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Decomposition of Corporate Credit Growth Using Granular Data

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Abstract

Applying a new method of decomposition of corporate credit growth, we estimated what part of credit expansion in Russia in 2018–2021 was accounted for by companies that had experience in credit borrowing in the past, and what part was due to newcomers to the corporate bank loan market. In absolute terms, the share of the loan portfolio attributable to companies that are new to the credit market (the extensive component of growth) is small. A fact that is not obvious at first glance, which we confirm in the course of the study, is that their contribution to fluctuations in the growth rates of credit aggregates, on the contrary, is large. The fact is that companies with existing credit relationships (the intensive component of growth) borrow and repay comparable amounts. Moreover, both the same borrower and different borrowing companies can borrow and repay - we draw a conclusion about their net activity. What unites them and allows us to consider such borrowers on a net basis is the presence of bank loans in the past (based on this fact, we can talk about such a set of borrowers as an intensive component of the growth of corporate bank loans). Thus, the net contribution of the intensive component to credit expansion is small.

During the acute phase of the pandemic (from June 2020 to May 2021), the role of lending on preferential terms increased noticeably and then decreased. For companies new to the lending market from affected industries (according to the list of the Russian Government), this growth was especially noticeable. This corresponds with other results: the massive inflow of borrowers at the beginning of the pandemic was sporadic and tightly linked to the state support measures. In this regard, the lower default rates of loans issued with the start of state support programs (between June and September 2020) probably do not imply better quality of borrowers, but reflect the features of the subsidised loans.

Within the framework of already existing credit relations (the intensive component of growth), the contribution of preferential lending to the growth of corporate credit was relatively stable until July 2021, after which the contribution of the non-preferential component began to grow rapidly.

An increase in the share of inactive borrowers, i.e., those who have open but unused credit lines starting from April 2021. Potentially, this type of borrowers may quickly increase their borrowings via open credit lines under adverse economic conditions. Thus, entail additional risks to banks. In this regard, we suggest the close monitoring of open and used credit lines. However, actual utilisation of credit lines could be bounded by terms of credit agreement, revaluation of collateral, and could led to smaller volumes of funds available during adverse economic conditions.

Contents

1. Introduction

In addition to analysing the dynamics of corporate credit growth at the aggregate level, it is advisable to consider the behavior of individual categories of borrowing companies.

We use corporate credit registry (granular data[1]) to analyse changes in the number and composition of borrowers from February 2018 to February 2022. Using the new tool, we decompose the overall credit growth into two components: the growth generated by existing borrowers (the *intensive component,* which represents existing credit relations) and the growth generated by new borrowers[2] (the *extensive component,* which represents newly created credit relations) we assess the contribution of each and track how their roles changed over time.

Methodologically guided by the work of Cuciniello and di Iasio (2020), we modify the approach proposed by the authors to determine the components of loan portfolio growth. As a result, we can say how much of the credit expansion (in this paper we are talking about the credit expansion observed in the period under review, but the same method can be applied to periods of credit contraction) was accounted for by companies that had experience in credit borrowing in the past, and which one is for newcomers to the corporate bank loan market. Using a new tool for analysing the corporate credit portfolio of Russian banks, we can answer some practical questions:

- Which companies took out the main volumes of bank loans in Russia in 2018 – 2021?
- Which companies accounted for the credit expansion and is it possible to talk about expanding access to credit and increasing financial inclusion in Russia during this period?
- What role did the volumes provided to borrowers under various preferential lending programs in 2018 – 2021 play in the overall corporate credit growth? Considering the pandemic shock in 2020 (accompanied by significant government support measures and special programs for providing preferential loans) as a particular example of preferential lending, what changes in the structure of corporate loans could we observe? Were these changes sustainable?

Our results confirm that the share of debt obtained by the firms who never borrowed before (extensive component) is low in ruble terms. What is not obvious and was revealed during the study is that the contribution of such firms to credit growth is significant. This is because firms with the existing bank-lender relationships (intensive component) borrow a lot and pay back a lot. For the subset of borrowers classified as small and medium-sized

[1] Corporate credit registries are a source of important information about banks' loans (e.g., interest rates, maturity, guarantees, etc.). According to the World Bank (2019), 122 of the 201 countries which took part in the 2019 Doing Business Survey had credit registries (this statistic includes both corporate credit registries and credit bureaus for households). The main benefit of corporate credit registries is that they provide disaggregated data about loans, which is necessary for the analysis of the whole distribution of parameters of interest, rather than only the mean values. This information may improve risk monitoring for the purpose of financial stability, as has been highlighted by Girault and Hwang (2010). Micro-level credit information also provides helpful insights into the distribution of risks within particular regions, sectors of economy, and segments of the credit market (Roy et al., 2017).

[2] We do not distinguish cases of changed ownership.

enterprises (SMEs), the contribution of the intensive component was even negative, which may indicate that SME companies with established lending relationships are choosing to reduce their borrowing volumes on non-preferential terms over time. Thus, the net contribution of the intensive component is low. This result is motivating for deeper research in assessing the extent of financial access in Russia.

Methodologically, the article closest to ours is that of Cuciniello and di Iasio (2020),[3] who try to find the determinants of the credit cycle by splitting credit activity into intensive and extensive components:[4] the extensive component reflects the creation of new bank-lender relationships or the termination of existing relationships. The intensive component reflects variation in the outstanding amount of debt within existing bank-lender relationships. Their results confirm that a significant part of credit expansion is explained by the extensive component. Moreover, they use a flow approach to show that variations in the extensive component are mostly driven by gross inflows of borrowers. The work of Davis et al. (1996) is interesting from the methodological point of view. They study job flows using plant-level data for the US manufacturing sector from 1972 to 1988. One important conclusion they provide is that over 10% of the jobs that exist at any point in time either did not exist a year prior or will not exist a year later. We suggest that this approach to the study of job flows can also be used with respect to borrower flows.

It should be noted that the period we are considering (from February 2018 to February 2022) was not homogeneous; it was hit by the pandemic shock, characterised by significant government support measures and special programs for providing preferential loans[5]. The question of whether preferential loans provided to companies within the framework of such state programs were a kind of opportunity to replace more expensive non-preferential loans with preferential ones is not considered in this work. However, some discussion on this topic is given in Burova et al. (2023).

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[3] Their primary dataset is the Italian Central Credit Register, which includes information about credit applications.

[4] For exact definition, refer to the work of Cuciniello and di Iasio (2020). The definition used in this study is presented in 'Methodology' (Section 3).

[5] Preferential loans were provided to borrowing companies before the pandemic. During the pandemic, additional special preferential lending programs were introduced and operated, primarily Payroll Fund 0 and Payroll Fund 2.0, later – Payroll Fund 3.0, as well as Program 8.5. For reference: Under the Payroll Fund 0 program (period of concluding a loan agreement from March 30 to October 1, 2020) a borrowing company received the right not to pay the loan until November 30, 2020, and the bank received compensation at a rate of 4% per annum, after which the obligation to pay was returned to the borrower at a rate not higher than the rate established for the bank under the preferential refinancing program of the Bank of Russia. The loan amount was calculated based on the number of employees of the borrowing company, the minimum wage in the region where the company operates and the number of months. Under the Payroll Fund 2.0 program (the period of concluding a loan agreement from June 1 to December 1, 2020, the loan period at 2% - from the date of conclusion of the agreement until April 1, 2021), up to 100% of the debt of the borrower company was written off, depending on the share retained staff size. Banks' costs under the program associated with raising funding and operating expenses were covered by a budget subsidy in favor of banks in the amount of 7% per annum on the average monthly loan balance. Banks also received a one-time subsidy when the agreement was included in the register of borrowers. At the end of the program (in April 2021), the loan was subject to write-off from the state budget if appropriate conditions were met, which removed the credit burden from borrowers and credit risk from bank. In March 2021, the Payroll Fund 3.0 program was introduced (for companies participating in the lending program under Payroll Fund 2.0) at 3% per annum, which replaces the ended Payroll Fund 2.0 program. Also, since January 2021, changes have been made to Program 8.5, allowing borrowers to receive a loan at a rate equal to the key rate increased by 2.75 percentage points, see in detail the information and analytical material of the Bank of Russia Assessing the effectiveness of measures support for SMEs, 2021, p.6. And also, the work of Bessonov et al. (2022), p. 14.

In this regard, our research could contribute to two[6] strands of the related literature. The first strand is the Schumpeterian *creative destruction process*. The second strand is about the inflow of previously unserved borrowers under an accommodative monetary policy stance, which connects us with the process of *financial deepening vs outsized financial booms*. Using as an the example the pandemic period[7], when preferential lending programs played an important role in providing access to credit for companies in the industries most affected[8] by the shock, we analyse not only the amount of debt owed to banks by different firms, but also the quantity and quality of these firms (*financial inclusion* or *financial access*), especially those which took loans for the first time.

We distinguish several groups of borrowers based on their activity and first appearance in the credit registry. Additionally, we distinguish the categories of 'preferential' and 'non-preferential' lending. Preferential lending includes subsidised loans, i.e. those issued under the state support programmes and marked within the credit registry. Non-preferential lending includes other lending activities (loans issued under market conditions). The role of preferential lending was significant during the acute period of the pandemic (from June 2020 to May 2021), but it decreased after. Within this analysis, we highlight several results. First, the massive inflow of borrowers at the beginning of the pandemic was sporadic and tightly linked to the state support measures. The conclusion of Chauvet and Jacolin (2015), who find that the positive results of financial deepening are visible only when borrowers are diverse (i.e., when banks have inclusive portfolios and a greater share of firms in an industry have access to bank loans), inspired us to undertake deeper analysis of an inflow of borrowers during the severe phase (from June 2020 to May 2021) of the COVID-19 pandemic. As the second result, we highlight an increase in the share of *inactive borrowers*, i.e., those who have open but unused credit lines starting from April 2021. Depending on terms of credit agreement, borrowers of this type may not transform the accessible credit funds into investments but accumulate them as a form of safety cushion including instances of servicing other debt when economic conditions worsen substantially. Practically, this is similar to the case of debt restructuring when borrower is unable to service debt. This behaviour, by postponing the exit of firms, may dampen the process of Schumpeterian creative destruction, which requires the reallocation of funds from firms, which

[6] Access to micro-level credit data has motivated several new strains of research. A number of authors use granular credit information to study either the impact of monetary policy or the effectiveness of macroprudential measures. Jimenez et al. (2014) study the impact of monetary policy on the supply of credit, in particular on banks' risk-taking, using data from the Spanish credit registry. They separate supply and demand factors and conclude that a lower overnight rate does indeed induce banks to grant more loans to ex-ante risky firms, to extend more credit, and to require less collateral after applications are approved. Ioannidou et al. (2009) also use credit registry data to analyse the impact of monetary policy on risk-taking. They study the economy of Bolivia from 1999 to 2003, whose banking system was highly dollarised, and find results similar to those of Jimenez et al. (2014): a decrease in the US federal funds rate prior to loan origination raises the probability of default and increases the probability that loans are extended to riskier borrowers with current or past non-performance or loans with subprime credit ratings. Bofondi et al. (2013) examine the impact of an increase in sovereign debt risk on financial intermediaries' supply of the credit using data from the Italian Central Credit Register. Goncharenko et al. (2021) study the effect of bank closure policy on firms and banks and show that bank closure policy has a cleansing effect on the structure of the economy in Russia (following the closure of a bad bank, bad firms go to bad banks which are still operating while good firms go to good banks).

