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Environmental and Climate Factors of Corporate Lending in Russia

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Abstract

This paper analyses how Russian banks incorporate environmental and climate factors into corporate loan pricing. Our findings suggest that, in the absence of any regulation of "green" finance in Russia, banks do not take into account the impact of borrowers on the environment when setting interest rates. While Russian banks impose markups on interest rates for loans to more polluting firms, those markups are economically insignificant. The largest markups are observed among large private domestic banks, while state-owned banks impose the lowest. Specifically, the interest rate on loans from large private domestic banks to highly-polluting firms is only 0.04–0.07 percentage points higher than that for 'green' firms. These minimal differences in loan pricing indicate that under the current regulations, Russian banks do not significantly differentiate lending terms between 'green' companies and others.

We examine the heterogeneity of the price setting across different bank groups — state-owned, foreign-owned, or privately-held banks — considering the intensity of CO_2 emissions at the industry and firm level, as well as firms' export status. For the analysis, we exploit unique monthly loan-level data provided by the Central Bank of Russia's credit register, covering the period from 2017 to 2022, along with firm-level data on environmental fees for pollution of air, water and waste disposal.

JEL: G21, G28, Q56, D22, E43, L51, O13

Keywords: Corporate loan pricing, credit register, Russian banks, loan-level data, "brown" companies, "green" companies, environmental fees, pollution, state-owned banks, export

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1. INTRODUCTION

The climate-related agenda, particularly the development of the sustainable finance market, is gaining increasing attention in Russia from key regulators such as the Ministry of Economic Development of Russia and the Central Bank of Russia, as well as from large companies and banks.

Banks can play a unique role in promoting sustainable development, managing risks, and improving their reputational capital by engaging with greener firms even in the absence of specific banking regulation. Recent research highlights that banks can significantly support green innovation by lending to firms committed to climate-sustainable practices, particularly within high-emission sectors (Huang et al., 2022).

In addition, lending to companies with a lower carbon footprint is an effective risk management strategy. Climate change is increasing business risks, and banks that prioritize climate-responsible firms can reduce their exposure to physical and transitional climate risks (Srivastava et al., 2024; Mueller and Sfrappini, 2022). Studies show that companies with strong climate and environmental management practices are more resilient during crises, such as the COVID-19 pandemic, suggesting that their credit risk may decrease over time (Aristei and Gallo, 2024).

Prioritizing green companies allows banks not only to enhance their reputation capital, but also to attract socially responsible investors and clients who value sustainable development. This commitment can drive improvements in corporate governance and ethical practices in the banking sector, fostering a more sustainable financial ecosystem (Eccles et al., 2014; Pastor et al., 2023).

Recent research in green finance shows that it is generally easier for firms to secure funding for "brown" projects from banks rather than through the bond and equity markets internationally (De Haas, 2023; Beyene et al., 2021). This suggests that banks and firms can prioritize profit maximization over environmental concerns, potentially through opaque relationships (Giannetti et al., 2023; Gambacorta et al., 2023; Erten and Ongena, 2023). However, there is also evidence of a "green meets green" effect in international syndicated loans, where green banks, which charge higher interest rates to brown firms, offer substantial price discounts to 'green' firms (Degryse et al., 2023).

The literature on bank ownership commonly suggests that state-owned banks are generally less efficient than privately owned banks (La Porta et al., 2002). However, some studies show that state-owned banks can help stabilize the credit cycle during recessions by maintaining lending (Bertay et al., 2015). State-backed policies can play an important role in directing loans to 'green' firms, promoting investments in industries with a lower ecological impact that private banks may overlook due to their focus on short-term returns (Buchetti et al., 2024; Erten and Ongena, 2023). However, large state-owned banks may not fully account for transition risks, which could lead to mispricing of such risks (Huang et al., 2021).

Our research focuses on the following aspects.

1. Firm's environmental consciousness and loan prices. We aim to understand how Russian banks treat environmental and climate externalities in their corporate loan pricing. Due to the lack of reliable publicly available GHG emissions data at the firm level, we use various indicators characterizing the impact of firms on the environment, including the share of fuel costs in total material costs at the industry level, data from the state registry of firms with adverse environmental impact, and annual payments for adverse environmental impact at the firm level.

2. Rising government ownership of banks. We examine the role of state-owned versus private banks in lending. The increased dominance of Russian state-owned banks during 2010s necessitates a closer look on the role they play in lending to green vs. brown firms.[1]

Using data from The Russian credit register and the "4 TER" form (Fuel and Energy Resources) on pollution by Russian firms / industries, we track the composition of lenders over time to identify which banks are willing to lend to the firms in the most brown industries.

Our analysis shows that, in the absence of any regulation of "green" finance in Russia, banks impose markups on interest rates for loans to more polluting firms, but those markups are economically insignificant. Specifically, the interest rate on loans from large private domestic banks to highly polluting firms is only 0.04–0.07 percentage points higher than that for 'green' firms. The observed positive markups are too small to suggest that Russian banks apply any significant differences in lending terms between 'green' companies and others. In our regressions, state-owned banks tend to charge "brown" firms less than large private banks. Thus, in the absence of regulation of 'green' finance in the banking sector, there is little evidence that large state-owned banks are early movers forward in green finance.

The rest of the paper is structured as follows. Section 2 provides the details on the data

[1]During the 2010s, the share of the four largest banks in Russia increased sharply from about 40 to 70% of the banking system total assets.

sources we use in our research. Section 3 presents the methodological framework and the baseline estimation results. Section 4 concludes.

2. DATA

2.1 Stylized facts on the Russian banking system

Before analyzing the prospects of green lending in Russia, it is necessary to understand the major trends in the banking system over the last two decades: how the Russian banks operate and what type of regulation they face.

Following the global financial crisis of 2007–2009, the Russian banking system underwent substantial regulatory change: the Central Bank of Russia initiated the bad banks closure policy, which lasted for at least 5 years and resulted in the closure of approximately two-thirds of all operating banks due to revealed fraud (Goncharenko et al., 2022). By the end of 2021, the system consisted of around 400 banks but their contribution to the real economy risen significantly, reaching 110% of GDP.

Given the bad banks closure policy and recurrent economic crises, it is unsurprising that the Russian banking system has seen increasing concentration in recent years. Indeed, the mean Herfindahl-Hirschman Index (HHI), computed based on branch-level data on bank loan issuance, shows that the concentration in the system rose from 1,600 in mid-2013 to 2,500 in 2020, following the active phase of the policy (see Fig. 1) (Ivanova et al., 2024). This rise in concentration is largely attributed to state-owned banks, which have captured nearly 10% market share from domestic privately-held banks (see Fig. 2). The key question remains whether this increase in the government banking in Russia would be able to facilitate green lending in the future.

2.2 CO_2 emissions data and exporting status

One of the major obstacles for research on the green agenda in Russia is the lack of reliable, publicly available GHG emissions data at the firm level. A nationwide mandatory carbon reporting system, established by the Federal Law No.296 “On limiting greenhouse gas emissions”, began in 2023. Initially, only the largest enterprises in the fuel and energy sector and manufacturing[2], whose activities are associated with greenhouse gas emissions of 150,000 tons of CO_2 equivalent

[2] A company or individual entrepreneur falls under the Federal Law ”On Limiting Greenhouse Gas Emissions” if it meets the criteria specified in the Resolution of the Government of Russia dated March 14, 2022, No. 355.

per year or more, are required to report. In 2025, this requirement will extend to all companies emitting more than 50 thousand tons CO_2e.

Public accessibility to the reported data remains restricted. Companies often prefer to reference their Environmental, Social, and Governance (ESG) reports rather than make specific details of their emissions publicly available. This practice raises concerns about the transparency and accountability of corporate environmental stewardship.

To enforce compliance with the reporting requirements, the legislation includes a schedule of fines that will take effect starting July 1, 2025. These fines, outlined in Federal Law No. 218-FZ dated June 13, 2023, are tiered based on the type of entity in violation. Officials of regulated organizations may face fines ranging from 10,000 to 50,000 rubles. For individual entrepreneurs, the fines increase to a range between 50,000 and 150,000 rubles. Legal entities face the highest fines, with penalties ranging from 150,000 to 500,000 rubles.

Meanwhile, we have to rely on the available data, which is mostly available at a detailed industry level. For assessing industry-level emissions, we utilize data from the Russian State Statistical Agency (Rosstat) on the use of fossil fuels by industry (the "4-TER" form, which contains information about residues, fuel receipt and consumption of fuel, collection and use and waste oil products). This dataset is publicly available (www.fedstat.ru) for years 2005–2022. We use guidelines of the Ministry of Natural Resources and Environment to assess GHG emissions at the industry level, based on data on fossil fuel for combustion for stationary and mobile sources of emissions (Order No.300, June 30$^{\text{th}}$, 2015). This allows us to estimate levels of CO_2 and other GHG emissions (CH_4, N_2O) for each industry according to the classification in the 4-TER database for the years 2017–2022.

Our estimate of total industrial CO_2e emissions from combustion, based on the 4-TER data for 2018 is 1,214,867 kt of CO_2e. This compares closely to 1,246,002 kt of CO_2e reported for fuel combustion by energy industries, manufacturing, construction, and transport in Russia's National Inventory Report, differing by only 2%. However, our estimate does not cover several important emissions categories, such as fuel combustion in other sectors (primary residential), fugitive emissions from fuels, emissions from industrial processes and product use, agriculture, and waste. These additional categories collectively contribute 800 mln ton of CO_2e (see Figure 3).

