Cum. DF in 3 years	-	3.50	18.00	33.00	70.00
13 quarters		0.30	1.20	2.40	1.80
14 quarters		0.30	1.20	2.00	2.70
15 quarters		0.50	0.90	1.60	2.80
16 quarters		0.60	0.80	2.00	0.60
Cum. DF in 4 years	-	5.20	22.00	41.00	77.80
17 quarters		0.90	0.60	1.90	0.70
18 quarters		1.10	0.20	1.40	1.60
19 quarters		1.60	0.40	1.20	1.50
20 quarters		1.80	0.20	1.1	1.40
Cum. DF in 5 years	-	10.60	23.40	46.60	83.00

Source: Author's own calculations.

Figure 3. Comparison of quarterly default frequency increment for credit classes



Source: Authors' own calculations.

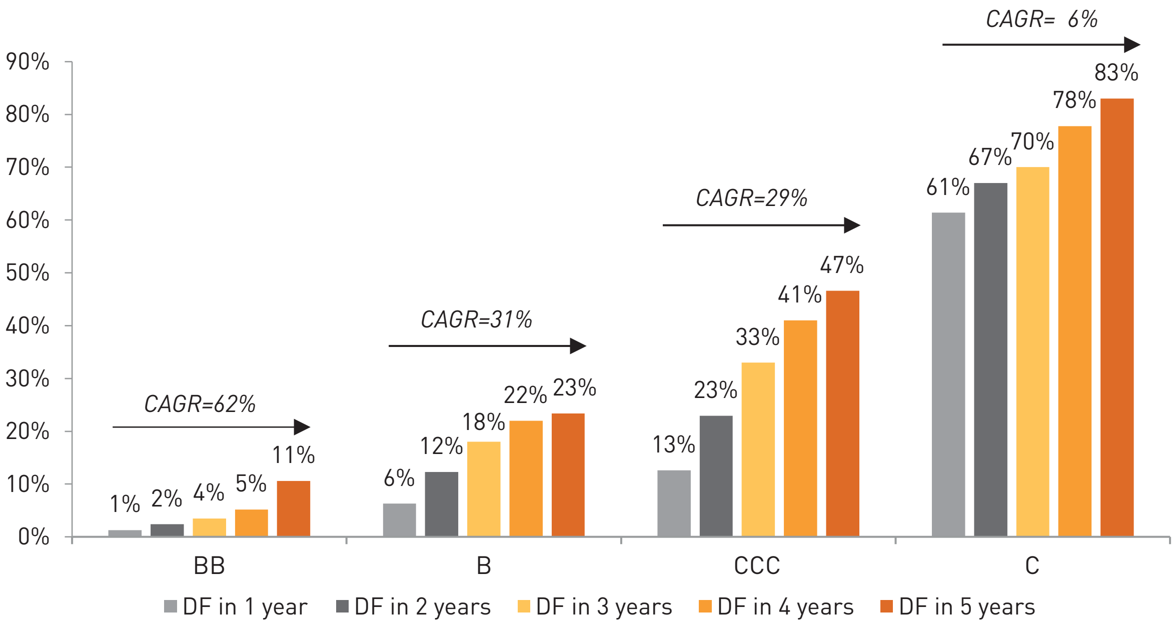
With the help of Table 1, an economic agent can understand the quantitative estimate of credit risk associated with a particular credit rating of Russian bank on the basis of default frequencies analysis. Each credit rating can be easily converted into a clear PD estimated by default frequency. The dynamic scale allows to evaluate the credit risk both annually and quarterly. Table 1 presents the annual cumulative DFs and an incremental DF per quarter. We notice that banks with newly assigned credit ratings tend to have a higher credit risk. This tendency sharpens for the lower-rating assignments. As an example, consider that a bank with credit rating B receives credit rating CCC, which is not a very dramatic downgrade. The probability that this bank defaults after one period is now 5.30%. The probability of default of the bank is significantly higher than of a similar one that has received credit rating CCC a year ago (it would have PD after one quarter of 2.40%).