[7] We repeat the analysis for several subsamples (e.g., short-term lending or lending only to companies in exposed industries

[8] By *exposed* industries, we mean industries that were severely affected by the pandemic. For this purpose, we use the list of affected industries proposed within the state support measures.

borrow only to service their debt[9] (and the possible consequences of extending non-performing loans for liquidity purposes) to firms with higher growth potential, which borrow to invest. In this sense, we are inspired by the work of Pattanaik et al. (2022), who find that indirect evergreening may happen when weak firms still have access to external funds by taking loans through the companies of their groups. In this case, the oversized share of zombie firms may harm the process of creative destruction in the economy. Potentially, this type of borrowers may entail additional risks to banks and financial stability because they may quickly increase their borrowing under adverse economic conditions. However, actual utilisation of credit lines is bounded by terms of credit agreement, revaluation of collateral, and could led to smaller volumes of funds available. This is why we suggest the close monitoring of its dynamics and its possible use as an early warning indicator. Percic et al. (2013) study several early warning systems in their article and, in general, highlight the importance of these systems in the context of the mix of policies applied by monetary authorities after the Global Financial Crisis. At the same time, the authors stress the difficulty of quantifying the macroeconomic characteristics, which reveal vulnerabilities. In this matter, our paper has the advantage of using granular data, which makes it easier to identify the earlier accumulation of risks.

Finally, we analyse how the quality of debt changes. We analyse the quality of new vs existing borrowers. We distinguish several groups of borrowers based on their activity and first appearance in the credit registry:

- those with credit histories longer than 12 months who also took new credit during the last 12 months;
- those with credit histories longer than 12 months but without loans issued during the last 12 months;
- those with credit histories shorter than 12 months.

We use the NPL ratio and vintage analysis to identify possible sources of vulnerabilities in credit portfolios that can be attributed to particular types of borrowers[10]. We pay particular attention to the period from June 2020 to September 2020 when the massive inflow of borrowers took place[11]. As an anecdotal example, Leao et al. (2017) document the main features of the US subprime crisis and the ensuing global financial crisis[12]. This episode thus highlights the inevitable trade-off between financial deepening and the possible accumulation of excessive risks, which may lead to a financial crisis.

This paper has the following structure: Section 2 describes the data used; Section 3 details the methodology; Sections 4, 5, and 6 present the results of our analysis; Section 7 concludes.

[9] These are called 'zombie'-firms

[10] We do not distinguish cases of debt restructuring, refinancing, changed interest rate and the frequency of interest payment.

[11] For example, Dell'Ariccia and Marquez (2006) examine the role of information asymmetry in the evolution of credit standards, whether an inflow of new borrowers leads to the erosion of lending standards or whether loose credit standards provoke new and unknown borrowers to emerge.

[12] An inflow of previously unserved borrowers to the mortgage lending market preceded the subprime crisis. Greater access to mortgage lending had significant social benefits. However, what at first seemed to be financial deepening turned out to be one of the causes of the financial crisis, as the provision of funds to new borrowers was also associated with additional risks. Along with other factors such as a high level of securitisation and OTC trade, lax credit standards, etc.

2. Data

2.1. Aggregate data on corporate credit growth in Russia

We start our analysis by inspecting the data. Several distinct features draw our attention.

The annual growth rate of 12-month cumulative *rouble loans issued*[13] *by Russian banks* to non-financial resident companies (Figure 1a) [14] comprised 14% in February 2018, i.e. at the beginning of researched period. Gradually decreasing through the whole 2018 year, it reached negative zone in January 2019. In December 2019, however, it was 4% and reached a peak of 20.8% by July 2020 (starting from June 2020 the active phase of State support programs began). The indicator slowed down and hit the minimum of 1% by March 2021. After that, it has accelerated to near-peak values and reached 19.3% by February 2022. Overall, the growth rate of *rouble loans issued by Russian banks* both to financial and non-financial resident companies was volatile. Because of the buoyant dynamics of credit to financial companies, its share in all *rouble loans issued by Russian banks* (12-month cumulative) increased to 47.2% by September 2021, but it has been decreasing since then (based on our calculations).

The growth rate of non-financial resident companies' *outstanding rouble debt*[15] (i.e., the *stock of debt)* owed to Russian banks (Figure 1b) showed mixed dynamics up until June 2021 when it reached 13%. It has accelerated starting from July 2021 (15.7%) and reached a peak of 21.4% in February 2022[16].

Looking ahead, we note that since July 2021, volumes provided on non-preferential terms to borrowers with a pre-existing history of bank borrowing began to play an increasingly noticeable role in the corporate credit growth.

Non-financial resident companies' stock of rouble debt as a share of GDP[17] increased from 18.1% in the 4th quarter of 2019 to 19.7% in the 4th quarter of 2021 (Figure 1c). The corresponding figures for all resident companies were 23.3% and 24.8% of GDP.

[13] By 'loans issued', we mean all the loans that were issued (i.e., the flow variable) by Russian banks in a particular period (e.g., a month or 12-month cumulative), not the outstanding debt (which is the stock of debt, i.e., the stock variable).

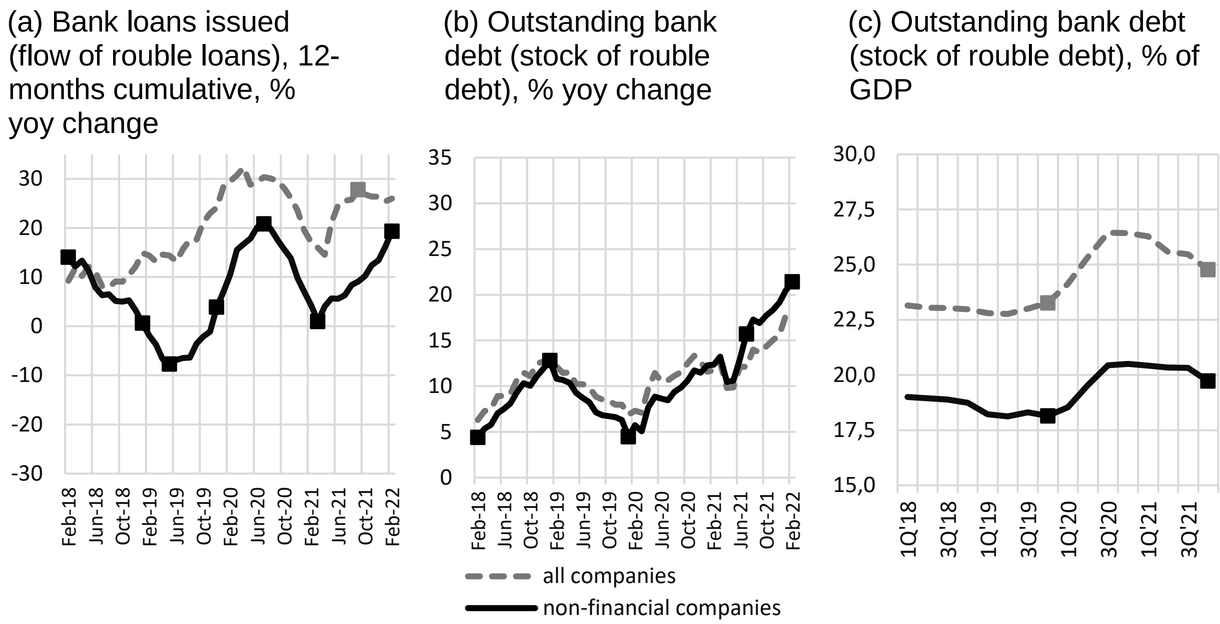
[14] As explained in the methodology section, financial companies include those, other than banks, belonging to industries 64–66 in the Russian industry classifier ('ОКВЭД', which corresponds to the NACE industry classification). All other industries include non-financial companies. Interbank lending is not covered in this paper.

[15] In this paper, 'debt' means only loans from banks and does not include market debt such as bonds, foreign currency debt, and external debt.

[16] The trends for all resident companies (financial and non-financial) were similar, as financial companies' debt constitutes less than 20% of all outstanding rouble debt owed by resident companies to Russian banks.

[17] GDP is calculated as the last four quarters cumulative (i.e., on a rolling basis).

Figure 1. Debt outstanding and loans issued by Russian banks to corporate resident borrowers in Russia



Source: Bank of Russia (loans issued to the corporate sector, loans issued to non-financial companies, outstanding debt of the corporate sector, outstanding debt of non-financial companies), Rosstat (GDP), authors' calculations.

Notes: 'Non-financial companies' includes those not belonging to industries 64–66 as in the Russian industry classifier 'ОКВЭД' (which is an equivalent of the NACE industry classification); % yoy change is calculated as the ratio of cumulative loans issued in months [t-11; t] to the corresponding value issued in months [t-23; t-12]. The values are aggregated at the economy level and zero values in the denominator are impossible.

2.2. Granular data

To determine the contribution of each resident company and attribute this contribution to the intensive or extensive component of the corporate credit growth, the general dynamics of which we described in the previous section, we use a micro-level (granular) database administrated by the Bank of Russia. The total indicators from the database match the values of the aggregate indicators from the previous section.

Granular database contains information about the portfolio (stock) of debt and all new loans issued by Russian banks to the corporate sector (corporate residents) in Russia starting from February 2017.[18] Figures for the *extensive* and *intensive* components are thus available starting from February 2018.[19] The database includes detailed information on the currency and amount of the loans issued to Russian companies, the amount of debt outstanding at the end of each month, the lending rates, the original and remaining maturities, the collateral attached, the date and amount of credit agreement, loan issue date.

The focus of this paper is the domestic currency (RUB) Russian bank debt of the *non-financial* corporate sector (NFCs residents) in Russia. Based on the credit registry data, which reconciles with the official statistics, the average share of domestic currency (RUB) debt in the total amount of rouble and foreign currency bank debt of Russian NFCs owed to Russian banks increased from 78% in 2018 to 83% in February 2022. Due to this fact, debt denominated in foreign currency was excluded from the analysis.

By 'financial' companies, we mean those in industries 64–66 in the Russian industry classifier ('*ОКВЭД*'), which is an equivalent of the NACE industry classification. Financial companies are those involved in investment, factoring, leasing, accounting, and similar activities. Companies in all other industries constitute non-financial companies.

Due to the data restrictions, bonds, foreign currency debt, external debt, and interbank lending are not covered in this paper (also excluded from the presentation of aggregated indicators in Figure 1). We also split our sample based on initial loan maturity and consider three different subsamples: loans with maturities of less than 1 year, those with maturities from 1 to 3 years, and those with maturities of more than 3 years.

Furthermore, we expand our study by separately analysing sectors that were highly *exposed* to (*affected by)* the pandemic and those that were not. For this purpose, we use the classification proposed within the state support measures.[20]

[18] Hereinafter, we refer to it as the 'credit registry' (Form 0409303). The detailed methodology and description of the form are available here.
[19] Both components are obtained by splitting credit growth, which is a year-over-year series.
[20] For the full list of exposed industries, refer here.

3. Methodology

3.1. Definition of intensive and extensive components of corporate credit growth

To analyse the source of credit growth in non-financial companies' stock of debt, we compare the stock of debt (portfolio) reported in the current month with that of the same month of the previous year and decompose the change in the stock of debt into two components: intensive and extensive. The crucial difference between them is that the *intensive component* represents pre-existing credit relations, while the *extensive component* represents only newly created relations.