Total CO_2e emissions at the industry level provide useful information for identifying the most polluting industries. However, to assess abatement potential, it is also important to relate emission levels to some measure of economic activity within each industry. We calculated an emission coefficient for each industry as a ratio of CO_2e emissions to the value of output in nominal terms. Using a detailed input-output table for 2018, we derived the value of output at the industry level (see Figure 4). There is significant variation in emission coefficients across industries. Some industries emit relatively small amounts of GHG emission but, due to small value of output, have high emission coefficients. In the most polluting sectors, high emission levels coincide with high levels of emission coefficients.

Only 11 industries are responsible for 85% of all GHG emissions from combustion: generation, transmission and distribution of electricity (OKVED2 code 35.1; 36.9% of total CO_2e from combustion); production of steam and hot water (thermal energy) (OKVED2 code 35.3; 11.7%); manufacture of ferrous metals (OKVED2 codes 24.1, 24.2, and 24.3; 10.5%); pipeline transport activities (OKVED2 code 49.5; 7.4%); manufacture of petroleum products (OKVED2 codes 19.2 and 19.3; 4.3%); extraction of natural gas (OKVED2 code 06.2; 3%); manufacture of base precious metals and other non-ferrous metals (OKVED2 code 24.4; 3%); manufacture of chemical products (OKVED2 code 20; 2.3%); manufacture of paper products (OKVED2 code 17; 2.1%); extraction of crude oil (OKVED2 code 06.1; 2.1%); and manufacture of other non-metallic mineral products (OKVED2 code 23; 1.6%).

These 11 most carbon-intensive industries are highlighted in the scatter plot, which depicts the logarithm of emissions coefficients and export shares for industries (see Figure 5). Export shares data for each industry is calculated based on the detailed input-output tables for 2018. Examining the scatter plot, one can observe a diversity of combinations of export shares and log emission coefficients across the 117 industries depicted. Although there is a tendency for the most brown industries to occupy north-eastern frontier of the scatter plot, not all highly polluting industries are export-oriented. However, if we focus on industries with an export share above 35%, the prevalence of most carbon-intensive industries becomes evident.

To achieve broader industrial coverage (expanding from 117 industries, as limited by input-output data to over 2,000), this study utilizes data from Rosstat's comprehensive database, "Basic Information on the Organization's Activities." This database covers data on all legal entities, irrespective of ownership structure, and includes information for branches and divisions operating outside Russia, as well as foreign organizational divisions within the Russian Federation. It includes data on production and shipment of goods, works, and services, along with associated production and sales costs. The database also captures expenses related to material purchases, such as raw materials, fuels, semi-finished products, and components.[3] We use share of fuel costs (coal, oil products and natural gas) in total material costs as a proxy for CO_2 emissions and share of exports in total sales.

Moreover, there are two potential sources of ecological data at micro level. We use two datasets for emission proxies. The State Registry of Objects with Adverse Environmental Impact is a database established by the Russian Federation's environmental governance according to the Articles 69 of Law No. 7-FZ "On Environmental Protection," as well as by the government decree No. 830, dated May 7, 2022, titled "Rules Governing the Establishment and Maintenance of the State Registry of Objects with Adverse Environmental Impact."

This registry, overseen by Rosprirodnadzor holds information on emissions and discharges of harmful substances and greenhouse gases (GHGs) that are considered harmful (in tonnes of CO_2 equivalent). While updates are required annually, the data lacks a clear indication of the reference year. As of the latest data, the registry consists of approximately 385,000 objects that have an adverse environmental impact. These are categorized into two levels: 117,000 objects at the federal level and 268,000 at the regional level. The registry lists 39,000 firms that report emissions of CO_2 equivalent greater than zero.

Another essential source of information about emissions and ecological status at micro level is the amount of fees on emission of harmful substances (source: the Central Bank of the Russian Federation payment system). Every company registered as an object with adverse impact is required to pay for its impact on the environment. The value of the environmental payment is proportionate to the amount of pollution, though rates for different harmful pollutants vary significantly. We use this data as a proxy for firm-level emissions. This data covers the period from 2017 to 2022. The total annual fees in our dataset surpass the corresponding annual totals reported by the Accounts Camber (Accounts Chamber, 2021) (see Figure 6).

The database contains detailed information about different types of fees: flaring, air pollution, releases of harmful substances to water, and waste disposal. We see that the largest category of emissions is waste disposal. Fee on air emissions do not represent a substantial part of total fees on emission of harmful substances, see Figure 7.

[3] Detailed information regarding the underlying Form No. 1-enterprise used in data collection can be found in Rosstat Order No. 29 (January 25, 2024).

2.3 Firm-, bank-, and loan-level data

In this paper we combine several datasets. All variables, including proxies characterizing the impact of firms on the environment, are listed in Table 1.

First, to identify bank-firm lending relationship, we use monthly data from the Russian credit registry (the Bank of Russia's reporting form No. 0409303). This data covers the period from January 2017 to December 2022 and contains detailed information about loans, including interest rates, loan amounts, maturity, and loan quality score. The average interest rate (11.5%) significantly exceeds the average key interest rate over the analyzed period, see Table 2. Average ex-ante loan quality score is close to 2 (where 1 means the lowest credit risk and 5 stands for the highest credit risk, almost worthless loans), see Figure 8.

Second, given the limitations of firm-level data, we do not define a firm as "brown", but instead work with continuous variables that approximate a firm's climate and ecological footprint. In our regression models, we consider several proxies characterizing the impact of firms on the environment: the share of fuels in total material costs ($Fuel.Share$) at the detailed industry level, data from the state registry of firms with adverse environmental impact ($CO_2.Eq$), and data on annual payments for adverse environmental impact on the firm level ($AirFee$, $Emission.Fee$), see Section 2.2 for description.

Third, regarding different types of bank ownership, we consider the following six ownership groups: $Big.STATE$ ($Other.STATE$) contains the state-owned banks within (outside of) the top-30 of all banks by total assets, $Big.FOREIGN$ ($Other.FOREIGN$) includes foreign-subsidiary banks within (outside of) the top-30, and $Big.PRIVATE$ ($Other.PRIVATE$) includes domestically privately-owned banks within (outside of) the top-30. State and private banks are defined by their controlling interest (source: SPARK Interfax). The $Big.PRIVATE$ group is used as the reference. Applying this categorization to the loan-level data, we observe that 39% of all loans are granted by the big state-owned banks, while big foreign banks hold only a 3% share, on average. When examining the 10 most brown industries (2-digit OKVED2 classification), we find that these industries primarily receive loans from state-owned banks, see Figure 9. For instance, firms in the electricity industry—the most polluting sector of the economy—receive 76% of all loans from state-owned banks. This trend is consistent across the next eight industries,with exception of the food products industry, where only 37% of loans come from government banks, while 52% come from foreign-owned banks.

Fourth, firm-level data with annual frequency covering the period from 2017 to 2022 sourced from the SPARK database. We assume that banks can imply different interest rates to firm not only based on emission levels but also due to other firm characteristics. Including firm controls helps to capture demand-side factors affecting the establishment of bank-firm relationship. For each firm in our sample we calculate the following four variables to capture basic characteristics: firm size (logarithm of total assets), leverage (ratio of total liabilities over total assets), return on assets (ROA), and firm age. ROA is calculated as the ratio of earnings before interest and taxes (EBIT) to total assets. The firms have a high level of debt, with an average leverage ratio of nearly 31%. Firms with bank loans show an average profitability ratio of 8%, with considerable variation (see Table 2).

As described in Section (2.2), in the absence of firm-level emissions data, we use two databases as proxies: the state registry of objects with adverse environmental impact and data on annual payments for adverse environmental impact. The average firm in our sample has a low level of both CO_2 equivalent emissions and emission fees relative to sales.

Additionally, we include productivity levels, categorizing firms into leaders, followers, and laggards based on productivity deciles within narrowly defined industries. We begin by assessing labour productivity for each firm in our sample, then compute the gap between each firm's productivity level and the highest productivity level in its industry (175 narrowly defined industries). Firms are categorized into 10 productivity deciles for each industry and year, with 10 representing the most productive firm and 1 -– the least productive. For regression analysis, we use three groups of firms: leaders (the 9^{th} and 10^{th} deciles), followers (the 6^{th}, 7^{th} and 8^{th} deciles), and laggards (the remaining five deciles).

After matching all datasets, excluding subsidized loans and trimming the sample for outliers (1 and 99 percentiles over a year and narrowly defined industries) we have 246,000 firms having relationship with 541 banks.

