Bank of Russia

MEASURING THE RISK-TAKING OF RUSSIAN BANKS: MICRO-LEVEL DATA APPROACH

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The views expressed in this presentation are solely those of the authors and do not necessarily reflect the official position of the Bank of Russia.

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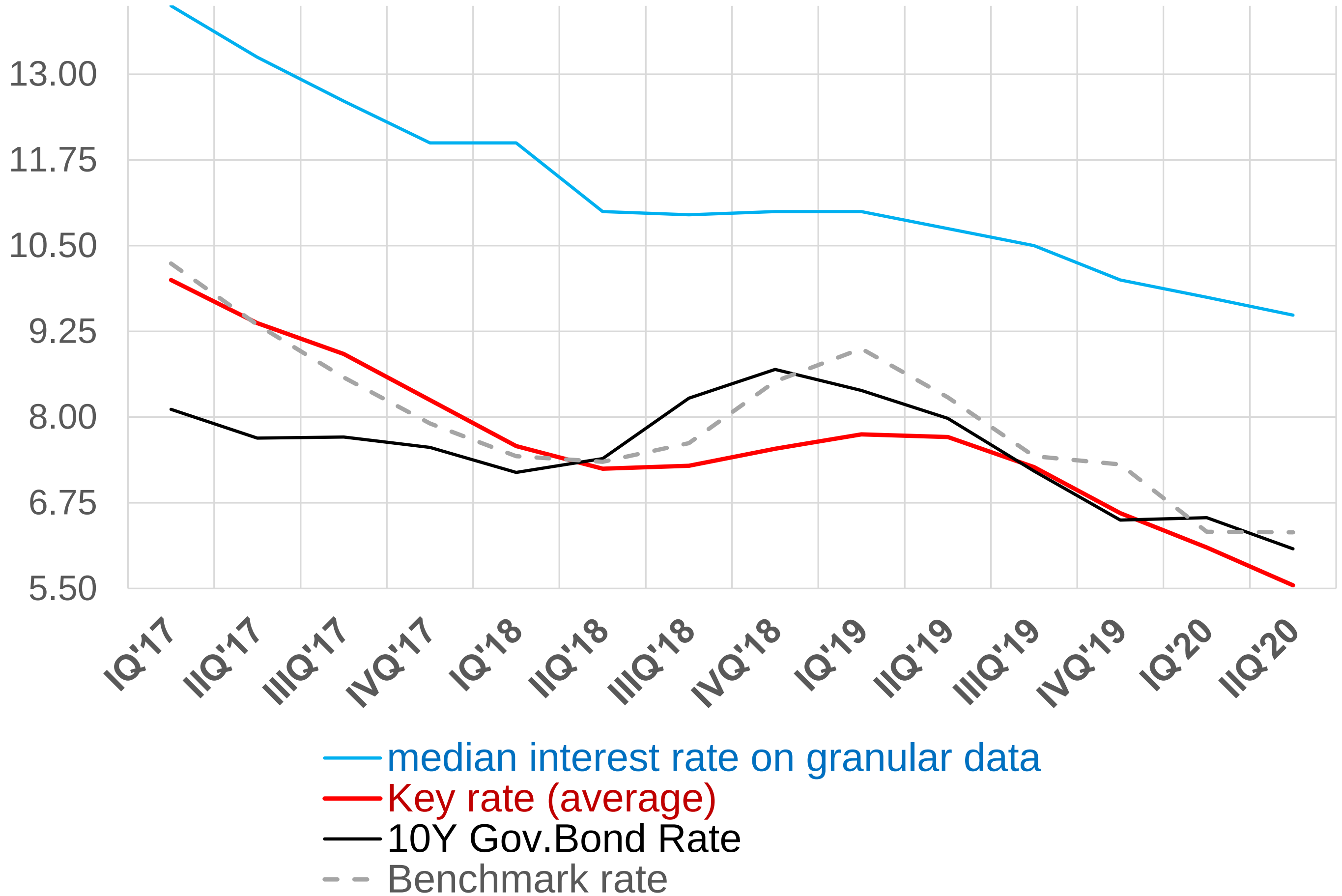
1. Motivation

Risk-taking is important concept for central banks
Borio, C., and H. Zhu (2012), Adrian, T., and H. S. Shin (2011)

Simple measures of ex-ante risk-taking, reported by lenders:

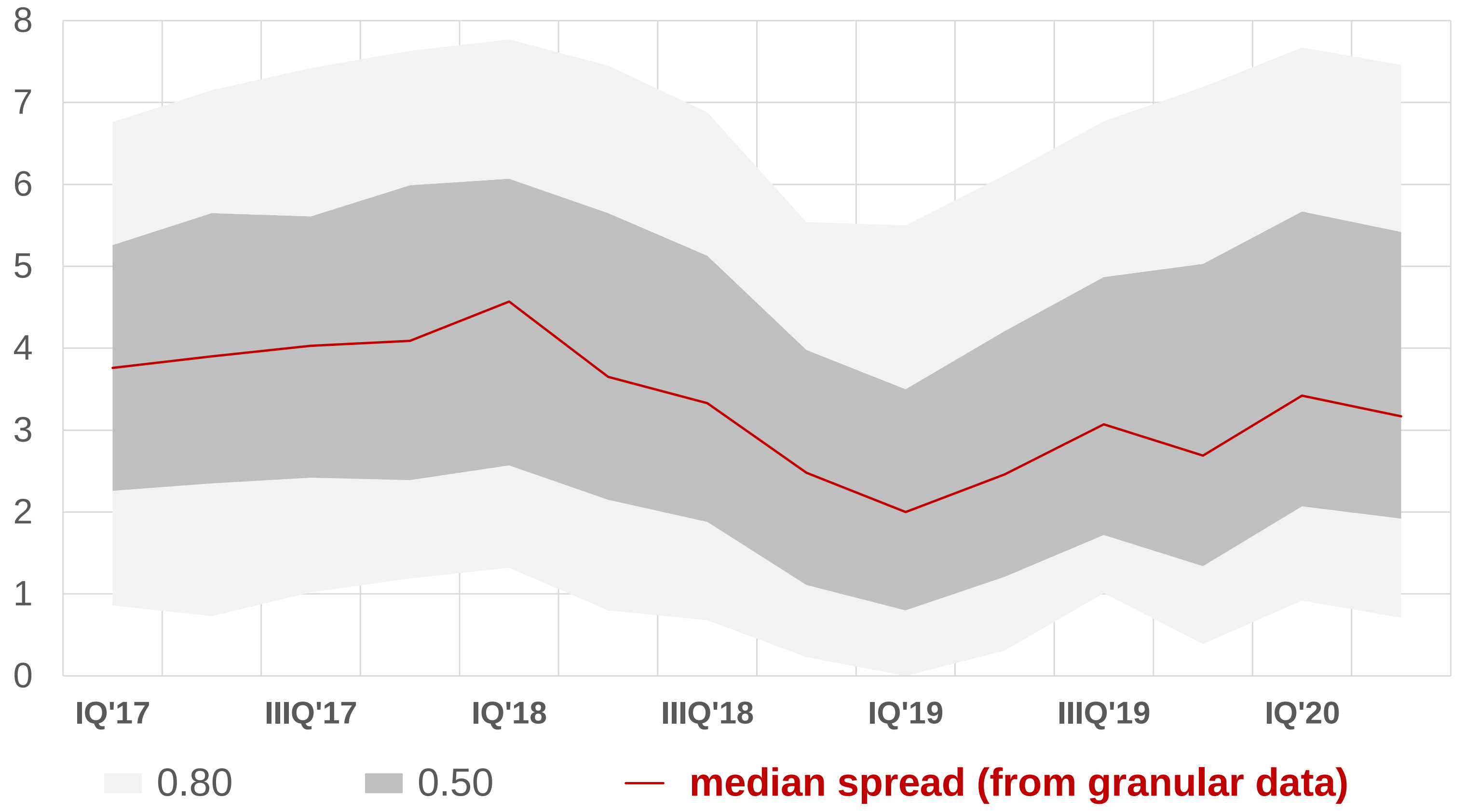
- Credit quality groups, Ioannidou, V. P., & Penas, M. F. (2010), Ioannidou, et al. (2015)
- Surveys of bank lending standards, Buch, C. M., et al. (2014), Dell'Ariccia, G., Laeven, L., & Suarez, G. A. (2017)
- A spread in credit interest rate, Delis et al. (2017), Paligorova, T., & Santos, J. A. (2017), Maddaloni, A., & Peydró, J. L. (2011)