We assume that the *intensive component* reflects the stock of debt (portfolio) of borrowers who already had a credit relationship with one or several banks 12 months before the reporting date or earlier.[21] Therefore, we define the intensive component as:

$$Intensive.component_{\ t} = \frac{\sum_{i=1}^{N}(debt_{i,t}^{int} - debt_{i,t-12}^{int})}{\sum_{i=1}^{N} debt_{i,t-12}}, \tag{1}$$

where $debt^{int}_{i,t}$ is the stock debt at month t of borrower i who already had a credit relationship at t-12 or earlier; $debt_{t-12}$ is the stock of debt at time t-12; and N is the total number of borrowers in the credit registry.

Conversely, the *extensive component* reflects the stock of debt of borrowers who initiated credit relationships with one or several banks within the last 12 months and did not have any debt before that. Thus, we define the extensive component as:

$$Extensive.component_{\ t} = \frac{\sum_{i=1}^{N}(debt_{i,t}^{ext} - debt_{i,t-12}^{ext})}{\sum_{i=1}^{N} debt_{i,t-12}}, \tag{2}$$

where $debt^{ext}_{i,t}$ is the stock of debt at month t of borrower i who initiated credit relationships in the period between t-12 and t and had no debt at t-12. Technically, $debt^{ext}_{i,t-12}$ is equal to 0.

We would like to highlight that our approach differs from those presented in the related literature (Figure 2). For example, Cuciniello and di Iasio (2020) decompose the overall growth rate of the stock of debt using the formula:

$$\frac{\Delta L_t}{L_{t-1}} = \underbrace{\sum_{f\in F}\sum_{b\in B}\frac{l_{fbt}^{I} - l_{fbt-1}^{I}}{L_{t-1}}}_{\textit{Intensive margin}} + \underbrace{\sum_{f\in F}\sum_{b\in B}\frac{l_{fbt}^{C} - l_{fbt-1}^{D}}{L_{t-1}}}_{\textit{Extensive margin}}, \tag{3}$$

Source: Cuciniello and di Iasio (2020)

The first term in this formula is the intensive component and the second term is the extensive component. As Cuciniello and di Iasio (2020) state, $l_{fb,t}^{I} - l_{fb,t-1}$ denotes the change in the stock of debt owed by borrower b to bank f (the relationship between the bank and the borrower was initiated in t-1 or earlier and is still active in t). l_{fbt}^{C} is the stock of debt owed by a new borrower b to bank f (in which borrower b has a loan from f for the first time in t), and $l_{fb,t}^{D}{}_{-1}$ is the stock of debt provided by bank f to a borrower b which is no longer f's client (but was in t-1).

[21] Here, credit relationship does not necessarily mean positive debt. For example, it can be a line of credit which haven't be used by now so the amount of debt is 0 in that case.

The main difference between these two methods is that Cuciniello and di Iasio (2020) consider borrowers which leave the credit market as part of the *extensive* component, while we consider them as any other pre-existing borrowers and analyse them within the *intensive* component (because these borrowers are not new to the banks). Thereby, our estimation of the *intensive* component may be higher, other things being equal. Our definition of the intensive and extensive component is motivated by data restrictions[22] and by the focus of the paper, which is to study the source of credit expansion and the inflow of borrowers to the Russian credit market. As a case study, we focus on the pandemic period, which was accompanied by government support measures. Furthermore, borrowers who start credit relationship with a new bank while they already have existing relations with another bank are part of the *intensive* component in our baseline analysis. Our primary interest is borrowers who are new to the credit market *as a whole*, not to a particular bank. On the other hand, Cuciniello and di Iasio (2020) consider these borrowers part of the *extensive* component in their basic specification. However, they also check the alternative for robustness purposes and find no qualitative differences.

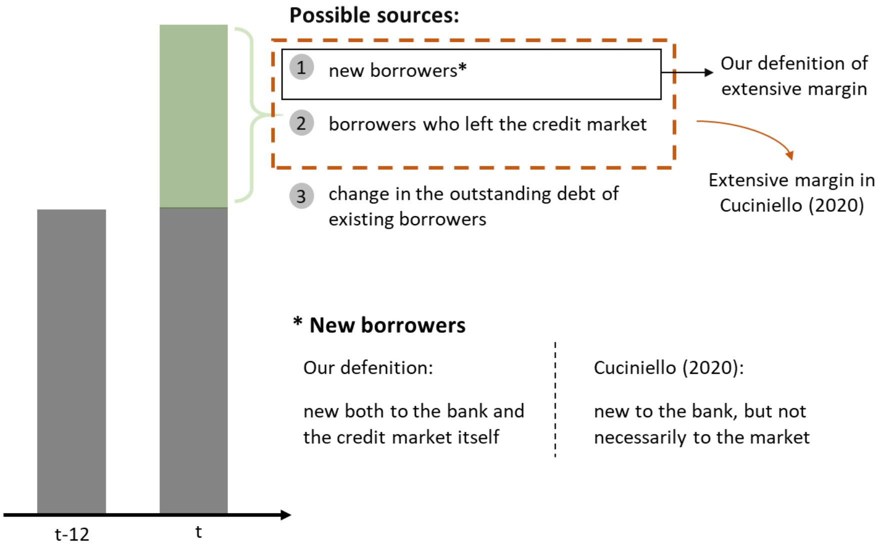
The subsidized loans are marked within the credit registry. We define the intensive and extensive components separately for *preferential* (subsidised loans including those provided under the state support program) and *non-preferential lending*. As a result, there are four components (see also Table 2):

- extensive, preferential (ext_p);
- extensive, non-preferential (ext_np);
- intensive, preferential (int_p);
- intensive, non-preferential (int_np).

Additionally, we analyse sectors that were highly affected by the pandemic (*exposed industries*) and participated in the state support programmes. For the full list of exposed industries refer to the list of affected industries defined in Government documents - Decree of the Government of the Russian Federation No. 434 of 03.04.2020 “On approval of the list of sectors of the Russian economy that were most affected by the worsening situation as a result of the spread of the new coronavirus infection.” For the brief description of the state support programmes particularly introduced during the acute phase of the COVID-19 pandemic, refer to the Introduction.

[22] Unlike Cuciniello and di Iasio, we have no data on credit applications.

Figure 2. Differences among definitions



For summary statistics, see Table B in the Appendix.

3.2. Measurement of extensive and intensive components

To assess the role of each component, we compute the simple average of the whole sample. For example, we use the following formula for the extensive component:

$$C^{ext} = \frac{\sum_{t=1}^{N} C_t^{ext}}{N} \tag{4}$$

where C_t^{ext} is the extensive component at month *t*. We additionally compute the standard deviations and provide the results for several subsamples (e.g., for short-, medium-, and long-term credit separately based on initial maturity). The results are presented in Section 4.

3.3. Definition of borrower type based on activity in credit registry

To analyse the number and composition of borrowers, i.e. the detailed flow of borrowers, we define four groups of borrowers, as presented in Table 1 and Figure 3.

- *'New borrowers'* are those who appear in the credit registry in given month *t* (the range of *t* is from February 2018 to February 2022).
- *'Old borrowers'* are those borrowers who appeared before month *t* (pre-existing borrowers, in other words).
- *'Active borrowers'* are those who have non-zero bank debt or arrears.
- *'Inactive borrowers'* are those for whom both bank debt and arrears are equal to zero. However, most of these borrowers have open, unused credit lines (including project finance), which explains their presence in the credit registry.

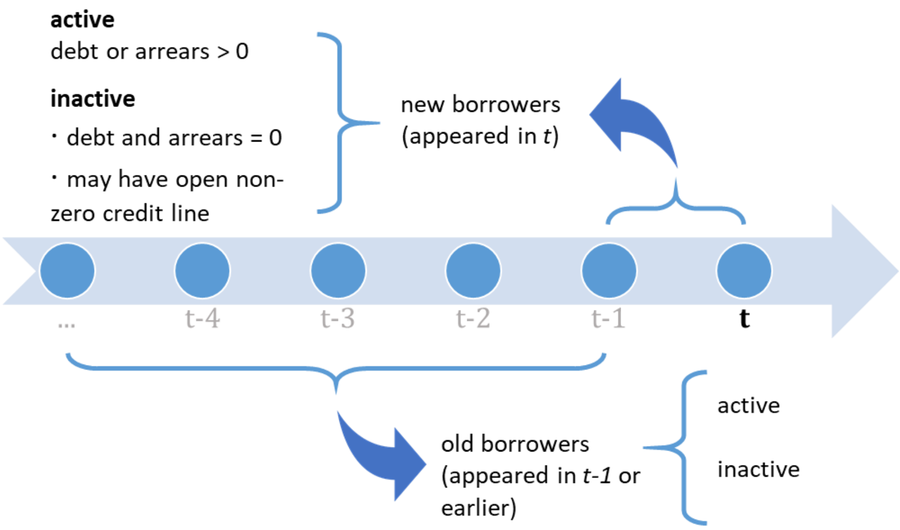
This set of definitions is used to analyse the flow of borrowers (e.g., in Figures 10–11). We further narrow down the definition of "*new borrowers*" to the purpose of vintage analysis (Figure 15).

Table 1. Types of borrowers

	(1) First appearance	(2) Debt, NPL
new_inactive	t	debt = 0, NPL = 0
new_active	t	debt > 0 or NPL = 1
old_inactive	[0; t]	debt = 0, NPL = 0
old_active	[0; t]	debt > 0 or NPL = 1

Notes: Here, NPL is a dummy variable, which equals 0 if a borrower has no NPL and 1 otherwise.

Figure 3. Timeline definition for different types of borrowers



3.4. NPL ratio and vintage analysis

We compute the NPL ratio of stock of debt and perform vintage analysis by evaluating default rates of loans issued. The difference between these two indicators is that the NPL ratio is an indicator of stock that is used to assess the share of non-performing loans (NPL) in the overall stock of corporate debt at a particular point in time, whereas the default rate shows the share of non-performing loans during a particular period (12 months). We compute the default rates of different cohorts of loans issued: a cohort is the set of loans issued to borrowers who appeared in the credit registry in a particular month. In both cases, non-performing loans (NPL) are defined as loans for which the scheduled payments are overdue by 90 days or more.

We calculate the NPL ratio in two alternative ways. In the first, we assess the share of borrowers who have at least one non-performing loan (B) in the overall number of borrowers (N):

$$NPL_{quantities} = \frac{B}{N} \tag{5}$$

In the second, we compute the share of all debt outstanding[23] of borrowers who have at least one non-performing loan (*A*) in the total stock of debt (*M*):

$$NPL_{volumes} = \frac{A}{M} \tag{6}$$

As for the vintage analysis, we calculate default rates for new borrowers only. In this, we further specify the definition previously introduced. For instance, we establish that 'new borrowers' are those which not only appeared in the credit registry in month *t* but which also took loans. In addition, the period between the establishment of the loan agreement and the first tranche should not exceed 30 days. The default rate is calculated as the share of all borrowers who have at least one loan overdue by 90 days or more in the initial number of borrowers in the cohort (recall that a cohort is the set of all borrowers who took their first loan in the given month).

It should be noted that in both cases - both when calculating the non-performing debt ratio (NPL) for a certain date, and in the case of vintage analysis with calculating the level of non-payments on issued loans for a certain period, the fact of a delay in payment of a loan by 90 days or more is recorded in credit registry, regardless of whether the debt was recognised by the bank as problematic or whether regulatory relaxations or a moratorium on bankruptcy could be applied to it.