3. BASELINE ESTIMATION RESULTS

With the described data at hand, we are ready to examine whether banks apply a markup or discount to loan interest rates for firms from more or less "brown" industries, conditional on the industries' export shares. To answer this question, we run the following regressions:

$$
\begin{aligned}
Y_{b,f(i),t} = \alpha_t + \beta_1 Emission.Proxy_{i,t} + \beta_2 Export_{i,t} + \Big(Emission.Proxy_{i,t} \times Bank.OWN_{b(g),t}\Big)' \Gamma(g) \qquad (1) \\
+ \Big(Emission.Proxy_{i,t} \times Export_{i,t} \times Bank.OWN_{b(g),t}\Big)' \Theta \\
+ Bank.OWN'_{b(g),t} \boldsymbol{\Omega} + \boldsymbol{\Psi}_{\mathbf{b},\mathbf{t}} + Firm.Control'_{f,t} \boldsymbol{\Phi} \\
+ Loan.Control'_{b,f,t} \boldsymbol{\Xi} + \varepsilon_{b,f(i),t}
\end{aligned}
$$

where $Y_{b,f(i),t}$ represents the loan interest rate granted by bank b to firm f in industry i at month t, for the period t from January 2017 to December 2022. α_t is time fixed effect. $Emission.Proxy_{i,t}$ are (i) share of fuel costs in total costs at the industry level, (ii) ratio of GHG emission (CO_2 equivalent kg per) year over sales at the firm level, (iii) fees on air emission of harmful substances over sales at the firm level, (iv) fees on all emission of harmful substances over sales at the firm level. $Export_{i,t}$ is the ratio of export to output at the industry level. $Bank.OWN_{b(g),t}$ is a set of indicator variables reflecting bank b's ownership type g: state-owned banks inside (outside of) the top-30 banks by total assets, foreign-subsidiary banks inside (outside of) the top-30, and domestic privately-owned banks inside (outside of) the top-30, resulting in six groups in total. The $Big.PRIVATE$ group is the reference. $Firm.Control'_{f,t}$ $Loan.Control'_{b,f,t}$ are the control variables at the firm- and loan levels, as discussed in the data section (see Section 2.3). To control for technological level differences, we also include dummies for productivity groups. We do control for firm fixed effects due to data limitations.

Our data does not include applications for new loans, so the results likely reflect an equilibrium in the loan market. To account for demand versus supply factors, we saturate the model with $firm \times month$ or $bank \times month$ fixed effects where necessary. Firm fixed effects would drop emission and export regressors, so, we include some firm time–varying characteristics (size, leverage, profitability and age) to capture demand-side effects[4]. We include $bank \times time$ fixed effects to control for all banks' time-varying characteristics. $\varepsilon_{b,f(i),t}$ represents the regression error. The regression model includes industry dummies (9 broad groups) and regional dummies (8 federal districts).

[4]Due to the lack of data, we do not control for the firm ownership status (state-owned or privately-held), though we plan to include this data in our future work.

Our baseline hypothesis is that, as the carbon regulation was not yet adopted in 2017-2022, banks do not price the CO_2 emissions by firms on average ($\beta_1 = 0$ statistically). However, they may set markups to interest rates for more polluting firms in more exporting industries ($\Theta_g > 0$ for $g = 1...6$). This is because export may face carbon regulation abroad following the Paris agreement of 2015. We also hypothesize that banks set these markups deferentially depending on their ownership. For example, foreign-owned banks are, by nature, more aware of the carbon regulation in their home countries than domestic banks, whether state- or privately-held. Finally. we remain neutral regrding the potential sign of the regression coefficient associated with export status. A positive coefficient may imply that banks impose higher interest rates on exporters, potentially due to the perceived risks or costs involved in international trade. On the other hand, a negative coefficient might suggest that exporters benefit from lower interest rates, possibly reflecting relationship lending with specialised banks (Paravisini et al., 2023), as well as the stability and profitability associated with their export activities (Goldbach and Nitsch, 2014) ($\beta_2 >< 0$).

To reduce the risk of omitted variables bias, we control for loan characteristics, including ex-ante loan quality assessment, maturity, and loan size. This is important because price discounts or markups for belonging to more or less "brown" industries could be confounded by whether the industries export, whether the firms are profitable or not, and whether they have higher or lower leverage, among other factors.

The estimation results of equation (1) are presented in Table 3. Columns (1)–(3) contain the results for $Y_{b,f(i),t}$, which represents the loan interest rate. We use the fuel share as a measure of CO_2 emissions.

Column (1) of Table 3 shows that the estimated coefficient on the emission indicator variable is positive, close to zero in size, and statistically significant. This suggest that, on average, banks did price the climate and ecological factors of firms during the sample period before the adoption of carbon regulation in Russia. However, the standardised coefficients on the emission equals to 0.018. This means that an increase in fuel share by one standard deviation will result in an expected increase in the interest rate of 0.081 percentage points ($4.5 \times 0.018 = 0.081$p.p., where 4.5 p.p. is the standard deviation of the interest rate variable, see Table 2), which is economically insignificant. Table 4 presents the coefficients for our control variables, which generally align with economic intuition.

However, when analyzing the heterogeneity of the "brown" industry effect across bank ownership types, we find a non-trivial result. Compared to the reference group (big privately-held banks) and after controlling for all bank-, firm-, and loan-level characteristics, three bank ownership types impose discounts for belonging to "brown" industries—these are big and other state-owned banks and other private banks—while the other two groups do not significantly differ from the benchmark group.

Furthermore, the estimated coefficient on the export ratio itself is positive, moderately sized, and highly significant. This contradicts our expectations, indicating that more export-oriented industries have higher interest rates on loans from banks.

Finally, when examining the triple interactions, as suggested by equation (1), we obtain the most interesting result: each bank ownership group applies a different markup to the loan price if the loan is granted to a more polluting firm that has more export specialization.

Overall, in the absence of domestic carbon regulation, our results provide limited evidence that local banks do price higher CO_2 emissions when granting loans to more export-oriented firms.

In related research, (Erten and Ongena, 2023) investigate the impact of a firm's environmental footprint on loan prices. They use both direct and indirect measures of environmental costs and find that banks charge an average markup of 0.9 percentage points for environmentally damaging firms. In contrast, our results suggest that the markups in Russia are significantly smaller.

4. EXTENSIONS AND ROBUSTNESS CHECKS

4.1 New borrowers

The significant coefficients on climate and ecological factors could result from specific relationships between banks and borrowers. To address this, we examine a subsample of new borrowers, excluding any credit history of a borrower may have with a bank. Table 8 reports the estimation results for this subsample. We define new borrowers as those to whom a bank has not previously extended credit. The structure of the table coincides with the one in the baseline results (see Section 3).

Although the sample size drops significantly, we still have 158,935 observations at the loan level. The estimates in columns (1)–(3) strongly support the baseline results. Furthermore, they provide evidence that even firms with no prior relationship with a bank, have to pay a markup on loans if they are "brown", though this markup remains very small. However, the signs and significance of the double interactions change: there is a difference only between big private banks and state banks in terms of interest rate for new borrowers from more brown industries.

4.2 Big-4 banks

Credit market concentration in Russia is another important factor that could influence interest rate setting. Here, we exclude loans issued by the four biggest banks. Compare to the previous robustness check, the sample also decreases but to a less extent (by almost 25%).

The estimates in columns (1)–(3) in Table 9 also support the baseline results that the "brown" firms have to pay more for bank loans, though the size of this markup is small and less than in baseline results. However, signs for double interactions changed for big state-owned banks: there is a positive difference between big private banks and big state banks (except big-4 banks) in terms of interest rate for borrowers from more brown industries.

4.3 Different time span

Since March 2022 Russian economy has experienced negative shocks that could potentially affect how banks set interest rates. To mitigate this effect, we examine a subsample of newly issued loans up until December 2021. Table 10 reports the results for this subsample. We observe that results remain largely consistent: loans from 2022 do not significantly impact the baseline results.

To isolate the role of state banks in cushioning the COVID-19 shock in Russia, we exclude subsidized loans from the baseline regression estimation. Evidence from the literature suggests that private investors committed to green financing rebalanced their portfolios away from green firms following the COVID-19 shock in order to sustain higher profits (Döttling and Kim, 2024). Here, we rigorously exclude COVID-19 loans and their potential effect by considering the time until December 2019. The estimation results for this subsample are shown in Table 11. While the baseline show statistically significant markups, they are economically insignificant. In this case, the coefficients on climate and ecological factors become statistically insignificant.

4.4 Additional controls on firm efficiency

Having established significant climate and ecological coefficients, we now question whether there are unobserved firm characteristics correlated with ecological impact and emission level. For instance, a firm with less technologically advanced and older equipment may have less effective production and greater GHG emissions, discharges of harmful substances, and waste disposal. We lack plausible data on equipment at the firm-level. To test this hypothesis, we include productivity deciles instead of productivity groups to capture the potential heterogeneity between firms in terms of technological level and re-run the regressions with these dummy variables. The estimation results appear in Table 12. In columns (1)–(3), we find significant coefficients on emission variable, though the size of this markup remains small. The main results remain the same.

4.5 Other proxies on GHG

When using the share of fuel costs in total costs at the industry level, we obtain average constant markup estimations for each firm within an industry. However, Figure 10 shows significant heterogeneity across firms within a single industry. Therefore, to achieve more robust results, we attempt to use more granular data on ecological impact. In Tables 5, we see the estimated results for regression with CO_2 equivalent as the emission proxy. The results are rearly identical to the previous results. We obtain a positive, significant coefficient on the emission proxy, though it remains economically small.

Table 6 presents the results using the fee on air emission as the explanatory variable for emissions. The results are consistent: a positive markup is observed, though small in terms of standardized coefficients.