Figure 3 illustrates the tendency explained above. We notice that banks with junk ratings (from class C) have a very high probability of failure after the first quarter of credit rating assignment (the default frequency is about 56%). However, the banks that survive after the first quarter have probabilities of default even lower than banks with ratings from a better class (class CCC) and for some periods the probabilities of default are even less than for credit ratings from class B. The intuition of this tendency is the following. The junk credit ratings are usually assigned to banks with very poor financial sustainability (these will hardly survive for more than two quarters) and small expanding banks (these have great chances to survive for a long period of time). Small banks have worse financial ratios than large and mature banks, but this does not mean that the probability of failure is extremely large for them. If they survive over the first quarters following receipt of a credit rating, their sustainability can be even better than those with ratings from a better class.

Moreover, from Figure 3 above we also notice that an increase in default frequencies is growing beginning from year 3 for almost each rating class. This pattern may be explained in two ways. Firstly, the competition in high rating classes is severe enough that it leads to a deterioration of financial stability for banks that do not prevail. Secondly, the internal management of banks with unchanged credit rating for several years may put less effort into development and innovations, which makes such banks less stable to external shocks.

This result does not allow us to reject the hypothesis of this paper, i.e. that banks with high ratings are more stable immediately following the rating assignment, while speculative bank's probability of default decreases over time. Hence, we conclude that investors should account for not only the current rating grade of a bank, but also how long ago it was assigned.

Figure 4. Distribution of annual cumulative Default Frequencies for credit rating classes



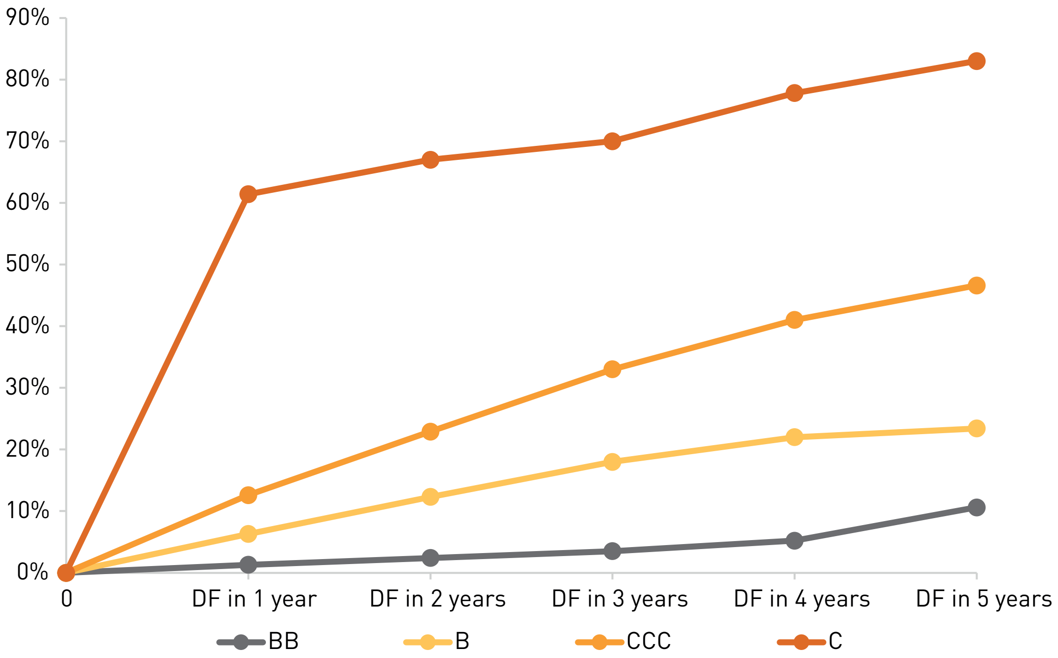
Source: Authors' own calculations.