[23] Including those that are not non-performing, so we consider all the loans of 'bad' borrowers.

4. Decomposition of corporate credit growth

4.1. Intensive and extensive components

We evaluate the intensive and extensive components, which represents the contribution of the existing or the newly created credit relations to the overall corporate credit growth of non-financial corporations. The results (Table 2) show that, on average, the extensive component is greater than the intensive component. For instance, the contribution of newly created credit relations (extensive component) is 66% on average (0.80 + 6.16 = 6.96, which is equal to 66% of 10.49. The corresponding figure for the *intensive* component, which represents existing credit relations, is 34%. These results support the findings of Cuciniello and di Iasio (2020), who highlighted that the *extensive* component plays a greater role.

Table 2. Average values of intensive and extensive components
(February 2018–February 2022)

	(1) extensive preferential	(2) extensive non-preferential	(3) intensive preferential	(4) intensive non-preferential	(5) credit growth, %
whole sample	0.80	6.16	2.85	0.67*	10.49
	(0.67)	(1.22)	(1.44)	(2.93)	(4.18)
by maturity:					
<1 year	0.22	1.12	1.13	-0.28	2.19
	(0.29)	(0.27)	(0.98)	(1.17)	(1.22)
1–3 years	0.19	1.54	0.32	0.89	2.94
	(0.18)	(0.40)	(0.23)	(1.30)	(1.63)
>3 years	0.39	3.49	1.40	2.08	7.35
	(0.26)	(0.88)	(0.38)	(1.89)	(2.39)
by industry:					
non-exposed industries	0.69	5.70	2.77	0.69	9.85
	(0.55)	(1.24)	(1.24)	(2.79)	(4.48)
exposed industries	0.11	0.47	0.08	-0.02	0.64
	(0.19)	(0.12)	(0.39)	(0.67)	(0.74)

Source: Bank of Russia, authors' calculations. Note. The average value of the intensive non-preferential component (0.67) is not equal to the sum by maturity (-0.28 + 0.89 + 2.08) due to the omitted maturity indicator for some loans in this category.

We additionally assess each component for several subsamples. According to the results, the relative role of the *extensive* component does not differ much across different maturities. For example, the *extensive* component, on average, contributes 61% of the average growth of the credit stock of short-term lending (i.e., 1.34%); 59% (1.73%) of mid-term lending, and 53% (3.9%) of long-term lending. However, the role of the extensive component is much different for the industries that were severely affected (*exposed*) during the pandemic and those that were not (*non-exposed*). In the first case, the *extensive* component contributes 90% (0.58 out of 0.64) of the average growth of the credit stock, while in the second case it contributes only 65% (6.39 out of 9.85%). The fact that the role of the extensive component turned out to be significantly higher specifically for companies from industries affected by the pandemic (exposed industries) may be associated with the active participation in state support programs (preferential lending) of borrowers from these industries who had not previously attracted loans (that is, did not have existing credit relationships).

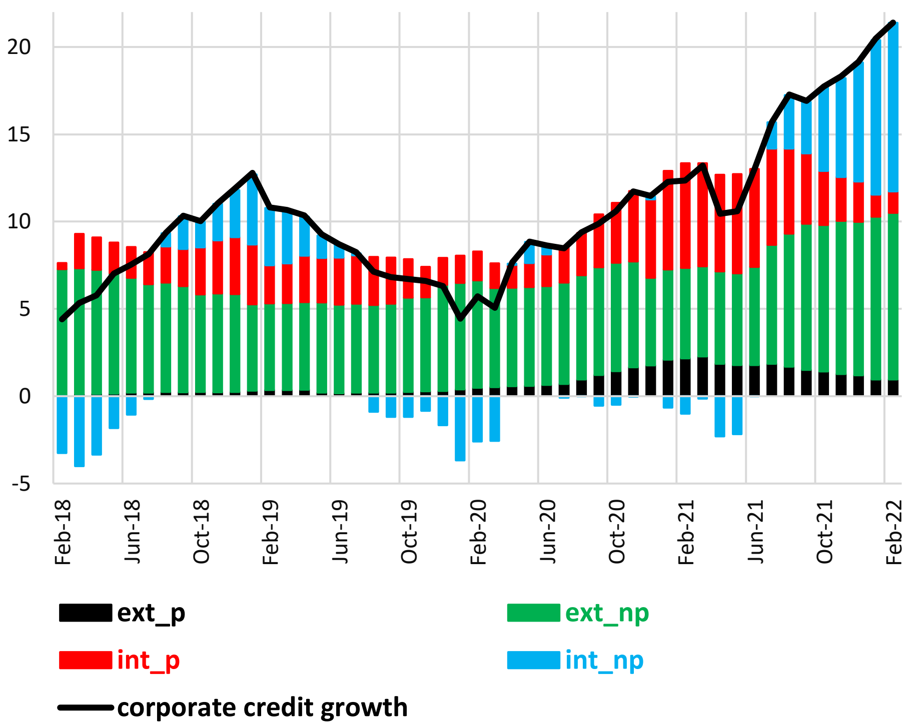
4.2. Changes in composition of corporate credit growth: all industries

We proceed by studying how the composition of credit growth changes across the sample. Specifically, we decompose credit growth into four parts:

- extensive, preferential (ext_p);
- extensive, non-preferential (ext_np);
- intensive, preferential (int_p);
- intensive, non-preferential (int_np)[24].

The results are presented in Figure 4. We can conclude that the *extensive, non-preferential* component is prominent and stable throughout the whole sample. On the other hand, the role of *preferential* lending is more volatile. During the coronavirus crisis (approx. *June 2020–May 2021*), it first increased sufficiently, both in the *intensive* and *extensive* components, but it then gradually decreased as the main state support programmes ended. The following period is characterised by an increase in the *intensive, non-preferential* component, which has recently become the main driver of credit growth.

Figure 4. Decomposition of credit growth by intensive and extensive components, % yoy



Source: Bank of Russia, authors' calculations.

*Notes: **ext_p** – extensive, preferential component, **ext_np** – extensive, non-preferential, **int_p** – intensive, preferential, **int_np** – intensive, non-preferential.*

[24] A detailed description is presented in the 'Methodology' section. In general, the distinction is based on two criteria: 1) Does a loan fit into the intensive or extensive component? 2) Are the conditions on the loan preferential or not? (i.e., is the loan subsidised or not?).

Additionally, we decomposed the corporate credit growth, dividing all companies into borrowers classified as small and medium-sized enterprises (SMEs) and all others. The attribution of the borrowing company to an SME was recorded by a mark in the corresponding column of the credit registry. We see that the contribution of the intensive non-preferential component differs significantly for these two groups of borrowers: for SMEs it was negative until October 2021, and for non-SME borrowers it was predominantly positive (except for the first quarter of 2020 and spring 2021). At the same time, the contribution of the extensive component is stable for both groups of borrowers.

Figure 4a. For non-financial corporate borrowers from small and medium enterprises, % yoy

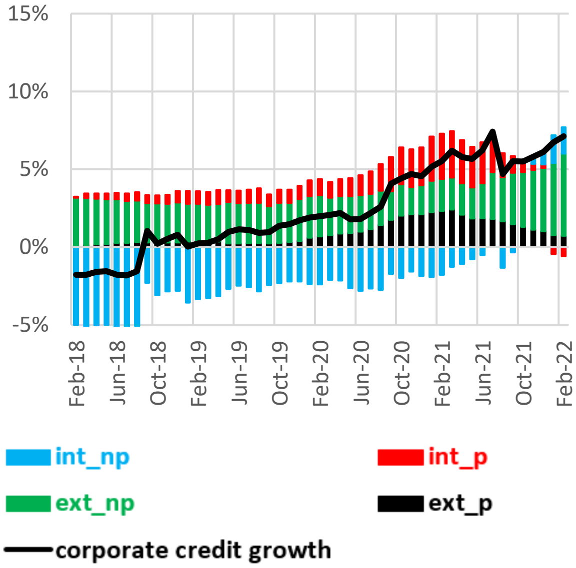
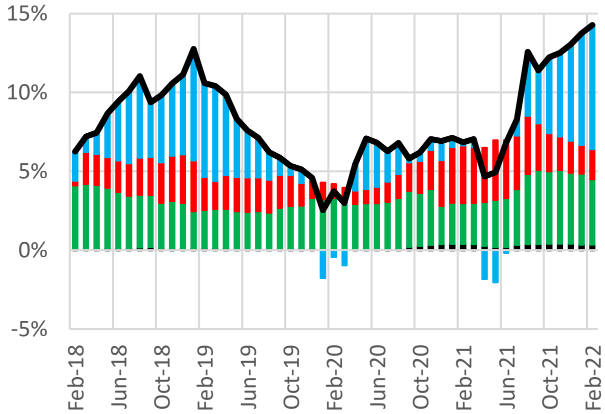


Figure 4b. For non-financial corporate borrowers from all other enterprises, % yoy



Source: Bank of Russia, authors' calculations.

Notes: ***ext_p*** *– extensive, preferential component,* ***ext_np*** *– extensive, non-preferential,* ***int_p*** *– intensive, preferential,* ***int_np*** *– intensive, non-preferential.*

There is also evidence of differences in credit activity across various loan maturities (Figures 5a, 6a, and 7a). For instance, short-term credit growth followed a hump-shaped path during the pandemic. These dynamics may be linked to the demand for liquidity and the realisation of the *preferential* loan programmes. During the severe phase of coronavirus crises, these programmes provided funds mostly for periods of less than one year, which explains the prominent role of preferential lending in short-term credit growth. As for mid- and long-term lending, it was subdued during the first year of the pandemic. Nevertheless, as the economy started recovering gradually (approximately from June 2021), the *intensive, non-preferential* component (mostly) pushed mid- and long-term lending to pre-pandemic levels or higher.