Key rate, 10Y GB yield and interest rates (on granular corporate credit registry data: borrowers have multiple credit relations), % per annum



Source: Bank of Russia, Bloomberg L.P., authors calculations

Interest rate spread on granular corporate credit registry data (borrowers have multiple credit relations), p.p. over benchmark interest rate



Source: Bank of Russia, authors calculations

Russian banking sector: high concentration vs. heterogeneity

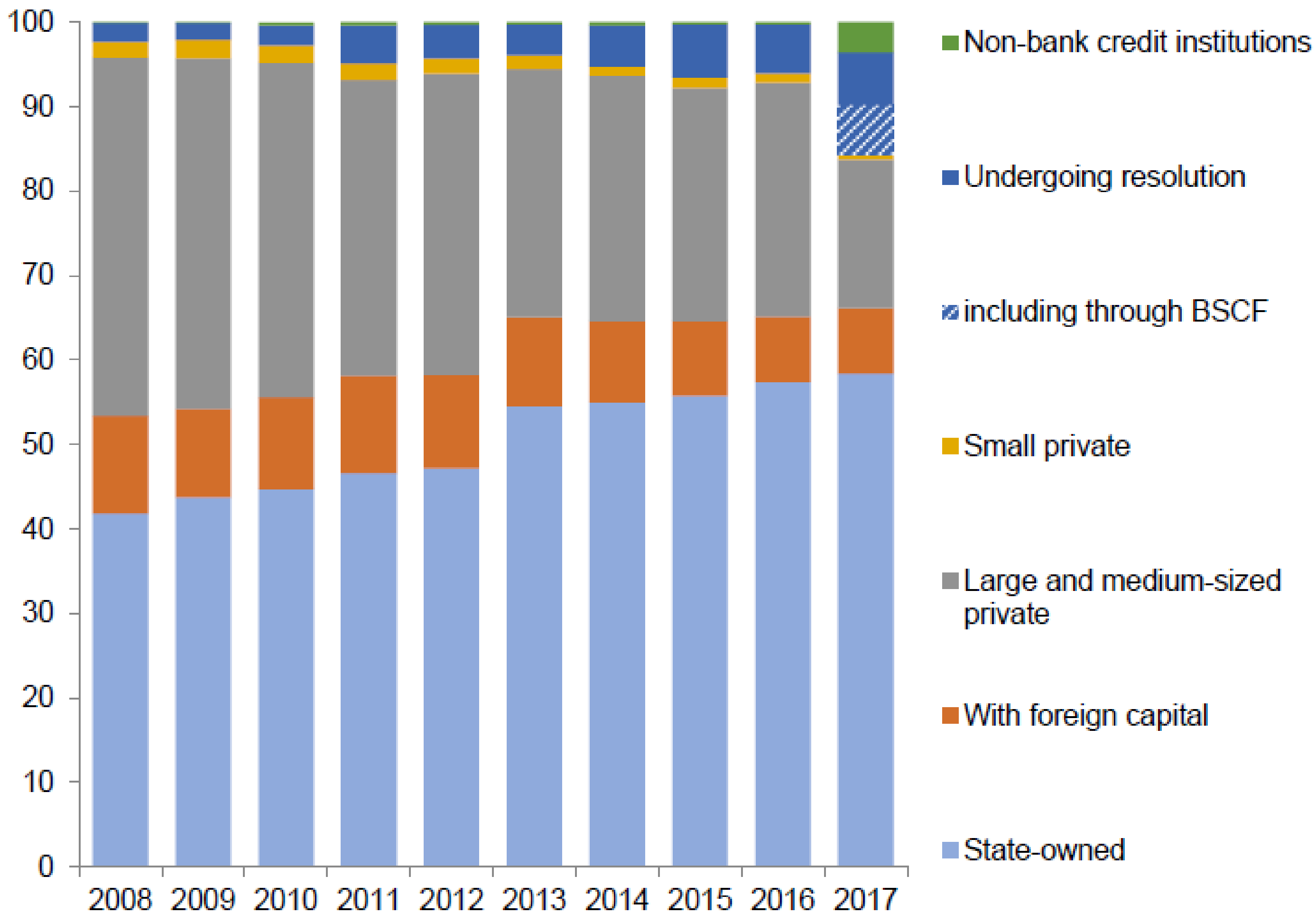
At the end of 2019

- Total number of banks is **402**

- Top 5 banks count for:
    - **60%** of all banking sector assets,
    - **60%** of deposits,
    - **70%** of corporate credit

- **Top 10** commercial banks include **5** state-owned banks

Chart 2. Structure of banking sector assets, by credit institution cluster, % (at year end)



Source: Simanovskiy, A. et al. (2018)

1. **Would like to identify bank-specific component of the spread and compare it for groups of banks**

Khwaja, A. I., & Mian, A. (2008) suggest identification strategy

Horny, et al. (2018) performs decomposition for euro area bond rates

Factors that drive the spread:

- macroeconomic conditions,
- loan terms (e.g. maturity, collateral),
- borrower characteristics (credit quality, probability of default),
- bank-specific factors, including banks’ risk attitude (risk-perception, risk-taking)

2. Would like to fill the gap: measure *ex-ante* risk-taking in Russian banking sector controlling for borrowers variation

Ex-post risk taking in Semina, I. (2020), Fungáčová, Z., & Solanko, L. (2009) –Z-score; Zhang, J. (2013) – NPLs;

Pestova, A., & Mamonov, M. (2013) separated role of macroeconomic and bank-specific factors in credit risk realizations (Overdue loan ratio)

Mamonov M. (2019) defines risk-taking through a share of retail funding and a share of corporate loans on the bank’s balance-sheet.

2. Contribution

1. We estimate time-bank specific component of the spread for Russian banks

2. We compare thus identified risk-perception in groups of banks

3. We study how bank specific component of the spread relates to bank-specific ex-ante probability of default of the bank’s new loans (objective measure of risk-taking).

We calculate a PD estimate for each corporate loan at time of loan issuance (ex-ante) using borrowers’ financial statements available at time of loan issuance.

3. Identification Strategy

Following the identifying strategy by Khwaja, A. I., & Mian, A. (2008), also Jiménez, G. (2014) we define

Lender's relative risk-perception (bank's risk-taking) is how the lender prices a loan spread with *given* terms to *a* borrower in *a given period* relative to how benchmark bank prices *the same loan to the same borrower*.

If the lender charges lower spread – it has lower risk-perception (takes higher risk)

Paravisini, D., et al (2015), Michelangeli, V. et al (2020) show restrictiveness of the approach

Illustration

Imagine, that we observe data that characterise *a firm* that borrowed from *several banks* in the *same* period of time. The loans terms *are the same.*

Interest rate spread=macro_component + loan-specific + firm-specific + risk-perception

	The spread to some benchmark rate	Common macroeconomic component	Loan-specific component of risk (maturity)	Firm-specific component (firm fundamentals)	Bank-specific component (risk-perception)
Bank 1	5	1	0.7	1.3	2
Bank 2	4	1	0.7	1.3	1
Bank 3	3	1	0.7	1.3	0

1. We collect Credit Registry Data (form No.0409303) on all new loans denominated in domestic currency from January 2017 to July 2020 issued to the *all* borrowers with *multiple* bank relationships in a particular quarter.

