Bank of Russia

Measuring Heterogeneity in Banks' Interest Rate Setting in Russia

WORKING PAPER SERIES

No. 77 / August 2021

Burova A., Ponomarenko A., Popova S., Sinyakov A., Ushakova Yu.

Bank of Russia, Research and Forecasting Department
Anna Burova
Email: burovaab@cbr.ru
Alexey Ponomarenko
Email: ponomarenkoaa@cbr.ru
Svetlana Popova
Email: popovasv@cbr.ru
Andrey Sinyakov
Email: sinyakovaa@cbr.ru
Yulia Ushakova
Email: ushakovayuv@cbr.ru

Authors thank José-Luis Peydró and other participants of the NES – Bank of Russia research workshop (Oct'2020) for their helpful comments and suggestions on an earlier version of this paper. Authors also thank Alexey Egorov (Bank of Russia) and all participants of the internal research seminar of the Bank of Russia for their comments and suggestions on the later version of the paper. All errors and omissions are of the authors.

Bank of Russia Working Paper Series is anonymously refereed by members of the Bank of Russia Research Advisory Board and external reviewers.

Cover image: Shutterstock.com

Address: 12 Neglinnaya street, Moscow, 107016
Tel.: +7 495 771-91-00, +7 495 621-64-65 (fax)
Website: www.cbr.ru

Abstract

We use credit registry data on all corporate loans issued by all Russian banks since 2017 to decompose the bank interest spreads into a common factor, as well as borrower and lender-related components while controlling for loan characteristics. We find that variation in loan rates associated with lender-specific factors (heterogeneity of banks) and borrower-specific factors (heterogeneity of borrowers) is substantial. We use the identified bank-specific components to measure fragmentation of the corporate credit market in Russia. We illustrate the developments in the Russian credit market during the pandemic using the obtained estimates. The results indicate that heterogeneity in banks' interest rate setting is high and increased in the early stage of the pandemic. The range of borrower-related premiums charged by banks also widened (mostly due to increase in rates of loans to companies in sectors presumably affected by the pandemic). Finally, our results suggest that banks tightened non-interest loan conditions during the pandemic.

Keywords: bank interest margin, bank interest spread, corporate credit, credit registry, financial stability, credit market fragmentation, Russian banking sector in the pandemic

JEL-classification: E44, E51, E52, E58, G21, G28

Contents

Introduction 5

1. Data 9

2. Empirical Strategy 11

3. Results 14

3.1 Components of the credit-spread: summary 14

3.2 Components of the credit-spread: pricing of loan terms 15

3.3 Bank-specific component of the credit-spread 17

3.4 Borrower-specific component of the credit-spread 23

4. Robustness 26

5. Concluding remarks 34

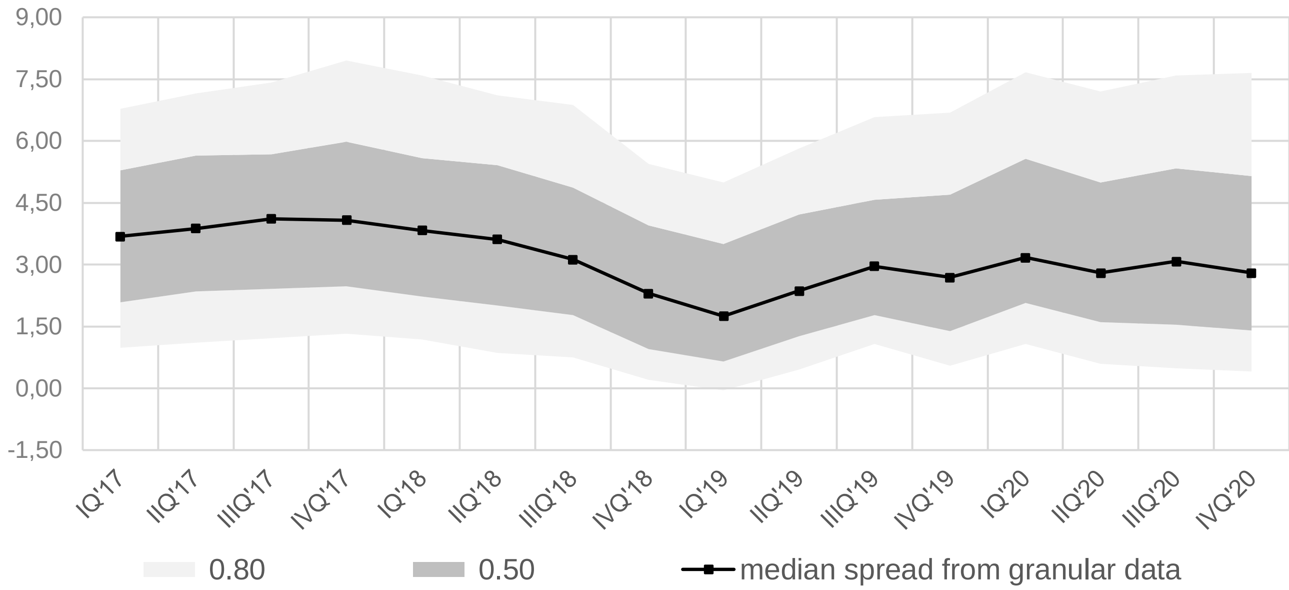
Annex 1. Descriptive statistics 36

REFERENCES 38

Introduction

An average for an economy corporate debt/loan interest rate spread is a useful indicator of monetary/economic conditions or risks for financial stability.[1, 2] However, corporate debt/credit interest rate spreads exhibit high cross-sectional heterogeneity in practice.[3] Granular data on corporate loans (including credit lines) issued by Russian banks to all Russian corporates (with multiple bank-credit relationships) draw the same picture (Fig. 1).

Figure 1. Interest rate spread on granular corporate credit registry data (borrowers have multiple bank-credit relationships), pp over the benchmark interest rate



Note: we exclude all FX loans, loans with rates in the first decile of the distribution (all loans with a rate less than 2.8%) and loans with an initial maturity of less than 30 days. The solid line is the median, and the shaded areas are the 50th and 80th percentiles of the spread distribution across all loans issued to borrowers with multiple bank-credit relationships in a particular quarter. Sources: Bank of Russia, authors' calculations

The heterogeneity of credit spreads of corporate loan interest rates may have several sources related to the heterogeneity of borrowers, lenders or loan terms.[4] For example, if

---

[1] Here and after we consider newly issued loans, not stock of loans (banks' corporate loans portfolios).
[2] On its use as an indicator for monetary/economic conditions see BIS Annual Economic report (2021), Gilchrist, S., & Zakrajšek, E. (AER'2012), Adrian and Liang (IJCB'2018). On its use for earlier identification of financial stability risks, see Adrian et al. (AER'2019), López-Salido, et al. (QJE'2017), Krishnamurthy, A., & Muir, T. (2017).
[3] A corporate credit interest rate spread is defined as the difference between an interest rate on a corporate loan and a particular benchmark. The credit spread on Fig. 1 is calculated as the spread between the loan rates relative to the benchmark rate. As the *benchmark rate* (Fig. 2), we use the average of interest rates charged by the *benchmark lender* on loans issued to the *benchmark borrower* in a quarter from 2017Q1 to 2020Q4. This rate resembles dynamics of the money market rates, common to all banks. On the heterogeneity of corporate loan interest rate spreads see Gambacorta, L., Mistrulli, P.E. (2014), on corporate bond spreads see Anderson, G., and Cesa-Bianchi, A. (2020), Zaghini, A. (2019), Horny, G. et al. (2018).
[4] On general structural sources of the heterogeneity, see Ioannidou, Ongena, and Peydró (RF'2015), Gambacorta and Mistrulli (JMCB'2014), Feyen, E., and Zuccardi Huertas, I. (2020).

borrowers have different credit risk characteristics, banks tend to price loans to these firms differently. Loan terms (maturity, collateral attached, etc.) are also different. Besides, bank-specific factors, unrelated to the heterogeneity of borrowers or loan terms, may be responsible for the observed heterogeneity of loan interest rates. This last source, i.e. the heterogeneity of banks, is the main focus of our paper. The heterogeneity of banks in interest rate setting for corporate loans can therefore be defined as how differently banks price a loan to the same borrower at the same moment in time and at the same loan terms.[5]

Bank-specific heterogeneity thus defined can be considered as an indicator of credit/bond market fragmentation.[6]

Fragmentation in the banking sector may have several policy implications. First, it may pose challenges to monetary policy setting and to its transmission mechanism.[7] Fragmentation means that average spread becomes less informative about prevailing monetary conditions in the economy.[8] In addition, the transmission of changes in the policy rate may slow down in fragmented markets. Moreover, financial shocks that change spread may be a more important source of average interest rate volatility than monetary policy. Second, it may have implications for financial stability.[9] In particular, the heterogeneity of loan interest rate spreads, especially driven by bank-specific or industry-specific factors (e.g. lower spreads charged by some banks or charged to some particular industries), may point to risk-taking activities ("overheating") by some part of the banking sector (cross-sectional dimension of financial stability).[10]

Anderson, G., and Cesa-Bianchi, A. (2020) note that "…heterogeneity is multi-dimensional and that there are potentially other relevant empirical proxies for financial constraints – such as age, size, liquid assets, etc., which are frequently considered in the literature."

[5] Changes in the composition of borrowers, lenders or loan terms for new loans may become an important factor of changes in the average interest rate spread. First, the level of the average corporate credit spread in the economy could vary (change in time) depending on macroeconomic factors common to all banks. For example, a declining interest rate spread may be a result of more favorable macroeconomic conditions and higher expected borrowers' income. The spread may also change due to changing lending conditions (loan structure by maturity, loans to affiliated entities or loans with collateral attached) or industry-specific and borrower-specific characteristics. For example, if more loans are issued to less risky borrowers because these borrowers increase demand for credit, a lower interest rate spread could be observed. Finally, some banks may decide to charge lower spreads relative to some other banks to the same borrowers – then it will be the bank-specific factor of the interest rate spread heterogeneity responsible for changes in the average interest rate spread. As a result, high heterogeneity reduces information content of the mean/median interest rate as "the central tendency" and makes the changes in the mean/median interest rate more exposed to changes in the composition of borrowers, lenders or loan terms.

[6] Iregui and Otero (EL'2013), Affinito and Farabullini (IJCB'2009), Martín-Oliver, et al. (JMCB'2007), for bond market see Horny, et al. (JRFM'2018).

[7] See, Altavilla, C., Canova, F., and Ciccarelli, M. (2020), Horvath, R. (2018), Ciccarelli, M., Maddaloni, A. and Peydró, J. L. (2013), Vari, M. (2014).

[8] For example, consider two economies with only two banks. Let the banks in the first economy have interest rates 5% when the key rate's curve is 4%, and let the banks in another economy have interest rates 0% and 10% with the same key rate's curve. The average spread in both economies is the same 1pp. But, uncertainty regarding prevailing monetary conditions in the second economy is much higher.

[9] Claessens, S. (2019). Fragmentation in global financial markets: good or bad for financial stability? Coimbra, N., and Rey, H. (2017). Financial cycles with heterogeneous intermediaries (No. w23245). National Bureau of Economic Research.

[10] See, Jiménez, G., Ongena, S., Peydró, J. L., and Saurina, J. (2014). There are several reasons why a bank may decide to charge a lower interest rate spread and take on relatively more credit risk as a result: a bank's competition strategy may induce the bank to price loans cheaper (Ross, 2010), there may be an information

The goal of our paper is to decompose the heterogeneity of credit spreads in corporate loan interest rates using granular data of the credit registry for Russia, with special focus on identifying bank-specific heterogeneity. The granularity helps us to identify several heterogeneity factors and to compute several measures of bank-specific heterogeneity as well as firm-specific one. We also study how different spread components behaved before and during the period of the COVID-19 pandemic. Understanding the *reasons* behind the theoretical or empirical heterogeneity of bank-specific factors is out of scope of this paper.

Our contribution is the following. First, we decompose the corporate loan interest rate spread along the lines a pseudo-experiment conducted by Khwaja, A.I., & Mian, A. (AER, 2008), Gambacorta, L. and Mistrulli, P.E. (JMCB, 2014), Horny, G. et al. (2018) on Russian credit registry data *to identify bank-specific component* of the spread. This is the first study of the banks' interest rate setting in Russia on such detailed data. Existing studies for Russia cover issues of the banks' heterogeneity in interest rate setting, but cannot address the issue of loan pricing heterogeneity with such granularity to identify the bank-specific component of the spread: Laeven, L. (2001), Claeys, S. and Vennet, R.V. (2008), Fungáčová, Z., and Poghosyan, T. (2011). Thus, we contribute to the existing empirical literature with the identification on Russian data.[11] Granular data help us identify the market price of particular loan terms (maturity, fixed or floating interest rate, affiliation, collateral) in Russia. The data also help us identify borrower-specific components in the credit spread.

The pseudo-experiment consists of selecting a subsample of borrowers having multiple-bank relationships at the same time. Such a subsample of borrowers help to isolate effects of borrower-related factors (="demand-side") on the interest rate setting. After controlling for loan terms there appears a possibility to identify bank-specific component of the spread. To form such a sample of firms with multiple-bank relationships we use detailed loan-firm-bank level data on bank loans from the Russian credit registry. The database covers *all* loans issued by *all* Russian banks to *all* Russian corporates in 2017–2021. We define the spread as the difference between the rate on a newly issued loan and the base rate of a loan issued by the benchmark *bank* to the benchmark *borrower*. To identify components of the spread, we regress the spread against a set of quarterly time-varying dummy variables for *individual* lender- and borrower-related components, and control for the loan characteristics.[12] A bank-specific component of the spread for a given loan to a given borrower is how the lender prices a loan spread with given terms (maturity, type of interest rate, collateral, affiliation of the bank and the borrower) to the borrower in a given period relative to how the benchmark bank prices the same loan to the same borrower.

Second, as far as we know, our paper is the first that *measures heterogeneity* of bank-specific components on granular data – analyses the distribution of bank-specific components and changes of the distribution in time. Existing papers address the issue of

---

asymmetry among banks (including relationship lending): Sharpe, S.A. (JF, 1990), Rajan (1992), Hauswald, R., and Marquez, R. (2006); or larger/lower income may stimulate to take more risk (moral hazard), see Repullo, R. (JFI, 2004), Boyd, J. and De Nicolo, G. (JF, 2005).

[11] This literature is cited in footnote 2.

[12] As a robustness check we also repeat the exercise on data with monthly frequency.

measuring heterogeneity (as an indicator of banking sector fragmentation) using macro-level, Affinito&Farabullini (IJCB'2009), or bank-level data, Gambacorta (EER'2008). The closest paper is by Martín-Oliver, et al. (JMCB'2007) who considered similar exercise, but studied heterogeneity along the line of banks and credit market products, not along "banks-borrowers". Gambacorta and Mistrulli (JMCB'2014) considered the same identification scheme but didn't calculate measures of heterogeneity of bank-specific components of the spread and analyse how this heterogeneity changes in time. In close papers the identification methodology is used to study sensitivity of loan interest rates, Ioannidou, et al. (RF'2015), or measures of credit risk, Jiménez, et al. (Ecca'2014), to monetary policy shocks or, as in Banerjee et al. (2021), to study effects of relationship banking on credit provision during the global financial crisis.