Figure 4 illustrates the graduate cumulative increase in annual default frequencies for each rating class. As expected, lower probabilities of default are associated with a rating class BB [12-13.5] (the best class of ratings presented), while the PDs in the High Speculative Grade are larger for poorer rating classes. However, we can observe an interesting pattern: the cumulative annual growth rate (CAGR) of default frequencies decreases as credit ratings become lower. CAGR is calculated for each rating class as:

$$CAGR = \left(\frac{DF_{year5}}{DF_{year1}}\right)^{1/5} \quad (7)$$

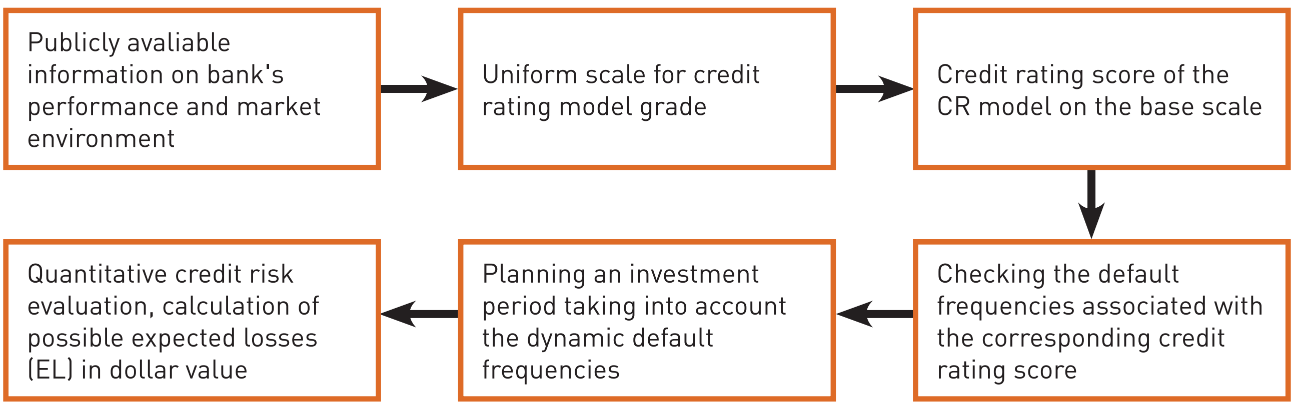
From the figure above, we can see that in the class C [18.5-21] (although it contains junk credit ratings), a bank which is able to survive for one year after the rating issue has a lower incremental PD on the horizon of the next five years (as CAGR value shows). We conclude that the better the financial sustainability of a bank, the higher the CAGR of PD is. An analysis of default frequencies shows us that PD increases in time at a faster rate in the better rating classes. We are able to formulate a capital rising strategy. Investment in banks with better credit ratings will minimise credit risk right after the rating issue and is efficient to be held for the short run period. However, to achieve the lowest risk from an investment in banks with highly speculative rating grades, it is optimal to choose a long run investment 1 or 2 years after the rating assignment. This is demonstrated with the help of CAGR values in classes BB [12-13.5] and C [18.5-21]. In class BB, CAGR of PD equals to 62%, which is more than ten times higher than the value of CAGR in class C (6%). The intuition behind this is similar to that of the previous results. Banks from a better credit rating operate in a more competitive environment, so there is high probability (almost 11%) that within a 5 year time period a bank will shift to lower rating classes and even become defaulted. On the other side, banks form the worst rating class have a high probability to default immediately (within 1 quarter), but if they have survived for the longer period, there is a clear tendency of improvement in rating grade.

Figure 5. Average cumulative Default Frequencies for credit rating classes



Source: Authors' own calculations.

Figure 6. Method of credit risk assessment presented in the thesis



Source: Authors' own calculations.

