How Do Russian Banks Evaluate the Retail Credit Risks?

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Abstract: We use novel data for the lending rate offers by the Russian banks since November 2020 to April 2021. The data source is the aggregator website banki.ru. It had initially retail loan offers from 19 banks. We control for the cost of funding and the bank's risk-appetite in terms of the Return on Equity (ROE). As the result, we are able to decompose the lending rate into transaction- and bank-specific components. As with the research on the international banks for the variability in the risk-weights we find that the banks running IRB approach tend to evaluate retail credit risk higher and set higher interest rates. Banks with the foreign ownership, inversely, tend to price in lower risk all else being equal and set lower lending rates. The narrow segment of banks with the available planned ROE data allow us to say that the state-owned banks evaluate the retail credit risk and set the rates higher, though the magnitude is lower than for the IRB impact. For the narrow segment also we do not find statistically significant differences in the risk assessment for the listed banks, though we see that they impose higher lending rates all else being equal.

1 INTRODUCTION

This is not surprising that banks may offer different lending rates when the very same borrower applies. One may easily guess that the bank funding mix or its risk-appetite matter. For instance, expensive deposits require a bank to impose higher lending rates. Wishing to obtain higher return on equity (ROE) a bank may also claim higher lending rates. We do not discuss here the perverse consequences when higher lending rates attract less creditworthy borrowers and thus may result in lower return or even in a bank failure.

However, if we were able to extract the above components from the lending rate, we could see how a bank prices the risk associated with a loan. A baseline hypothesis would naturally be that banks price the very same risk similarly. That should particularly be true when the banks use own default data and models, and not solely rely upon the prudential estimates. The former approach is known as the internal-ratings based (IRB) one. Many studies discuss its specifics (Gordy, 2000), (Gordy, 2003) including such shortcomings like procyclicality (Gordy & Howells, 2006), infinite granularity assumption (Gordy & Lütkebohmert, 2013), and its implications to bank risk-taking (Repullo, 2004).

Regulators and researchers also departed from this assumption when studying IRB-banks. However, both stakeholders came to disappointing findings that the banks are materially not in concordance in their risk assessments (BCBS, 2013c), (BCBS, 2016), (Behn, et al., 2016). Nevertheless, a recent study counterargues that the differences in the risk-assessments are more due to the fundamentals (EBA, 2021).

All the studies above considered European countries, except Russia. That is why we wish to verify what the situation in Russia is, i.e., do banks evaluate the very same borrowers and transactions similarly or not. Such a verification means that bank-specific factors (other than funding costs or risk-appetite) should not impact neither the risk assessment, nor the ultimate lending rate.

To undertake such a verification, we lay down our methodology and describe available data in section 2. We present our findings in section 3. Section 4 concludes.

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2 MATERIALS AND METHODS

We follow the straightforward approach presented by (Horny, et al., 2018) when studying the EU sovereign bond yields. As (Diebolt, 2015) recommends, we try to fit the best full sample model without breaking the subsample into the training and testing ones. This limitation also originates from the scarce data we possess at our disposal. Let us cover in more detail our methodology and data below.

2.1 Methodology

We wish to decompose the lending rate $Rate_{ijt}$ at time t for bank i and loan type j into time dummies T_t, bank-specific drivers X_{it} (including funding costs and risk-appetite) and risk component Y_{jt}. Latter one comprises de facto of the transaction-specific factors. We denote the respective vectors of estimates as $\mathbf{\Omega}_t$, $\mathbf{B}_i$, $\mathbf{\Phi}_j$. To account for heteroskedasticity we use robust estimates for the model residuals ε_{ijt} in (1).

$$Rate_{ijt} = T_t\mathbf{\Omega}_t + X_{it}\mathbf{B}_i + Y_{jt}\mathbf{\Phi}_j + \varepsilon_{ijt} \quad (1)$$