We measure fragmentation in the Russian banking sector (corporate credit segment) along the lines of Horny, G. et al. (2018) applied to the European bond market. We move from the country-based application of Horny, G. et al. (2018), to bank-level analysis, where "the law of one price" is also expected to hold, according to Affinito, M. and Farabullini, F. (2009), Martín-Oliver A. et al. (2007). "The law of one price" being applied to corporate bank loans assumes that loans issued with the same risk profile and other loan terms should have the same price, not systematically dependent on the asset holder (the bank that has issued the loan). When it holds, it means that credit risks are spread homogeneously across the banking sector, which, in turn, implies better resilience of the banking sector in a time of crisis. Thus, it is natural to expect that banks should price loans to the same firm with the same loan terms during the same period of time equally (not statistically different). The deviation from uniform pricing is used by Horny, G. et al. (2018) as an indicator of bond market fragmentation.[13]

We measure such defined fragmentation using the identified bank-specific components of the spread, i.e. the component of the spread that is not driven by borrower fundamentals. In absence of fragmentation all banks should have the same bank-specific component as the benchmark lender, i.e. the coefficients of the bank dummies should be zeros. With presence of fragmentation, some banks will have bank-specific components different from zero. Heterogeneity of this component signals the presence of wedges which are internalised by banks differently. On the other hand, "the law of one price" holds if the continuum of asset holders is not fragmented. We will compare this measured heterogeneity of loan pricing for well-defined groups of banks (state-owned vs. private, domestic vs. foreign, large vs. small). In this respect, our analysis contributes to the literature that studies banking sector fragmentation (see Lucotte, Y. (2015)), but applies granular data to the literature that studies banking sector heterogeneity in Russia with other measures (Simanovskiy, A. et al. (2018)). Heterogeneity of the spread and loan rates means that monetary policy conditions are also heterogeneous. Large heterogeneity, especially if it is attributed to a bank-specific component of the spread (banks setting different rates to the

[13] In the author's notation "countries" refer to "banks" in our study: "The coefficient associated with the country dummy represents our main measure of financial fragmentation".

same borrowers with the same loan terms) may imply that the banking sector is fragmented.[14]

Third, using the results of our decomposition and measurement, we analyse changes in Russian banks' pricing behaviour and corporate credit market fragmentation during the pandemic. To this end, we compare the identified components of the credit spread before (2019) and during the pandemic (2020). Our findings contribute to those in the literature on changes in bank loan pricing behaviour during the pandemic in Russia, Bessonova, E. et al. (2021), and in other countries, like Beck, T. and Keil, J. (2021).

This paper proceeds as follows: in the first section, we describe the data. In the second section, we proceed with presenting our identification strategy to measure bank-specific and lender-specific components of the spread as well as market prices of loan terms. In the third section, we present empirical results: measures of bank- specific and borrower-specific heterogeneity of the spread, and evolution of the market prices for loan terms. Here we compare cross-sectional variation of the bank-specific and the borrower-specific components. In the fourth section, we check robustness of our results for alternative identification assumption: monthly rather than quarterly frequency of defining "*the same moment"* of loans issuance for a firm with multiple-bank relationship. In the fifth section, we draw conclusions and suggest policy implications.

1. Data

We use a comprehensive micro-level database comprising all new loans issued by banks to the non-banking sector in Russia starting from 2017.[15] The database is a standard credit registry database that many other central banks collect and use.[16] It contains detailed information on the currency and amount of loans issued to Russian companies, the amount of debt outstanding as of the end of each month, lending rates, original and remaining maturity, collateral attached, borrower-lender affiliation, the amounts of debt repayment (including interest payments and the amortisation of the principal amount of debt).[17]

To study the heterogeneity of credit spreads in corporate loan interest rates, we use only domestic currency loans, i.e. we exclude FX loans (which is just 1% of the total number of loans) from our sample.

We deal with a subset of loans issued to entities (borrowers) with multiple (n-banks, where n>1) relationships in a particular quarter from 2017Q1 to 2020Q4. In the robustness

[14] Indeed, Horny, G. et al. (2018) defined market fragmentation in a similar manner in their study of corporate bond pricing in the Europe. Here we follow their tradition but apply the definition to the banking sector.
[15] Referred hereafter to as the credit registry (Form 0409303). The webpage with methodology and detailed description of the form can be found at
http://www.cbr.ru/eng/statistics/pdko/sors/summary_methodology/#highlight=0409303
[16] For example, AnaCredit by ECB
(https://www.ecb.europa.eu/explainers/tell-me-more/html/anacredit.en.html)
[17] The data in the credit registry contain information on a registered company basis and doesn't contain any indication of whether a given company is a member of a larger business group or a subsidiary of a holding company. Group-based identification would need much more data to control for intragroup variation in loan-demand.

check we use monthly frequency to define firms having multiple-bank relationship: if a firm has loans (credit lines) issued by more than one bank in a given month it is selected in the sample.

We also exclude all loans with an initial maturity of less than 30 days, which comprise approximately 5% of the sample.[18]

We exclude loans with rates in the first decile of the distribution (all loans with a rate less than 2.8%). We have a practical rationale for this – in 2020Q2 the state programme to support the economy during the pandemic was initiated with a 2% loan rate and a postponed interest payments scheme for qualified firms. We believe that such loans may not fully reflect market pricing conditions and would introduce some noise in the results.

Our data include not only loans, but also tranches of credit lines.[19]

See the table with sample descriptive statistics after all corrections in Annex 1.

Considering data seasonality, one may want to discuss how it could translate into the results of fragmentation measures. We show that the potential effect of seasonality is rooted in the smaller number of observations (N) in the 1st quarter (Fig. 2) or month (Fig.3) of each year. This translates into less stable and reliable estimates produced for these periods. Therefore, the fluctuations of lender- and borrower-related components (beta2 and beta3) observed in such periods should be interpreted with caution.[20]

Figure 2. Number of observations for each quarter

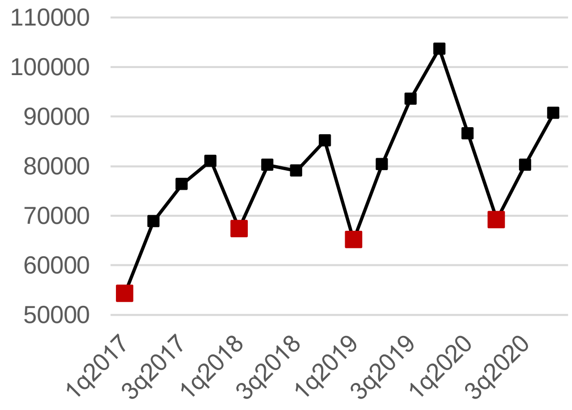
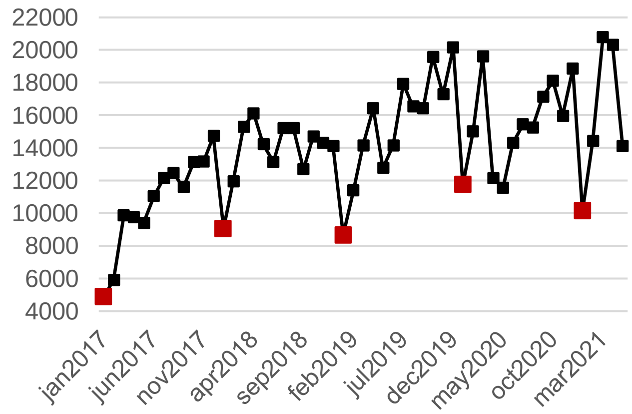


Figure 3. Number of observations for each month



Sources: Bank of Russia, authors' calculations

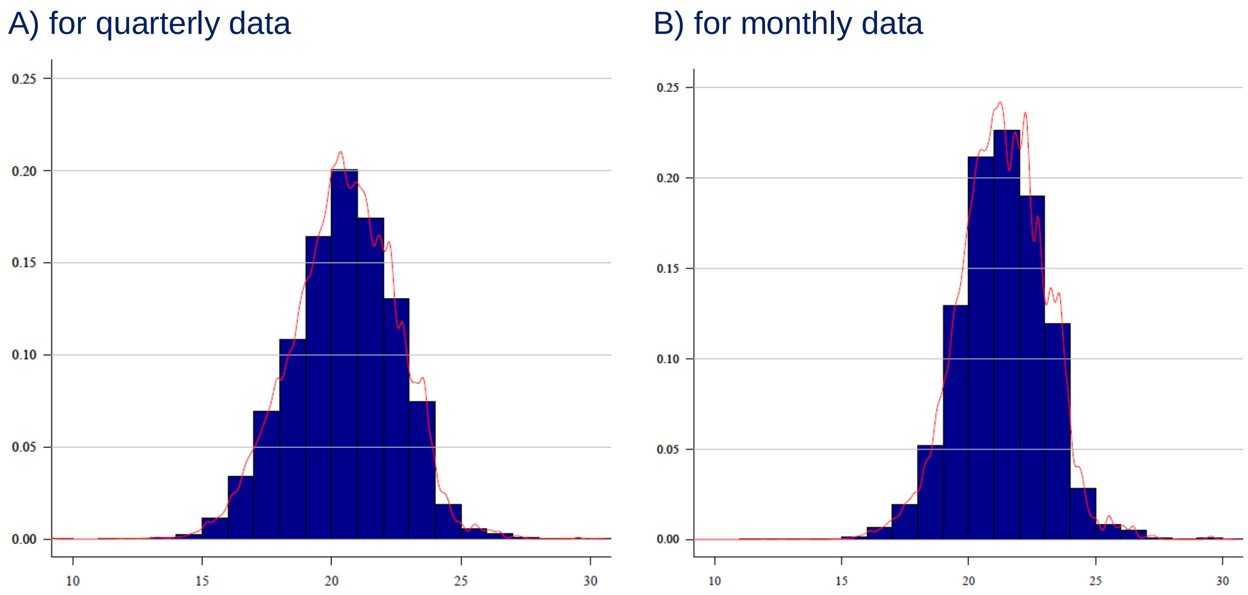
[18] When we use quarterly frequency of identifying firms with multiple-bank relationship it might be the case that with maturity of 30 days such relationship may indeed be a consequence of loans issued and repaid by one bank and a loan issued after that by another bank(-s). For quarterly frequency considering the maturity of 90 days would help to exclude such case of the wrong identification in multiple-bank relationship. Given that only 5% of the loans have maturity of less than 30 days, to keep consistency with monthly frequency of multiple-bank relationship identification (in the robustness check section), we decided not to recalculate the sample with the threshold of 90 days for choosing loans into our sample.

[19] As a robustness check we tried to exclude all credit lines (as they usually fix the loan terms, including the interest rate, not in a given quarter (month) but in a moment of the credit line issuance, which may be a cause of the wide variation observed in the spread) to compare the results. But as credit lines dominate the stand-alone loans: approximately 1000 thousand tranches of credit lines versus approximately 200 thousand of loans.

[20] We also tested seasonality in measures of market fragmentation – see Section 4.

As we deal with a subsample of firms having multiple-bank relationships in a given quarter (month) only, a question naturally arises why such firms choose to have multiple credit relationships. As the question is out of the scope of this paper, we don't study it in the detail. However, we addressed the hypothesis claiming that only very large firms are subject to such multiple relationships due to credit constraints and inability of any particular bank to meet the demand of such large borrowers. Figure 4 shows the distribution of borrowers' assets (firm size) when borrowers have multiple-bank relationships (data are pooled for all months/quarters). It is evident that the sample of firms with multiple-bank relationships is very diverse with the size of the median firm of around 500 million rubles.

Figure 4. Distribution of borrowers' assets (firm size) for borrowers with multiple-bank relationships, pooled data all months, natural logarithm of assets in rubles



Sources: Bank of Russia, authors' calculations

2. Empirical Strategy

To illustrate the identification approach, let us consider the following example. Two banks, Bank A and Bank B, issued a loan to the same firm at the same period of time (in a given quarter). The loan terms are also the same. How would the banks price the loan? If we observe that an interest rate spread of the loan charged by Bank A is smaller, we can assign the difference only to bank-specific factors.

The reason of lower spreads may be differences in capital or income on the deposit side, or different risk attitude by the banks.[21] For example, Bank A may charge a lower deposit rate and as a result may earn an additional margin on the deposit side. Whatever the reason for Bank A to assign a lower interest rate spread relative to Bank B's spread (when the opportunity cost of money for both banks is the same), the lower spread implies

[21] See Jiménez, G., Ongena, S., Peydró, J. L., and Saurina, J. (2014)

that Bank A will not receive the same compensation for the loan to the same borrower with the same conditions. [22]

Turning to the technical side of identification, we use data that characterise *a firm* that borrowed from *several banks* in the *same* period of time (quarter).[23] We also control for the loan terms. To estimate the lender-related component of the credit spreads we employ a dummy regression technique. We refer to Khwaja, A.I., & Mian, A. (AER, 2008), Gambacorta, L. and Mistrulli, P.E. (JMCB, 2014) and to Horny, G. et al. (2018) who used this methodology to measure financial fragmentation episodes in the euro area.

The spread of the loan rates (credit spreads) relative to the benchmark could be decomposed into *lender-related, borrower-related*, and *loan-related* components by estimating the following regression for a triple *I = {borrower, bank, loan characteristics}*:

$$Spread_{i,t} = \beta_{1,t} \cdot \delta_{quarter,t} + \beta_{2,t} \cdot \delta_{borrower,\,t} + \beta_{3,t} \cdot \delta_{lender,\,t} + \beta_{4,t} \cdot \delta_{loan,\,t} + e_{i,t} \quad \text{(eq. 1)}$$

$Spread_{\,i,t}$ – credit spread (difference between the loan i rate and the benchmark rate)

$\delta_{quarter,t}$ – time fixed effect (common macroeconomic conditions)

$\delta_{borrower,\,t}$ – dummy for the borrower (borrowing company) – borrower-time fixed effect

$\delta_{lender,\,t}$ – dummy for the bank (lender) – bank-time fixed effect

$\delta_{loan,\,t}$ – dummy for loan characteristics (maturity, 1 if maturity > 1 year), dummy for the type of interest rate (0 if fixed, 1 otherwise). We also include a dummy for collateral attached to the loan (1 if there is a collateral), a dummy for affiliation of a bank and a borrower (1, if there is an affiliation). All dummies are taken from corresponding fields of the credit registry database.[24]

The objective is to estimate the coefficients $\beta_{1,t}$, $\beta_{2,t}$, $\beta_{3,t}$, $\beta_{4,t}$, where the coefficients $\beta_{2,t}$ and $\beta_{3,t}$ are the primary focus of this paper. We use a time-varying dummy for each

[22] Adverse selection in lending for lower values of the interest spread is thought to result in attracting less risky borrowers applying for the loan. Thus, a lower spread may not imply larger risk taking. This argument does not apply to our identification scheme as it deals with the same borrower who obtains two loans with different interest rates. Another argument that challenges the idea that a lower spread corresponds to taking on more risk is that a lower spread makes it easier for the borrower to pay out the debt, while a larger spread increases debt service burden on the borrower, which raises the probability of default. We are going to check how the bank-specific component of the spread relates to ex ante and ex post risk-taking by the banks. By hypothesis, banks charging a lower spread, other things equal, should have a lower probability of default at the time of loan issuance and lower actual defaults for a given vintage of loans.

[23] We will reduce the time span to a month in the robustness check.

[24] This list doesn't include many other loan terms, such as conditionality or options attached. We used only those terms that 1) are included on the bank reporting form and 2) have a small number of missed values (as reporting of some loan terms is not obligatory for a reporting bank). We also don't control for the *relationship lending* as the credit registry data starts only in 2017, which is rather a short time period to identify unbiasedly the effect of the relationship lending. For example, Banerjee et al. (2021) tracked a bank-firm relationship since 1998, 6 years before the credit registry time-series for Italy they used (in 2003). They tracked the history to reduce the bias given their observation that the median duration of a bank-firm relationship is around 6 years. As we don't have alternative sources of information to track the relationship before 2017, we can only indirectly test the role of relationship lending for correct identification of the bank-specific component (see Section 3.3).