Figure 5 above illustrates the graduated differences between the default frequencies of banks with ratings from classes BB, B and CCC. PD is much larger for credit class C, we notice that banks with credit ratings on the range from 18.5 to 21 are extremely unstable during the first year after the credit rating assignment compared even to the banks with very similar ratings from class CCC. However, if such banks can survive during this period, an incremental PD for them is not substantial and lower than for banks from better rating classes.

To sum up, it was concluded that the better the financial sustainability of a bank, the higher CAGR of PD is. Analysis of default frequencies shows us that PD increases in time at a faster rate in the better rating classes. As a result the capital rising strategy was formulated. Investment in banks with better credit ratings will minimise credit risk right after the rating issue and is efficient to be held for the short run period. However, to achieve the lowest risk from an investment in banks with highly speculative rating grades, it is optimal to choose a long run investment 1 or 2 years after the rating assignment.

Therefore, our paper provides an algorithm which can be useful for investors for credit risk evaluation based on publicly available info on Figure 6.

If one wants to evaluate the credit risk of a Russian bank, and it hasn't been assigned a rating grade by any RA, one can estimate it using the CR model provided in the paper [11]. In order to do that, only publicly available financial info will be needed. Then the forecasted rating grade will be estimated in the terms of base scale. If initially a public RA grade was available, then this grade could be transformed to the base scale using the table in Appendix 1. Then, to assess the quality of information enclosed in the credit rating scores obtained, the calibration scale should be applied. This scale will help in planning an investment horizon taking into account the dynamic default frequencies, the obtaining of a quantitative credit risk evaluation, and calculation of possible expected losses (EL) in dollar value. This proves the significance of individual credit rating models, and shows the possibility of their practical use, as the forecasted credit ratings on a base scale are interdependent with estimated PD. Moreover, the following methodology can be used in increasing forecasting power of the existing PD models that are widely used in recent research: [17; 18; 19; 20; 21].

Conclusion

In this paper we present the method of credit risk estimation for banks. The forecasted CR score can be used to evaluate the credit risk of a bank using a dynamic transmission scale, which relates a rating score to average default frequencies of Russian banks. The uniform calibration scale that allows us to estimate probability of default in different time frames after credit rating assignment was empirically constructed using a random sample of 395 Russian banks (86 of them defaulted) for the period of 2007-2017. With the help of this scale, investors obtain not only the numeric credit rating, but also the quantitative measure of credit risk, which is more comprehensive. This helps them to plan their investment strategy and to calculate the expected losses (EL) in dollar value.

We fail to reject the stated hypothesis, as we discovered that banks with high ratings are more stable just after the rating assignment, while a speculative bank's probability of default decreases over time. Hence, we conclude that investors should account for not only the current rating grade of a bank, but also how long ago it was assigned. We are able to formulate a capital rising strategy. Investment in banks with better credit ratings will minimise credit risk right after the rating issue, and is efficient enough to be held for the short run period. However, to achieve the lowest risk from an investment in banks with highly speculative rating grades, it is optimal to choose a long term investment 1 or 2 years after the rating assignment.

The novelty of this paper arises from the process of calibration of a rating grade to dynamic PD scale in order to evaluate the optimal time horizon of investments into a bank in each rating class. The proposed scale has three superior features compared to the existing scales: dynamic nature (quarterly PD estimates), compatibility with all RAs (base scale CR) and focus on Russian banks. This approach can be improved by the inclusion of additional information about rating migrations. Currently, the scale accounts only for the moment of a rating assignment but not for the period spent in a specific rating class. Additionally, in further research, it is possible and advisable to study the calibration of the credit ratings on the historic default frequencies of a developed country, and to compare the transition scale with the Russian one.