To derive the risk component directly, we first compute the break-even lending rate R_{it}^{MIN}. It captures the funding mix by accounting for the capital adequacy ratio CAR_{it} as the equity portion proxy. CAR is the ratio of the bank's capital over its risks. Simplistically, the risk amount equals to the risk-weight multiplied by the asset (or exposure) amount. The equity funding cost or the bank risk-appetite is the return over equity ROE_{it}. We will consider the actual and planned values where available. The non-equity cost of funding is the deposit rate r_{it}^{D} in local currency as the loans are offered in our dataset only in RUB.

$$R_{it}^{MIN} = r_{it}^{D}\cdot\left(1-CAR_{it}\right) + ROE_{it}\cdot CAR_{it} \quad (2)$$

We assume that the risk component is the differential of the actual lending rate and the break-even one. We call it as the probability of default (PD) because it generally combines the factors leading to default on a particular loan.

$$\mathbf{PD_{ijt}} = Rate_{ijt} - R_{it}^{MIN} \quad (3)$$

Having obtained PD estimate, we may run regression over it in (4) where $\dddot{X}_{it}$ does not comport ROE, CAR and deposit rate like X_{it} had. This is equivalent by estimating model (1) with restrictions over particular coefficients.

$$\mathbf{PD_{ijt}} = T_t\mathbf{\Omega}_t + \dddot{X}_{it}\mathbf{B}_i + Y_{jt}\mathbf{\Phi}_j + \varepsilon_{ijt} \quad (4)$$

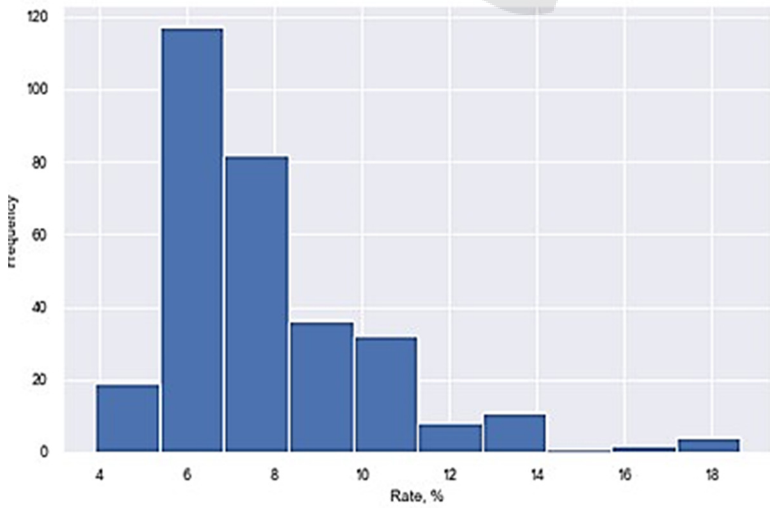

Figure 1: Lending Rate Frequency Distribution.

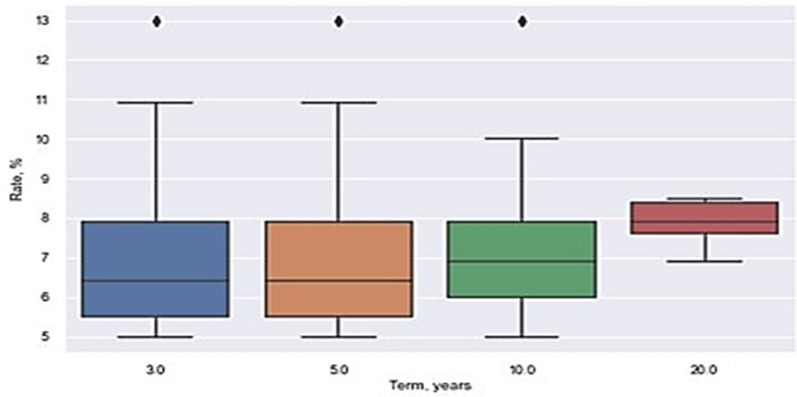

Figure 2: Lending Rate Distribution By Maturity (Term).