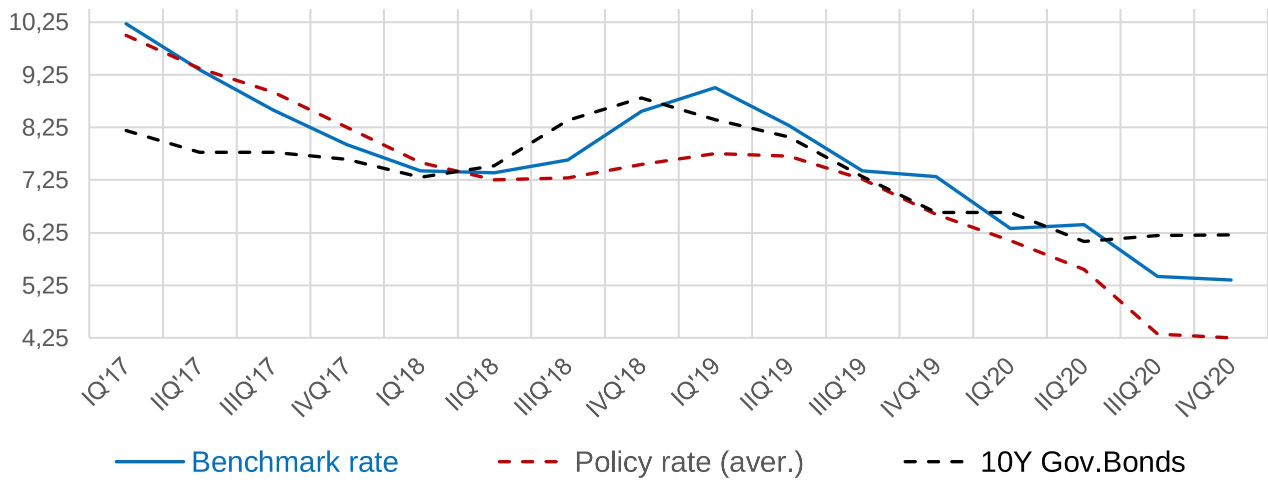
bank and for each borrower. The time fixed effect absorbs macro factors and other factors that uniformly affect all loans and their pricing.[25]

We construct an aggregate measure of bank-specific components for well-defined groups of banks (state-owned banks vs. private banks, banks with foreign capital vs. other domestic banks, top 30 banks vs. other banks),[26] and for the aggregate sectors of the economy the borrower operates in.

Following Horny, G. et al. (2018), we measure banking sector fragmentation as the average value of the bank-specific component $\beta_{3,t}$. We also tried other characteristics of $\beta_{3,t}$'s distribution (across banks): standard deviation and the difference between the 95th and 5th percentiles.

We disentangle the spread relative to the benchmark into bank-related and loan-related components. As the *benchmark rate* (Fig. 5), we use the average of the interest rates charged by the *benchmark lender* on the loans issued to the *benchmark borrower* in a particular quarter from 2017Q1 to 2020Q4. As the *benchmark lender*, we choose one of the TOP-30 banks. As the *benchmark borrower*, we choose a company that had persistently borrowed from the benchmark lender every quarter for 16 quarters (time span) and had multiple relationships with other banks during the same quarter.

Figure 5. Benchmark rate* for the identification of the credit spread, % p.a.



**Periods when the benchmark rate was below the policy rate are periods when rates on government bonds (OFZs) were lower than the policy rate. Sources: Bank of Russia, authors' calculations*

For the identification purpose, we considered only those borrowers who had taken loans from multiple banks (more than one bank-credit relationship in Table 1 represented by the shaded area) in a given time period (a quarter, in our main case, a month – in the robustness check). In particular, we considered the following observations: "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 terms in quarter Q". There are 1.2 million such

[25] Cases when borrowers are not uniformly affected by the external factors are left for future research where we plan to introduce an industry-specific dummy.
[26] These are usual groupings for studies of the Russian banking sector, Simanovskiy, A. et al. (2018).

observations – borrowers with multiple bank-credit relationships. For these banks we run the regression eq. 1.

Table 1. Number of loans (tranches of credit lines) issued to entities (borrowers) with multiple (*n*-banks) relationships in a particular quarter

n_banks relationship (quarterly)	Freq.	Per cent
1	5,111,925	80%
2	857,706	13%
3	232,088	4%
more than 3	172,392	3%
Total	6,374,111	100%
Total in scope	***1,262,186***	**20%**

Sources: Bank of Russia, authors' calculations

Consequently, we assess the distribution of specific components in the credit spread of newly issued loans with a quarterly frequency and aggregate results for the groups of banks and at industry level.

3. Results

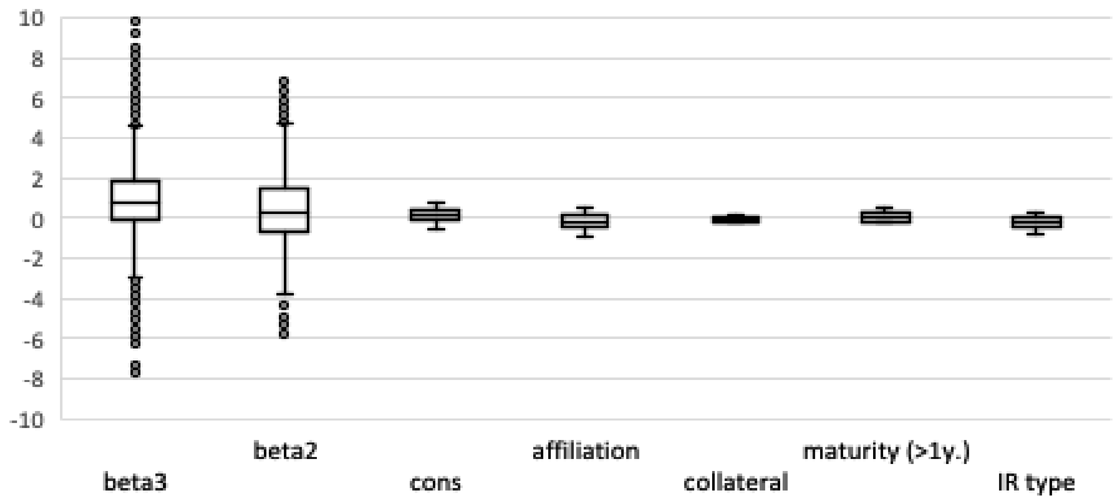
To identify the bank-specific ($\beta_{3,t}$) and the borrower-specific ($\beta_{2,t}$) components, we run the regression specified in eq. 1 for spreads on loans issued by lenders to borrowers with multiple bank-credit relationships in a *given* quarter from 2017Q1 to 2020Q4. This condition does not imply that the lender should issue such loans *every quarter*. This makes our panel unbalanced, but this is a sufficient condition for pointwise estimates of $\beta_{3,t}$ and $\beta_{2,t}$ in eq. 1.

However, in order to apply the concept of heterogeneity to the bank-specific or borrower-specific component correctly, we need to control for lender (borrower) composition in each particular quarter. Thus, for aggregating, presenting, and interpreting the results, *hereinafter* we do this for the $\beta_{3,t}$ and $\beta_{2,t}$ estimates for those banks (borrowers) who had issued (received) loans from multiple bank-credit relationships in *all 16 quarters*. In total, 202 of 493 banks issued loans to 391 borrowers in all 16 quarters.

3.1 Components of the credit-spread: summary

Pooled estimates of eq. 1 are shown in Fig. 6 along with their 50% confidence intervals (top and bottom of the boxes). The bank-specific component has wider distribution (fat tails) on both sides compared with the borrower-specific component. Control components (presence of affiliation and collateral) have a relatively minor contribution to the level of credit spreads.

Figure 6. Variation of different components in the credit spreads, pp: beta2 is the borrower-related component, beta3 is the lender-related component; other components are a dummy for affiliation (1 if there is an affiliation), collateral (1 if there is a collateral), maturity (1 if >1 year), and IR type (1 if not fixed)



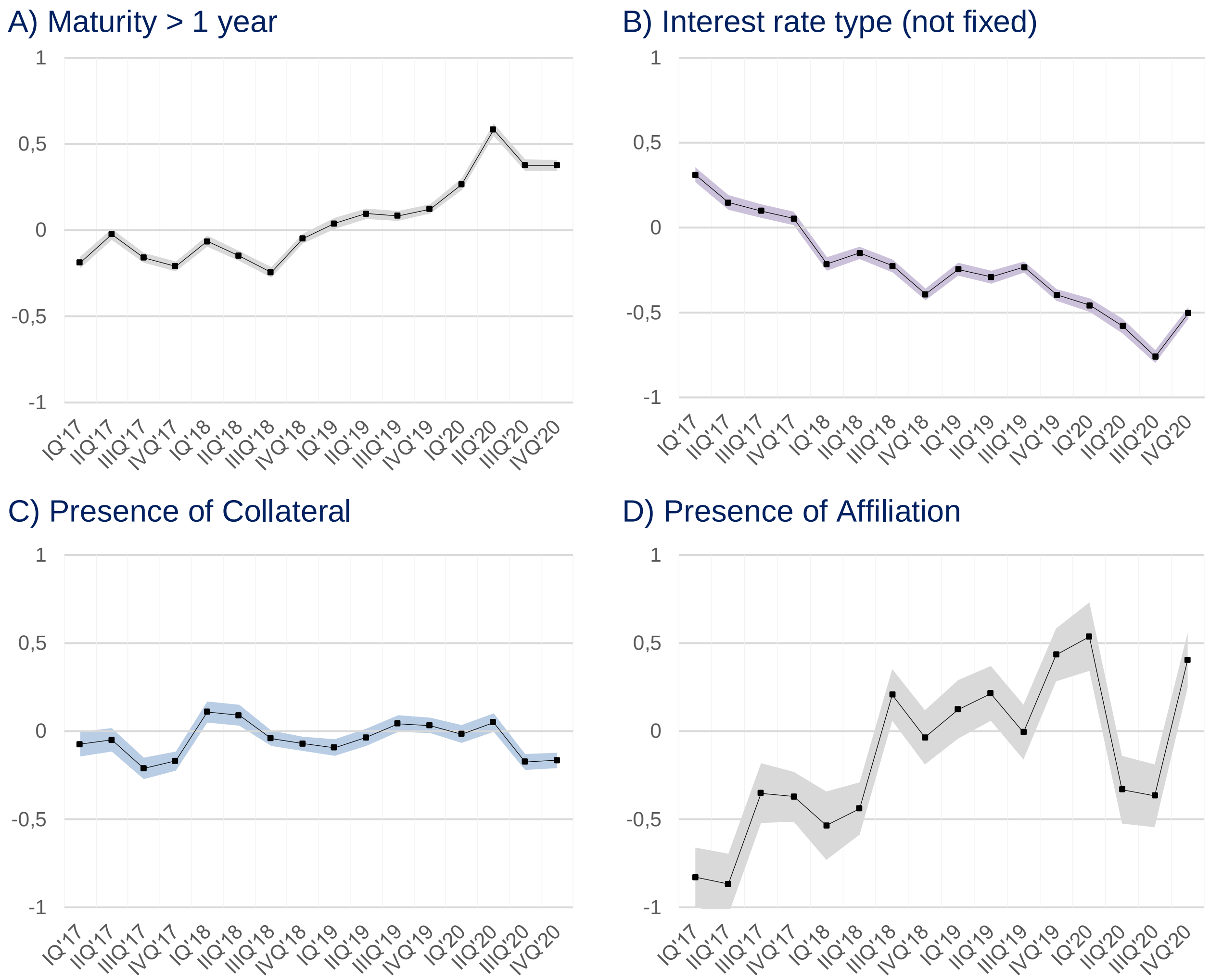
Note: the horizontal line within each box shows the median, top and bottom of the box refers to the 25th and 75th percentiles of the sample, the upper and lower whisker are adjacent values (box top/bottom +/-1.5 interquartile range), and the dots refer to outliers. Sources: credit registry data, authors' calculations

Thus, the main drivers of the observed heterogeneity in corporate loan rates are the heterogeneity of borrowers and differences among banks in some characteristics that are important for interest rate setting.

3.2 Components of the credit-spread: pricing of loan terms

Estimates of eq. 1 on granular data help us to assess the market prices for some loan terms (Fig. 7). We can also measure how these prices change in time, in particular, we can analyse changes during the pandemic.

Figure 7. Estimates of loan characteristics in the credit spread (beta4), pp



Note: the solid lines are pointwise estimates and the shaded bands are 95% confidence intervals.
Sources: credit registry data, authors' calculations

According to Fig. 7A, the pandemic resulted in a higher market price of longer-dated loans compared to shorter-dated ones, probably reflecting larger credit risk estimates. As we show in the robustness check – the result for the price of maturity doesn't hold on a sample with monthly frequency. At the same time, there was a significant drop in the market price of floating rate loans compared to fixed rate loans – Fig. 7B.

According to Fig. 7C, the relative price of collateralised loans reduced only slightly. The most acute variation was observed in the market price of loans to affiliated entities – Fig. 7D: the price of such loans dropped almost 1pp in the aftermath of the pandemic, stayed low for two quarters and then increased in the fourth quarter of 2020.

It is interesting to note that that the loan market reacted to heightened credit risks during the pandemic not with a lower price of collateralised loans, but with a lower price of loans to affiliated entities (Fig. 7D).

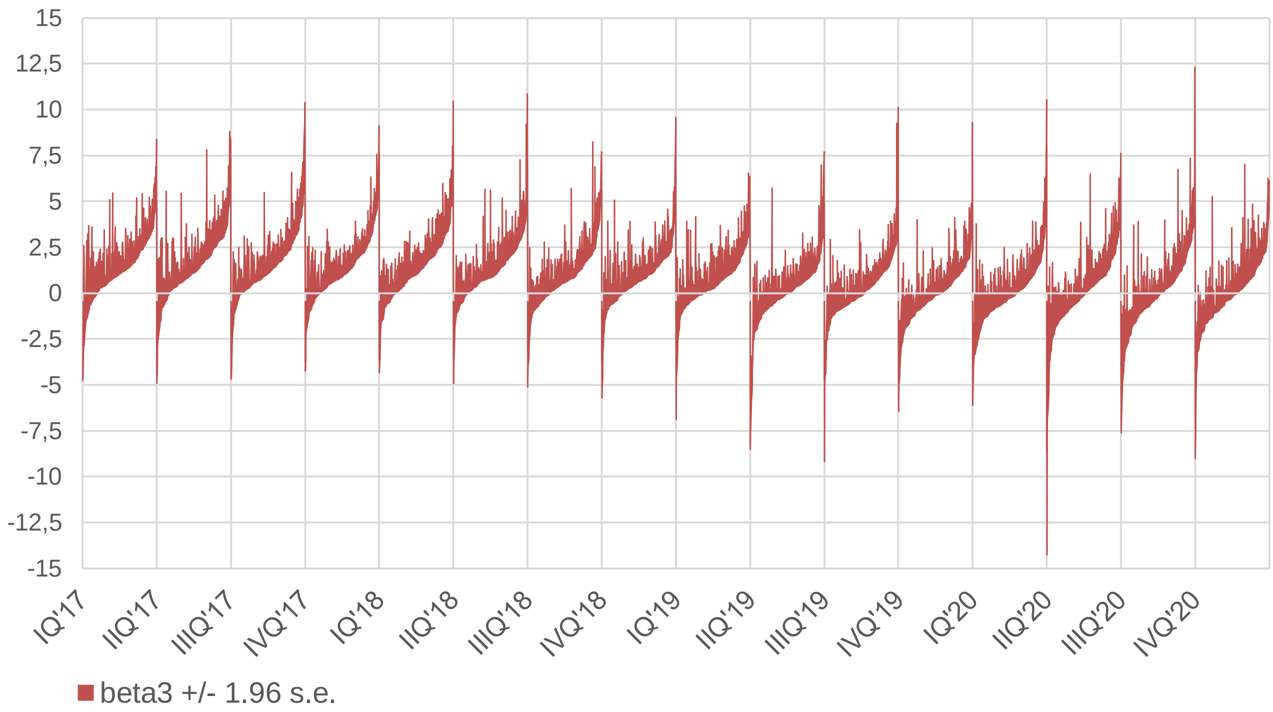
Now we describe our results regarding borrower and lender-related components and calculate the fragmentation measure.

3.3 Bank-specific component of the credit-spread

To identify the bank-specific component, which is the coefficient $\beta_{3,t}$ in eq. 1, we run the regression for loans issued to borrowers with multiple bank-credit relationships in a *given* quarter. However, not all the banks had issued loans to such borrowers *in all 16 quarters consequently* from 2017Q1 to 2020Q4. We control for lender composition in each particular quarter by aggregating and analysing the pointwise estimates of $\beta_{3,t}$ only for those banks that had issued loans to borrowers with multiple bank-credit relationships in all 16 quarters.