In Table 7, we have the estimated results for regression using the fee on all emissions as the emission proxy. The corresponding results are statistically insignificant, suggesting that general ecological status does not influence banks' decisions on corporate interest rates.

Overall, we find that the baseline result holds across various robustness checks. Firms with higher CO_2 emissions face higher interest rates on loans, though the size of these markups remains economically small.

5. CONCLUSION

This paper examines how Russian banks incorporate climate and environmental factors into corporate loan pricing. Our findings suggest that in the absence of regulations of "green" finance in Russia, banks do not take into account the impact of borrowers on climate and environment when setting interest rates. Although Russian banks impose markups on interest rates for loans to more polluting firms, these markups are economically insignificant. Specifically, interest rates on loans from large private domestic banks to highly polluting firms are only 0.04-0.07 percentage points higher than those for 'green' firms. These minimal differences indicate that Russian banks do not offer significant differences in lending terms between 'green' companies and others.

We also explore the heterogeneity in the pricing of different types of banks - state-owned, foreign-owned, and privately held - considering the intensity of CO_2 emissions at the industry and firm levels, as well as the export status of the firms. Our analysis utilizes unique monthly loan-level data from the Central Bank of Russia's credit register, covering the period from 2017 to 2022, along with firm-level data on environmental fees for pollution of air, water and waste disposal.

This paper contributes to the literature on green finance in several ways. We provide evidence that Russian banks do not price environmental and climate risks in their corporate loan pricing models to the same extent as banks in countries with more stringent environmental regulations. We show that the small markups imposed by banks are insufficient to incentivize firms to adopt greener practices.

To develop "green" financing and reduce the environmental and climate impact of businesses, the implementation of stricter rules and additional incentives may be necessary. This will help banks properly assess environmental and climate risks. Policies requiring banks to consider company environmental and climate performance can contribute to the transition to a nature-preserving economy. Increasing transparency and improving access to data on companies' climate and environmental performance will also allow for more accurate assessment of environmental and climate risks.

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FIGURES

Figure 1. Time evolution of regional credit market concentration (HHI)

Note: HHI is computed for each and every region in each month as a sum of squared shares of each bank's branch credit in total region credit. Credit = loan issued by the bank's branch to non-financial firms.

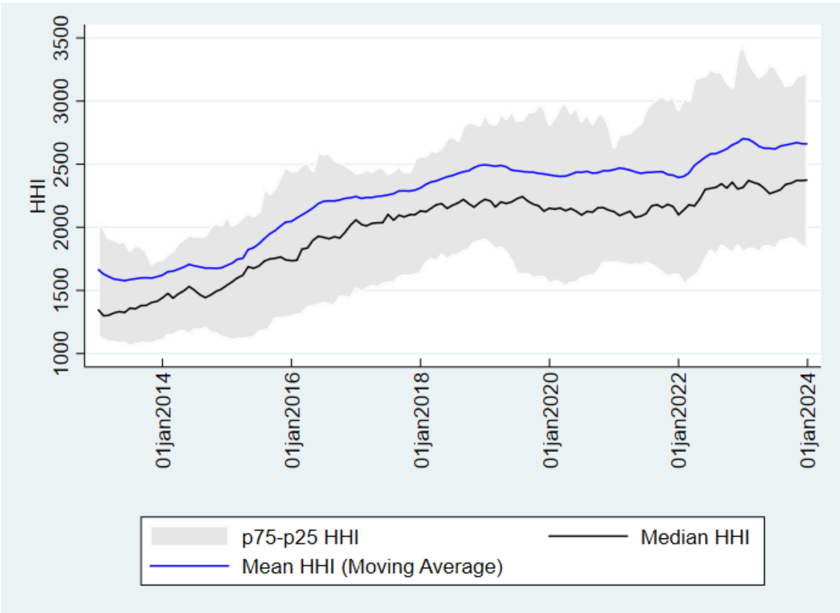


Figure 2. Concentration of assets across bank ownership types

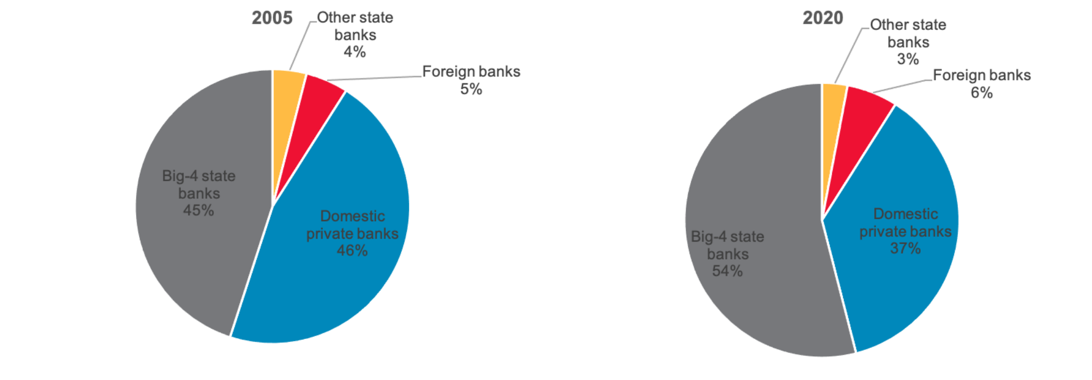


Figure 3. Russian National inventory report 2018: CO2e emissions

1. Energy	A. Fuel combustion	1. Energy industries	825 088,89
		2. Manufacturing, construction	166 836,30
		3. Transport	254 077,22
		4. Other sectors (Residential)	207 834,50
		5. Other	19 597,71
	B. Fugitive emissions from fuels		205 798,81
2. Industrial processes and product use			243 282,58
3. Agriculture			112 824,98
5. Waste			98 240,62