Figure 5. Intensive and extensive components (maturity of less than 1 year), % yoy

(a) all industries (b) exposed industries

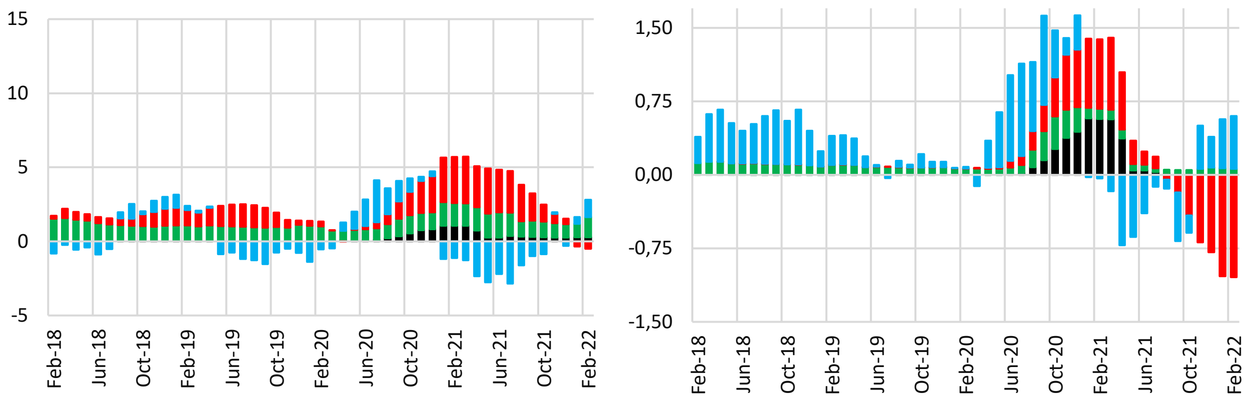


Figure 6. Intensive and extensive components (maturity from 1 to 3 years), % yoy

(a) all industries (b) exposed industries

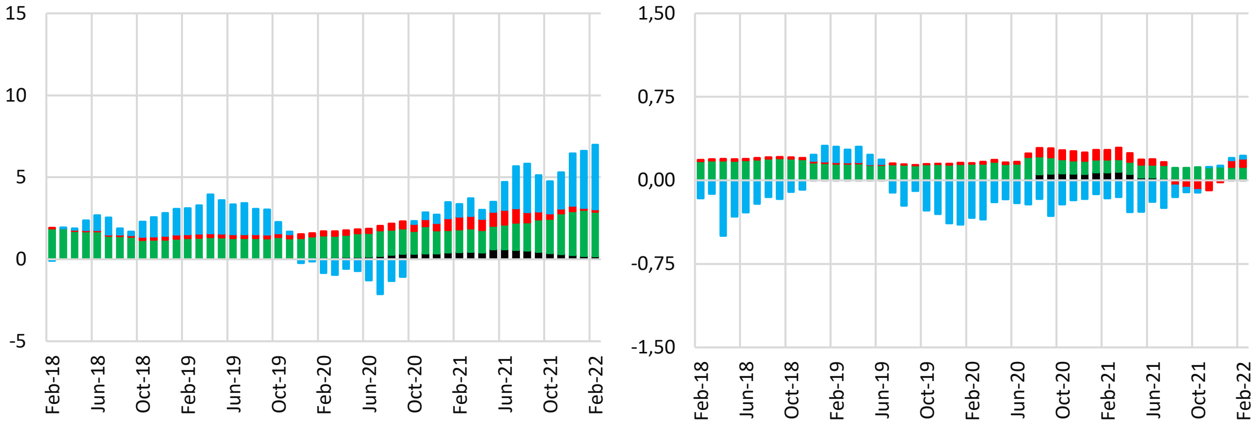
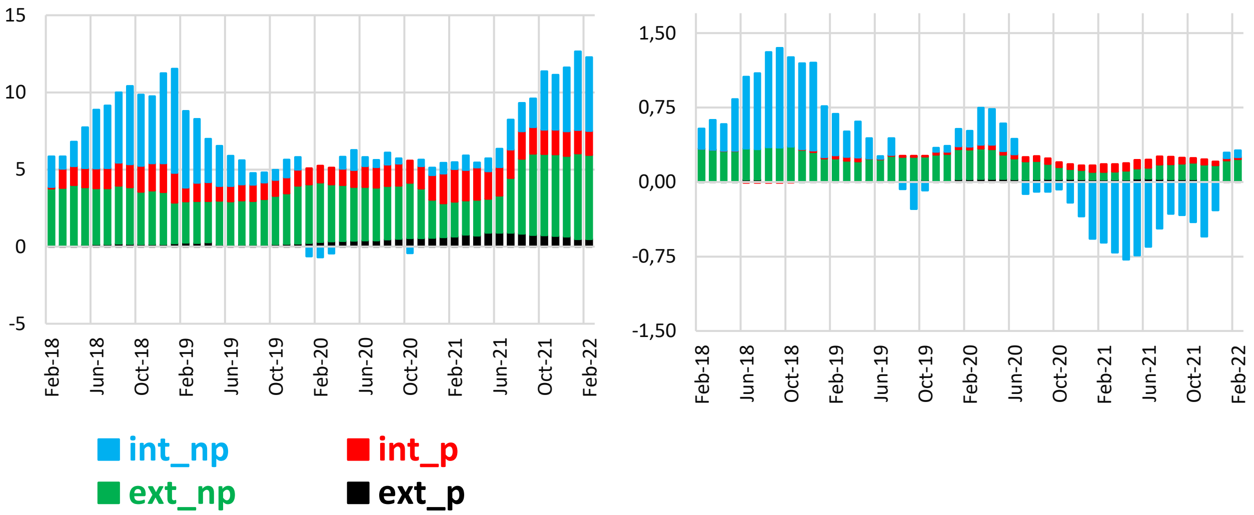


Figure 7. Intensive and extensive components (maturity of more than 3 years), % yoy

(a) all industries (b) exposed industries



Source: Bank of Russia, authors' calculations.
Note: ***ext_p*** *– extensive, preferential component,* ***ext_np*** *– extensive, non-preferential,* ***int_p*** *– intensive, preferential,* ***int_np*** *– intensive, non-preferential.*

4.3. Changes in composition of corporate credit growth: exposed industries

To extend the analysis, we separate the exposed and non-exposed industries during the coronavirus crisis. As companies in non-exposed industries constitute the majority of the sample, their dynamics are similar to the general trend, and so we do not provide results for these industries and focus further on the exposed industries only. The results, which are presented in Figure 8, allow us to draw several conclusions. First, the credit growth of companies in the exposed industries has a relatively small impact on the overall results, given its small share (as it can be seen simply from the magnitude of the *y*-axis). Second, during the pandemic, the contribution of *preferential lending* to credit growth was greater for the exposed industries in both the intensive and extensive components. These industries also experienced a drop in non-preferential debt in the intensive component between June 2020 and May 2021 (unlike companies in the non-exposed industries). This pattern can be a result of two factors:

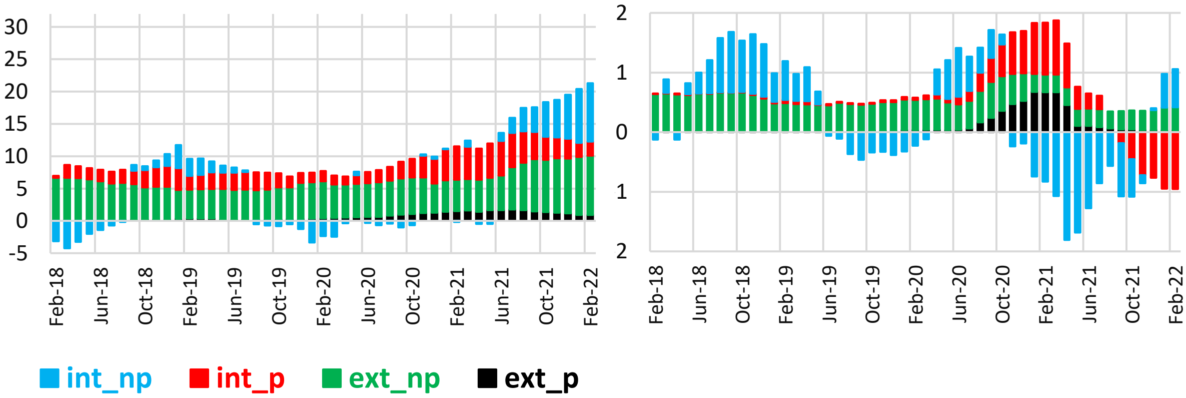
1) the fact that companies from the exposed industries substituted non-preferential lending with preferential lending because they had access to it (which was not the case for most other companies)

2) the possible reluctance of banks to provide funds to companies which were highly affected by the pandemic via channels other than preferential lending (which included government guarantees). However, the trend reversed in the period between September 2021 with a negative contribution from the *intensive, preferential* component and a positive contribution from the *intensive, non-preferential* component, which was probably linked to the termination of the government support measures in the first half of 2021.

Similar analyses of growth in credit of different maturities only for companies from the affected industries are presented in Figures 5b, 6b, and 7b. The main finding is that *preferential* lending almost completely explains these companies' short-term credit movements during the pandemic. On the other hand, the growth of mid- and long-term debt was affected by the fall in the *intensive, non-preferential* component.

Figure 8. Decomposition of credit growth into intensive and extensive components by industries, % yoy

(a) non-exposed industries (b) exposed industries



Source: Bank of Russia, authors' calculations. Note: ***ext_p*** *– extensive, preferential component,* ***ext_np*** *– extensive, non-preferential,* ***int_p*** *– intensive, preferential,* ***int_np*** *– intensive, non-preferential.*

4.4. In-depth analysis of intensive component

We perform an in-depth examination (Figure 9) of the intensive component (which represents the contribution of the existing credit relations to the overall corporate credit growth of non-financial corporations). In particular, we split it into two subcomponents: its positive (the increase in the stock of debt by borrowers with credit histories longer than 12 months)[25] and negative parts (the decrease in the stock of debt by borrowers with credit histories longer than 12 months). Our motivation is twofold: first, we want to show how the intensive component is formed; second, we want to analyse the intensive and extensive components in a more comparable way. In this section, we present the parts of the intensive component separately (unlike in the previous sections) to make the comparison clear.[26]

We define the two parts of the *intensive* component as follows:

1. The *positive* part (**INT_P_UP** for preferential lending and **INT_NP_UP** for non-preferential lending) is the increase in the stock of debt on the contracts of current borrowers in the last 12 months (including new contracts);
2. The *negative* part (INT_P_DOWN and **INT_NP_DOWN**) is the decrease in the stock of debt on the other contracts of current borrowers in the last 12 months.

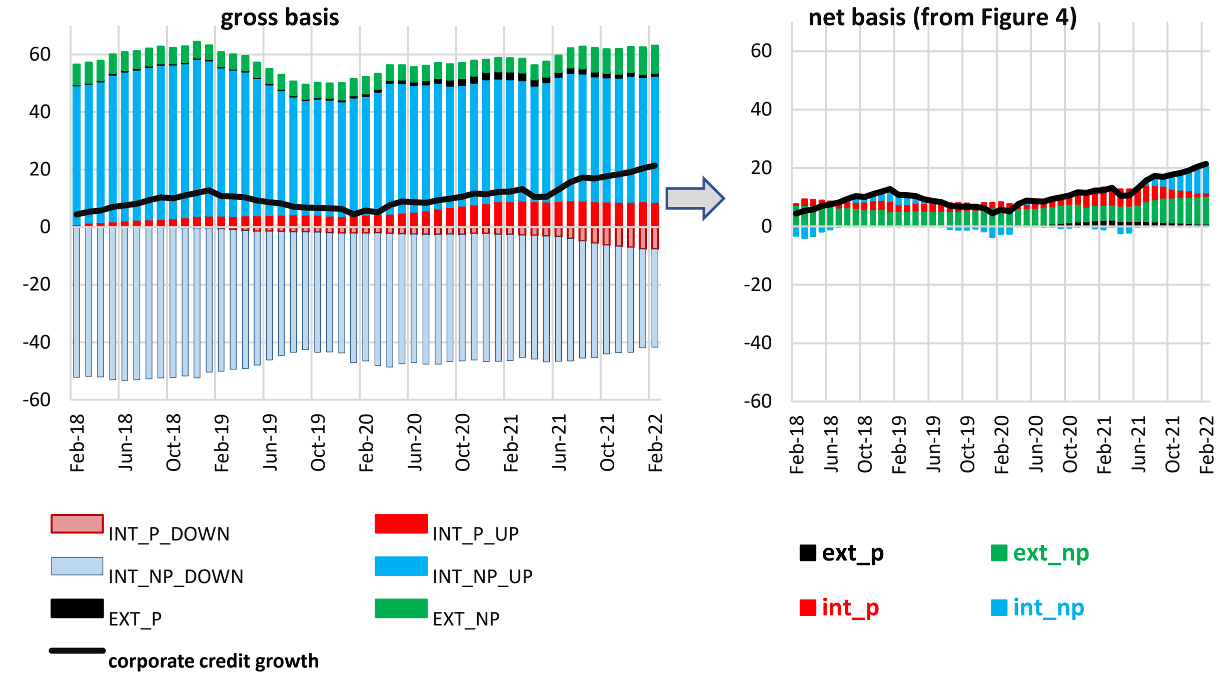
The sum of the *positive* and *negative* parts is equal to the *intensive* component described in the previous sections (i.e., the net change of the stock of the debt of borrowers with credit histories longer than 12 months).