2. Regressions for a triple i={borrower, bank, loan maturity}

$$Spread_{i,t} = \beta_{1,t} \cdot \delta_{quarter,t} + \beta_{2,t} \cdot \delta_{borrower,t} + \beta_{3,t} \cdot \delta_{lender,t} + \beta_{4,t} \cdot \delta_{loan,t} + e_{i,t};$$

$Spread_{\ i,t}$ – credit spread (difference of loan i rate and the benchmark rate)
$\delta_{quarter,t}$ – time fixed effect
$\delta_{borrower,t}$ – dummy for borrower (borrowing company) – bank-time fixed effect
$\delta_{lender,t}$ – dummy for lender (lending bank)
$\delta_{loan,t}$ – dummy for loan characteristics (maturity, 1 if maturity > 1 year).

$\beta_{3,t}$ - the time-varying risk-perception of a particular bank

3. We construct the medians of $\beta_{3,t}$ for some groups of banks (State-owned banks, banks with foreign capital, TOP-30 banks – see. Simanovskiy, A. et al. (2018)

4. Data

Credit Registry Data (form No.0409303)
The data from 2017Q1 to 2020Q2 contain information:

- Borrower ID. Can be matched with borrowers info (financial statements) from other databases

- Loan terms (interest rate, maturity, currency, refinancing/new loan, etc.)

- Lender ID. Can be matched with lenders info (financial statements) from other databases

Total: 7.3 mln strings “firm X borrowed from bank Y with loan term Z in quarter Q”

Subsample we use: 1.4 mln observations - borrowers with multiple bank relationship

Strings “firm X borrowed from bank Y with loan term Z in quarter Q where firm X also borrowed from some other bank(s) with some loan term in quarter Q”

216 of 493 banks issued loans to such borrowers in all 14 quarters

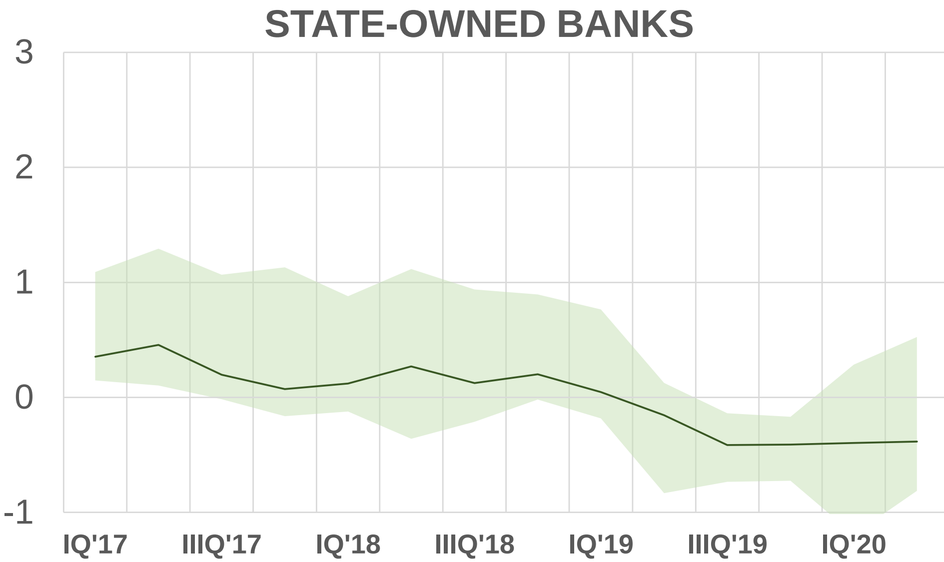
Table 1. Number of loans (observations) issued to the entities with the multiple (*n*-banks) relationships in a particular quarter

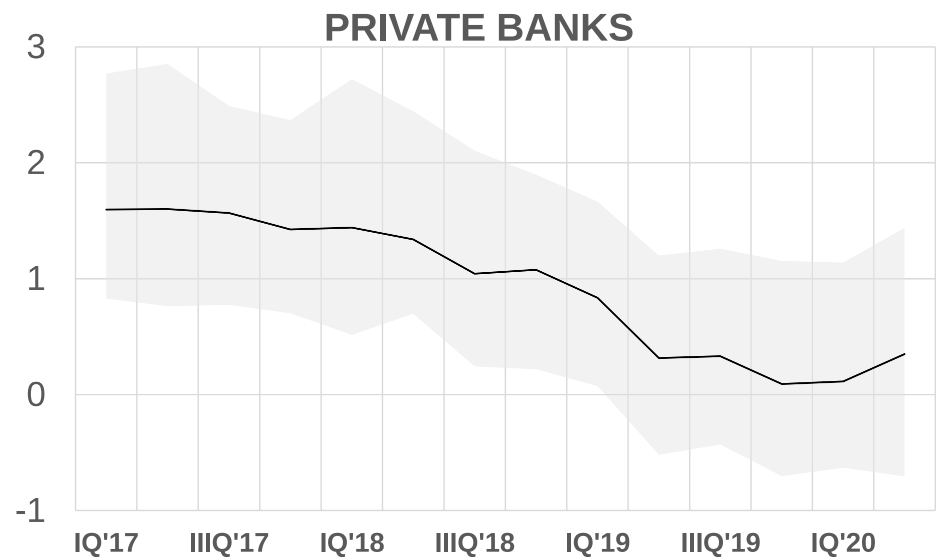
*n*_banks relationship (quarterly):	Freq.	Percent
with 1 bank	5,919,727	81%
with 2 banks	969,355	13%
with 3 banks	242,142	3%
with more than 3 banks	177,243	2%
Total	7,308,467	100%

Source: Bank of Russia, authors calculations

5. Empirical findings

Dynamics of the implied risk-perception (measured as the lender-related component in the credit spread) for the groups of banks





Note: shaded areas represent 25th and 75th percentiles
Source: authors' calculations

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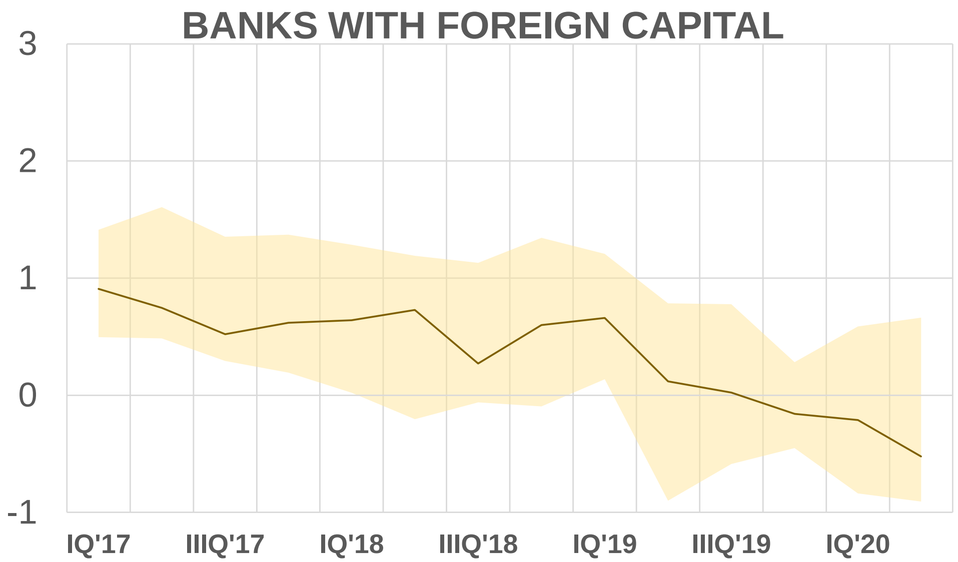