1 246 002,40 kt CO2e

Figure 4. Volume of CO2e emissions and emission coefficients

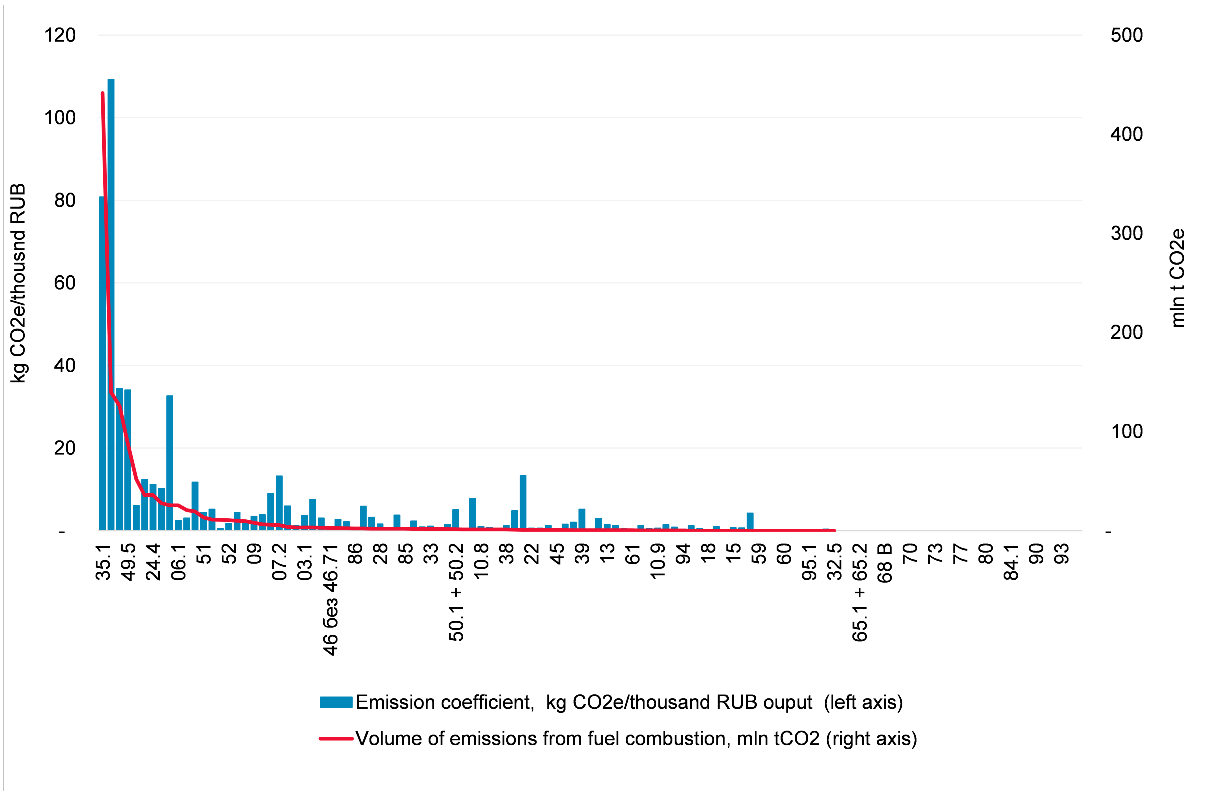


Figure 5. Export shares and emission coefficients

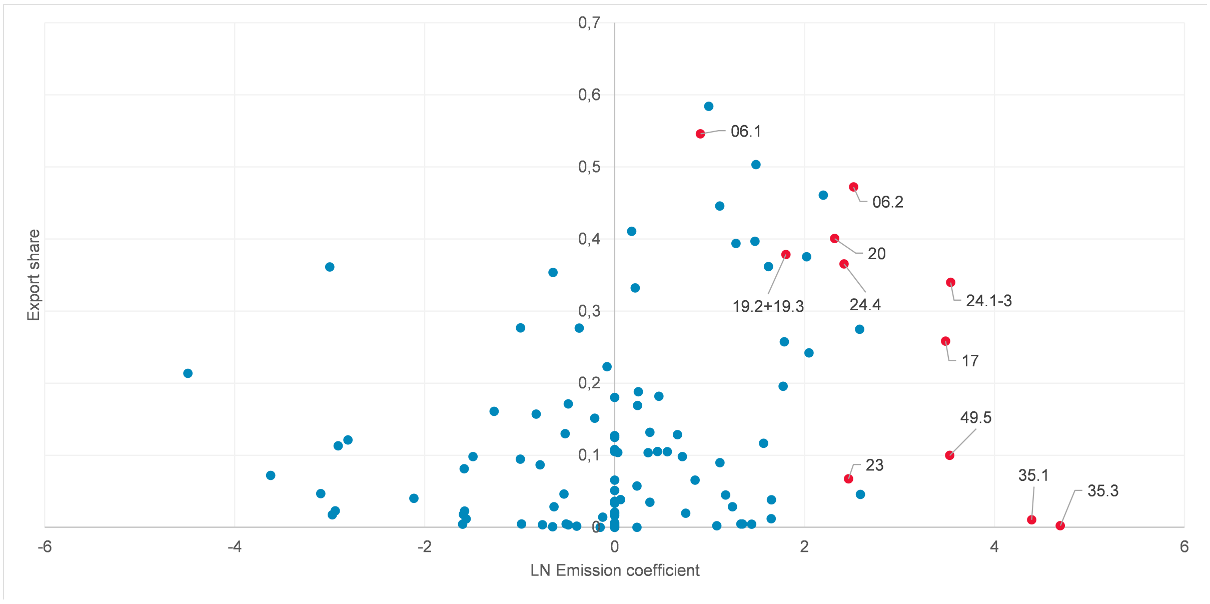


Figure 6. Fee data comparison: Bank of Russia and Accounts Chamber

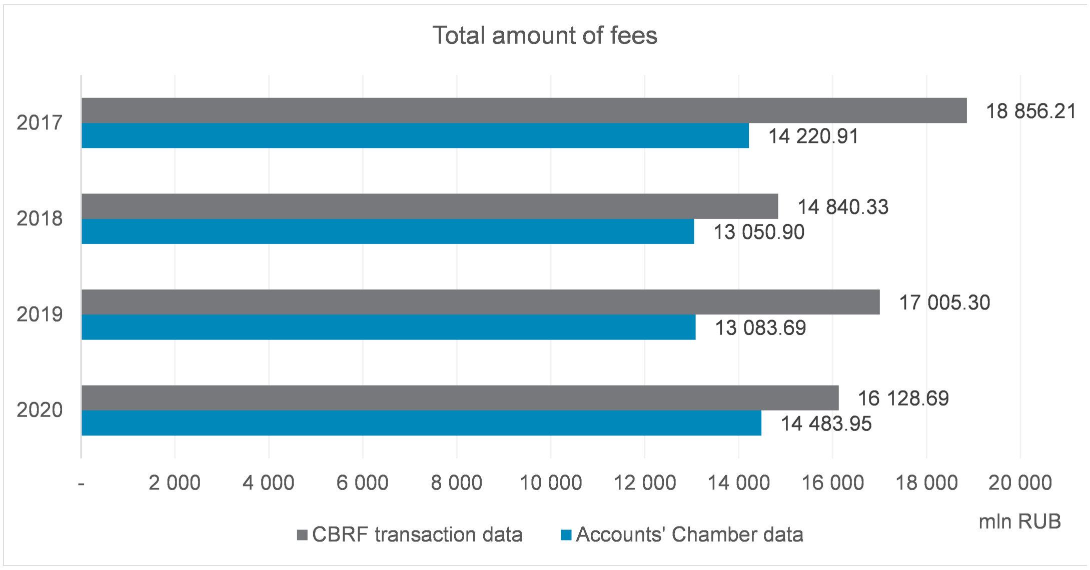


Figure 7. Fees on emission of harmful substances (mln RUB)

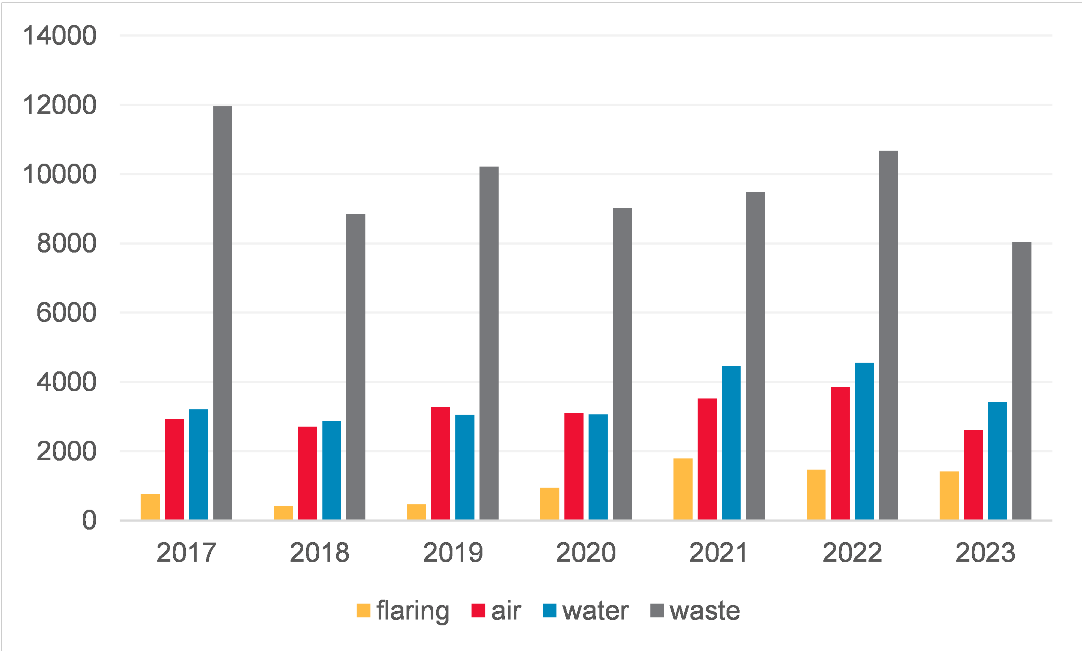


Figure 8. Credit register data: loan quality score (1=the best quality, 5=the worst quality)

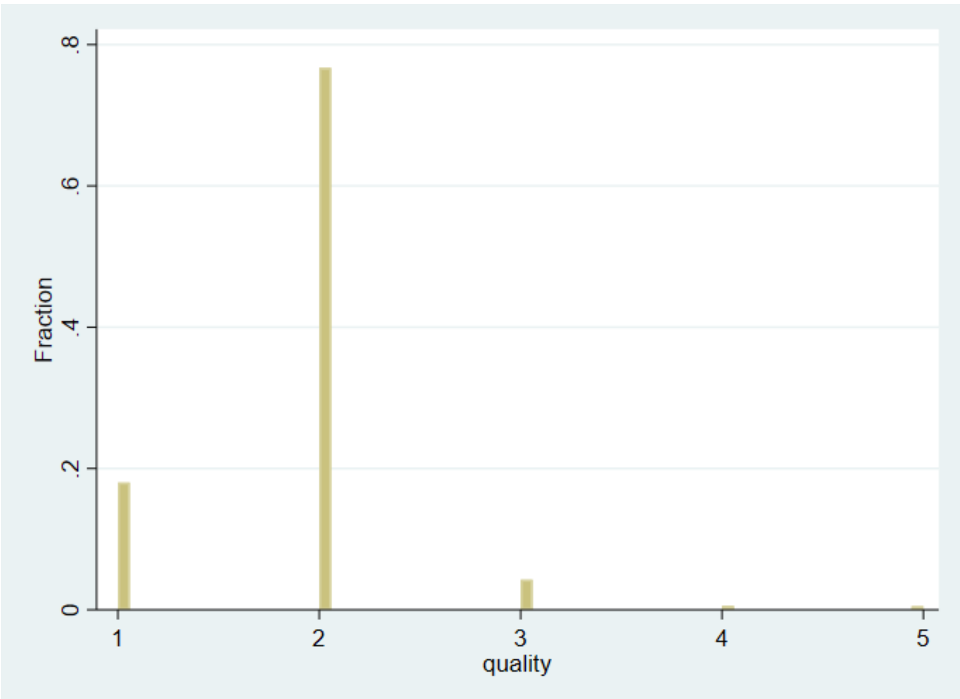


Figure 9. Average share of new loans by type of a bank (state, foreign, other) in 2018-2021 for "brown" industries