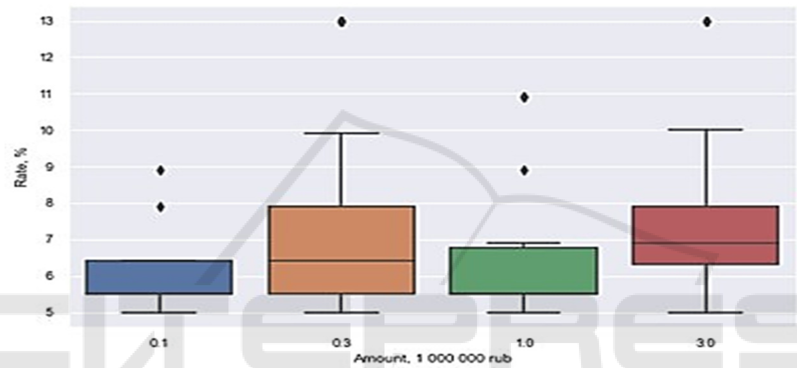

Figure 3: Lending Rate Distribution By Volume (Amount).

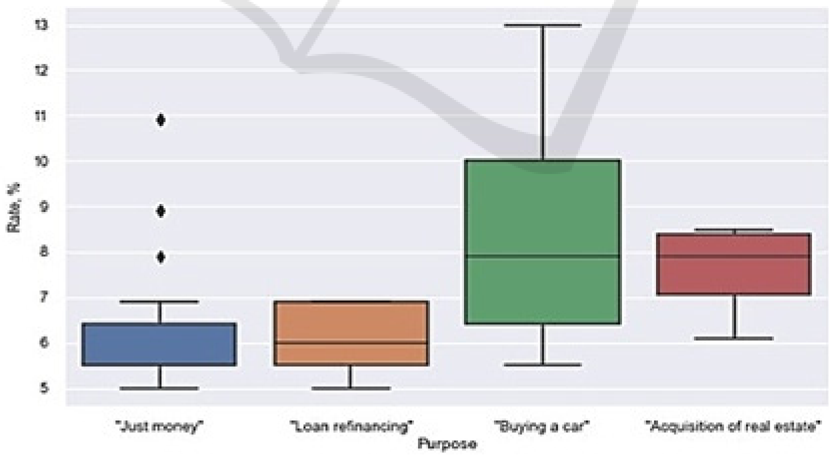

Figure 4: Lending Rate Distribution By Loan Purpose.

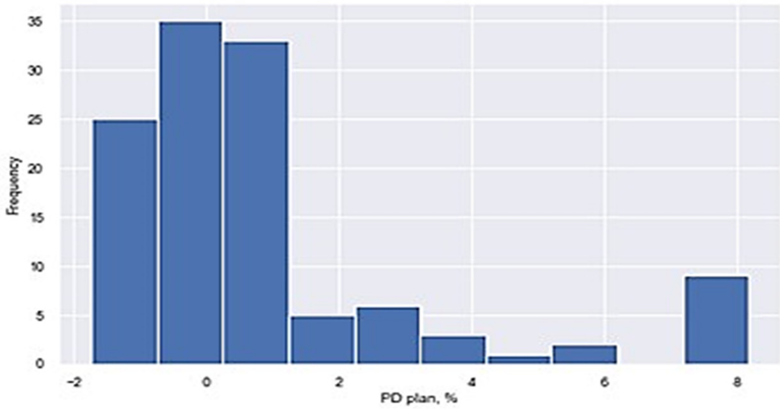

Figure 5: Planned PD Frequency Distribution.