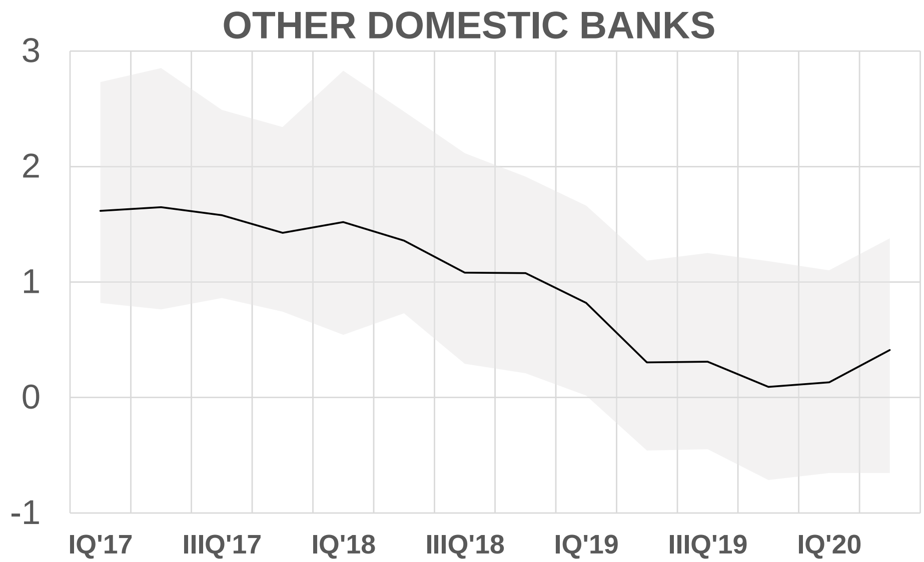

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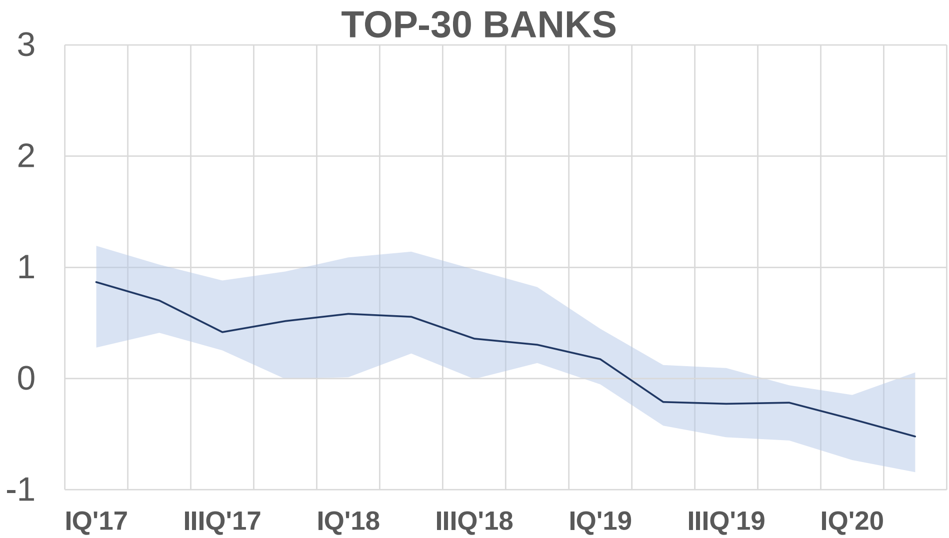
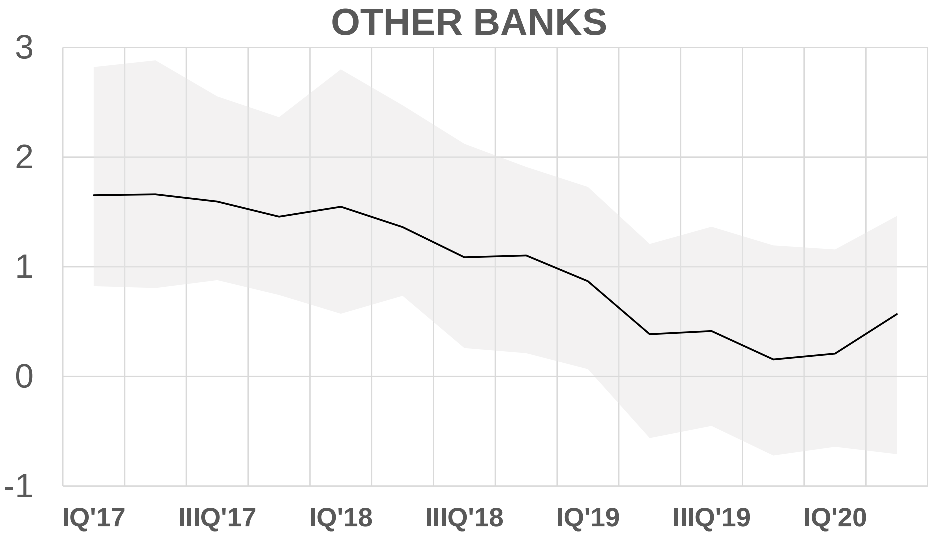
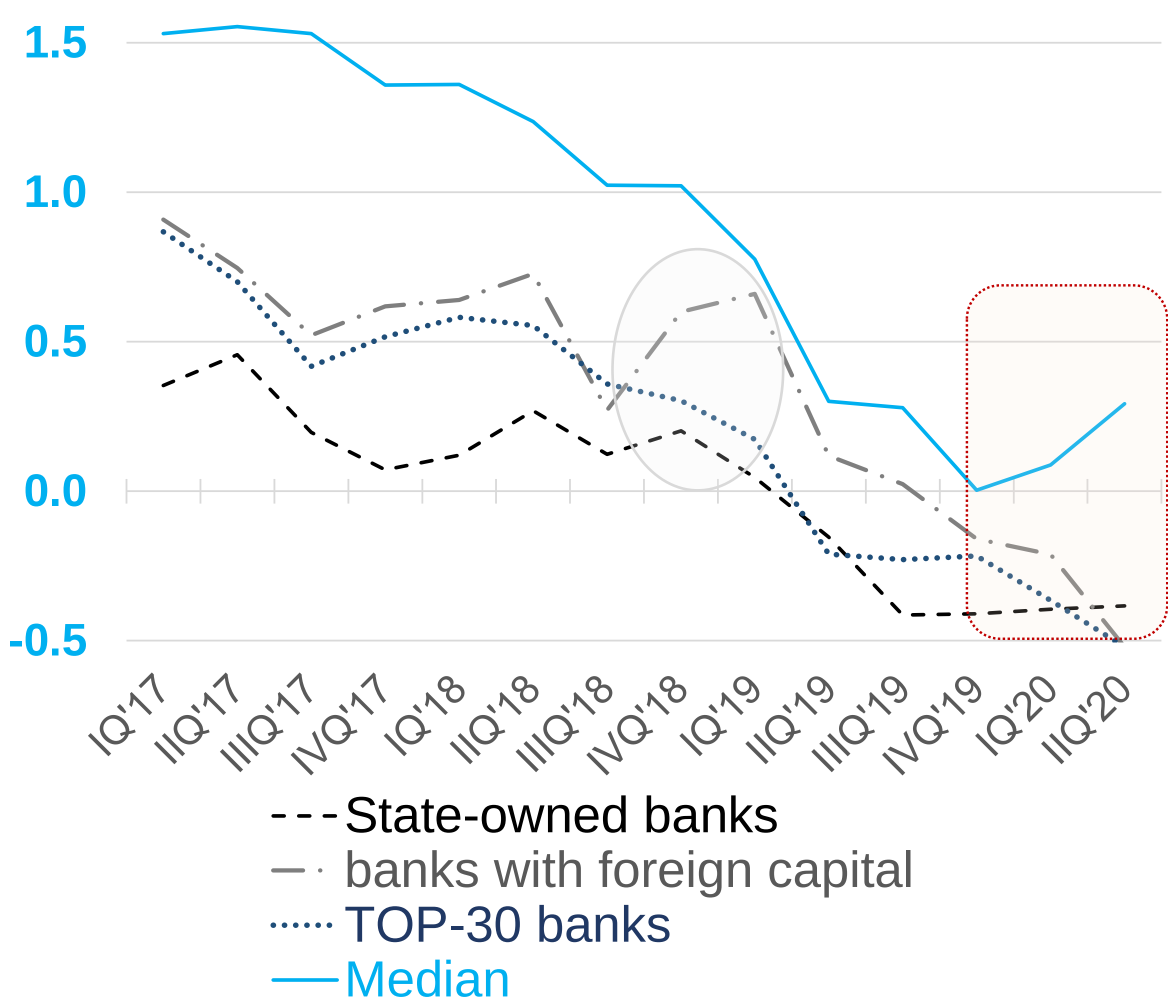