The results show that the *extensive* component is actually quite small relative to both the positive and negative parts of the *intensive* component, an observation that was not evident before (Figure 4). Thus, we can conclude that the stock of debt attributable to current borrowers (the positive part of the *intensive* component) is several times higher than the stock of debt attributable to new borrowers (the *extensive* component). In other words, current borrowers have larger portfolios of debt (stock of debt) than new borrowers do. However, the ***net effect of the intensive component is comparable to or even smaller than the effect of the extensive component***, since the increase in the stock of debt of certain current borrowers is partly offset by the decrease in the stock of debt of other current borrowers.

[25] This is not necessarily new contracts. Instead, it may also be increases in debt amounts under existing contracts.

[26] For instance, we can now compare the *extensive* component, which is always positive by definition, with the positive part of the *intensive* component.

Figure 9. Intensive and extensive components (gross basis vs net basis), % yoy



Source: Bank of Russia, authors' calculations.

Notes: Intensive component: INT_P_UP – increase in indebtedness on contracts of current preferential borrowers; INT_P_DOWN – decrease in indebtedness on contracts of current preferential borrowers; INT_NP_UP – increase in indebtedness on contracts of current non-preferential borrowers; INT_NP_DOWN – decrease in indebtedness on contracts of current non-preferential borrowers. Extensive component: EXT_P – extensive, preferential; EXT_NP – extensive, non-preferential.

5. Changes in number and composition of borrowers

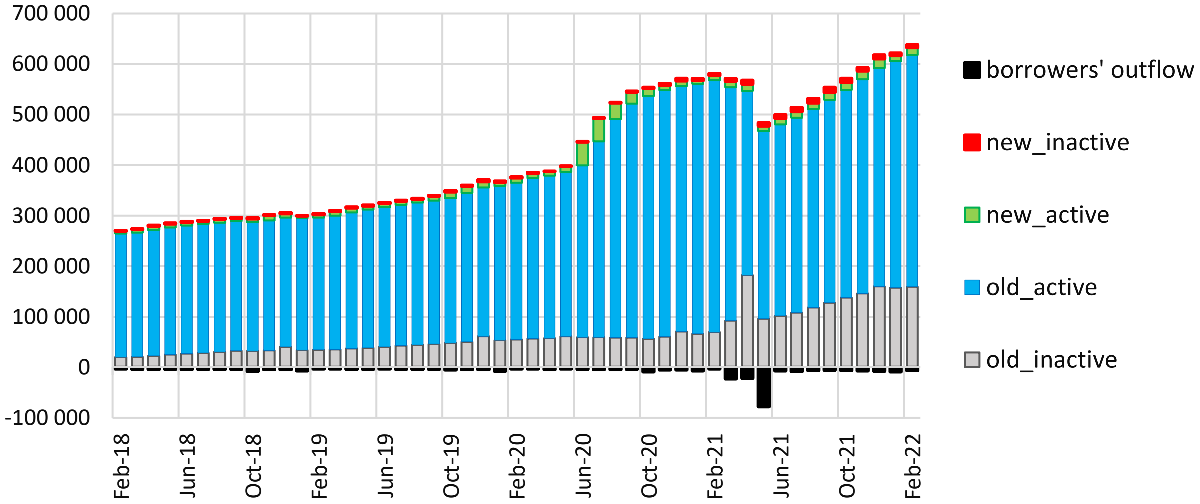
5.1. Quantitative changes in composition of borrowers and the state support programmes

We follow by analysing changes in the number and composition of borrowers. We distinguish four separate groups of borrowers (a description of every group is provided in the 'Methodology'):

- *'New active borrowers';*
- *'New inactive borrowers';*
- *'Old active borrowers';*
- *'Old inactive borrowers'.*

As an example of the impact of an external shock on the number of borrowers in different groups, we examine in detail the period of the pandemic, starting from June 2020. Initially, we observe a massive increase in the number of borrowers (Figure 10). The number of borrowers drastically increased due to the record inflow of new active borrowers shortly after the initial shock in spring 2020 (**green bars**, Figure 10 and Figure 11a). Almost 50,000 companies initiated credit relations for the first time in June 2020. The inflow of new borrowers was tightly linked to the realisation of state support programmes (black dotted line, Figure 11a). These measures included subsidised loans for companies in the affected industries. They were offered funds at a basic rate of 2% in the period between *June 2020 and May 2021*.[27] Both the credit itself and the interest may also be forgiven if a company retains 90% of its employees. The programme was reintroduced under stricter conditions in November 2021. Companies could get credit at a basic rate of 3% for 18 months if they participated in the first part of the programme.

Figure 10. Number of borrowers, by group



Source: Bank of Russia, authors' calculations.
Notes: the outflow of borrowers is computed as: ∆Number of borrowers$_t$ - New borrowers$_t$.

[27] For details, see, for example, Resolution of the Government of the Russian Federation No. 696, dated 16 May 2020 ('On Approval of the Rules for Granting Subsidies from the Federal Budget to Russian Credit Institutions ...').

The initial increase was followed by a comparable decrease in the following year. Approximately 80,000 borrowers left the credit market in May 2021,[28] which roughly coincides with the duration of the first part of the subsidised loan programme (**black bars**, Figure 10). This dynamic and the initial increase and further fall in the number of borrowers may indicate ***'come and go' behaviour in credit relations initiated during the acute phase of the pandemic***. To test this hypothesis, we additionally study the post-pandemic activity of borrowers who first appeared in the credit registry *between June 2020 and May 2021* and took out subsidised loans. Our results suggest that, among these borrowers (135,000), only 12.6% received loans again between January and August 2022 and only 7.4% of the initial number borrowed money under market conditions.

The following period, *from June 2021 to February 2022*, was characterised by the rapid growth of the number of borrowers. However, a distinct feature was the rising role of *new inactive borrowers* (**red area**, Figure 11a). The cumulative inflow of this type of borrower between the beginning of June 2021 and February 2022 was 63,000, which contributed to an increase in the number of *old inactive borrowers* from 96,000 to 160,000 in the same period (+64,000)[29]. As a result, the share of *old inactive borrowers* reached 25% of all borrowers in February 2022, while it was only ~15% before the pandemic (Figure 11b). This type of borrowers mostly includes those which do not have any debt or arrears, but which do have open credit lines (~85% of them)[30], including credit lines for project finance. We suggest that a rise in the share of *inactive borrowers* may indicate hidden risks in that these borrowers may quickly increase their borrowing under adverse economic conditions (however, actual utilisation of credit lines may be restricted by terms of credit agreement). We elaborate this point further in the following section.

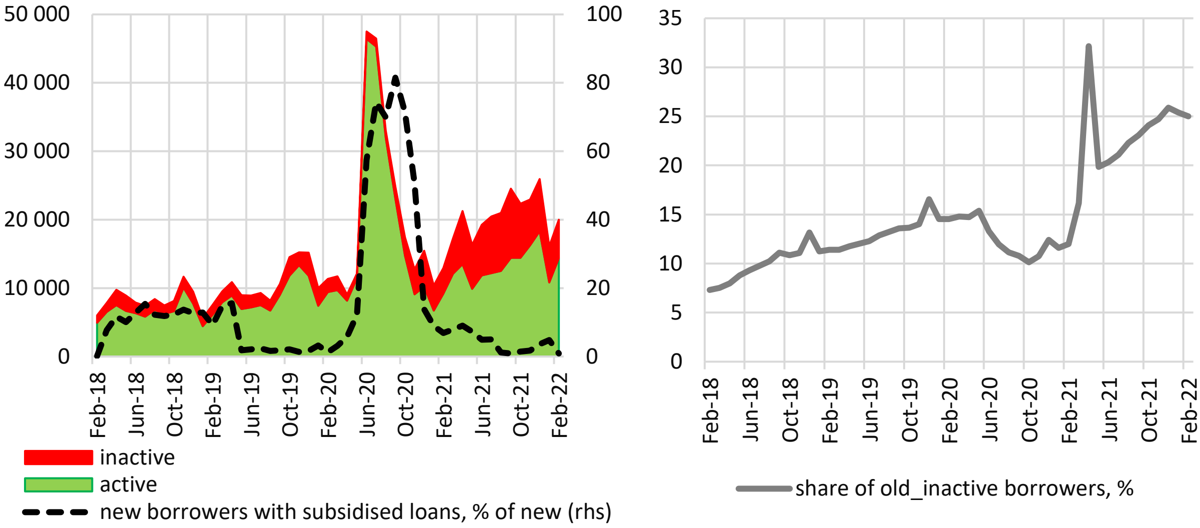
[28] Due to the way we define borrower groups, these borrowers initially changed their status from *old active* to *old inactive* before they finally left the market (see Figure A.1 in the Appendix). For instance, the number of *old inactive* borrowers increased from 70,000 at the beginning of March 2021 to 182,000 (+112,000) in just two months, while the number of *old active* borrowers decreased from 498,000 to 364,000 (-134,000) in the corresponding period. This also explains the 'grey spike' in April 2021 in Figure 10.

[29] There are two sources of growth in the number of *old inactive* borrowers: *new inactive* and *old active* borrowers. The lack of conversion of *old active* into *old inactive* in this period (Figure A.1) proves the decisive role of the transition channel from *new inactive* into *old inactive* borrowers.

[30] The rest are those which have no debt, arrears, or open credit lines. Most of them borrowed and paid off their debt within one month. As a result, we can observe them in the credit registry, although they have no debt, arrears, or open credit lines at the end of the month.

Figure 11. Increasing share of inactive borrowers

(a) New borrowers, by status (b) Share of old inactive borrowers, %



Source: Bank of Russia, authors' calculations.
Notes: we consider that a new borrower took a subsidised loan if it did so at any point since it appeared in the credit registry (not necessarily at the exact time of its first appearance).