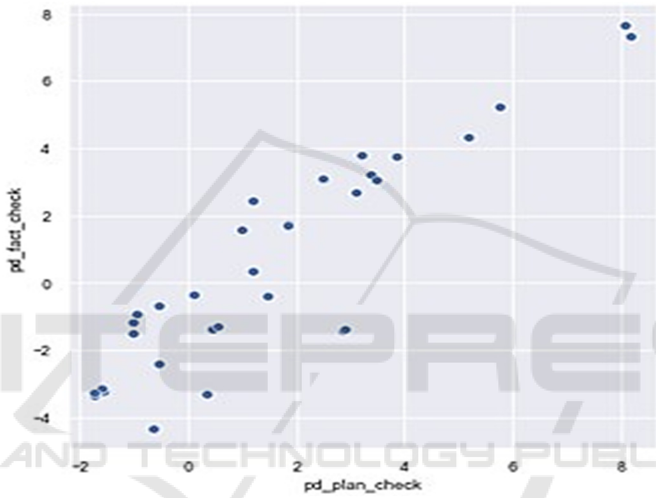

Figure 6: Planned and Actual PD Co-Dependence.

In the principal part of the manuscript we present the regression estimates for the significant variables only (Table 1), where as Appendix has the output for the entire list of variables even if the respective coefficient was insignificant (Table 5).

2.2 Data

We wished to utilise a country-wide dataset of loans, applications and the respective risk assessments equivalent to that of (Jimenez, et al., 2014). However, those are not publicly available.

That is why we utilise a unique publicly available dataset from the Russian aggregator website banki.ru. It has no archive. That is why we were lucky to have made downloads in November 2020, March and April 2021. The website allows a person to enter one's quasi-personal data and obtain a set of lending offers from several banks. We tried entering difference income, age etc. parameters, but always obtained the same minimum lending rates. That is why we proceed with the study of these minimum offered rates for a single profile inputted to the website.

Importantly, no one – even ourselves included – knows the borrower risk. Thus, we do not claim to have perfect risk prediction, but we do compare risk assessments by different banks. We do not know which bank has a risk prediction closer to a true one, but what we wish to find out is to what extent and why estimates of different banks are misaligned.

Since April 2021 the number of loan offering banks rose to a hundred. As we started in November with 19 banks only, we proceed with these 19 banks. The lending rate varies from 4% to 18% (Fig. 1). Larger rates are observed for car loans and mortgages (two right boxes at Fig 4), than for consumer loans or loan refinancing purposes (two left boxes there).

The mean rates rise when the loan maturity (term) goes up. However, the dispersion of the observed rates – on the contrary – shrinks when the maturity rises.

Table 1: Regression Output.

Determinant	PD_plan	PD_fact	PD_fact	Rate_plan	Rate_fact	Rate_fact
Intercept	-0.395	-0.948***	7.199***	10.124***	6.416***	7.419***
dt_march	-1.191***	-2.262***			-1.214***	
dt_nov			1.307***	-1.229**		0.779***
Loan Features						
term	0.124***	0.093**				0.128***
dg_CarLoan	2.565***	2.743***			2.340***	1.930***
dg_CashLoan				-1.808***		1.326***
dg_Refinance				-2.407***		1.049**
Bank Features						
CAR					-1.045***	0.117***
R_d						-0.690***
roe_fact					0.091***	
roe_plan				-0.784***		
t_foreign			-6.804***	-2.700***		-1.382***
t_government	0.893***	1.423***	-3.910***		2.451***	-0.623**
t_private	-1.288***	-2.371***	-3.192***	9.252***	3.965***	
t_irb	1.304***	2.580***		4.643***	5.077***	
t_listed			-5.403***	12.824***	5.421***	-0.728***
t_sifi			2.414***	-1.828**	3.446***	
Observations	119	119	312	119	119	312
R2	0.361	0.516	0.235	0.427	0.443	0.287
Adjusted R2	0.333	0.495	0.220	0.391	0.408	0.264
F Statistic	8.818***	35.079***	41.025***	403.069***	401.519***	19.378***
Note:	*p<0.1; **p<0.05; ***p<0.01					

We would also expect higher rates for larger loan volumes. However, there is no clear pattern here.