Note: shaded areas represent 25th and 75th percentiles
Source: authors' calculations

Dynamics of the lender-related component in the credit spread (implied risk-perception) for the groups of banks



Source: authors' calculations

Summary of empirical findings I

- **state-owned banks** have lower risk-perception than private banks – **take more risks**

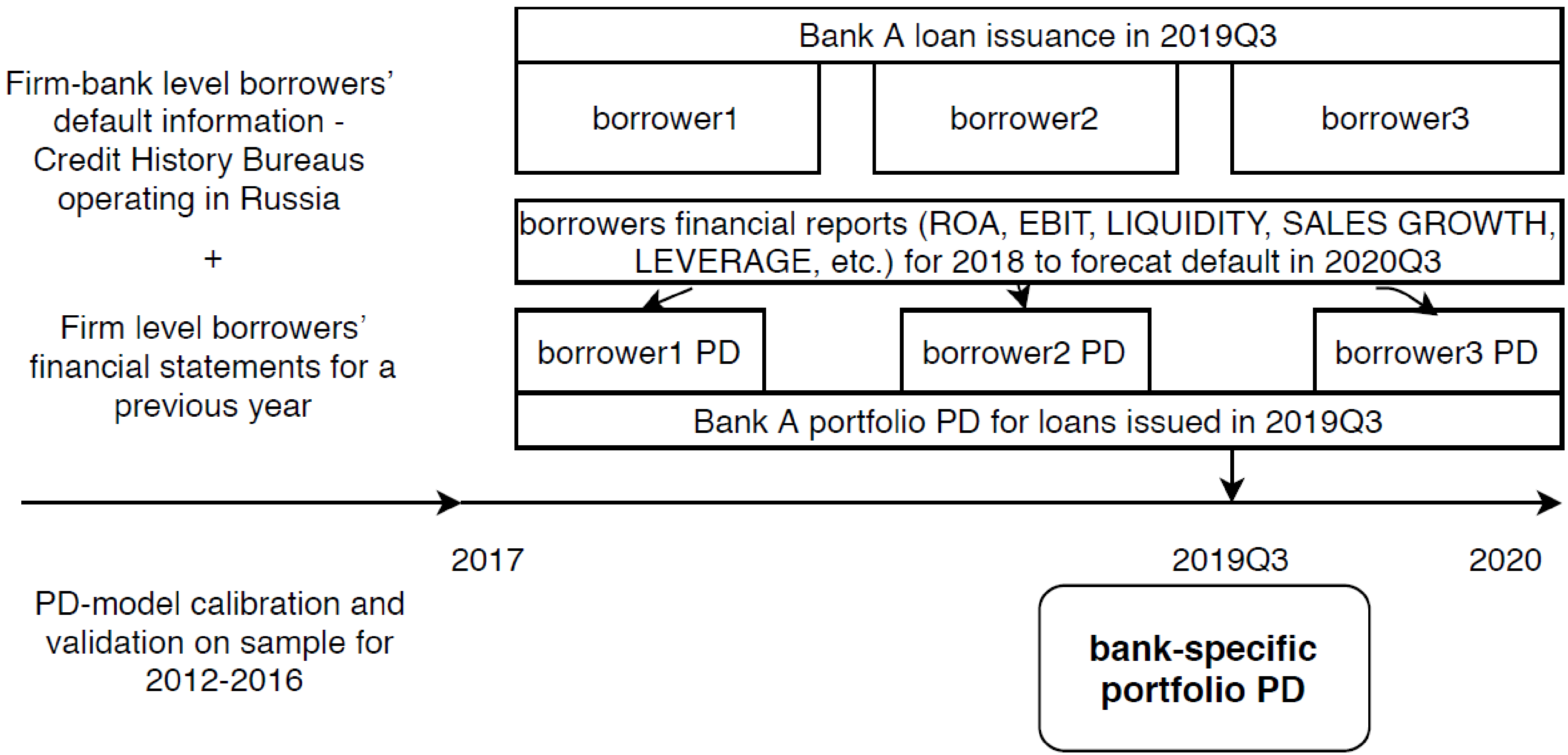
- **Banks with foreign capital** have lower risk-perception than other domestic banks – **take more risks**

- **Banks with foreign capita**l seem to become less ready to take risk by the end of 2018 (high uncertainty amid global and country-specific factors?)

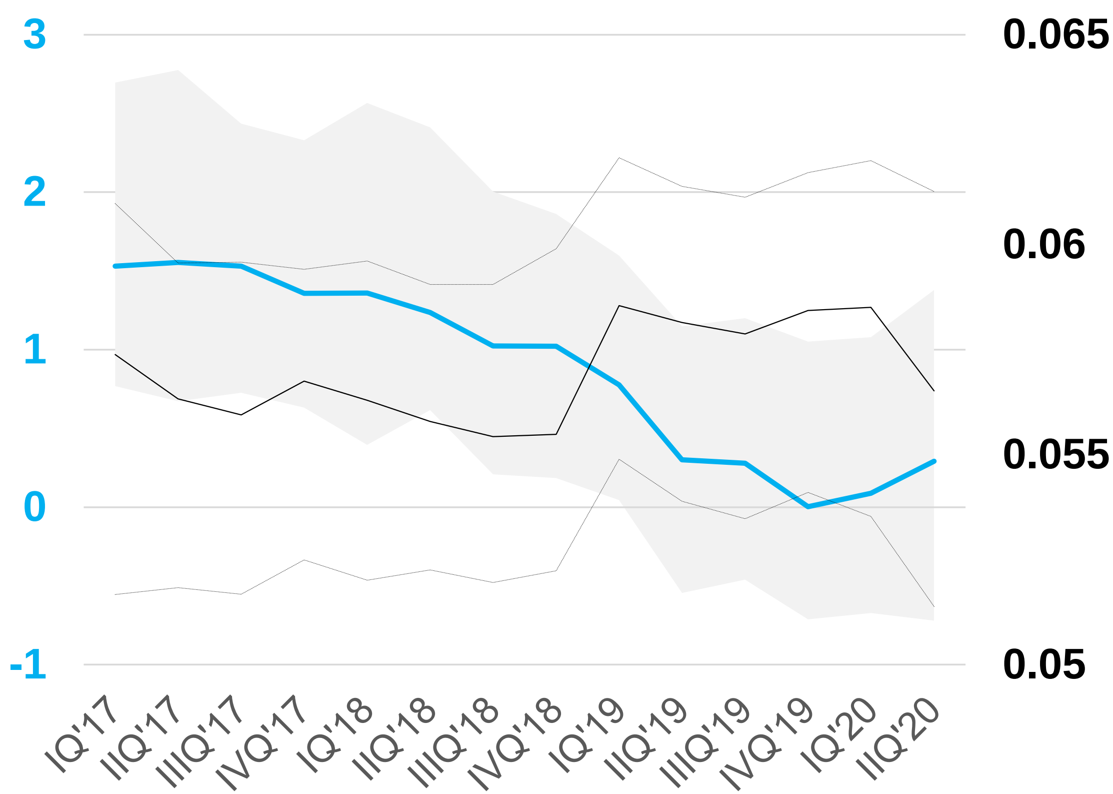
- **Top-30 banks** have lower risk-perception than smaller banks – **take more risks**

- **Median risk-perception** declined since 2017 to 2019. It has been increasing in 2020.