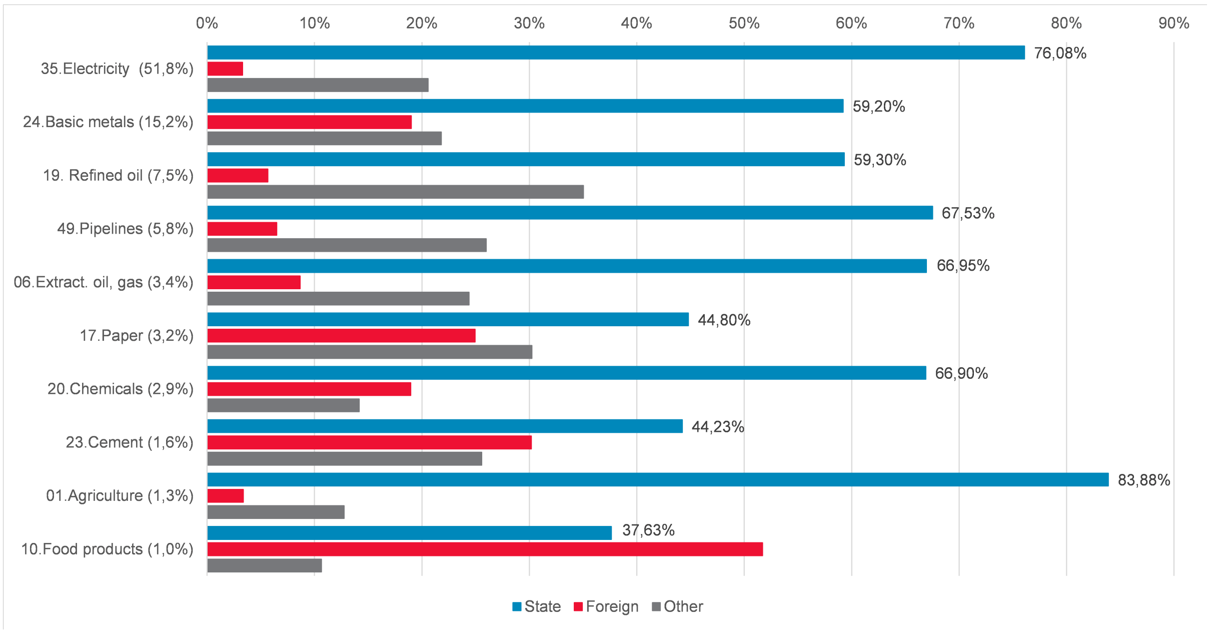
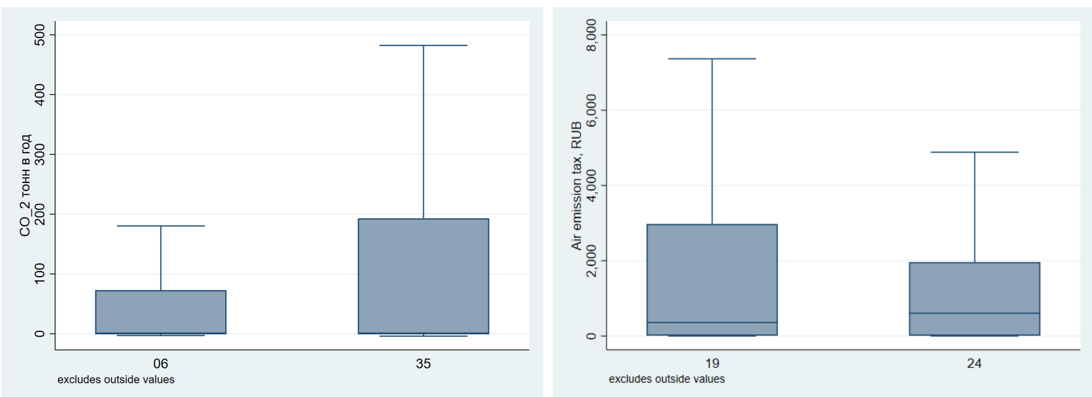


Figure 10. Heterogeneity of emission within industries: CO_2 equivalent and fee on air emissions



TABLES

Table 1. The list of variables for the regression analysis

Notation	Definition	Level	Period	Source
Emission proxy data				
Fuel.share	$\frac{\text{Fuel costs}}{\text{Total material costs}}$	Industry level	2017–2022 Annual	Rosstat
CO_2Eq	$\frac{CO_2\text{ equivalent (kg)}}{\text{Sales (RUB)}}$	Firm level	Cross-section	Rosprirodnadzor Income statement
Air.Fee	$\frac{\text{Emission fees (Air)}}{\text{Sales}}(\%)$	Firm level	2017–2022 Monthly	Bank of Russia Income statement
Emission.Fee	$\frac{\text{Emission fees (Total)}}{\text{Sales}}(\%)$	Firm level	2017–2022 Monthly	Bank of Russia Income statement
Loan controls				
Interest rate	Interest rate on new loan (%)	Loan level	2017–2022 Monthly	Bank of Russia
Volume	log of loan volume	Loan level	2017–2022 Monthly	Bank of Russia
Maturity	Loan maturity (days)	Loan level	2017–2022 Monthly	Bank of Russia
Quality group	Ex-ante loan quality score (1 – the lowest credit risk, 5 – the highest credit risk)	Loan level	2017–2022 Monthly	Bank of Russia
Firm controls				
Size	log of Total assets	Firm level	2017–2022 Annual	Balance sheet
Age	Firm age (in years)	Firm level	Fixed at 2019 Cross-section	Register of Legal Entities
Leverage	$\frac{\text{Total liabilities}}{\text{Total assets}}$	Firm level	2017–2022 Annual	Balance sheet
ROA	$\frac{\text{EBIT}}{\text{Total assets}}$	Firm level	2017–2022 Annual	Income statement Balance sheet
Productivity	Leaders, followers, laggards by labor productivity deciles	Firm level	2017–2022 Annual	Balance sheet
Export	Ratio of export to output	Industry level	2017–2022 Annual	Rosstat

Table 2. Descriptive statistics at the loan level

	Mean	Median	SD	Min	Max
Loan level					
Interest rate	11.47	11.83	4.50	0.01	35.40
log of loan volume	15.17	15.32	2.17	4.10	20.65
Maturity	428.0	317.0	411.6	0.00	3399.0
Quality group	1.85	2.00	0.54	1.00	5.00
Industry level					
Fuel share	0.04	0.02	0.08	0.00	1.00
Export share	0.02	0.001	0.06	0.00	1.00
Bank ownership types					
Big-4 state banks ($Big.STATE$)	0.39	0.00	0.49	0.00	1.00
Other state banks ($Other.STATE$)	0.01	0.00	0.07	0.00	1.00
Big foreign banks ($Big.FOREIGN$)	0.03	0.00	0.17	0.00	1.00
Other foreign banks ($Other.FOREIGN$)	0.01	0.00	0.08	0.00	1.00
Big private banks (reference group)	0.41	0.00	0.42	0.00	1.00
Other private banks ($Other.PRIVATE$)	0.15	0.00	0.36	0.00	1.00
Firm level					
log of total assets ($Firm.Size$)	18.75	18.62	2.19	11.96	25.16
Age	10.95	10.00	6.56	2.00	30.00
Leverage	0.31	0.25	0.25	0.00	2.29
ROA	0.08	0.05	0.15	–1.73	1.15
Emission fees (Air) / Sales (%)	0.0002	0.00	0.002	0.00	0.06
Emission fees (Total) / Sales (%)	0.001	0.000	0.01	0.00	0.23
CO_2 equivalent / Sales (kg/RUB)	0.001	0.00	0.005	0.00	0.20

Table 3. Baseline regression results: bank ownership types, fuel share, and the industries' export shares

Note: The table reports the estimates of equation (1). The estimation period is January 2017 to December 2022. The data covers 246,000 firms and having relationships with 541 banks. All necessary subproducts of the triple interactions are included but not necessarily reported for the sake of space. Time fixed effects are included.

	(1)	(2)	(3)
Fuel.share (*industry-level*)	1.057***	1.049***	1.026***
	(0.118)	(0.118)	(0.120)
Export.share (*industry-level*)		0.832***	0.623***
		(0.120)	(0.241)
Big.STATE × Fuel.share	-1.885***	-1.891***	-1.949***
	(0.140)	(0.140)	(0.143)
Other.STATE × Fuel.share	-2.769***	-2.766***	-3.015***
	(0.383)	(0.379)	(0.354)
Big.FOREIGN × Fuel.share	-0.040	-0.045	-0.299
	(0.565)	(0.569)	(0.569)
Other.FOREIGN × Fuel.share	-0.790	-0.800	-0.057
	(1.000)	(1.002)	(1.068)
Other.PRIVATE × Fuel.share	-0.362*	-0.379**	-0.487**
	(0.193)	(0.192)	(0.194)
Big.STATE × Export.share × Fuel.share			4.969
			(3.094)
Other.STATE × Export.share × Fuel.share			47.276**
			(20.604)
Big.FOREIGN × Export.share × Fuel.share			22.089***
			(7.583)
Other.FOREIGN × Export.share × Fuel.share			-69.986*
			(36.963)
Other.PRIVATE × Export.share × Fuel.share			7.873**
			(3.197)
Constant	23.568***	23.562***	23.563***
	(0.117)	(0.117)	(0.117)
Obs.	2,385,658	2,385,658	2,385,658
R^2_{adj}	0.640	0.640	0.640

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank-firm level and appear in the brackets under the estimated coefficients.

Table 4. Baseline regression results: bank ownership types, fuel share, and the industries' export shares. Coefficients of control variables.