We also switch to the PD data according to formulas (2) and (3). PD proxy lies in the range of -2% to +8% when we consider the planned ROE data. Same time we do not observe material differences in PD rankings when using planned or actual ROE values. Using planned ones, allows us to benefit from less observations with the negative PD estimates. Such values are de facto feasible as, for instance, a bank in our dataset offers lending rates for RUB 100k at 7.9% and for RUB 1m at 6.9% when the break-even level is 7.45%. Thus, the PD is -0.55% in the latter case, while it is +0.45% in the former one.

More granular description of the independent variables used in regression (1) is available in Table 2, its descriptive statistics come in Table 4. Table 3 explains how we assigned bank-specific indicators to particular banks.

3 RESULTS AND DISCUSSION

As a result, we test six model specifications. Three models where the PD is a dependent variable (see PD in the column header for specification (4)), and the three ones where the offered lending rate is a dependent one (see Rate in the column header for specification (1)). The first two sub-columns within each dependent variable type relate to the reduced set of five banks (119 observations). For those banks we run a regression with the planned ROE data in the first column and with the actual one in the second column. The third column relates to the enhanced data sample of 19 banks (312 observations). For those we use only the actual ROE values for comparability in-between different banks. Results for the significant coefficients are available in Table 1. If interested, the coefficients for all not-excluded variables are given in Annex.

We are more confident to interpret the determinants and their signs in case we do not see controversies in between various specifications.

Thus, we observe that lending rates in March 2021 were lower, than in April by around 1-2 pp. (see dt_march). We may remember that the Central Bank raised the key rate from 4.5% to 5.0% p.a. on April 23, 2021. However, this should not be priced in the PD estimates as the PD is already cleaned from the funding component. Unless the banks decided not to increase the deposit rates after the policy rate hike, but did it only for the lending rates.

Each RUB 1m adds around 0.1% to the risk (PD) estimate, as well as to the lending rate (see term).

As for the loan types, the association measure for the consumer and refinancing loans is mixed when looking at the lending rate and it is insignificant when looking at PD (see dg_CashLoan, dg_Refinance). Thus, we may more confidently conclude that the car loans are riskier than the mortgage ones by a level of

2-3 pp. As a result, the lending rate is also higher by that magnitude (see dg_CarLoan). We may recall here that the mortgage loans might be subsidized by the government. That might be the reason for the lower risk assessment in mortgages.

Interpreting actual ROE has a drawback of reverse causality (endogeneity) that we did not control for. The rates might be higher when the ROE target is high. Same time high rates may imply high actual ROE. To avoid such a discussion, we will look at the planned ROE. Importantly, we find a statistically significant negative sign for the lending rates. This means the higher the target ROE is, the lower lending rates the bank offers all else being equal. This is exactly the illustration of the bank risk-taking channel. The bank sets rates lower wishing to attract more clients and expecting to thus earn more profit. However, underpricing may result in extra losses and most probably harm the profit targets.

As for the bank-specific features, we have several quite robust findings. Foreign banks tend to underprice risk by up to -7 pp. and offer lower loan rates by 1-2 pp. That might be in part due to the use of the parent company risk models. When latter are calibrated in the developed economy, they might yield over-optimistic risk estimates in the emerging economy than they really are.

State-owned banks – at least in the reduced sample – demonstrate higher risk evaluation and setting higher rates than other banks by around 1-2 pp. This may come from their more prudent or more conservative credit policy when bank's safety is a higher priority than its earnings. However, the status of a systemically important bank does not seem to statistically significantly impact neither risk assessment, nor the loan ultimate pricing.

Banks that applied for the IRB permission systematically demonstrate higher risk-assessment by 1-2 pp. and set rates by 4-5 pp. higher. Such a difference may come from banks using own default statistics and thus being able to more correctly assess the retail credit risk.

Private and listed banks demonstrate interesting, though in part controversial trends. From one side, they are likely to underprice the retail credit risk from -1 to -5 pp. From another side, they tend to set lending rates – on the opposite – higher by 4-12 pp.