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Appendix

Appendix 1. Mapping RA to the base numerical rating scale

Base Rating Scale	S&P I/N* $	S&P RUB	S&P N** RUB	Fitch I/N $	Fitch RUB	Fitch N RUB	Moody's I/N $	Moody's RUB	Moody's N RUB	RAEX N RUB	Rus-Rating I/N RUB	Rus-Rating N RUB	AK&M N RUB	NRA RUB	Ria RUB
1	AAA	AAA	-	AAA	AAA	-	-	Aaa	Aaa	-	-	-	-	-	-
2	AA+	AA+	-	AA+	AA+	-	-	Aa1	Aa1	-	-	-	-	-	-
3	AA	AA	-	AA	AA	-	-	Aa2	Aa2	-	-	-	-	-	-
4	AA-	AA-	-	AA-	AA-	-	-	Aa3	Aa3	-	-	-	-	-	-
5	A+	A+	-	A+	A+	-	-	A1	A1	-	-	-	-	-	-
6	A	A	-	A	A	-	-	A2	A2	-	-	-	-	-	-
7	A-	A-	-	A-	A-	-	-	A3	A3	-	-	-	-	-	-
8	BBB+	BBB+	-	BBB+	BBB+	-	-	Baa1	Baa1	-	A+	-	-	-	-
8,5	-	-	-	-	-	AAA(rus)	-	-	-	-	-	-	-	-	-
9	BBB	BBB	ruAAA	BBB	BBB	-	Aaa.ru	Baa2	Baa2	-	A	-	-	-	-
9,5	-	-	-	-	-	-	-	-	-	-	-	AAA	-	-	-
10	BBB-	BBB-	-	BBB-	BBB-	AA+(rus)	-	Baa3	Baa3	A++	A-	-	-	-	-
10,5	-	-	-	-	-	-	Aa1.ru	-	-	-	-	AA+	-	-	-
11	BB+	BB+	ruAA+	BB+	BB+	AA(rus)	-	Ba1	Ba1	-	BBB+	-	-	-	-
11,5	-	-	-	-	-	-	-	-	-	-	-	AA	-	-	-
12	BB	BB	ruAA	BB	BB	AA-(rus)	Aa2.ru	Ba2	Ba2	-	BBB	-	-	AAA	-
12,5	-	-	-	-	-	A+(rus)	-	-	-	-	-	AA-	-	-	-
13	BB-	BB-	ruAA-	BB-	BB-	A(rus)	Aa3.ru	Ba3	Ba3	-	BBB-	A+	-	-	-
13,5	-	-	ruA+	-	-	A-(rus)	A1.ru	-	-	A+	-	A	-	AA+	-
14	B+	B+	ruA	B+	B+	BBB+(rus)	A2.ru	B1	B1	-	BB+	A-	A+	-	AA
14,5	-	-	ruA-	-	-	BBB(rus)	A3.ru	-	-	-	-	BBB+	-	AA	-
15	B	B	ruBBB+	B	B	BBB-(rus)	-	B2	B2	-	BB	-	-	-	AA-
15,25	-	-	ruBBB	-	-	BB+(rus)	Baa1.ru	-	-	-	-	BBB	A	AA-	-
15,5	-	-	ruBBB-	-	-	BB(rus)	-	-	-	A	BB-	-	-	A+	A+
15,75	-	-	ruBB+	-	-	BB-(rus)	Baa2.ru	-	-	-	-	BBB-	-	-	-
16	B-	B-	ruBB	B-	B-	B+(rus)	Baa3.ru	B3	B3	-	-	-	-	A	A
16,25	-	-	-	-	-	-	-	-	-	-	-	-	B++	-	-