Fig. 8 contains estimates of $\beta_{3,t}$ (with their confidence intervals) for all such banks (202 banks per each quarter). Most bank-specific components of interest rates are significantly different from zero. The variation of these components is very high, ranging from minus 5pp to plus 10pp.

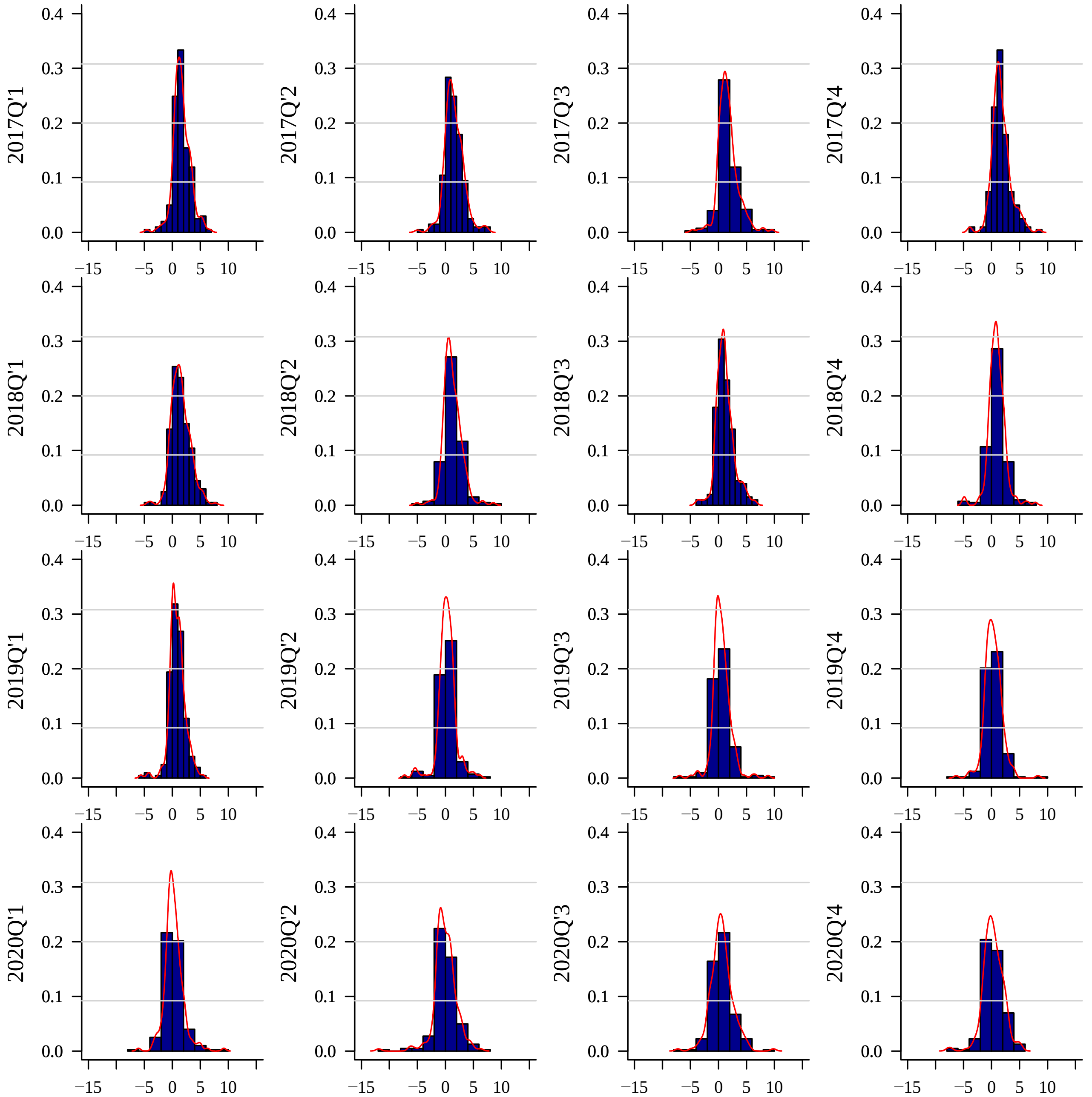
Figure 8. Confidence intervals of the lender-related component in the credit spread (beta3+/-1.96s.e.), for each quarter ascending order of the low-border of the confidence interval, pp



Sources: credit registry data, authors' calculations

The density of beta3 distribution across banks (Fig. 9) shows that bank-specific components became less concentrated around zero in the pandemic, and fat tales appeared. In this sense, the pandemic increased the heterogeneity of the bank-specific component of the spread – banking sector fragmentation.

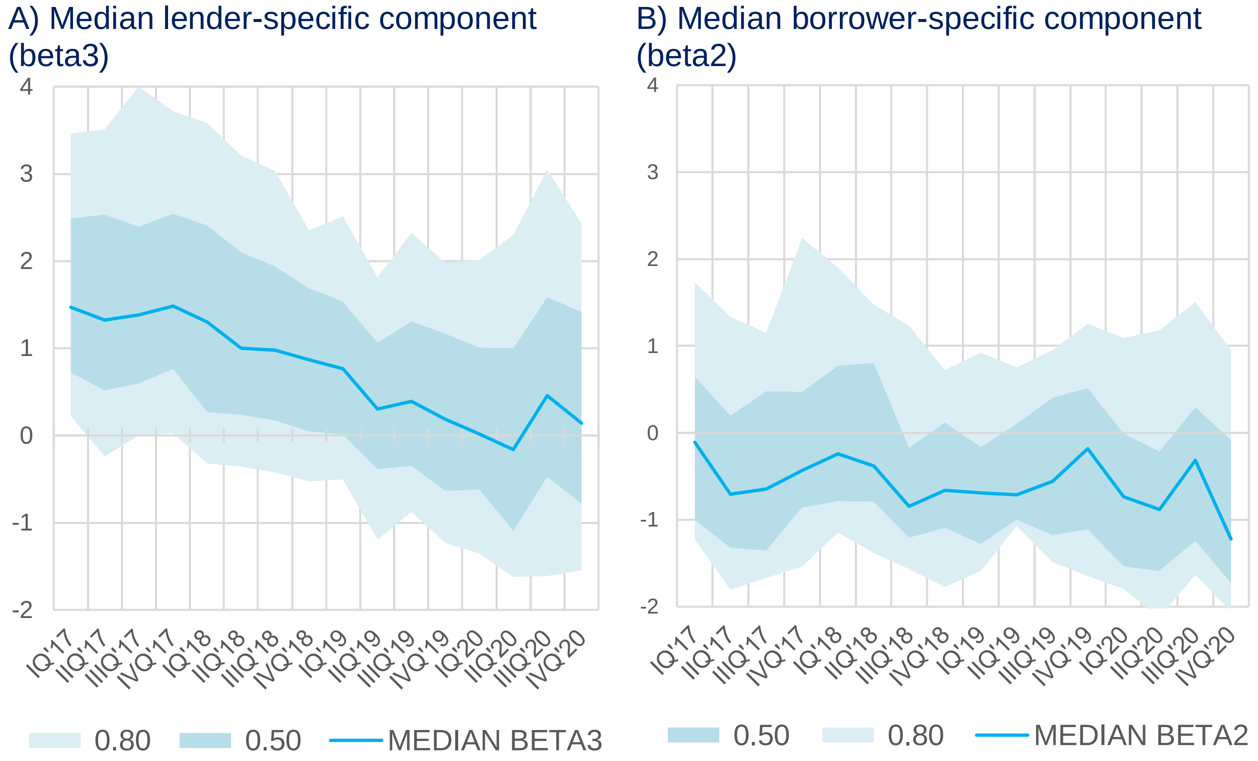
Figure 9. Kernel density of the lender-related component in credit spreads (beta3), pp



Note: the estimated values of the lender-related component (beta3) in pp are along the x-axis, density is along the y-axis, the red solid line is the kernel fit. Sources: credit registry data, authors' calculations

There is a notable heterogeneity in the bank-specific component: some banks price loans almost 5pp cheaper than the benchmark bank (and 10pp cheaper than some other banks), which implies that the banking sector is fragmented. To measure the fragmentation, we calculated several characteristics of the distribution of $\beta_{3,t}$ – see Fig. 10–11.

Figure 10. Distribution of lender-(beta3) and borrower-(beta2) related components in the credit spreads, pp

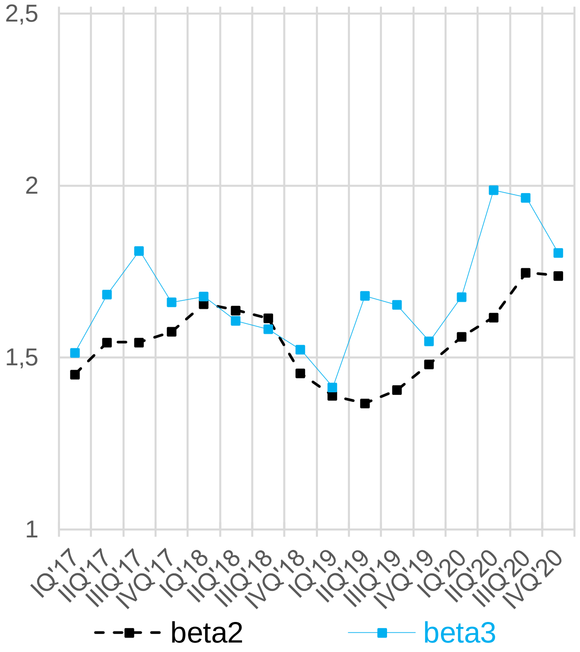


Note: the solid line is the median, the shaded areas are the 50th and 80th percentiles of the component distribution across all banks (beta3) or firms (beta2) with multiple bank-credit relationships in all quarters from 2017Q1 to 2020Q4 consequently. Sources: Bank of Russia, authors' calculations

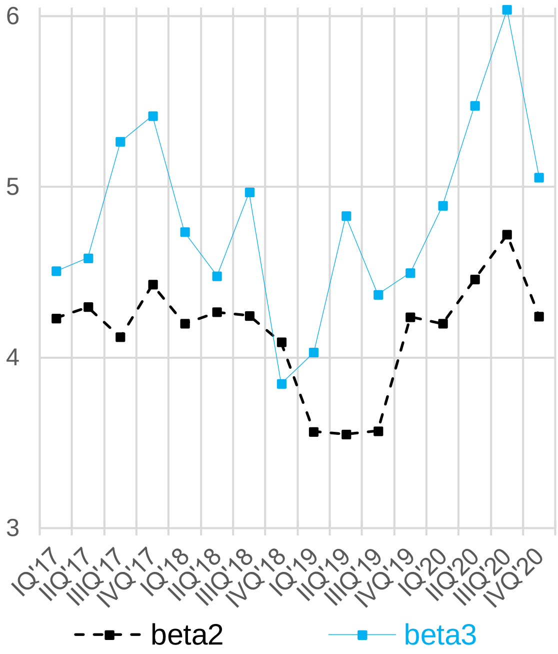
According to the median bank-specific component, by analogy with the "average country-specific component" in Horny, G. et al. (2018), fragmentation in the corporate lending market was on the decline from 2017 to 2020. The pandemic resulted in increased fragmentation of the corporate loans market. The borrower-specific component did not exhibit any significant changes.

Figure 11. Fragmentation measures of the **borrower-related (beta2)** and **lender-related (beta3)** components in the credit spreads, pp

A) Volatility of beta2 and beta3 components



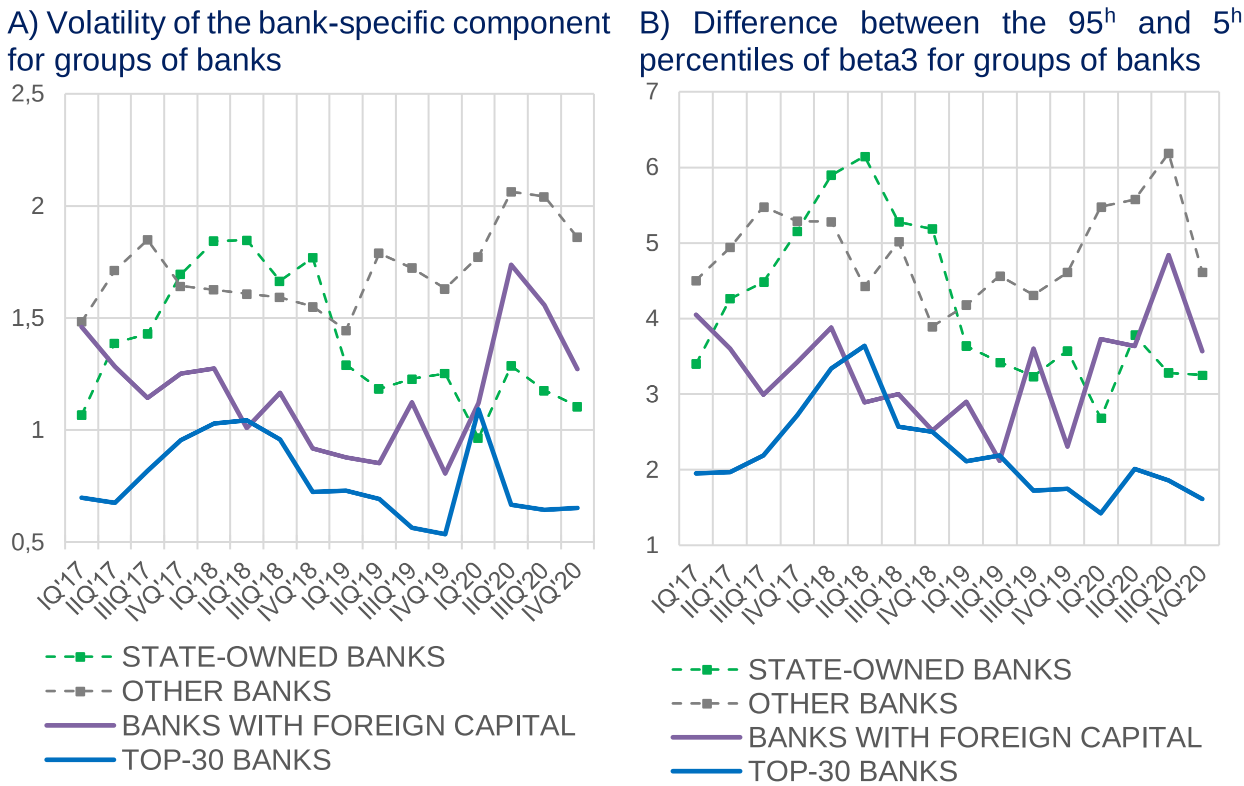
B) Difference between the 95th and 5th percentiles



Sources: Bank of Russia, authors' calculations

The observation that the pandemic resulted in a greater loan market fragmentation is supported by additional measures of fragmentation (Fig. 11): the cross-sectional volatility of the bank-specific component and the percentile differences. To gain a deeper insight into banking sector fragmentation, we calculated the characteristics of variation of $\beta_{3,t}$ for well-defined groups of banks (Fig. 12). Meanwhile, Fig. 13 represents the distribution inside the groups.

Figure 12. Fragmentation measures based on volatility of the **lender-related component (beta3)** in credit spreads for groups of banks, pp.