To sum up, we find that Russian banks tend to materially differently evaluate retail credit risk as well as differently price retail loans. This echoes the findings of the international prudential authority (BCBS, 2013c), (BCBS, 2016) and the academic researchers (Behn, et al., 2016). Some of the differences may originate from the differences in constraints applied to banks. For instance, IRB-banks compute risk and risk-weights themselves to derive the capital adequacy, whereas other banks are forced to utilize predefined fixed risk-weights. Positive coefficients for the IRB status imply that the prudential predefined risk-weights might be more optimistic as they under-assess the retail credit risk. A sort of implication for a bank might be not to file IRB application for a retail book as long as possible to benefit from the lower prudential risk-weights and CAR constraints.

4 CONCLUSIONS

Bank risk-taking is an important research stream within the Central Bank. People wish to investigate how risk-taking changes in response to changes in the monetary policy (Repullo, 2004), (Jimenez, et al., 2014).

The natural demonstration of the bank risk-taking behaviour is how it assesses risks and how it sets the lending rates afterwards. Earlier studies demonstrated that banks tend to materially differ in risk-assessment for the very same borrower (actual or hypothetical ones) (BCBS, 2013c), (Behn, et al., 2016).

In this paper we wished to screen Russian banks to verify whether they are different to their European counterparts from the above studies. Generally, we find out that Russian banks are not much different as they also produce different risk estimates and offer different lending rates after controlling for the funding costs and the bank risk-appetite proxied by actual and planned ROE values.

Our research is unique in several aspects. First, it uses unique, though not extensive dataset on the loan offered rated for the same person since late 2020. Second, we are the first to identify the differences in the risk perception by the Russian banks. Third, we found that most probably Russian banks decided to faster uplift the lending rates and their risk assessment after the key rate increase in April 2021, rather than to proportionately increase the deposit rates. Fourth, we uniquely study the specifics in the IRB-banks behaviour in Russia. To the best of our knowledge, no one considered IRB as a separate differentiating factor of Russian banks. The fair excuse is that most researchers before focused on data prior to 2018 when the first Russian banks launched IRB for CAR computation. Fifth, we seem to have found not only the determinants of the differences in risk-perceptions, but have concrete policy implications. We see that foreign banks and private banks tend to underassess the retail risk compared to the state and

IRB-banks. This may come from the usage of the parent datasets and models by foreign banks. On the contrary, IRB-banks have Russian up-to-date default data to be able to more adequately assess local risks. This implies that the local standardized (fixed) risk-weights might be too outdated and be too optimistic in retail credit risk assessment compared to the IRB risk-weights.

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APPENDIX

Table 2: The Variables Description.