Base	S&P			Fitch			Moody's			RAEX	Rus-Rating		AK&M	NRA	Ria
Rating	I/N*		N**	I/N		N	I/N		N	N	I/N	N	N		
Scale	$	RUB	RUB	$	RUB	RUB	$	RUB	RUB	RUB	RUB	RUB	RUB	RUB	RUB
16,5	-	-	ruBB-	-	-	B(rus)	Ba1.ru	-	-	-	B+	BB+	-	A-	A-
16,75	-	-	-	-	-	-	Ba2.ru	-	-	-	-	-	-	-	-
17	CCC+	CCC+	ruB+	CCC	CCC	B-(rus)	Ba3.ru	Caa1	Caa1	B++	B	BB	-	BBB+	-
17,25	-	-	-	-	-	-	-	-	-	-	-	-	-	BBB	-
17,5	-	-	ruB	-	-	-	B1.ru	-	-	-	-	-	B+	BBB-	BBB+
17,75	-	-	-	-	-	-	B2.ru	-	-	-	-	-	-	BB+	-
18	CCC	CCC	ruB-	CC	CC	-	B3.ru	Caa2	Caa2	B+	B-	-	-	BB	BBB
18,25	-	-	-	-	-	-	-	-	-	-	-	-	B	BB-	-
18,5	-	-	-	-	-	-	Caa1.ru	-	-	-	-	-	-	-	BB+
18,75	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
19	CCC-	CCC-	ruCCC-	C	C	-	Caa2.ru	Caa3	Caa3	B	CCC+	B	C++	-	C
19,25	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
19,5	-	-	-	-	-	-	Caa3.ru	-	-	-	CCC	B-	-	-	-
19,75	-	-	-	-	-	-	-	-	-	-	-	-	C+	-	-
20	-	-	-	-	-	-	Ca.ru	Ca	Ca	C++	C	CC	-	-	-
20,25	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
20,5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
20,75	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
21	D	D	ruD	D	D	D(rus)	C.ru	C	C	E	D	C	C	-	-

* I/N – International rating scale, N – National rating scale
Source: [11].

Appendix 2.

Intermediate matrix with default frequencies for credit score 17.5 (for periods 29-48)

	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
30	0,10%																			
31	1,20%	2,00%																		
32	0,96%	0,96%	0,97%																	
33	0,96%	0,96%	0,97%	2,04%																
34	0,96%	0,96%	0,97%	1,02%	2,22%															
35	1,92%	1,92%	1,94%	1,02%	1,11%	1,11%														
36	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%													
37	2,88%	2,88%	3,88%	5,10%	5,56%	4,44%	3,45%	3,41%												
38	0,96%	0,96%	1,94%	2,04%	2,22%	2,22%	2,30%	2,27%	4,55%											
39	0,96%	0,96%	0,97%	1,02%	1,11%	1,11%	1,15%	1,14%	1,14%	2,50%										
40	0,96%	0,96%	0,97%	0,00%	0,00%	0,00%	0,00%	1,14%	1,14%	1,25%	2,50%									
41	0,96%	0,96%	2,91%	3,06%	3,33%	3,33%	2,30%	2,27%	3,41%	3,75%	2,50%	3,85%								
42	2,88%	2,88%	2,91%	3,06%	3,33%	3,33%	3,45%	2,27%	2,27%	2,50%	2,50%	2,56%	1,32%							
43	2,88%	2,88%	1,94%	2,04%	2,22%	2,22%	3,45%	3,41%	3,41%	2,50%	1,25%	1,28%	1,32%	2,53%						
44	2,88%	2,88%	2,91%	3,06%	2,22%	2,22%	2,30%	2,27%	1,14%	1,25%	1,25%	1,28%	2,63%	2,53%	3,70%					
45	0,96%	0,96%	0,00%	0,00%	0,00%	0,00%	1,15%	2,27%	2,27%	2,50%	2,50%	1,28%	1,32%	1,27%	1,23%	3,85%				
46	1,92%	1,92%	1,94%	2,04%	1,11%	1,11%	1,15%	1,14%	1,14%	1,25%	2,50%	2,56%	2,63%	2,53%	2,47%	2,56%	3,90%			
47	1,92%	1,92%	1,94%	2,04%	2,22%	2,22%	2,30%	2,27%	2,27%	2,50%	2,50%	2,56%	2,63%	2,53%	2,47%	2,56%	2,60%	3,95%		
48	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	1,14%	1,25%	1,25%	1,28%	1,32%	1,27%	1,23%	1,28%	1,30%	1,32%	4,35%	
49	0,96%	0,96%	0,97%	1,02%	1,11%	1,11%	1,15%	1,14%	1,14%	1,25%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	1,41%

Appendix 3.