Note: The table reports the estimates of equation (1) for control variables. The estimation period is January 2017 to December 2022. The data covers 246,000 firms and having relationships with 541 banks. Wholesales&Retail industry is set as a reference group. Central Federal district is set as a reference group. Quality=1 is set as a reference group. Leaders is set as a reference group.

	(1)	(2)	(3)
Firm Level			
Construction	0.301***	0.304***	0.304***
	(0.026)	(0.026)	(0.026)
Forestry&Agriculture	-2.003***	-2.026***	-2.047***
	(0.056)	(0.056)	(0.056)
Hotels&Restaurants	-1.424***	-1.422***	-1.423***
	(0.047)	(0.047)	(0.047)
Manufacturing	-0.059***	-0.110***	-0.090***
	(0.017)	(0.019)	(0.019)
Mining	0.080	0.029	0.019
	(0.087)	(0.087)	(0.088)
Other	-0.528***	-0.528***	-0.527***
	(0.026)	(0.026)	(0.026)
Transportation	-0.200***	-0.205***	-0.195***
	(0.031)	(0.031)	(0.031)
Utilities	0.121**	0.119***	0.131***
	(0.052)	(0.052)	(0.052)
Siberian.FD	-0.027	-0.027	-0.027
	(0.022)	(0.022)	(0.022)
FarEast.FD	0.208***	-0.212***	-0.211***
	(0.042)	(0.042)	(0.042)
Volga.FD	-0.114***	-0.114***	-0.113***
	(0.018)	(0.018)	(0.018)
Northwestern.FD	-0.174***	-0.178***	-0.182***
	(0.029)	(0.029)	(0.029)
NorthCaucasian.FD	-0.047	-0.043	-0.040
	(0.055)	(0.055)	(0.054)
Ural.FD	-0.133***	-0.132***	-0.131***
	(0.029)	(0.029)	(0.029)
Southern.FD	-0.159***	-0.159***	-0.158***
	(0.029)	(0.029)	(0.029)
Firm.Size	-0.526***	-0.525***	-0.525***
	(0.007)	(0.007)	(0.007)
Leverage	-1.059***	-1.061***	-1.059***
	(0.033)	(0.033)	(0.033)
ROA	-0.188***	-0.188***	-0.188***
	(0.031)	(0.031)	(0.031)
Age	-0.207***	-0.207***	-0.207***
	(0.007)	(0.007)	(0.007)
Followers	-0.021	-0.019	-0.019
	(0.014)	(0.014)	(0.014)
Laggards	-0.242***	-0.239***	-0.239***
	(0.017)	(0.017)	(0.017)
Loan Level			
log of loan volume	-0.104***	-0.104***	-0.104***
	(0.004)	(0.004)	(0.004)
Maturity$>1yr$	-0.810***	-0.809***	-0.808***
	(0.014)	(0.014)	(0.014)
Quality=2	1.233***	1.233***	1.233***
	(0.022)	(0.022)	(0.022)
Quality=3	1.537***	1.536***	1.537***
	(0.035)	(0.035)	(0.035)
Quality=4	1.814***	1.813***	1.811***
	(0.084)	(0.084)	(0.084)
Quality=5	-0.354***	-0.355***	-0.353***
	(0.115)	(0.115)	(0.115)
Obs.	2,385,658	2,385,658	2,385,658
R^2_{adj}	0.640	0.640	0.640

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank-firm level and appear in the brackets under the estimated coefficients.

Table 5. Baseline regression results: bank ownership types, CO_2 equivalent, and the industries' export shares

Note: The table reports the estimates of equation (1). The estimation period is January 2017 to December 2022. The data covers 246,000 firms and having relationships with 541 banks. All necessary subproducts of the triple interactions are included but not necessarily reported for the sake of space. Time fixed effects are included.

	(1)	(2)	(3)
CO_2Eq (*firm-level*)	0.041	0.238	0.085
	(3.009)	(3.011)	(3.185)
Export.share (*industry-level*)		0.909***	0.772***
		(0.121)	(0.186)
Big.STATE × CO_2Eq	-5.844	-5.644	-5.418
	(3.648)	(3.636)	(3.892)
Other.STATE × CO_2Eq	15.152**	14.932**	4.979
	(6.431)	(6.113)	(5.359)
Big.FOREIGN × CO_2Eq	-1.111	-0.305	-31.073*
	(14.337)	(14.181)	(17.610)
Other.FOREIGN × CO_2Eq	-79.322**	-78.185**	-25.223
	(36.676)	(36.820)	(40.274)
Other.PRIVATE × CO_2Eq	6.093	6.291	7.601*
	(3.829)	(3.853)	(3.975)
Big.STATE × Export.share × CO_2Eq			-12.045
			(25.598)
Other.STATE × Export.share × CO_2Eq			76.367**
			(37.346)
Big.FOREIGN × Export.share × CO_2Eq			1070.122**
			(513.761)
Other.FOREIGN × Export.share × CO_2Eq			-1310.244***
			(471.642)
Other.PRIVATE × Export.share × CO_2Eq			-35.308
			(27.776)
Constant	22.972***	22.966***	22.969***
	(0.110)	(0.111)	(0.110)
Obs.	2,381,783	2,381,783	2,381,783
R^2_{adj}	0.634	0.634	0.634

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank-firm level and appear in the brackets under the estimated coefficients.

Table 6. Baseline regression results: bank ownership types, fee on air emission of harmful substances , and the industries' export shares

Note: The table reports the estimates of equation (1). The estimation period is January 2017 to December 2022. The data covers 246,000 firms and having relationships with 541 banks. All necessary subproducts of the triple interactions are included but not necessarily reported for the sake of space. Time fixed effects are included.

	(1)	(2)	(3)
Air.Fee (*firm-level*)	23.374***	23.218***	26.263***
	(5.069)	(5.080)	(5.750)
Export.share (*industry-level*)		0.900***	0.794***
		(0.121)	(0.186)
Big.STATE × Air.Fee	-45.628***	-45.372***	-47.196***
	(8.651)	(8.661)	(9.371)
Other.STATE × Air.Fee	-23.362	-25.095	-29.361
	(22.395)	(22.132)	(22.956)
Big.FOREIGN × Air.Fee	-75.600***	-74.635***	-77.498**
	(25.768)	(25.889)	(31.384)
Other.FOREIGN × Air.Fee	-159.264***	-160.015***	-125.309**
	(46.431)	(46.675)	(62.953)
Other.PRIVATE × Air.Fee	-2.909	-2.918	-4.273
	(7.946)	(7.966)	(8.655)
Big.STATE × Export.share × Air.Fee			33.951
			(80.872)
Other.STATE × Export.share × Air.Fee			-35.532
			(177.456)
Big.FOREIGN × Export.share × Air.Fee			176.839
			(528.804)
Other.FOREIGN × Export.share × Air.Fee			-317.104
			(562.520)
Other.PRIVATE × Export.share × Air.Fee			58.579
			(108.059)
Constant	22.990***	22.983***	22.985***
	(0.111)	(0.111)	(0.111)
Obs.	2,382,025	2,382,025	2,382,025
R^2_{adj}	0.634	0.634	0.634

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank-firm level and appear in the brackets under the estimated coefficients.

Table 7. Baseline regression results: bank ownership types, fee on all emissions of harmful substances , and the industries' export shares

Note: The table reports the estimates of equation (1). The estimation period is January 2017 to December 2022. The data covers 246,000 firms and having relationships with 541 banks. All necessary subproducts of the triple interactions are included but not necessarily reported for the sake of space. Time fixed effects are included.

	(1)	(2)	(3)
Emission.Fee (*firm-level*)	0.280	0.297	0.032
	(1.276)	(1.276)	(1.422)
Export.share (*industry-level*)		0.904***	0.766***
		(0.121)	(0.188)
Big.STATE × Emission.Fee	-4.207**	-4.203**	-4.143**
	(1.663)	(1.662)	(1.821)
Other.STATE × Emission.Fee	2.413	2.119	-1.402
	(6.364)	(6.313)	(6.492)
Big.FOREIGN × Emission.Fee	-14.150***	-14.104***	-16.460***
	(4.735)	(4.742)	(4.852)
Other.FOREIGN × Emission.Fee	-4.699	-5.332	-14.664
	(8.367)	(8.078)	(9.226)
Other.PRIVATE × Emission.Fee	3.735**	3.761**	3.636**
	(1.651)	(1.652)	(1.797)
Big.STATE × Export.share × Emission.Fee			-6.698
			(18.563)
Other.STATE × Export.share × Emission.Fee			45.395
			(86.466)
Big.FOREIGN × Export.share × Emission.Fee			100.043**
			(42.949)
Other.FOREIGN × Export.share × Emission.Fee			155.985*
			(83.440)
Other.PRIVATE × Export.share × Emission.Fee			7.014
			(24.264)
Constant	22.981***	22.974***	22.977***
	(0.111)	(0.111)	(0.111)
Obs.	2,381,526	2,381,526	2,381,526
R^2_{adj}	0.634	0.634	0.634

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank-firm level and appear in the brackets under the estimated coefficients.

Table 8. Baseline regression results: bank ownership types, fuel share, and the industries' export shares. New borrowers.