6. Comparing measure of risk-perception to new loans ex ante probability of default (PD)

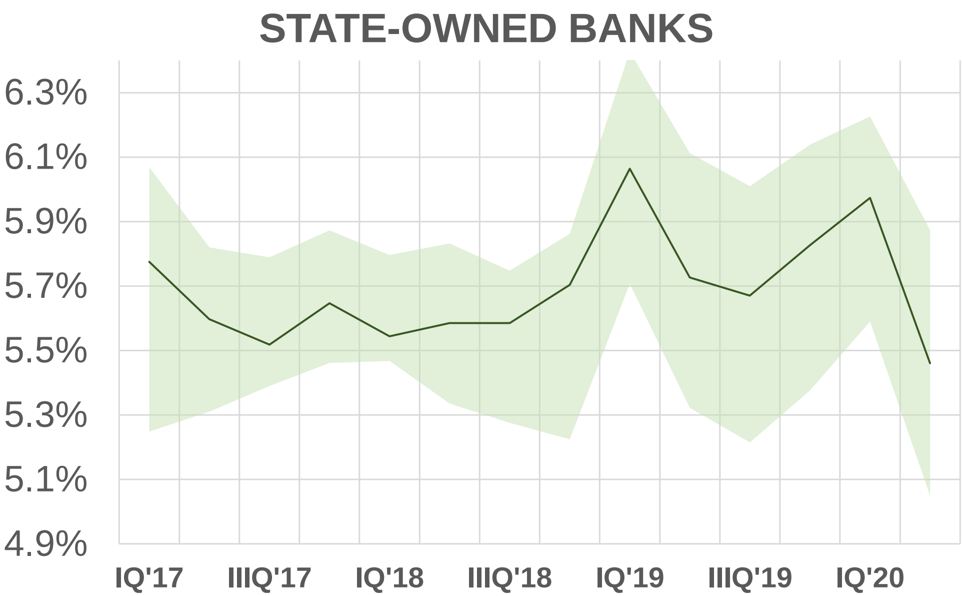

Firm-bank level borrowers' default information - Credit History Bureaus operating in Russia
+
Firm level borrowers' financial statements for a previous year
Bank A loan issuance in 2019Q3
borrower1
borrower2
borrower3
borrowers financial reports (ROA, EBIT, LIQUIDITY, SALES GROWTH, LEVERAGE, etc.) for 2018 to forecat default in 2020Q3
borrower1 PD
borrower2 PD
borrower3 PD
Bank A portfolio PD for loans issued in 2019Q3
2017
2019Q3
2020
PD-model calibration and validation on sample for 2012-2016
bank-specific portfolio PD

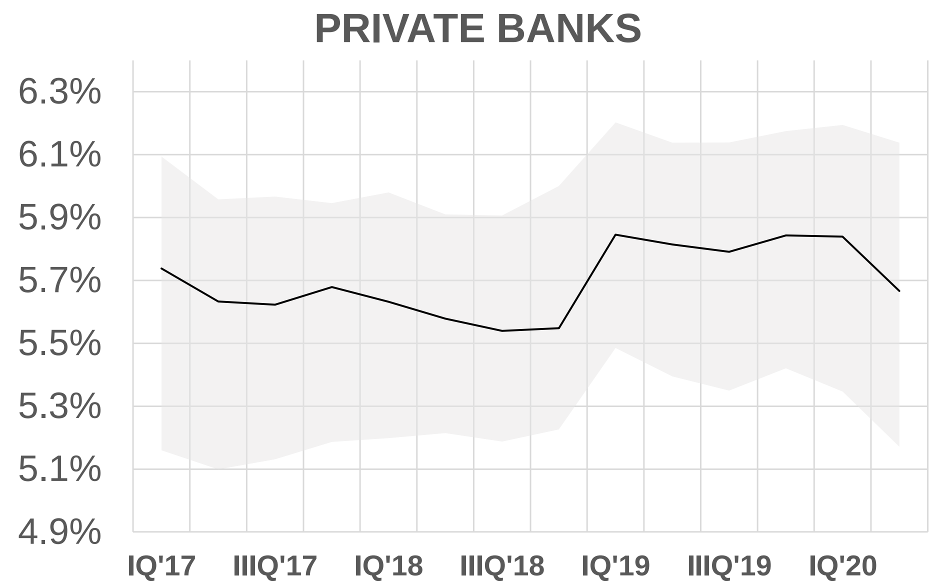
Dynamics of the lender-related component in the credit spreads (implied risk-perception – left axis) for the group of banks aligned with the median probability of default on the portfolio of newly issued loans (solid black line – right axis)



Note: shaded areas represent 25th and 75th percentiles
Source: authors' calculations

Ex-ante credit risk (PD) distribution of the portfolio of new loans. Results are aggregated for the groups of banks.





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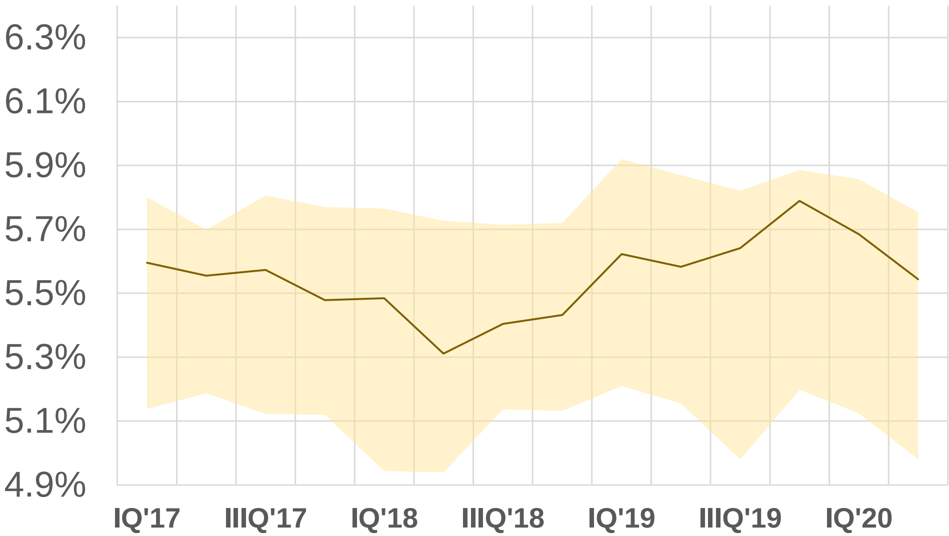
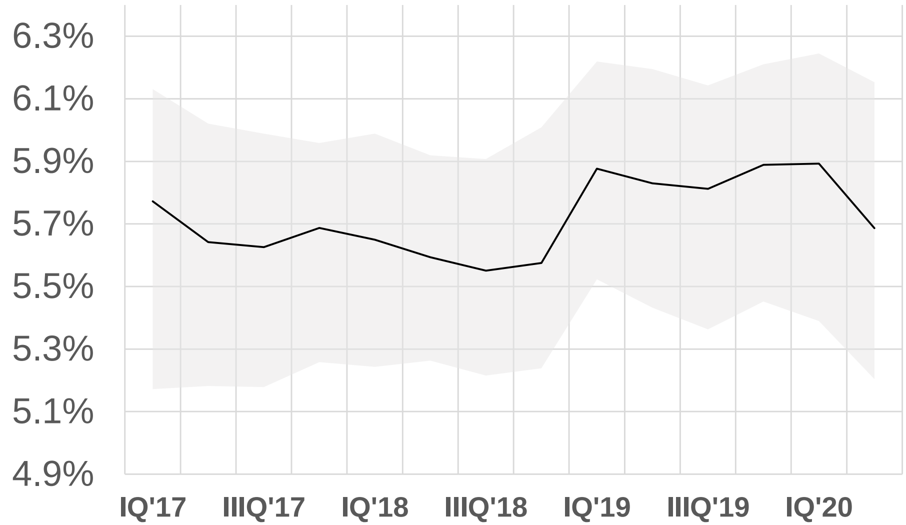
Source: authors' calculations

Ex-ante credit risk (PD) distribution of the portfolio of new loans. Results are aggregated for the groups of banks.