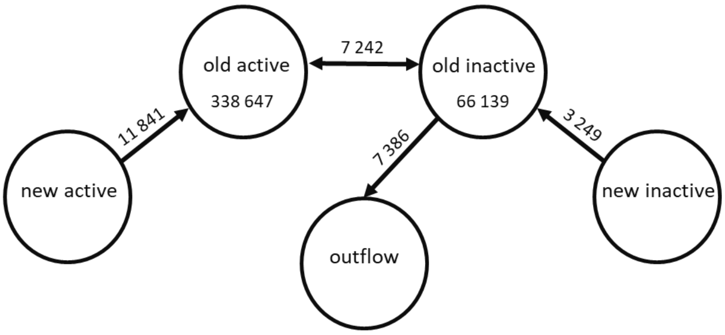
5.2. Appearance of inactive borrowers: general patterns

There are two possible sources of growth in the number of *old inactive* borrowers. The first is when *old active* borrowers become *old inactive* borrowers by paying off their debts and leaving the credit registry, i.e., by creating an *outflow* of borrowers. The risk associated with this type of borrowers is usually in the form of realised credit risk, i.e., when a borrower stops servicing its debt and subsequently defaults. This is generally explicit when realised. The second is when *new inactive* borrowers become *old inactive* borrowers. This channel may entail the accumulation of additional financial stability risks. Borrowers who represent this channel are those who have open credit lines which they have not yet used (i.e., they have no debt on their balance sheets but have the ***right*** to start using their open credit lines whenever they wish). The risk associated with this type of borrower is that they may start using the funds in their open credit lines exactly when economic conditions worsen, and this represents hidden risk to banks. Our decomposition allows us to measure this risk. It may be higher if the terms for the open credit lines are fixed upon issue. On top of this, an increase in the share of *old inactive* borrowers may distort the monetary policy transmission mechanism by squeezing banks' ability to provide funds under new credit contracts not bounded by previously issued credit lines (see, for example, the works of Acharya et al.(2021) and Kapan and Minoiu (2021)).

To complement the analysis in the previous section, we also explore the general patterns of all borrower groups and the flows among them, including statistics on the size and volatility of each group (or the flow), which are presented in Figure 12. It should be noted, however, that these figures were highly influenced by the significant inflow of new borrowers in 2020 and the one-off outflow of borrowers at the end of the subsidised loan programme in 2021.

For particular periods, e.g., February 2018–May 2020, June 2020–May 2021, or June 2021–February 2022, see Figures A.2–A.4 in the Appendix.

Figure 12. Borrower flows



Source: Bank of Russia, authors' calculations.

Notes: The numbers within the circles represent the average values of the loan stock. The one-way arrows represent average flows from one group to another, while the two-way arrow between the old active *and* old inactive *groups represents the average net flow from the former to the latter.*

6. Analysis of credit quality

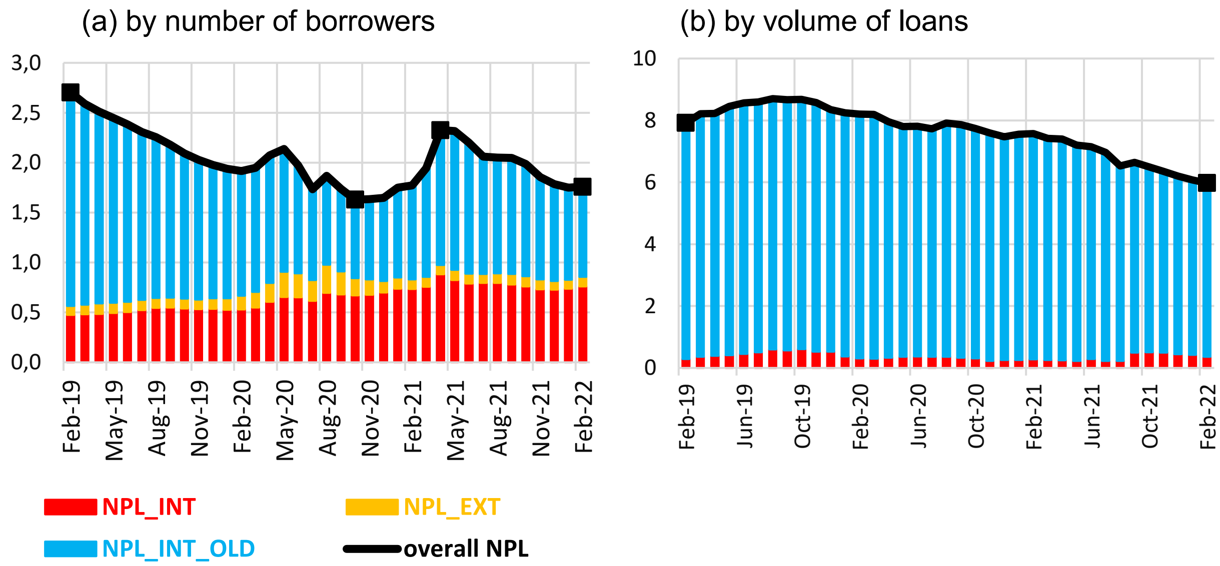
6.1. NPL ratio

In the final section, we analyse how the quality of the credit stock and the loans issued changes. For this purpose, we use the NPL ratio and vintage analysis.[31] Both when calculating the overdue debt ratio (NPL) for a certain date, and in the case of vintage analysis with the calculation of the level of non-payments on issued loans for a certain period, the fact of a delay in payment of a loan by 90 days or more is recorded in the credit registry, regardless of whether the debt was recognized by the bank as problematic or regulatory relief or a moratorium on bankruptcy could be applied to it. We identify possible sources of vulnerability using the NPL ratio and vintage analysis as described in the 'Methodology' section. We compute the NPL ratio in two alternative ways:

- as the share of borrowers who have at least one non-performing loan (by quantity);
- as the share of the stock of non-performing loans (by volume).

In the first case (**black line**, Figure 13a), the NPL ratio initially decreased from 2.7% in February 2019 to 1.6% in October 2020. It bounced back to 2.3% in April 2021 but later decreased to 1.8% in February 2022. In the second case (**black line**, Figure 13b), we observe a decrease in the NPL ratio, from 7.9% in February 2019 to 6% in February 2022.

Figure 13. Overall NPL ratio, %



Source: Bank of Russia, authors' calculations.

[31] See the 'Methodology' section for a detailed description.

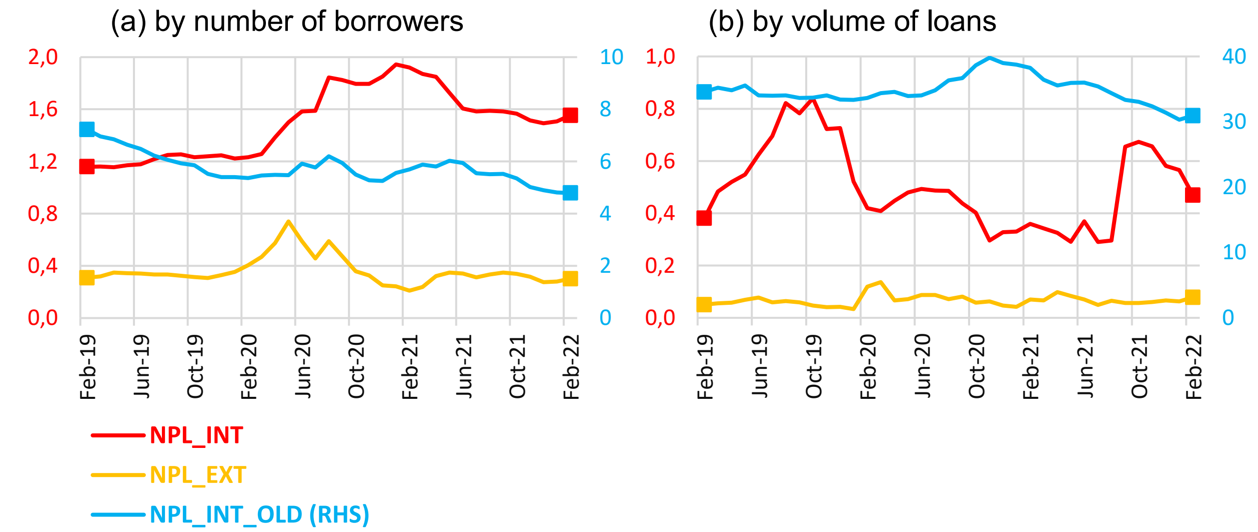
We additionally calculate the contribution to the NPL ratio by the following groups of borrowers (Figures 13a, 13b):

1) borrowers with credit histories longer than 12 months and with new credit taken during the last year (for simplicity, **NPL_INT**)
2) borrowers with credit histories longer than 12 months but with no credits newly taken in the last year (**NPL_INT_OLD**)
3) borrowers with credit histories shorter than 12 months, i.e., those which took their *first* loans in the last year (**NPL_EXT**)

In this analysis, we notice that borrowers with credit histories longer than 12 months and new credits taken in the last year (**NPL_INT**) play an increasing role. However, this trend can be explained by two factors: 1) the growth of the NPL ratio for this particular group; and 2) the growth in the number of borrowers of this type or the stock of debt of these borrowers (depending on the indicator used).

For this reason, we additionally analyse the NPL ratios of each group individually (Figures 14a, 14b). The NPL ratio decreases for borrowers with credit histories longer than 12 months but with no credits newly taken in the last year (**NPL_INT_OLD**), from 7.2% in February 2019 to 4.8% in February 2022 (**blue line**, Figure 14a) or from 34.6% to 31% if we compute the NPL ratio by volume (**blue line**, Figure 14b). For borrowers with credit histories longer than 12 months and with new credits taken during the last year (**NPL_INT**), the indicator increases from 1.2% in February 2019 to 1.6% in February 2022 when we compute the NPL ratio by quantity (**red line**, Figure 14a) and from 0.4% to 0.5% when we calculate it by volume (**red line**, Figure 14b). This may be explained by the slight decrease in delinquency rates among large borrowers and increase among smaller borrowers. For those borrowers who took their first loans in the last 12 months (**NPL_EXT**), the indicator fluctuates at very low levels during the whole period.

Figure 14. NPL ratio by group of borrowers, %



Source: Bank of Russia, authors' calculations.

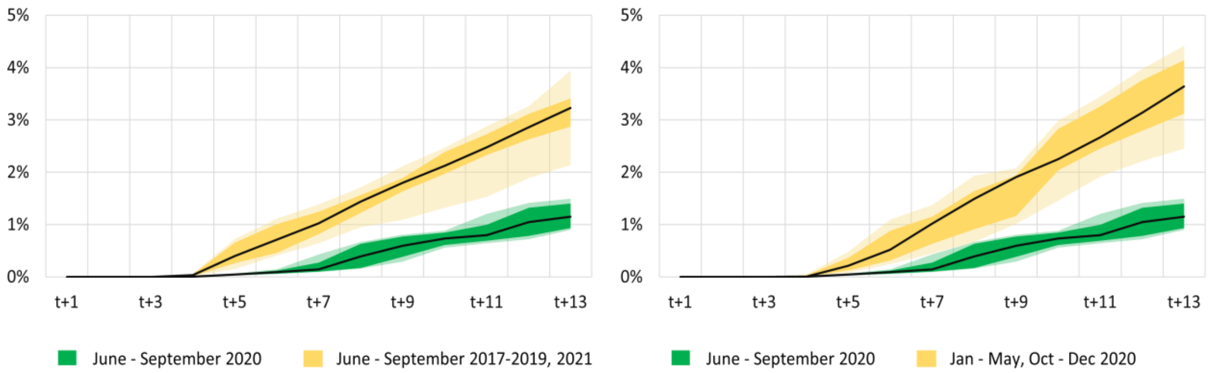
6.2. Vintage analysis

Using the framework of vintage analysis, we investigate how the quality of loans issued changes.[32] We especially focus on the period of the buoyant inflow of new borrowers between June and September 2020 (this period was particularly chosen because of a massive inflow of new borrowers, described in Section 5 'Changes in number and composition of borrowers').