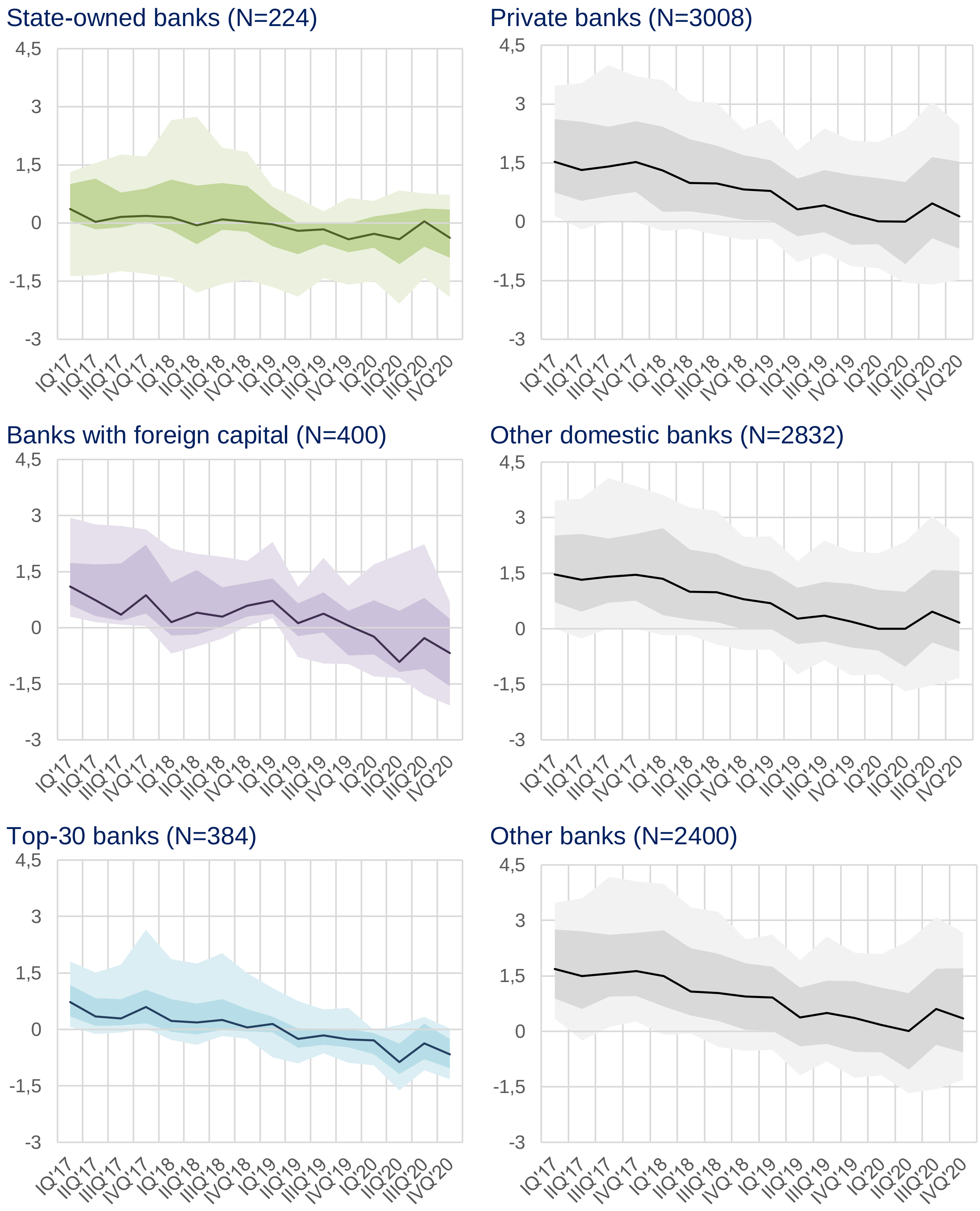
Sources: Bank of Russia, authors' calculations

The top-30 banks (Fig. 12) visually tend to have the smallest heterogeneity of the bank-specific spread relative to other banks. The possible explanation is that these banks may have tighter competition with each other and more *homogeneous* fundamentals. The pandemic resulted in much higher heterogeneity in pricing for banks with foreign capital and for all other banks (small private), which means that banks inside these groups reacted differently to the pandemic shock (the group became less *homogeneous*).

According to Fig. 13, banks in the largest banks group priced loans higher than the benchmark bank before 2019; yet they started pricing loans cheaper afterwards, especially during the pandemic – Fig. 13. For other groups this tendency works mostly only for the median. We observe that state-owned banks have a systematic skewness in pricing to the downside (Fig. 13) relative to the benchmark (which may be a result of subsidised loans issued by some of them).

At the start of pandemic, the spreads widened for private banks and for banks with foreign capital. These groups became more heterogeneous. The observation that the 30 largest banks represent quite a homogeneous group, which also reacted to the pandemic in a similar way, means that the largest part of the loan market in Russia is not fragmented.

Figure 13. Distribution of the lender-related component in the credit spread for groups of banks, pp



Note: the solid line is the median, the shaded areas are the 50th and 80th percentiles of the lender-related component distribution (beta3) for all banks that issued loans in all quarters from 2017Q1 to 2020Q4 consequently to borrowers with multiple bank-credit relationships. Sources: Bank of Russia, authors' calculations

We also tried to analyse how much of the β_3 variation for each bank is explained by the composition of the bank's borrowers. As the composition of borrowers with multiple bank-credit relationships changes from quarter to quarter, the lower interest rate spread may be explained by the composition of borrowers – the so-called "relationship lending".[27] We run the following bank-level regression *for each lender*: $\beta_{3\,[lender]} = const_{[lender]} + C_1 \cdot \delta_{borrower} + \varepsilon$, where: $\beta_{3\,[lender]}$ is *a 1 by 16* vector, $\delta_{borrower}$ is a borrower dummy (*N by 16)*, where *N* is the total number of borrowers with multiple bank-credit relationships in the whole sample, C_1 *is a 1 by N* vector of coefficients. For each bank, we have sixteen β_3 (one β_3 for each bank in each quarter) and a pool of loans issued to borrowers who have multiple bank-credit relationships in each quarter. We associate each loan with a particular dummy$borrower$. We are interested in R-squared – the higher R-squared is, the more variation in the bank-specific component of the interest rate spread ($\beta_{3\,[lender]}$) is explained by the composition of its borrowers.

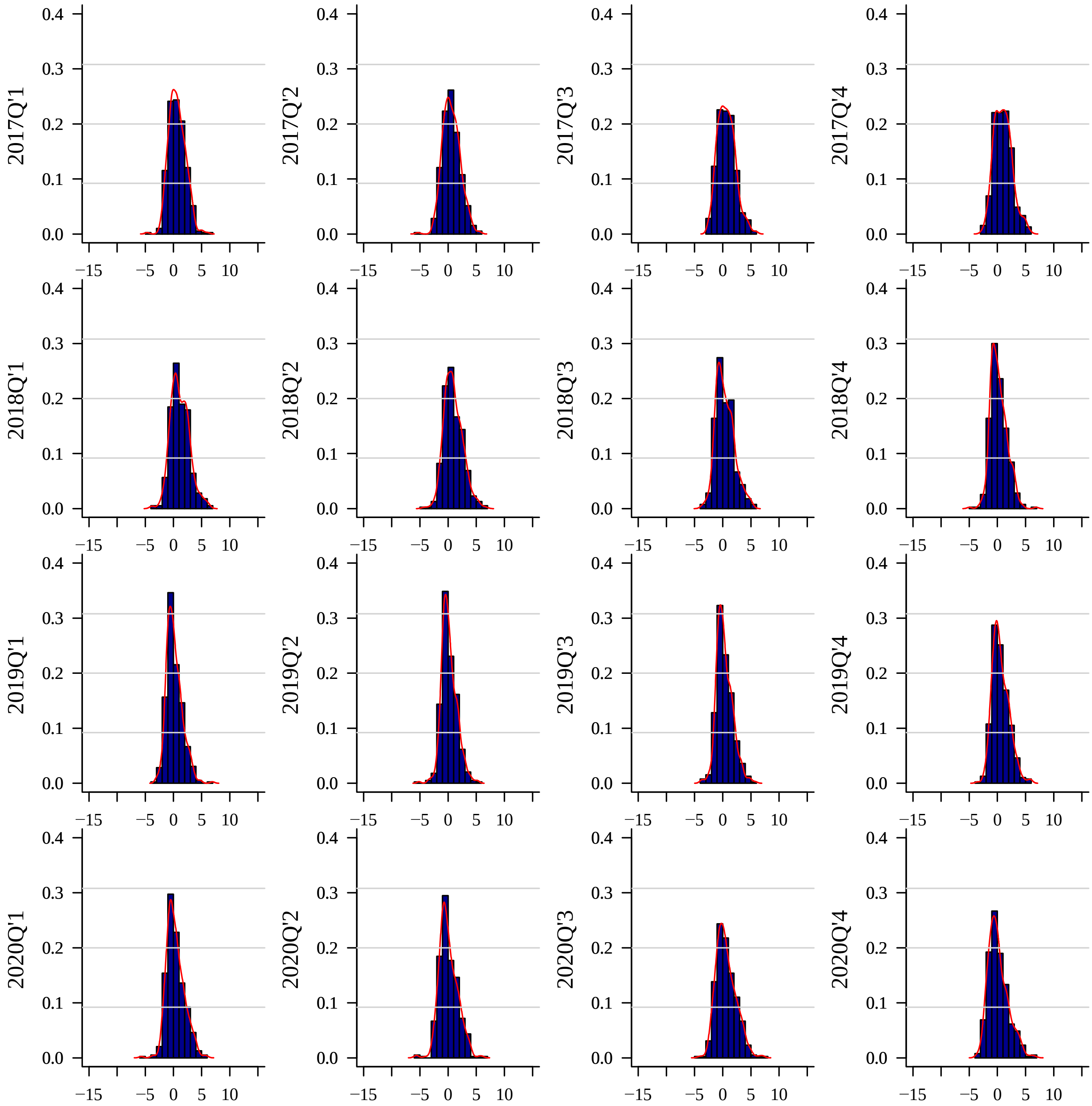
The level of R-squared could be interpreted as the magnitude of the otherwise non-observable lender-borrower relationship and its influence on the bank's risk perception. For 75% of banks, borrower composition helps to explain the 30–90% variation in bank-specific spreads across banks. Thus, relationship lending may be a driver of observed heterogeneity in the size of the bank-specific component of the spread.

3.4 Borrower-specific component of the credit-spread

We present the borrower-related component of the spread (beta2 for each borrower) and its evolution in time for the set of borrowers who had loans from several banks *in all quarters* consequently from 2017Q1 to 2020Q4 (total of 391 borrowers) – Fig. 14. The heterogeneity is large (in the case of the lender-related component). Thus, banks do charge different borrowers with different interest rates, other things being equal.

[27] Note that we used an affiliation of a borrower and a bank as it is reported in the credit registry. The different concept is *relationship banking*, see Banerjee et al. (2021) for a survey, which focuses on the duration of a firm and a bank relationship. As Russian credit registry data start in 2017, we have only 4 years data to measure the relationship banking.

Figure 14. Kernel density of the borrower-related component in credit spreads (beta2), pp



Note: the estimated values of the borrower-related component (beta2) in pp are along the x-axis, the density is along the y-axis, and the red solid line is the kernel fit. Sources: credit registry data, authors' calculations

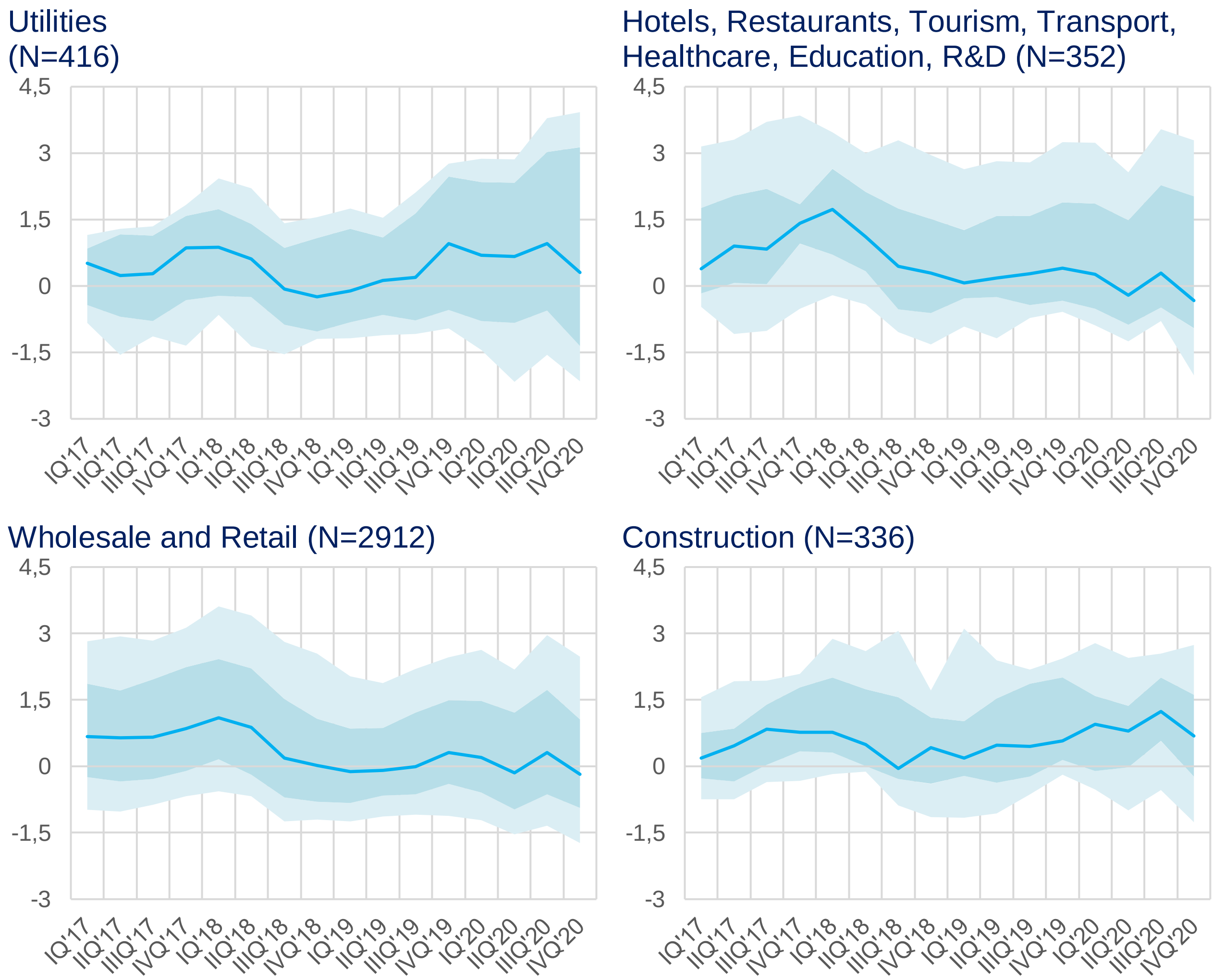
At aggregate level, we do not confirm any notable changes in heterogeneity in the borrower-related component, so we disaggregate it by industry (Fig. 15).

Disaggregation at industry level shows some differences across industries. The borrower-related component for entities in Metals, Machinery, Equipment Manufacturing, Mining, Refinery Products and Chemicals Production are significantly lower than for companies operating in Construction, Hotels, Restaurants, Tourism, Transport, Healthcare, Education, R&D, Insurance, Finance, Accounting and Law, Leasing, and Real Estate.

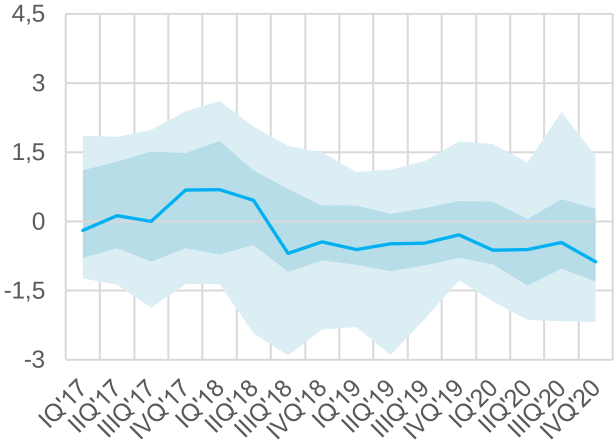
These differences may reflect differences in estimates of credit risk and, correspondingly, in credit risk premiums assigned by banks or the prevalence of subsidised loans in industries with lower values of beta2 (e.g. in Agriculture, which may still reflect lower credit risks for banks as they receive compensation from the government).