Intermediate matrix with default frequencies for credit score 15.5 (for periods 29-48)

	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
30	0,00%																			
31	0,00%	1,14%																		
32	1,15%	1,14%	2,20%																	
33	1,15%	1,14%	1,10%	3,30%																
34	1,15%	1,14%	1,10%	1,10%	3,23%															
35	0,00%	0,00%	0,00%	1,10%	1,08%	4,35%														
36	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	3,19%													
37	4,60%	4,55%	3,30%	2,20%	2,15%	2,17%	3,19%	3,33%												
38	1,15%	1,14%	1,10%	1,10%	1,08%	1,09%	1,06%	1,11%	4,40%											
39	3,45%	3,41%	3,30%	3,30%	3,23%	3,26%	3,19%	3,33%	3,30%	4,30%										
40	5,75%	5,68%	5,49%	6,59%	6,45%	6,52%	6,38%	5,56%	5,49%	5,38%	6,67%									
41	3,45%	3,41%	3,30%	2,20%	2,15%	2,17%	2,13%	2,22%	2,20%	3,23%	3,33%	5,81%								
42	1,15%	1,14%	1,10%	1,10%	1,08%	1,09%	1,06%	1,11%	1,10%	1,08%	1,11%	1,16%	6,98%							
43	3,45%	3,41%	4,40%	4,40%	4,30%	4,35%	3,19%	3,33%	3,30%	4,30%	5,56%	5,81%	5,81%	8,75%						
44	3,45%	3,41%	4,40%	4,40%	5,38%	5,43%	5,32%	5,56%	6,59%	6,45%	6,67%	6,98%	5,81%	6,25%	12,33%					
45	1,15%	1,14%	2,20%	2,20%	2,15%	2,17%	1,06%	1,11%	1,10%	1,08%	1,11%	1,16%	1,16%	1,25%	1,37%	9,86%				
46	1,15%	1,14%	1,10%	1,10%	2,15%	2,17%	2,13%	2,22%	1,10%	1,08%	1,11%	1,16%	2,33%	2,50%	2,74%	2,82%	4,62%			
47	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	1,69%		
48	4,60%	4,55%	5,49%	5,49%	5,38%	5,43%	5,32%	5,56%	4,40%	4,30%	4,44%	4,65%	4,65%	5,00%	5,48%	4,23%	4,62%	5,08%	4,84%	
49	1,15%	1,14%	1,10%	1,10%	1,08%	1,09%	1,06%	1,11%	1,10%	1,08%	2,22%	2,33%	2,33%	2,50%	2,74%	2,82%	3,08%	3,39%	3,23%	8,33%

Appendix 4.

R code for default frequencies matrix calculations

```
getwd()
setwd(«/Users/romanmacbook/Desktop»)
install.packages(«openxlsx»)
library(openxlsx)
file <- read.csv2(«file.csv»)

file_matrix <- function(r) {
m <- matrix(nrow = 40, ncol = 40)
colnames(m) <- seq(1,40)
rownames(m) <- seq(2,41)

for (i in 1:40){
for (j in i:40){
a <- subset(file, bank %in% file$bank[file$rating == r & file$quarter == i])
sum_defaulted_quarter <- sum(a$fact_of._default[a$quarter == j])
sum_rated_quarter <- sum(ifelse(file$rating == 21
& file$quarter == i, 1, 0))
m[j,i] <- round(sum_defaulted_quarter/sum_rated_quarter, 2)
}
}
return(m)
}
View(file_matrix(21
))
write.xlsx(file_matrix(21
), '21.xlsx', row.names = T, colnames = T)
```

Source: Author's own calculations.