No.	*Variable*	*Units.*	*Source*	*Description*	*Note*
1	dt_march	Dummy	Banki.ru	Indicator for March 2021 data;	1
2	dt_nov	Dummy		Indicator for November 2020 data	1
				Loan Features	
3	amount	RUB mln	Banki.ru	The loan amount that a client may choose	
4	term	Years	Banki.ru	The contract loan maturity when requested	
5	dg_CarLoan	Dummy	Banki.ru	Indicator for the loan to purchase a car, i.e., collateralized loan;	2
6	dg_CashLoan	Dummy	Banki.ru	Indicator for the consumer loan (in Russian - 'Just Cash' or 'Prosto Den'gi'), i.e., UNcollateralized loan;	2
7	dg_Refinance	Dummy	Banki.ru	Indicator for the loan to refinance an existing one; we cannot definitely say whether it is collateralized or not (depends upon the original loan type to be refinanced)	2
				Bank Features	
8	CAR	pp.	Banki.ru	The actual total capital adequacy ratio (N1.0); we use it as a proxy for the share of equity in the total funding mix of a bank; respectively, (1-CAR) is the proportion of the non-equity funding	
9	R_d	pp.	Banki.ru	the cost of the non-equity funding. It is the deposit rate in local currency (RUB) for the closest maturity to that of the loan. We extract the rate from the same website, but from another webpage devoted to deposits (we thank Denis Shibitov for help in deposit data collection). We collapse our data by maturity for all deposit offers. Thus, we take an average RUB deposit rate for a bank on the eve of our loan data collection date	
10	roe_fact	pp.	Banki.ru	Actual return on equity (roe) on the eve (the preceding month) to the loan data collection; we take it as one of the two costs of equity funding. It is available for all banks	3
11	roe_plan	pp.	Authors	Planned return on equity. We take it as a second proxy for the equity funding component of a bank. We were able to publicly find values for the five banks only	3
12	t_foreign	Dummy	Authors + (Vernikov, 2015)	The indicator (FOR) that a bank has a foreign ownership stake; generally speaking, it is a foreign bank subsidiary in Russia	2
13	t_government	Dummy		The indicator (GOV) that a bank has a state ownership component; in common citizen's perception it is a government (state-owned) bank	2
14	t_private	Dummy		The indicator that a bank is a local private bank, i.e., it has neither foreign ownership, nor the state one	2
15	t_irb	Dummy	Authors	The indicator that a bank has filed application for the use of the Basel II own default statistics and own models; also known as Internal-Ratings-Based Approach (IRB), regulated by local legislation No. 483-P and 3752-U. At the moment of the research preparation three Russian banks filed an application for the IRB to the Central Bank, two of them (Sberbank and Raiffeisen) fully run it since 2018 and 2019, respectively	4
16	t_listed	Dummy	Authors	The indicator that a bank or its Russian subsidiary under consideration is or was listed on the stock exchange in Russia or abroad	
17	t_sifi	Dummy	Authors	The indicator that a bank belongs to the list of the domestic systemically important banks (D-SIBs), or in other word is a systemically important financial institution (SIFI)	

Notes:
1) the respective regression coefficient signals for differences against recent (April 2021) data.
2) the respective regression coefficient is benchmarked against the mortgage loans.
3) we also call it the bank's risk-appetite.
4) see https://bosfera.ru

Table 3: Bank Features.

Regn	Name	Gov	For	Priv.	IRB	SIFI	Listed*	ROE_plan	notes
316	Home Credit (OOO "KHKF Bank")		1						
354	Gazprombank (Bank GPB (AO))	1				1			
429	PAO KB "UBRiR"			1					
650	Postbank (PAO "Pochta Bank")	1							
902	PAO "Norvik Bank"	1							
912	PAO "MInBank"	1							
963	PAO "Sovkombank"			1					
1000	Bank VTB (PAO)	1				1	VTB	15%	1
1326	AO "AL'FA-BANK"		1	1	1	1		15%	2
1481	PAO Sberbank	1			1	1	SBER	20%	3
1810	"Aziatsko-Tikhookeanskij Bank" (PAO)	1							
1978	PAO "MOSKOVSKIJ KREDITNYJ BANK"			1		1	CBOM		
2209	PAO Bank "FK Otkrytie"	1				1	OPEN	18%	4
2673	AO "Tin'koff Bank"			1			TCS LI	30%	5
2707	KB "LOKO-Bank" (AO)			1					
2776	OOO "ATB" Bank			1					
3073	PAO "RGS Bank"	1							
3138	AO "Bank BZHF"			1					
3251	PAO "Promsvyaz'bank"	1				1			
3292	AO "Rajffajzenbank"		1		1	1			
3354	KB "Renessans Kredit" (OOO)			1					

Notes: * where applicable, a ticker is given; if a unity is not marked for a dummy, a zero value is used.
1) https://www.vtb.ru
2)https://alfabank.ru
3) Statement by VTB IB analyst team for the Sberbank valuation, made on April 12, 2021.
4) https://cdn.open.ru
5)https://acdn.tinkoff.ru

Table 4: Descriptive Statistics for The Considered Independent Variables.