Most heterogeneity at industry level was observed for borrowers operating in Utilities, Hotels, Restaurants, Tourism, Transport, Healthcare, Education, R&D and Wholesale and Retail. The pandemic resulted in a notable increase in heterogeneity in Utilities. In Hotels and Restaurants, we find some decline in the borrower-related component. Meanwhile, in Construction there was an increase in the median level of borrower-related components (banks started charging a larger spread to companies in this industry).

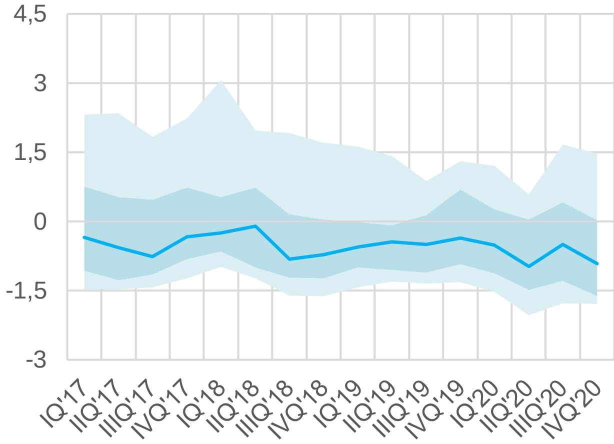
Figure 15. Distribution of the borrower-related component in the credit spread (beta2) by industry, pp



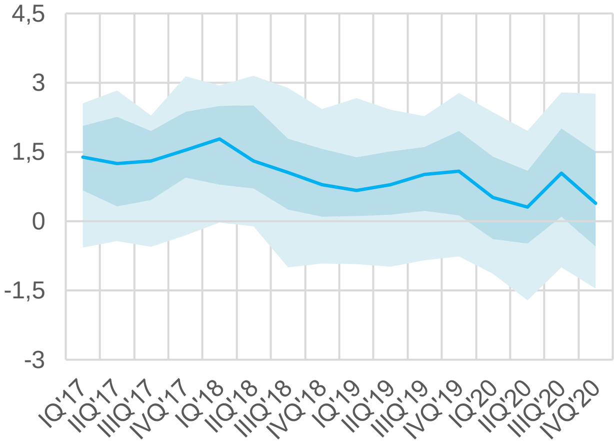
Food, Drinks, Tabaco, Paper Manufacturing, Agriculture, Fishery and Forestry(N=448)



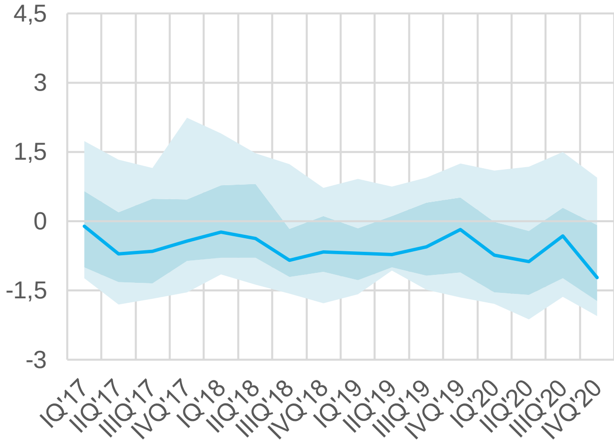
Metals, Machinery, Equipment Manufacturing (N=560)



Insurance, Finance, Accounting and Law, Leasing, Real Estate and Other (N=864)



Mining, Refinery Products and Chemicals Production (N=368)



Note: the solid line is the median, the shaded areas are the 50th and 80th percentiles of the borrower-related component distribution (beta2) for all borrowers who had newly issued loans from multiple banks in all quarters consequently from 2017Q1 to 2020Q4. Sources: Bank of Russia, authors' calculations

4. Robustness

In this section, we check the robustness of our results to an alternative length of the period used to define companies having multiple-bank relationships during the period: a month versus a quarter, which was used in our main results. Below we select loans (including credit lines, but excluding overdrafts) with a maturity of more than 30 days to be sure that the detected multiple-bank relationships are not a consequence of a loan issued by one bank and repaid in the same month and another loan issued by another bank after the loan of the first bank had been repaid.

We expand the sample for it to include January – May 2021, thus the whole monthly sample covers 2017M1-2021M5.

The structure of the sample is given in Table 2.

Table 2. Number of loans (observations) issued to the entities (borrowers) with the multiple (*n*-banks) relationships in a particular month

n_banks relationship (monthly)		Freq.	Per cent
	1	5,027,958	87%
	2	526,072	9%
	3	125,133	2%
	more than 3	93,028	2%
Total		5,772,191	100%
Total in scope		***744,233***	***13%***

Note: we exclude overdrafts from our sampling. Due to this fact the initial number of observations was smaller than the number of observations from Table 1. Sources: Bank of Russia, authors' calculations

Contrary to quarterly identification, only 63 banks and 14 companies had multiple-bank relationship during the whole monthly sample.

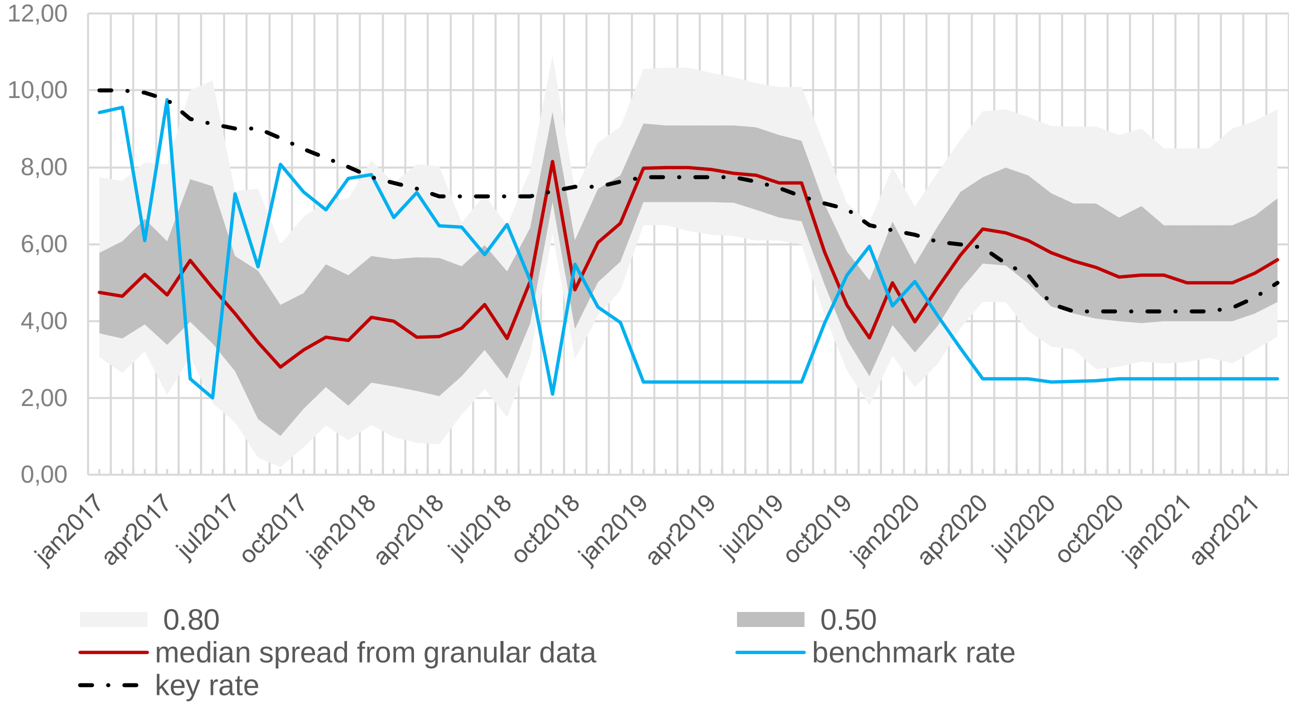
Descriptive statistics for the sample of firms with multiple-bank relationship on a monthly basis are given in the Table 3.

Table 3. Descriptive statistics for a sample defined on a monthly basis

Total number of months	**53**			
N observations	**744233**			
	mean	**sd**	**min**	**max**
BENCHMARK RATE	4.23	2.09	2.00	9.76
SPREAD	5.61	2.70	(7.46)	13
MATURITY, days	424	482	30	8061
MATURITY PERIOD (dummy variable, 1 if >1year, 0 otherwise)	0.30	0.46	0	1
INTEREST RATE TYPE (dummy variable, 0 if fixed,1otherwise)	0.34	0.47	0	1
COLLATERAL (dummy variable, 1 if yes, 0 otherwise)	0.04	0.20	0	1
AFFILIATION (dummy variable, 1 if yes,0 otherwise)	0.02	0.15	0	1

Sources: Bank of Russia, authors' calculations

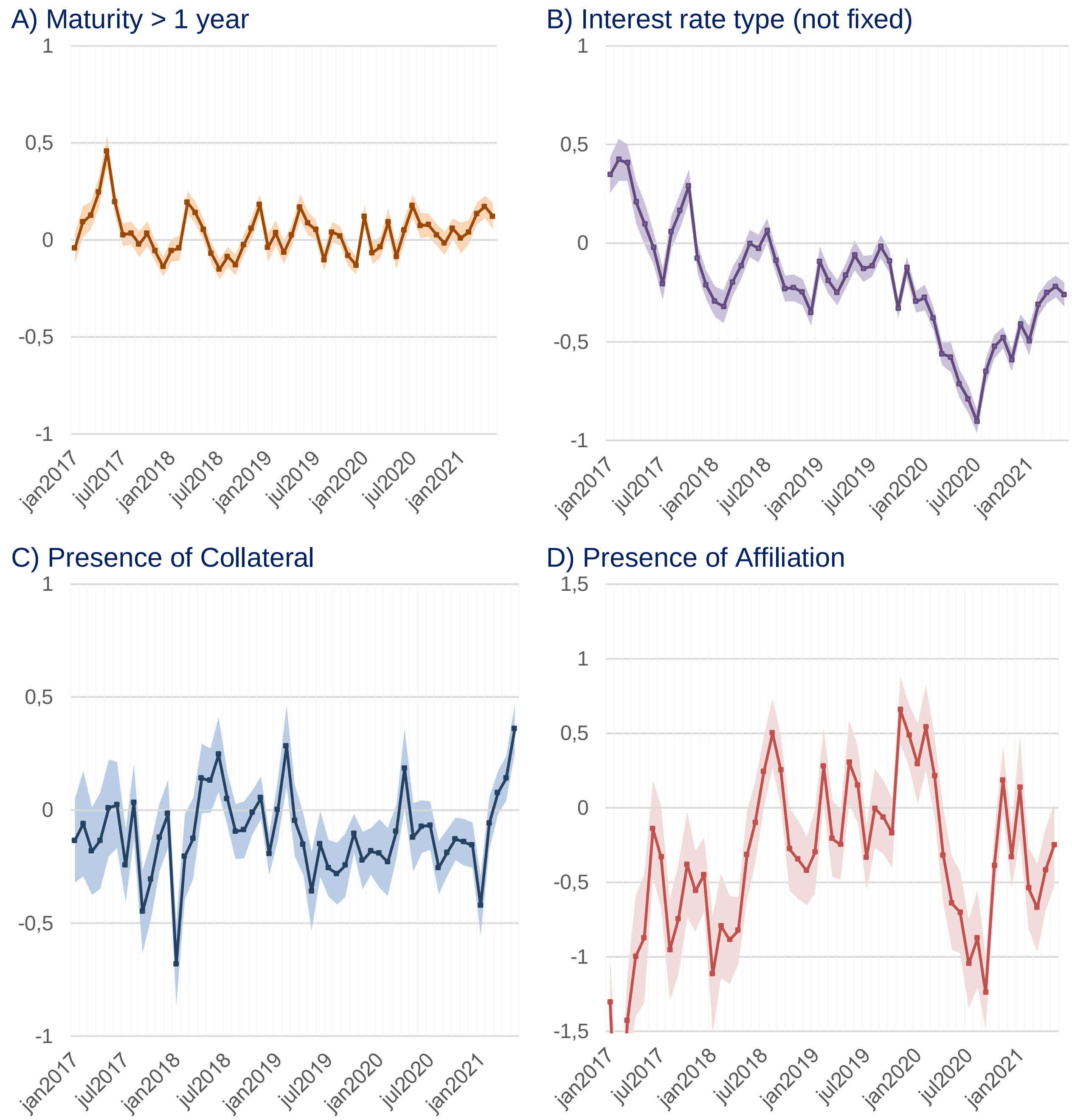
Figure 16. Interest rate spread on granular corporate credit registry data (borrowers have multiple credit relations), pp over the benchmark interest rate



Note: we exclude all FX loans, overdrafts, loans with rates in the 5th and 95th percentiles of the distribution (all loans with a rate less than 2% and more than 15%) and loans with an initial maturity of less than 30 days. The solid line is the median, and the shaded areas are the 50th and 80th percentiles of the spread distribution across all loans issued to borrowers with multiple bank-credit relationships in a particular month. Sources: Bank of Russia, authors' calculations

Estimates of market prices for some loan terms and their dynamics that we get on the monthly basis in the robustness check except for the price of maturity confirm our previous findings in general. There is no spectacular increase in a price of longer dated loans on the monthly basis (Fig.17) contrary what we found on the quarterly basis.

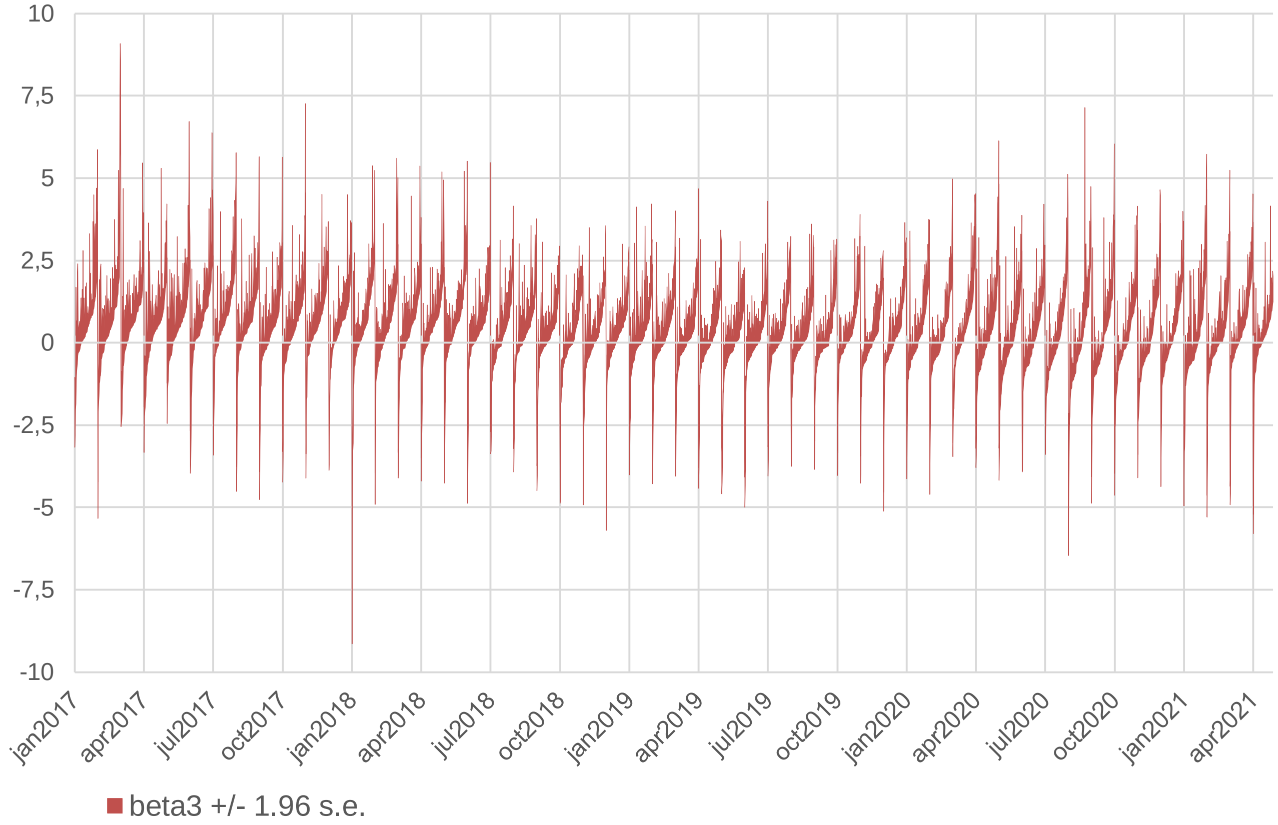
Figure 17. Estimates of loan characteristics in credit spread (beta4), pp