BANKS WITH FOREIGN CAPITAL

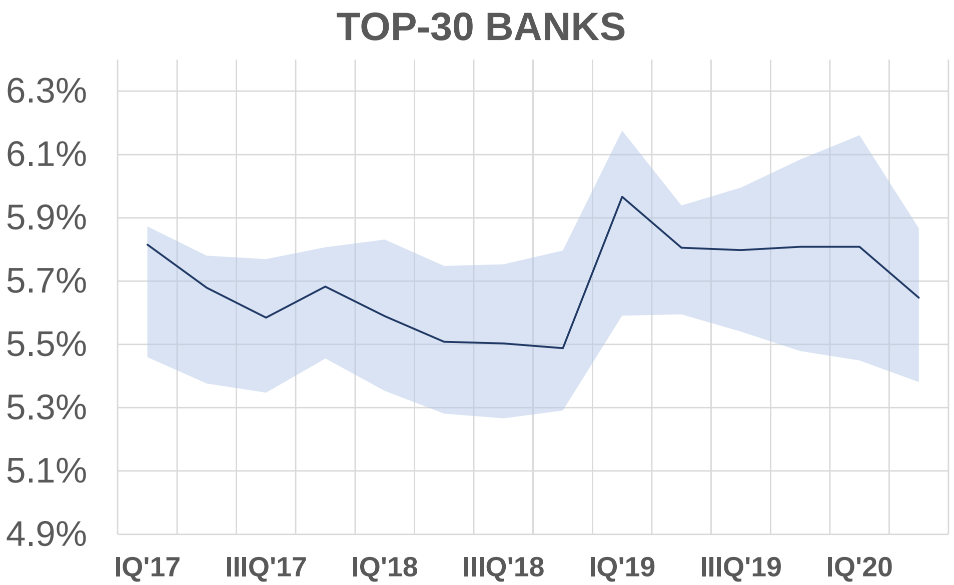


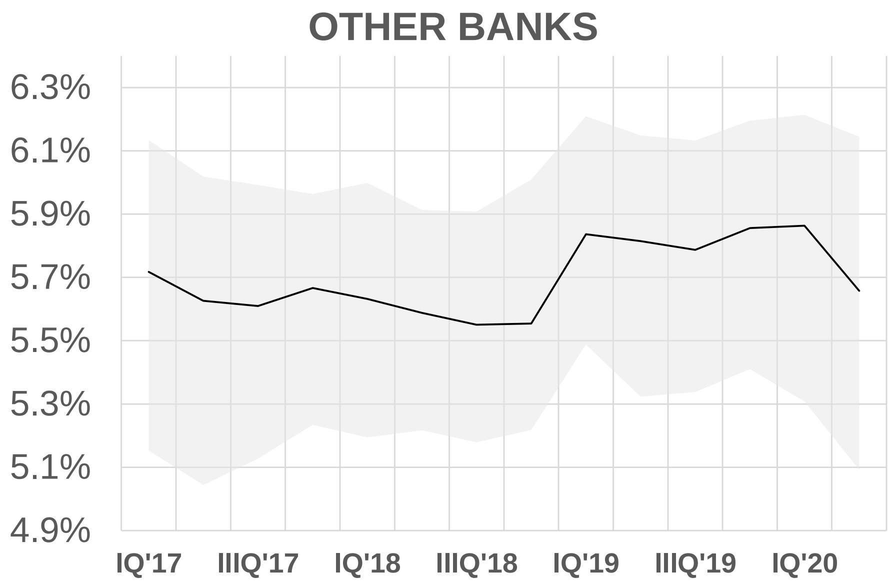
OTHER DOMESTIC BANKS



Note: shaded areas represent 25th and 75th percentiles
Source: authors' calculations

Ex-ante credit risk (PD) distribution of the portfolio of new loans. Results are aggregated for the groups of banks.





Note: shaded areas represent 25th and 75th percentiles
Source: authors' calculations

Summary of empirical findings II

- Comparing to 2018, median risk-perception declined in 2019, while median PD pointed to higher risks in 2019

- Differences of bank portfolio PDs among groups of banks are small

- Banks with foreign capital have a bit smaller PDs then other domestic banks

7. Conclusion

Identified bank-specific component of the spread can be used:

To provide new insights for prudential policy calibration: What if largest banks perceive less risks comparing to smaller banks?

To evaluate effectiveness of macroprudential policy in Russia (including spillovers from tighter macropru in consumer lending to corporate lending), Ahnert et al. (2018)

To test strength of policy transmission channels in Russia, along the lines of Jiménez, G., et al. (2014)

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Back up slides

We refer to the model specification introduced by Moody's Risk Calc v3.1 methodology

$$P(Y=1)=\frac{1}{1+e^{-X\beta+\varepsilon}}$$

Y=1 in a given month (say Feb.2012) if a borrower overdue payment for more than 90 days or if it was officially liquidated in the month *one year forward.* For example, overdue starts in Feb. 2013

X- set of borrower financial characteristics, known in Feb.2013 (!), namely, its financial report for 2012.

The model estimated in a such way will let, when we live in July. 2020 to predict defaults happening in a year starting *from* July 2021 using financial statements known up to July 2020 (2019 reporting year)

On PD-models for Russian banking sector see Karminsky, A. M., & Kostrov, A. (2014)

	Days overdue	Mark of default event (to identify the month of default event)	***Extended*** mark of default event (to cover the year of default)	***12m backward shift*** of default event (to match with)
2012m01	0	0	0	0
2012m02	**0**	**0**	**0**	**1**
2012m03	0	0	0	1
2012m04	0	0	0	1
2012m05	0	0	0	1
2012m06	0	0	0	1
2012m07	0	0	0	1
2012m08	0	0	0	1
2012m09	0	0	0	1
2012m10	0	0	0	1
2012m11	0	0	0	1
2012m12	30	0	0	1
2013m01	60	0	0	1
2013m02	**90** ➔	**1** ➔	**1**	**0**
2013m03	0	0	1	0
2013m04	0	0	1	0
2013m05	0	0	1	0
2013m06	0	0	1	0
2013m07	0	0	1	0
2013m08	0	0	1	0
2013m09	0	0	1	0
2013m10	0	0	1	0
2013m11	0	0	1	0
2013m12	0	0	1	0
2014m01	0	0	1	0
2014m02	**0**	**0**	**0**	
2014m03	0	0	0	
2014m04	0	0	0	
2014m05	0	0	0	
2014m06	0	0	0	
2014m07	0	0	0	
2014m08	0	0	0	
2014m09	0	0	0	
2014m10	0	0	0	
2014m11	0	0	0	
2014m12	0	0	0	
2015m01	0	0	0	