	119 obs (5 banks)				312 obs (19 banks)			
Variable	**Mean**	**St.Dev.**	**Min**	**Max**	**Mean**	**St.Dev.**	**Min**	**Max**
dt_march	0.34	0.48	0	1	0.21	0.41	0	1
dt_nov	0.18	0.38	0	1	0.32	0.47	0	1
Loan Features								
amount	1.38	1.27	0.1	3	1.32	1.22	0.1	3
term	6.20	3.98	3	20	6.11	3.74	3	20
dg_CarLoan	0.31	0.46	0	1	0.28	0.45	0	1
dg_CashLoan	0.25	0.44	0	1	0.41	0.49	0	1
dg_Refinance	0.32	0.47	0	1	0.22	0.42	0	1
Bank Features								
CAR	12.78	1.09	11.20	15.42	14.25	5.95	3.70	54.11
R_d	4.19	0.75	1.56	5.52	4.31	0.79	1.56	5.52
roe_fact	27.37	15.31	4.12	58.53	13.81	20.75	-53.29	64.95
roe_plan	19.77	6.50	15.00	30.00				
t_foreign	0.21	0.41	0.00	1.00	0.18	0.39	0.00	1.00
t_government	0.51	0.50	0.00	1.00	0.37	0.48	0.00	1.00
t_private	0.49	0.50	0.00	1.00	0.53	0.50	0.00	1.00
t_irb	0.25	0.44	0.00	1.00	0.16	0.37	0.00	1.00
t_listed	0.25	0.41	0.00	1.00	0.32	0.47	0.00	1.00
t_sifi	0.72	0.45	0.00	1.00	0.40	0.49	0.00	1.00

Table 5: Regression output with all variables included.

Determinant	PD_plan	PD_fact	PD_fact	Rate_plan	Rate_fact	Rate_fact
Intercept	-0.010	-1.003**	4.327***	10.068***	6.175***	7.650***
dt_march	-1.303***	-2.393***	-1.355**	-0.421	-0.978**	-0.520
dt_nov	-0.887*	0.003	0.890*	-1.495**	-0.223	0.595*
Loan Features						
amount	-0.013	-0.068	0.195	-0.030	-0.054	0.075
term	0.079	0.097	0.076	0.007	0.020	0.129***
dg_CarLoan	1.668*	2.957***	2.561***	0.921	1.668**	2.116***
dg_CashLoan	-1.253	-0.168	2.289***	-1.193	-0.554	1.439**
dg_Refinance	-0.869	0.509	2.324***	-1.649**	-0.863	1.189*
Bank Features						
CAR				0.528	-0.743	0.105***
R_d				-0.000	-0.440	-0.765***
roe_fact					0.074***	-0.006
roe_plan				-1.111*		
t_foreign	-0.709	-0.759	-6.495***	-4.113	1.066	-0.726
t_government	0.946***	1.203***	-3.688***	-0.392	2.247***	-0.474
t_private	-0.955*	-2.206***	-2.942***	10.460***	3.928***	0.238
t_irb	2.154	2.764**	0.062	4.810	3.003	-0.712
t_listed	0.699	-0.245	-5.343***	14.181***	5.109***	-0.620
t_sifi	0.237	0.444	2.643***	-4.505	3.313***	0.117
Observations	119	119	312	119	119	312
R2	0.389	0.523	0.253	0.446	0.465	0.296
Adjusted R2	0.332	0.479	0.221	0.377	0.399	0.258
Residual Std. Error	2.098 (df=108)	2.243 (df=108)	4.168 (df=298)	1.682 (df=105)	1.652 (df=105)	2.189 (df=295)
F Statistic	4.765***	18.982***	20.699***	252.347***	263.071***	15.820***
df	(df=10; 108)	(df=10; 108)	(df=13; 298)	(df=13; 105)	(df=13; 105)	(df=16; 295)
Note:				*p<0.1; **p<0.05; ***p<0.01		