Note: the solid lines are pointwise estimates and the shaded bands are 95% confidence intervals.
Sources: credit registry data, authors' calculations

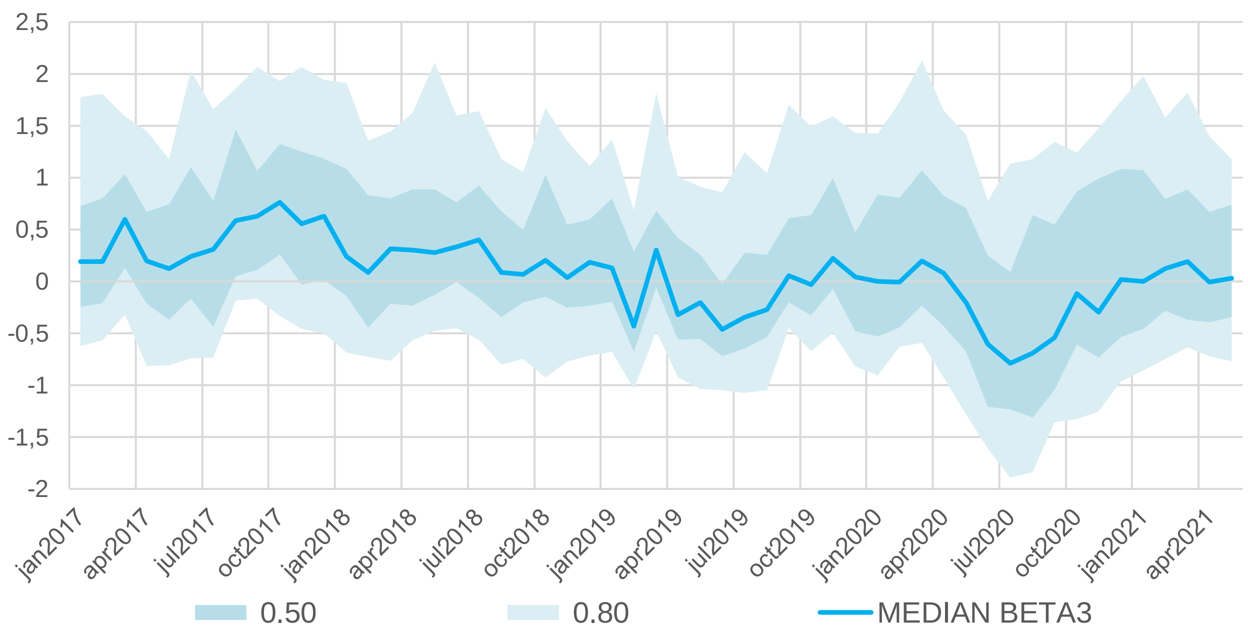
Monthly data show that at the start of the pandemic more banks started charging larger spread, while in the fourth quarter the situation normalized (Fig.18).

Figure 18. Confidence intervals of lender-related component in credit spread (beta3+/-1.96s.e.), for each month ascending order of the low-border of the confidence interval, pp



Sources: credit registry data, authors' calculations

Figure 19. Distribution of the lender-related (beta3) component in the credit spreads, pp

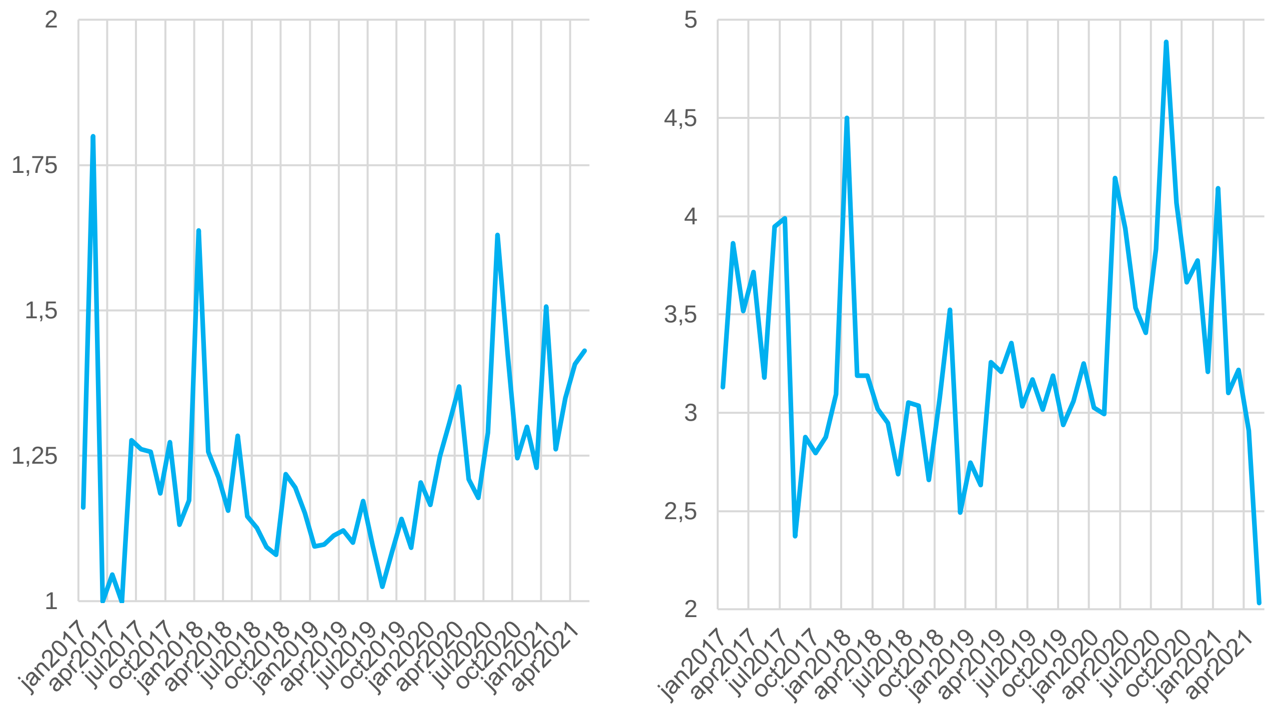


Note: the solid line is the median, the shaded areas are the 50th and 80th percentiles of the beta3 distribution across all banks that issued loans in all months from January 2017 to May 2021 consequently to borrowers with multiple bank-credit relationships. Sources: Bank of Russia, authors' calculations

Fragmentation measures increased notably during the pandemic; however, by the end of 2020, two measures drew different pictures: volatility of the bank-specific component remained high, but the difference between the largest 5% and the smallest 5% of the bank-specific components narrowed significantly, thus pointing to the observation that volatility became concentrated in the outliers of the distribution (Fig. 20). Comparing with the results on the quarterly basis, the fragmentation inside state-owned banks (as a group) has increased since the end of 2020 (Fig. 21).

Figure 20. Fragmentation measures of lender-related (beta3) component in the credit spreads, pp

A) Volatility of beta3 for banking sector B) Difference between 95th and 5th percentiles



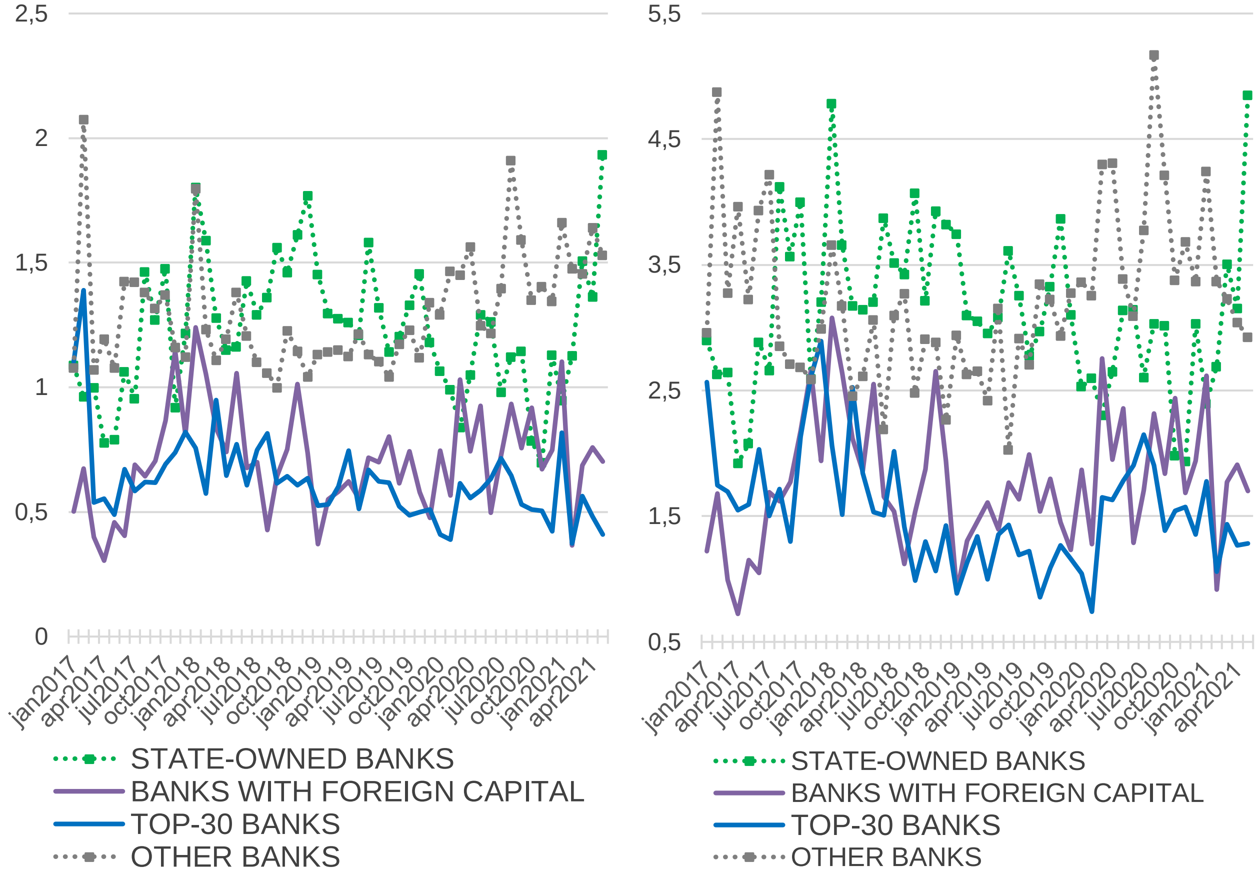
Sources: credit registry data, authors' calculations

We also tested seasonality in measures of market fragmentation (for results on monthly basis – Figure 20) using Wald test to enter restriction on equality of seasonal dummies. Results don't support presence of seasonality in the measures of fragmentation.

Figure 21. Fragmentation measures based on volatility of the lender-related component (beta3) in the credit spreads for groups of banks

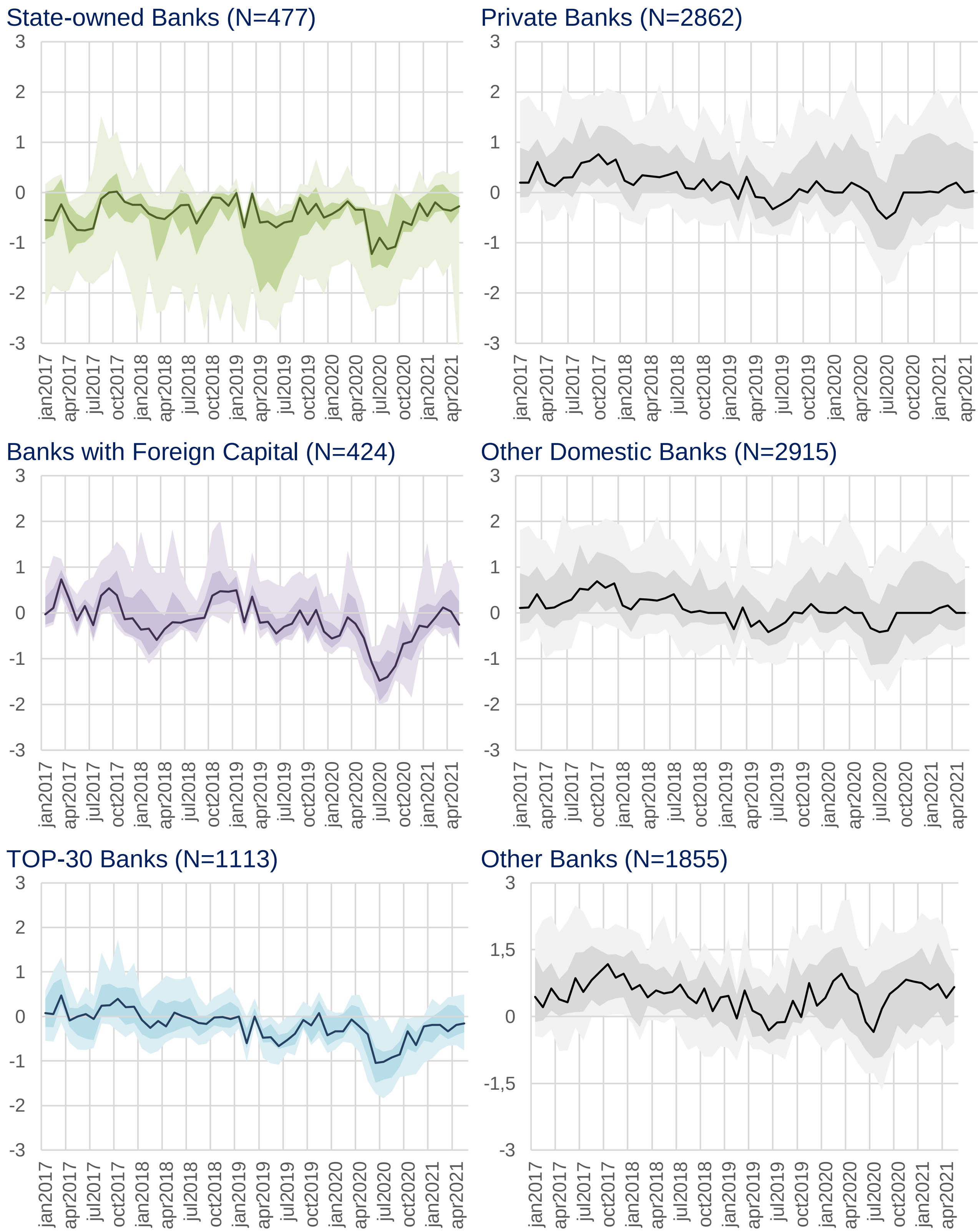
A) Volatility of bank-specific component for groups of banks

B) Difference between 95h and 5h percentiles of beta3 for groups of banks



Sources: credit registry data, authors' calculations

Figure 22. Distribution of the lender-related component in the credit spread for groups of banks, pp



Note: the solid line is the median, the shaded areas are the 50th and 80th percentiles of the lender-related component distribution (beta3) across all banks that issued loans in all months from January 2017 to May 2021 consequently to borrowers with multiple bank-credit relationships. Sources: Bank of Russia, authors' calculations.