Note: The table reports the estimates of equation (1). The estimation period is January 2017 to December 2022. The data covers 134,458 firms and having relationships with 498 banks. All necessary subproducts of the triple interactions are included but not necessarily reported for the sake of space. Time fixed effects are included.

	(1)	(2)	(3)
Fuel.share (*industry-level*)	1.041***	1.039***	0.969***
	(0.145)	(0.145)	(0.146)
Export.share (*industry-level*)		0.881***	0.088
		(0.155)	(0.309)
Big.STATE × Fuel.share	-1.630***	-1.636***	-1.668***
	(0.160)	(0.162)	(0.162)
Other.STATE × Fuel.share	-1.926***	-1.904***	-1.960***
	(0.575)	(0.575)	(0.575)
Big.FOREIGN × Fuel.share	-0.370	-0.369	-0.024
	(0.760)	(0.760)	(0.799)
Other.FOREIGN × Fuel.share	0.403	0.382	-1.687
	(2.529)	(2.526)	(2.799)
Other.PRIVATE × Fuel.share	-0.274	-0.281	-0.342
	(0.292)	(0.292)	(0.301)
Big.STATE × Export.share × Fuel.share			3.826
			(4.129)
Other.STATE × Export.share × Fuel.share			28.702
			(46.888)
Big.FOREIGN × Export.share × Fuel.share			-36.027
			(34.159)
Other.FOREIGN × Export.share × Fuel.share			177.807***
			(62.560)
Other.PRIVATE × Export.share × Fuel.share			5.000
			(8.448)
Constant	18.609***	18.606***	18.603***
	(0.130)	(0.130)	(0.130)
Obs.	158,935	158,935	158,935
R^2_{adj}	0.80	0.80	0.80

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank-firm level and appear in the brackets under the estimated coefficients.

Table 9. Baseline regression results: bank ownership types, fuel share, and the industries' export shares. Exclude big-4 Russian banks.

Note: The table reports the estimates of equation (1). The estimation period is January 2017 to December 2022. The data covers 192,402 firms and having relationships with 509 banks. All necessary subproducts of the triple interactions are included but not necessarily reported for the sake of space. Time fixed effects are included.

	(1)	(2)	(3)
Fuel.share (*industry-level*)	0.577***	0.575***	0.606***
	(0.119)	(0.119)	(0.120)
Export.share (*industry-level*)		0.351***	0.626***
		(0.134)	(0.242)
Big.STATE × Fuel.share	0.501***	0.501***	0.485***
	(0.188)	(0.188)	(0.192)
Other.STATE × Fuel.share	-2.538***	-2.537***	-2.674***
	(0.363)	(0.362)	(0.359)
Big.FOREIGN × Fuel.share	-0.057	-0.059	-0.360
	(0.544)	(0.544)	(0.548)
Other.FOREIGN × Fuel.share	-0.763	-0.767	-0.155
	(0.955)	(0.956)	(1.008)
Other.PRIVATE × Fuel.share	-0.757***	-0.763***	-0.839***
	(0.179)	(0.179)	(0.182)
Big.STATE × Export.share × Fuel.share			1.245
			(3.984)
Other.STATE × Export.share × Fuel.share			28.310
			(19.002)
Big.FOREIGN × Export.share × Fuel.share			25.853***
			(8.140)
Other.FOREIGN × Export.share × Fuel.share			-59.991
			(38.636)
Other.PRIVATE × Export.share × Fuel.share			6.130*
			(3.281)
Constant	24.339***	24.337***	24.334***
	(0.122)	(0.122)	(0.122)
Obs.	1,798,213	1,798,213	1,798,213
R^2_{adj}	0.597	0.597	0.597

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank-firm level and appear in the brackets under the estimated coefficients.

Table 10. Baseline regression results: bank ownership types, fuel share, and the industries' export shares. 2017–2021.

Note: The table reports the estimates of equation (1). The estimation period is January 2017 to December 2021. The data covers 227,846 firms and having relationships with 507 banks. All necessary subproducts of the triple interactions are included but not necessarily reported for the sake of space. Time fixed effects are included.

	(1)	(2)	(3)
Fuel.share (*industry-level*)	1.027***	1.025***	1.002***
	(0.119)	(0.119)	(0.121)
Export.share (*industry-level*)		0.942***	0.610**
		(0.125)	(0.270)
Big.STATE × Fuel.share	-2.108***	-2.119***	-2.218***
	(0.139)	(0.139)	(0.141)
Other.STATE × Fuel.share	-2.777***	-2.777***	-3.020***
	(0.368)	(0.364)	(0.346)
Big.FOREIGN × Fuel.share	0.149	0.139	-0.144
	(0.554)	(0.554)	(0.558)
Other.FOREIGN × Fuel.share	-0.777	-0.795	-0.114
	(0.930)	(0.934)	(0.984)
Other.PRIVATE × Fuel.share	-0.211	-0.234	-0.365*
	(0.193)	(0.192)	(0.194)
Big.STATE × Export.share × Fuel.share			8.541***
			(4.148)
Other.STATE × Export.share × Fuel.share			47.620**
			(23.202)
Big.FOREIGN × Export.share × Fuel.share			25.250***
			(8.212)
Other.FOREIGN × Export.share × Fuel.share			-63.342*
			(36.290)
Other.PRIVATE × Export.share × Fuel.share			9.801***
			(4.217)
Constant	21.509***	21.502***	21.506***
	(0.099)	(0.099)	(0.099)
Obs.	2,133,680	2,133,680	2,133,680
R^2_{adj}	0.662	0.663	0.663

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank-firm level and appear in the brackets under the estimated coefficients.

Table 11. Baseline regression results: bank ownership types, fuel share, and the industries' export shares. 2017–2019.

Note: The table reports the estimates of equation (1). The estimation period is January 2017 to December 2019. The data covers 84,598 firms and having relationships with 495 banks. All necessary subproducts of the triple interactions are included but not necessarily reported for the sake of space. Time fixed effects are included.

	(1)	(2)	(3)
Fuel.share (*industry-level*)	0.213	0.205	0.211
	(0.191)	(0.191)	(0.199)
Export.share (*industry-level*)		0.861***	0.582
		(0.179)	(0.475)
Big.STATE × Fuel.share	-1.133***	-1.153***	-1.408***
	(0.246)	(0.245)	(0.252)
Other.STATE × Fuel.share	-2.417***	-2.412***	-2.763***
	(0.744)	(0.736)	(0.671)
Big.FOREIGN × Fuel.share	0.295	0.292	0.002
	(0.649)	(0.649)	(0.659)
Other.FOREIGN × Fuel.share	0.068	0.057	0.801
	(0.993)	(0.994)	(1.097)
Other.PRIVATE × Fuel.share	0.591***	0.578***	0.378
	(0.260)	(0.260)	(0.265)
Big.STATE × Export.share × Fuel.share			14.227***
			(6.463)
Other.STATE × Export.share × Fuel.share			47.974**
			(22.697)
Big.FOREIGN × Export.share × Fuel.share			23.844***
			(9.129)
Other.FOREIGN × Export.share × Fuel.share			-61.911
			(42.754)
Other.PRIVATE × Export.share × Fuel.share			13.165***
			(6.715)
Constant	27.903***	27.897***	27.903***
	(0.136)	(0.136)	(0.136)
Obs.	917,284	917,284	917,284
R^2_{adj}	0.557	0.558	0.558

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank-firm level and appear in the brackets under the estimated coefficients.

Table 12. Baseline regression results: bank ownership types, fuel share, and the industries' export shares. Productivity deciles.

Note: The table reports the estimates of equation (1). The estimation period is January 2017 to December 2022. The data covers 134,458 firms and having relationships with 498 banks. All necessary subproducts of the triple interactions are included but not necessarily reported for the sake of space. Time fixed effects are included.

	(1)	(2)	(3)
Fuel.share (*industry-level*)	1.095***	1.086***	1.054***
	(0.118)	(0.118)	(0.119)
Export.share (*industry-level*)		0.909***	0.546**
		(0.121)	(0.241)
Big.STATE × Fuel.share	-1.807***	-1.814***	-1.874***
	(0.160)	(0.142)	(0.146)
Other.STATE × Fuel.share	-2.787***	-2.784***	-2.988***
	(0.382)	(0.378)	(0.359)
Big.FOREIGN × Fuel.share	-0.140	-0.145	-0.411
	(0.545)	(0.546)	(0.549)
Other.FOREIGN × Fuel.share	–0.908	–0.919	–0.260
	(0.932)	(0.935)	(0.988)
Other.PRIVATE × Fuel.share	–0.386**	–0.405**	–0.508**
	(0.189)	(0.188)	(0.190)
Big.STATE × Export.share × Fuel.share			5.115
			(3.234)
Other.STATE × Export.share × Fuel.share			41.854*
			(21.879)
Big.FOREIGN × Export.share × Fuel.share			23.239***
			(7.748)
Other.FOREIGN × Export.share × Fuel.share			–61.977
			(37.719)
Other.PRIVATE × Export.share × Fuel.share			7.490**
			(3.355)
Constant	23.077***	23.070***	23.074***
	(0.112)	(0.112)	(0.112)
Obs.	2,385,658	2,385,658	2,385,658
R^2_{adj}	0.635	0.635	0.635

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank-firm level and appear in the brackets under the estimated coefficients.