12 months without default event

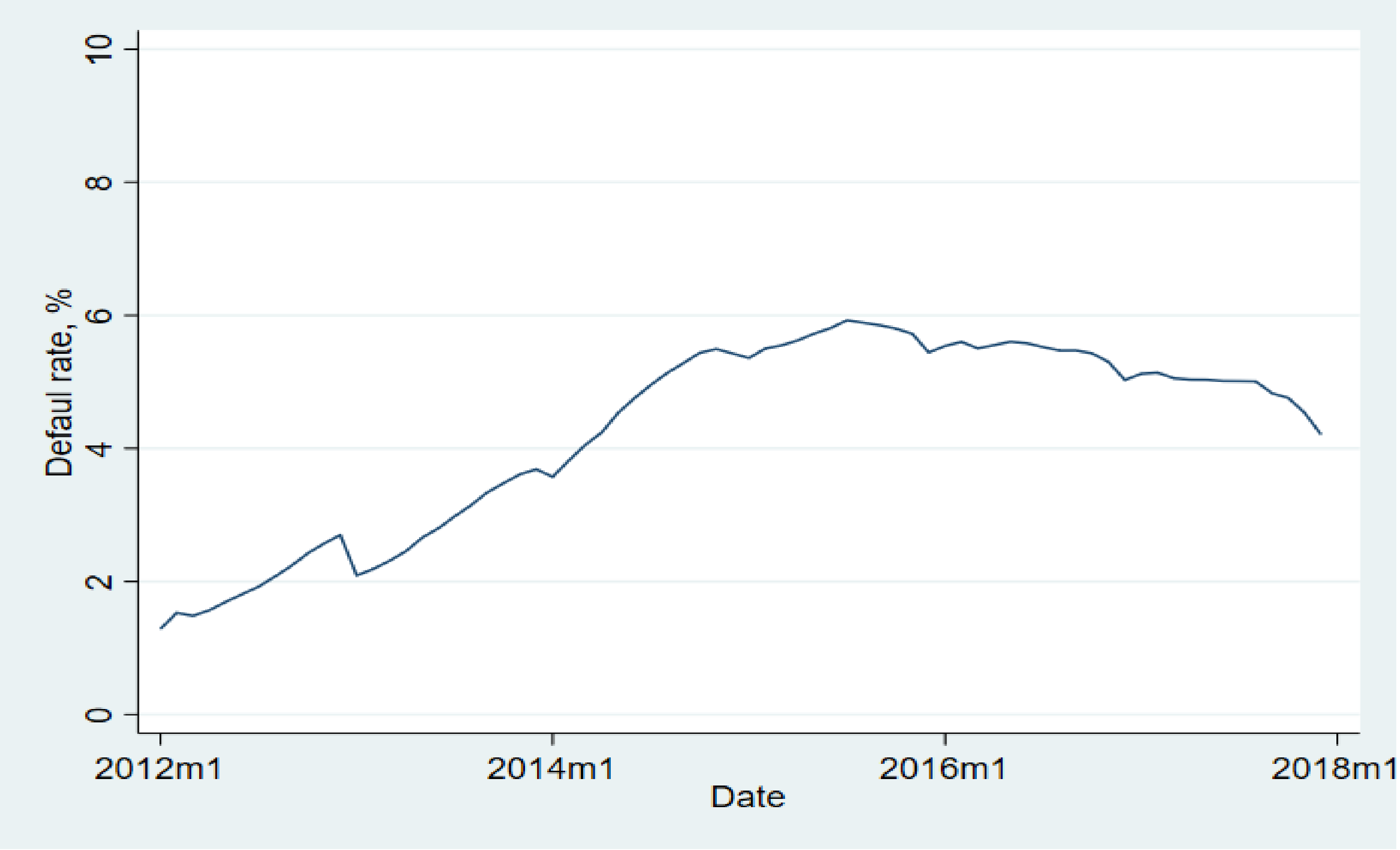
Data we use to estimate PD model.

Matched data from:

- Firm level borrowers' financial statements. SPARK database contains financial (quantitative) and non-financial (qualitative) information on the business entities operating in Russia. The database is available from the Interfax News Group https://spark-interfax.com

- Firm-bank level borrowers' default information from the four Credit History Bureaus operating in Russia

Economy wide default rate calculated using Credit History Bureaus data



Source: Bank of Russia, authors calculations

Table 1. Dataset composition and identification of defaults

Operation applied	**No. of observations**	**No. of defaults**
Dataset initialisation	16 114 889	
Entities with loans overdue of more than 90 days		535 575
Entities liquidated (identified from SPARK database)		2 509
Default mark assigned		134 481
Default mark 12m backward shift (defaults of next year are matched with firm IDs in current year)	(3 095 820)	(17 336)
Censored outliers at 0.5% and 99.5%	(669,292)	(44,686)
Total	**12,349,777**	**610,543**

Source: Bank of Russia, authors calculations

Financial variables

Table 4. Definition of financial ratios

Code	Definition	Calculation
ACTIVITY	The ratio of account payable to sales	AP/SALES
DEBTCOVER	The ratio of operating profit to total amount of liabilities	PROFIT_OPERATING/(ST_DEBT+LT_DEBT+AP)
GROWTH	Growth rate of sales	$(SALES_t-SALES_{t-1})/(SALES_{t-1})$
LEV_EQ	The share of equity in total assets	EQUITY_TOTAL/ASSETS_TOTAL
LEV_RE	The ratio of retained earnings to current liabilities	RE/(ST_DEBT+AP)
LIQUIDITY	The ratio of cash to total assets	CASH/ASSETS_TOTAL
EBIT	Earnings before interest and tax	PROFIT_OPERATING+DIVIDEND_INCOME+ INTEREST_RECEIVABLE
ROA	EBIT divided to total assets	EBIT/ASSETS_TOTAL

Source: SPARK, authors calculations

Table 5. Descriptive statistics

Variable	Default mark	Mean	Std. Dev.	Min	Max
ACTIVITY	Default	1.770	6.942	0	127.179
	Non-default	0.804	3.946	0	127.195
DEBTCOVER	Default	0.360	0.980	-3.714	32.582
	Non-default	0.600	1.917	-3.718	32.701
GROWTH	Default	-0.017	0.081	-0.5	0.719
	Non-default	0.014	0.075	-0.5	0.720
LEV_EQ	Default	0.104	0.617	-8.703	1
	Non-default	0.277	0.455	-8.704	1
LEV_RE	Default	0.917	3.438	-5.293	111.771
	Non-default	1.380	5.580	-5.294	111.790
LIQUIDITY	Default	0.046	0.075	0	1
	Non-default	0.073	0.120	0	1
EBIT	Default	6 204.709	25 473.10	-87 302.3	783 263.4
	Non-default	10 355.370	43 602.83	-87 315.5	783 440.2
ROA	Default	0.076	0.202	-1.493	3.340
	Non-default	0.124	0.250	-1.494	3.342

PD model validation

We split the sample into training and test one as 70% and 30%

We use F1-score as a model performance metric

$$F1 = \frac{2TP}{2TP + FP + FN}$$

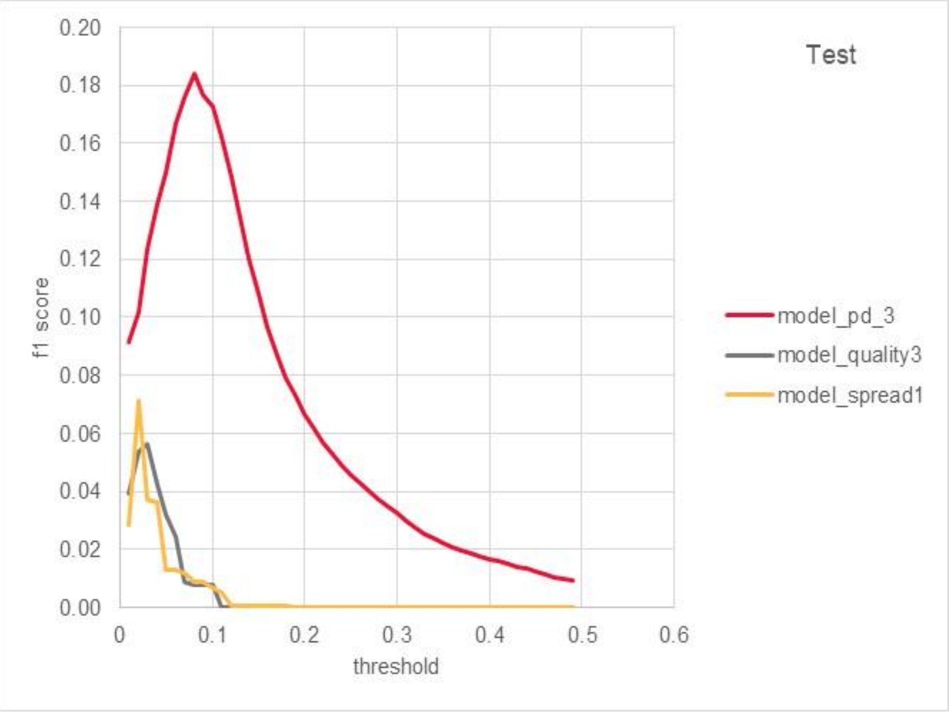
where TP stands for the observation correctly classified as “default”, FP – observation incorrectly classified as “default, FP – observations incorrectly classified as “non-default”

We also calculated more frequently used metric: AUROC (test sample)=0.72

PD model outperforms other metrics of risk-taking in its ability to predict defaults in pseudo real time forecasting exercise

- Credit spread
- Quality group (to which a lender places the loan at time of loan origination, from 1 to 5)

F1 score evolution for different threshold levels and alternative measures of ex-ante credit risk



Source: Bank of Russia, authors calculations