5. Concluding remarks

Based on a large loan-by-loan database of Russian corporate loans (credit registry) we identify bank-specific, borrower-specific (heterogeneity of borrowers) and loan-terms-specific factors of corporate loan interest rate spreads. We find that heterogeneity of banks and borrowers is very large. Some banks tend to charge a spread up to 5pp larger/smaller than the benchmark bank when issuing loans to the same borrowers (controlling for the loan characteristics). Our results motivate further research to create a better understanding of the causes of such high bank heterogeneity.

We calculate several fragmentation measures for the Russian corporate lending market and for some groups of banks. These measures are defined as deviations from the "one price", governed by the bank-specific components of the spread. We find that in general, the corporate loan market is quite fragmented (the standard deviation of the bank-specific spread is around 3pp – the size of the median spread during the whole period) and fragmentation had been declining until the pandemic. The measures of banking sector fragmentation point to an increased fragmentation of the lending market in Russia during the first half of the 2020, the early stage of the pandemic.

Regarding fragmentation between some specific groups of banks, we find that the 30 largest banks are quite a homogeneous group, which also priced loans to the same borrowers with the same terms more homogeneously compared to banks from other groups. Given the role this group plays in corporate lending in Russia (taking into account the volume of loans), we may conclude that the issue of fragmentation should not be an issue for monetary policy or financial stability. However, there is still fragmentation on the loan market: the group of the largest banks prices loans differently compared to all other banks. Moreover, other well-defined groups of banks (especially the group of small private banks) are also fragmented, and the fragmentation increased during the pandemic. Some attention of the regulator may be needed to reduce the fragmentation across these dimensions (however, for that, we need to have a better understanding of the causes of the fragmentation between the largest and all other banks and inside these well-defined groups).

We find some evidence that relationship lending may be an important driver of the observed heterogeneity in the credit interest rate spread.

Decomposition of the spread provides some insights into changes in market prices of some loan terms during the pandemic. We find that banks have started pricing a larger spread for long-term loans and a lower spread for floating-rate loans since 2020. Moreover, with the start of the pandemic, banks started providing discounts to affiliated borrowers but kept pricing loans with collateral attached as before the pandemic. All these changes point to a tightening of loan conditions during the pandemic. In their study, Beck, T. and Keil, J. (2021) reached a similar conclusion regarding the behaviour of US banks during the pandemic.

Our findings also confirm that the pandemic resulted in a notable increase in heterogeneity in loans to Utilities. We also find that borrowers in Hotels, Restaurants, Tourism and Transport (the most affected industries) were charged with a lower spread (approximately 1.5pp for the low bound of the confidence interval). Meanwhile in Construction, there was an increase in the median level of borrower-related components (banks started charging a larger spread to companies from these industries). Both findings may be a result of subsidised loans being issued to some firms in these sectors to support them during the pandemic. According to Bessonova, E. et al. (2021) who tried to identify subsidised loans (through a lower spread to the key rate, i.e. with rates below 2%), the number and volume of such loans increased during the pandemic. To address the issue of outliers, we excluded the first decile of loans (those cheaper than 2.8%), thus automatically excluding loans cheaper than 2% – the largest part of subsidised loans. However, some non-market-priced loans might still be present in our data. Moreover, after Bessonova, E. et al. (2021) excluded such loans from the data sample, the weighted-average interest rate spread did not change much compared to its pre-pandemic level, which is what our data show too (Fig. 1). However, contributing to their results, we find that heterogeneity (fragmentation) increased during the period.

Our results can be used by policymakers along several dimensions:

First, the distribution of the bank-specific component (beta3) can be used to select those banks from the tails of the distribution that deserve more attention by the regulator, at least to understand the reasons of their strong deviation from other banks in corporate loan pricing.

Second, corporate credit market fragmentation measures can be used in periodical reviews of the market developments to timely detect changes in the efficiency of the corporate credit market.

Third, using panel data on fragmentation measures calculated on granular data for corporate loan markets in many jurisdictions can help to test early warning properties of the heterogeneity for financial stability purposes or to test their role in dynamics of corporate lending during crises.

Annex 1. Descriptive statistics

Quarter	1Q2017				2Q2017				3Q2017				4Q2017			
N observations	**54304**				**68860**				**76388**				**81110**			
	mean	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**
BENCHMARK RATE	10.22	-	10.22	10.22	9.35	-	9.35	9.35	8.58	-	8.58	8.58	7.92	-	7.92	7.92
SPREAD	3.75	2.52	(7.32)	20.73	3.98	2.64	(6.55)	26.65	4.21	2.59	(5.78)	33.58	4.33	2.76	(5.12)	34.31
MATURITY, days	377	434	31	5,474	373	410	31	5,474	381	414	31	5,476	395	430	31	5,478
MATURITY PERIOD (dummy variable, 1 if >1year, 0 otherwise)	0.26	0.44	0	1	0.25	0.43	0	1	0.26	0.44	0	1	0.28	0.45	0	1
INTEREST RATE TYPE (dummy variable, 0 if fixed,1otherwise)	0.27	0.45	0	1	0.26	0.44	0	1	0.27	0.44	0	1	0.27	0.44	0	1
COLLATERAL (dummy variable, 1if yes, 0 otherwise)	0.04	0.19	0	1	0.04	0.19	0	1	0.04	0.20	0	1	0.05	0.21	0	1
AFFILIATION (dummy variable, 1if yes,0 otherwise)	0.01	0.12	0	1	0.01	0.12	0	1	0.01	0.11	0	1	0.02	0.14	0	1
Quarter	**1Q2018**				**2Q2018**				**3Q2018**				**4Q2018**			
N observations	**67391**				**80245**				**79119**				**85197**			
	mean	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**
BENCH MARK RATE	7.42	-	7.42	7.42	7.39	-	7.39	7.39	7.63	-	7.63	7.63	8.55	-	8.55	8.55
SPREAD	4.12	2.81	(4.62)	29.08	3.84	2.86	(4.59)	34.61	3.51	2.76	(4.83)	42.37	2.63	2.60	(5.75)	33.57
MATURITY, days	376	402	31	5,478	395	419	31	5,463	391	411	31	5,783	396	419	31	5,463
MATURITY PERIOD (dummy variable, 1 if >1year, 0 otherwise)	0.26	0.44	0	1	0.28	0.45	0	1	0.28	0.45	0	1	0.30	0.46	0	1
INTEREST RATE TYPE (dummy variable, 0 if fixed,1otherwise)	0.26	0.44	0	1	0.28	0.45	0	1	0.29	0.45	0	1	0.29	0.46	0	1
COLLATERAL (dummy variable, 1if yes, 0 otherwise)	0.04	0.21	0	1	0.04	0.19	0	1	0.08	0.27	0	1	0.09	0.29	0	1
AFFILIATION (dummy variable, 1if yes,0 otherwise)	0.02	0.13	0	1	0.02	0.13	0	1	0.02	0.13	0	1	0.02	0.14	0	1

Descriptive statistics (cont.)

Quarter	1Q2019				Q2019				3Q2019				4Q2019			
N observations	**65132**				**65132**				**65132**				**65132**			
	mean	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**
BENCHMARK RATE	9.00	-	9.00	9.00	9.00	-	9.00	9.00	9.00	-	9.00	9.00	9.00	-	9.00	9.00
SPREAD	2.21	2.57	(6.20)	27.50	2.21	2.57	(6.20)	27.50	2.21	2.57	(6.20)	27.50	2.21	2.57	(6.20)	27.50
MATURITY, days	384	405	31	5,632	384	405	31	5,632	384	405	31	5,632	384	405	31	5,632
MATURITY PERIOD (dummy variable, 1 if >1year, 0 otherwise)	0.28	0.45	0	1	0.28	0.45	0	1	0.28	0.45	0	1	0.28	0.45	0	1
INTEREST RATE TYPE (dummy variable, 0 if fixed,1otherwise)	0.31	0.46	0	1	0.31	0.46	0	1	0.31	0.46	0	1	0.31	0.46	0	1
COLLATERAL (dummy variable, 1if yes, 0 otherwise)	0.09	0.28	0	1	0.09	0.28	0	1	0.09	0.28	0	1	0.09	0.28	0	1
AFFILIATION (dummy variable, 1if yes,0 otherwise)	0.01	0.11	0	1	0.01	0.11	0	1	0.01	0.11	0	1	0.01	0.11	0	1
Quarter	**1Q2020**				**2Q2020**				**3Q2020**				**4Q2020**			
N observations	**86570**				**86570**				**86570**				**86570**			
	mean	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**
BENCH MARK RATE	6.33	-	6.33	6.33	6.33	-	6.33	6.33	6.33	-	6.33	6.33	6.33	-	6.33	6.33
SPREAD	4.01	3.26	(3.53)	38.67	4.01	3.26	(3.53)	38.67	4.01	3.26	(3.53)	38.67	4.01	3.26	(3.53)	38.67
MATURITY, days	400	415	31	7,065	400	415	31	7,065	400	415	31	7,065	400	415	31	7,065
MATURITY PERIOD (dummy variable, 1 if >1year, 0 otherwise)	0.31	0.46	0	1	0.31	0.46	0	1	0.31	0.46	0	1	0.31	0.46	0	1
INTEREST RATE TYPE (dummy variable, 0 if fixed,1otherwise)	0.32	0.47	0	1	0.32	0.47	0	1	0.32	0.47	0	1	0.32	0.47	0	1
COLLATERAL (dummy variable, 1if yes, 0 otherwise)	0.07	0.25	0	1	0.07	0.25	0	1	0.07	0.25	0	1	0.07	0.25	0	1
AFFILIATION (dummy variable, 1if yes,0 otherwise)	0.02	0.13	0	1	0.02	0.13	0	1	0.02	0.13	0	1	0.02	0.13	0	1

REFERENCES

1. Adrian, T., Boyarchenko, N., & Giannone, D. (2019). Vulnerable growth. American Economic Review, 109(4), 1263-89.
2. Adrian, T., & Liang, N. (2018). Monetary policy, financial conditions, and financial stability.
3. Affinito, M., & Farabullini, F. (2009). 'Does the Law of One Price Hold in Euro-Area Retail Banking? An Empirical Analysis of Interest Rate Differentials across the Monetary Union.' *International Journal of Central Banking*.
4. Altavilla, C., Canova, F., & Ciccarelli, M. (2020). 'Mending the Broken Link: Heterogeneous Bank Lending Rates and Monetary Policy Pass-Through.' *Journal of Monetary Economics*, 110, 81-98.
5. Anderson, G., & Cesa-Bianchi, A. (2020). 'Crossing the Credit Channel: Credit Spreads and Firm Heterogeneity'. *IMF Working Paper No. 2020/267.*
6. Banerjee, R. N., Gambacorta, L., & Sette, E. (2021). The real effects of relationship lending. Journal of Financial Intermediation, 100923.
7. Beck, T. and Keil, J. (2021). 'Are Banks Catching Corona? Effects of COVID on Lending in the US'. *CEPR Discussion Paper 15869*.
8. Bessonova E., Popova S., Tsevetkova A. and Turdyeva N. (2021). 'Productivity and Lending During the Pandemic'. *Voprosy Ekonomiki*, forthcoming.
9. Boyd, J., and De Nicolo, G. (2005), 'The Theory of Bank Risk Taking and Competition Revisited'. *Journal of Finance 60*, 1329–1343.
10. Ciccarelli, M., Maddaloni, A., & Peydró, J.L. (2013). 'Heterogeneous Transmission Mechanism: Monetary Policy and Financial Fragility in the Eurozone'. *Economic Policy*, 28(75), 459–512.
11. Claessens, S. (2019). 'Fragmentation in Global Financial Markets: Good or Bad for Financial Stability? *BIS Working Papers*, No. 815, October 2019.
12. Claeys, S. and Vennet, R.V. (2008). 'Determinants of Bank Interest Margins in Central and Eastern Europe: A Comparison with the West'. *Economic Systems*, 32: 197–216.
13. Coimbra, N., & Rey, H. (2017). 'Financial cycles with heterogeneous intermediaries.' (No. w23245). National Bureau of Economic Research.
14. Feyen, E., & Zuccardi Huertas, I. (2020). 'Bank Lending Rates and Spreads in EMDEs: Evolution, Drivers, and Policies'. The World Bank.
15. Fungáčová, Z., & Poghosyan, T. (2011). 'Determinants of Bank Interest Margins in Russia: Does Bank Ownership Matter?'. *Economic Systems*, 35(4), 481–495.
16. Gambacorta, L. (2008). 'How do Banks Set Interest Rates?'. *European Economic Review*, 52(5), 792–819.
17. Gambacorta, L. and Mistrulli, P.E. (2014). 'Bank Heterogeneity and Interest Rate Setting: What Lessons Have We Learned since Lehman Brothers?'. *Journal of Money, Credit, and Banking*, 46, 753–778.
18. Gilchrist, S., & Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. American economic review, 102(4), 1692-1720.

19. Hauswald, R., & Marquez, R. (2006). 'Competition and Strategic Information Acquisition in Credit Markets'. *The Review of Financial Studies*, 19(3), 967–1000.
20. Horny, G., Manganelli, S., & Mojon, B. (2018). 'Measuring Financial Fragmentation in the Euro Area Corporate Bond Market'. *Journal of Risk and Financial Management*, 11(4), 74.
21. Horvath, R. (2018). 'Financial Market Fragmentation and Monetary Transmission in the Euro Area: What Do We Know?' *Journal of Economic Policy Reform*, 21(4), 319–334.
22. Ioannidou, V., Ongena, S., & Peydró, J. L. (2015). Monetary policy, risk-taking, and pricing: Evidence from a quasi-natural experiment. Review of Finance, 19(1), 95-144.
23. Iregui, A. M., & Otero, J. (2013). Testing the law of one price in retail banking: An analysis for Colombia using a pair-wise approach. Economics Letters, 118(1), 29-32.
24. Jiménez, G., Ongena, S., Peydró, J. L., & Saurina, J. (2014). 'Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank Loans Say about the Effects of Monetary Policy on Credit Risk-Taking?'. *Econometrica*, 82(2), 463–505.
25. Khwaja, A. I., Mian, A. 'Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market.' *American Economic Review* Vol. 98, No. 4, September 2008, 1413–42.
26. Laeven, L. (2001). 'Insider Lending and Bank Ownership: The Case of Russia'. *Journal of Comparative Economics*, 29(2), 207–229.
27. López-Salido, D., Stein, J. C., & Zakrajšek, E. (2017). Credit-market sentiment and the business cycle. The Quarterly Journal of Economics, 132(3), 1373-1426.
28. Lucotte, Y. (2015). 'Euro Area Banking Fragmentation in the Aftermath of the Crisis: a Cluster Analysis'. *Applied Economics Letters*, 22(13), 1046–1050.
29. Martín-Oliver, A., Salas-Fumás, V., & Saurina, J. (2007). 'A Test of the Law of One Price in Retail Banking'. *Journal of Money, Credit and Banking*, 39(8), 2021–2040.
30. Rajan, R.G. Insiders and Outsiders: 'The Choice between Informed and Arm's-Length Debt'. *The Journal of Finance*, September 1992, 47 (4), 1367–1400.
31. Repullo, R., 2004, 'Capital Requirements, Market Power, and Risk-Taking in Banking.' *Journal of Financial Intermediation* 13, 156–182.
32. Ross, D.G. (2010). 'The "Dominant Bank Effect": How High Lender Reputation Affects the Information Content and Terms of Bank Loans.' *The Review of Financial Studies*, 23(7), 2730–2756.
33. Sharpe, S.A. (1990). 'Asymmetric Information, Bank Lending, and Implicit Contracts: A Stylized Model of Customer Relationships'. *The Journal of Finance*, 45(4), 1069–1087.
34. Vari, M. (2014). 'Implementing Monetary Policy in a Fragmented Monetary Union'. Banque de France.
35. Zaghini, A. (2019). 'The CSPP at Work: Yield Heterogeneity and the Portfolio Rebalancing Channel'. *Journal of Corporate Finance*, 56, 282–297.