The results show that the default rates on loans issued in this period are noticeably lower than those originating in other periods. For instance, the realised default rate on loans with origination dates between June and September 2020 was only 1.2% after 12 months (Figure 15), while it was more than 3% on loans issued in the corresponding periods of other years (June–September 2017, 2018, 2019, and 2021). This may be explained by the fact that a significant share of borrowers who initiated credit relations for the first time in this period did so by taking subsidised loans. As previously mentioned, the interest rates on these loans were much lower than the market rate, the debts may be forgiven under certain conditions, and government guarantees were provided. Such loans were rather a subsidy from the state: if certain conditions were met, companies did not independently repay the loan and interest on it, the state did this for them (Burova et al., 2023).

Therefore, the lower than average default rates probably do not imply that the loans issued between June and September 2020 were of better quality, but rather reflect features of subsidised loans, which represent a significant share of the loans provided in this period.[33] This, in turn, may distort the credit histories of these borrowers if it is not considered specifically by banks.

Figure 15. Realised default rates, %



Source: Bank of Russia, authors' calculations.

Notes: The solid line is the median, and the areas around are the 25–75th percentile and 10–90th percentile intervals.

[32] The limitations of vintage analysis should also be mentioned. For example, a higher default rate for a particular cohort does not necessarily mean that the quality of the loans issued in this cohort is lower. Higher default rates may also be a result of worse macroeconomic conditions after the loans were issued.

[33] In terms of number of loans, but not in terms of volume.

7. Conclusion

We use granular corporate credit registry data to address several issues. First, we decompose corporate credit growth into the intensive and extensive components, assess each of their contributions, and track how their roles changed over time. We perform the analysis for several subsamples (such as based on initial maturity buckets, i.e., short-term vs long-term lending or based on the borrowers' exposure to pandemic shock). Second, we analyse the changes in the number of borrowers based on their patterns of borrowing activities and first appearance in the credit registry. The results that we wish to emphasise are:

1) Newly created credit relations (the *extensive* component of credit growth) explain the majority (66%) of the variation in credit dynamics, while the rest is due to existing relations (the *intensive* component), calculated on a net basis. However, when the analysis is conducted on a gross basis, i.e., when we explicitly show the increase in the stock of debt on certain contracts and the decrease in the stock of debt for other contracts by the same borrower, the amplitude of the growth rate for existing borrowers (the *intensive* component) is considerably higher. Net-basis analysis is useful in understanding the net contribution of different types of borrowers to the overall dynamics of the corporate credit portfolio.
2) There was an increase in the *share of inactive borrowers* (those with open but unused credit lines) starting from April 2021. It is important to monitor this dynamics because the possible utilization of credit lines under the adverse economic conditions may entail additional credit risks for banks.
3) The *massive inflow of borrowers* at the beginning of the pandemic was sporadic and tightly linked to the state support measures. For example, the results suggest that, among borrowers who first appeared in the credit registry during the pandemic and took out preferential loans, only 12.6% took out loans again in the post-pandemic period, and only 7.4% of the initial number borrowed money under market conditions. This observation reconciles with previously obtained results (Bessonova et al., 2022). The role of preferential lending was significant during the acute period of the pandemic, but it decreased after.
4) The *lower default rates* of loans issued between June and September 2020 probably do not imply better quality of borrowers, but reflect the features of the subsidised loans actively issued during this period under the state support measures. This, in turn, may lead to a favourable bias in the credit histories of these borrowers if this is not monitored by banks.
5) We note the increasing contribution of borrowers with credit histories longer than 12 months and new credits taken in the last year to *NPL formation* starting in November 2021. This may be due to the growth of the NPL ratio for this particular group of borrowers, but it may also be due to the growth in the number of borrowers of this type and/or the volume of credit issued to these borrowers. Deeper investigation of this particular issue is necessary.

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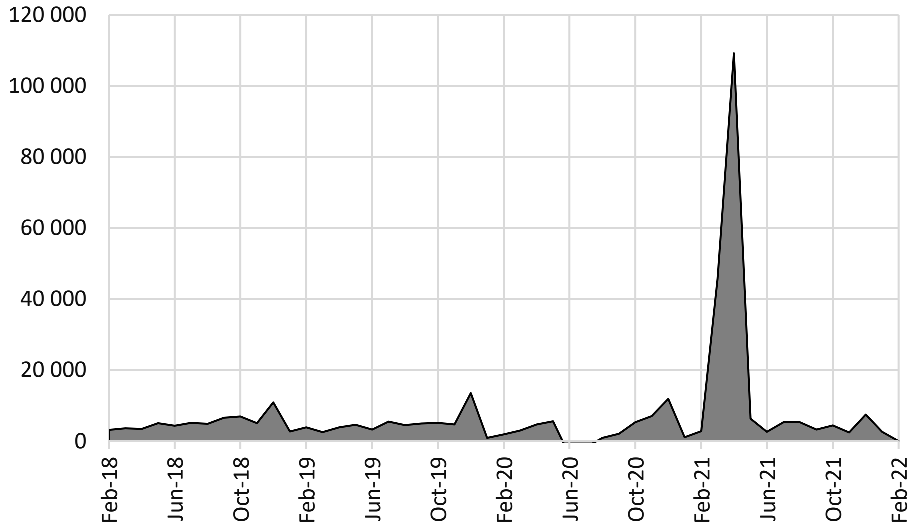
9. Appendix

A. Figures

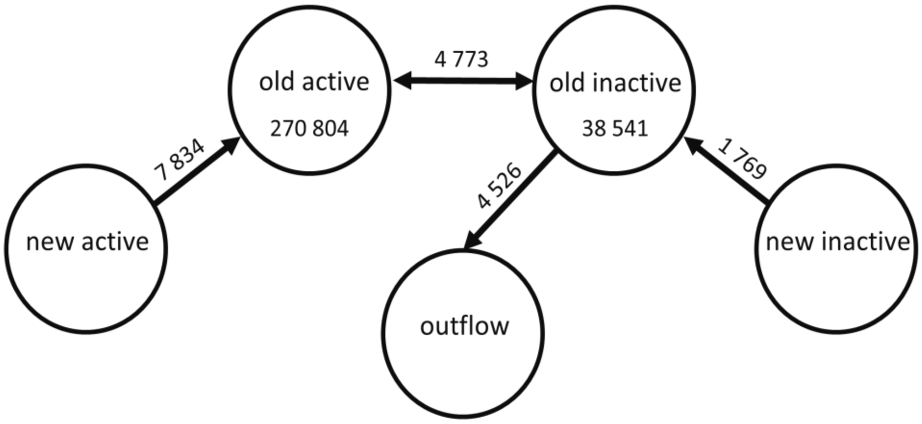
Figure A.1. Conversion of old active borrowers into old inactive



Source: Bank of Russia

Note: The conversion of borrowers is computed as: ∆Number of old_active borrowers$_t$ - new_active$_{t-1}$. It is assumed that new active borrowers become old active and that new inactive become old inactive, respectively.

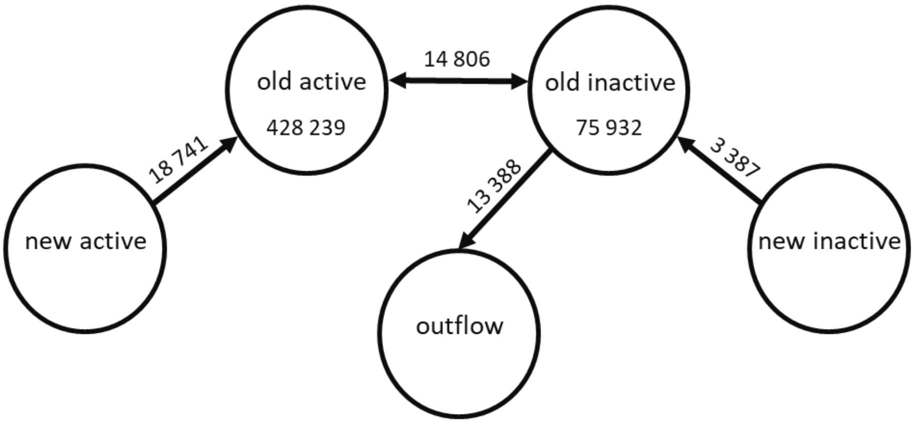
Figure A.2. Borrower flows (February 2018–May 2020)



Source: Bank of Russia, authors' calculations.

Note: The numbers within the circles represent the average values of the stock of loans. The one-way arrows represent the average flows from one group to another, while the two-way arrow between the old active and old inactive groups represents the average net flow from the former to the latter.

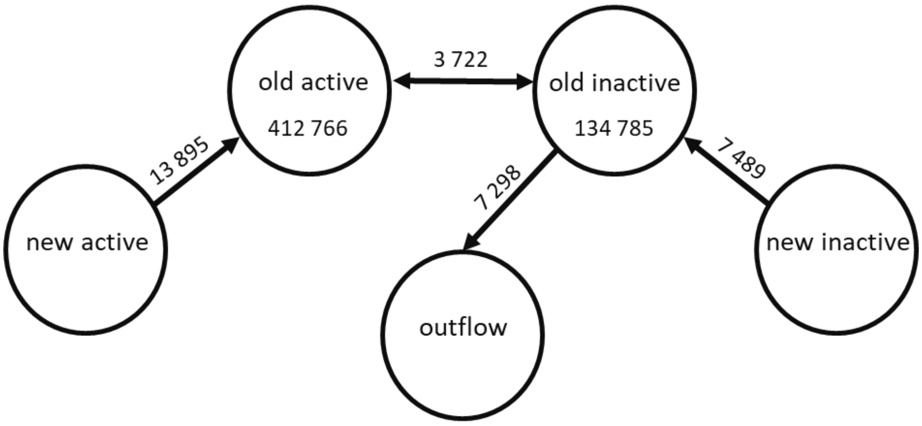
Figure A.3. Borrower flows (June 2020–May 2021)



Source: Bank of Russia, authors' calculations.

Note: The numbers within the circles represent the average values of the stock of loans. The one-way arrows represent the average flows from one group to another, while the two-way arrow between the old active and old inactive groups represents the average net flow from the former to the latter.

Figure A.4. Borrower flows (June 2021–February 2022)



Source: Bank of Russia, authors' calculations.

Note: The numbers within the circles represent the average values of the stock of loans. The one-way arrows represent the average flows from one group to another, while the two-way arrow between the old active and old inactive groups represents the average net flow from the former to the latter.

B. Table

Summary statistics

	mean	st.dev	min	max
Number of borrowers, #				
By components				
extensive preferential (ext_p)	30 820	53 540	379	157 273
extensive non-preferential (ext_np)	77 201	12 990	60 128	114 915
intensive preferential (int_p)	43 321	34 852	2 054	175 393
intensive non-preferential (int_np)	287 316	74 130	198 125	462 214
By type of borrowers				
new active	11 614	8 575	3 275	46 421
new inactive	3 152	2 504	719	10 121
old active	334 274	83 331	242 570	496 281
old inactive	63 288	40 180	19 294	181 903
Stock of Debt, trln RUR				
By components				
extensive preferential (ext_p)	0,22	0,18	0,01	0,57
extensive non-preferential (ext_np)	1,15	0,33	0,83	2,16
intensive preferential (int_p)	1,76	1,14	0,07	3,88
intensive non-preferential (int_np)	18,39	1,35	15,87	21,57
By type of borrowers				
new active	0,09	0,05	0,03	0,23
new inactive	-	-	-	-
old active	21,43	2,78	17,40	27,72
old inactive	-	-	-	-