Bank of Russia

Corporate credit in Russia during COVID-19 pandemic: the role of credit lines

WORKING PAPER SERIES

№ 110 / December 2022

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Abstract

We study corporate loan composition in Russia during the pandemic along two dimensions. First, we analyse the quality composition of borrowers of new loans. Like most existing studies, we measure the quality of borrowers at the levels observed before, not during (or after), the pandemic.

Using probability of default to measure borrower quality, we find that the share of loans provided by banks to firms with weaker fundamentals, as identified even before the pandemic, increased during the pandemic. This increase is economically significant. The result does not depend on the 'riskiness' of banks (as measured by the share of nonperforming loans on their balance-sheets). We argue that the subsidised loan programmes (with government guarantees) may help to explain this unpleasant result.

Second, we analyse the share of loans provided during pandemic through credit line utilisation as compared with new stand-alone loans. We find that credit line utilisation increased during the pandemic irrespective of firms' ex ante probabilities of default. Thus, credit lines played the role of an automatic stabiliser during the period of high demand for liquidity. At the same time, credit line utilisation decreased during the pandemic among firms in the exposed industries. We also find that financially weaker banks tended to have higher shares of credit line utilisation before and during the pandemic, and this may have implications for the banks' stability.

1. Introduction

The COVID-19 pandemic has negatively affected many sectors of the world economy, and Russia is not an exception (see, for example, the World Bank (2020) report). Many industries suffered significant losses due to the sharp decline in aggregate demand and restrictions on mobility. [1] Governments in different countries suffering from the crisis applied various measures in 2020–2021 to support producers, including concessional credit programmes for corporate or small and medium enterprises (SME) and regulatory easing for banks to stimulate lending. An overview and discussion of such measures can be found, for example, in the work of Baudino (2020) or Casanova et al. (2021). One important issue for economic and financial stability that arises with regard to corporate lending is how the structural composition of lending to corporate entities changed during the pandemic. Several aspects of this issue are of particular interest, both for commercial banks and for regulators. In this study, we focus on three of them:

- The credit quality of the borrowers in banks' portfolios of corporate loans issued during the pandemic
- The utilisation of credit lines which were approved before the pandemic but activated during the pandemic.
- The bank-side determination of lending composition (whether banks with stronger fundamentals provided more loans to lower quality borrowers during the pandemic period).

We formulate a number of hypotheses and estimate several regressions to address these issues.

Our analysis is descriptive in nature and does not address the issue of causal inference. As we lack data on loan applications, we cannot identify the demand (and, correspondingly, supply) factors behind the observed conditional correlations, as, for example, Jiménez et al. (2014) and Cuciniello and Di Iasio (2021) do.

Before proceeding, it is important to introduce several definitions. For the purposes of this study, we define the following categories:

- Loan — a general term describing a debt obligation of a given size (loan volume) of a firm to the bank that issued the loan (provided financing). Loans can have several forms. For the purpose of our research, we are particularly interested in credit lines and stand-alone loans (or term loans).
- Stand-alone loan (term loan) — a type of a loan in which the borrower receives either the entire volume of the loan as one tranche immediately after the loan contract is signed, or in several tranches over predetermined periods of time.
- Credit line — a type of a loan in which a borrower receives tranches of the loan when needed. This type of credit facility usually has limits on the total amount of debt outstanding, on the size of each tranche, or a combination of both.
- Loan tranche — the part of the loan that is transferred from the bank to the borrower in a single transaction. It usually equals 100% of the total loan volume in the case of stand-alone loans and less than 100% for credit lines.
- Ex ante credit line — a credit line that was approved by a bank before the period of time under consideration. This means that the company knows in advance that the credit facility is available and that it may be used if needed.

The first issue we focus on is the credit quality composition of newly issued loans as measured by the riskiness of the borrowers. The empirical evidence in the literature shows that the pandemic increased the credit risks on the balance sheets of banks (see, for example, Minoiu et al. (2021)). In the existing literature, this is a direct result of the pandemic, which worsened the credit quality of the borrowers. For example, imagine a firm which was a high-quality borrower before the pandemic which experienced a drop in sales due to the pandemic: the bank supplying the loan to this firm faced more credit risk during the pandemic than it did before the pandemic.

We focus on another mechanism behind credit risk accumulation during the pandemic which has not been focused on much in the literature. This mechanism is structural changes on the supply or

[1] See the World Bank (2020) report for statistical evidence concerning sectoral differences.

demand side which led to a higher share of loans to risky borrowers whose riskiness was unrelated to the effects of the pandemic. If, during the pandemic, a bank issued a loan to a firm which was a risky borrower even before the pandemic, instead of a loan to a healthier-before-the-pandemic firm, the bank would also have taken on more risk. In this case, although the pandemic may have worsened the risk-profiles of both borrowers symmetrically, the bank finds itself with a riskier portfolio composition, other things being equal.

To assess the changes in the risk composition arising from newly issued loans, we control for the endogenous effects of the pandemic on the credit risks of borrowers by studying how the credit quality composition of new loans evolves during the pandemic if the credit quality of borrowers is fixed at the levels observed before the pandemic. Thus, we do not consider the case in which banks increase or decrease their lending to borrowers for which the pandemic results in higher or lower credit risks. We analyse how banks treated borrowers that were already considered risky at the start of the pandemic. For example, Duignan, McGeever, et al. (2020) use loan-level data from Irish banks and show ‘that performing loans with weaker credit quality prior to the pandemic were moderately more likely to utilise a payment break. Similarly, loans with a record of having been previously nonperforming were more likely to have a payment break. Nonetheless, the majority of borrowers that took a payment break showed no explicit signs of vulnerability prior to the shock’. We focus on newly issued loans to such borrowers, rather than analysing the existing (performing) loans issued before the pandemic. The issue of borrowers’ risk profile is important, as estimating it may help in the evaluation of the side effects of the subsidised loan programmes with explicit government guarantees, which has implications for policy design during crises.

We find that during the pandemic, Russian banks issued more loans to firms with high ex ante probabilities of default (PD), i.e., to firms that had already been weak before the crisis. Given that the number of loans during the pandemic was almost 65 per cent larger than before it, mostly due to subsidised loans, the government subsidies for the credit market may help explain this result (see Bessonova et al. (2021)).

We suppose that the result may be partially attributed to the programmes of subsidised (’FOT 0’) or fully guaranteed government loans (’FOT 2.0’ and certain others for SMEs) in action during the period of observation. We argue that the programmes, especially ’FOT 2.0’, might have reduced the stimulus for banks to screen borrowers.[2] Thus, during the pandemic, the programmes might have provided financing to firms with weaker fundamentals and higher credit risks, when such risks are fixed at the levels measured before the pandemic. In this regard, the programmes may have created inefficiency in credit distribution by allocating funds to weaker (or even ’zombie’) firms (see Caballero et al. (2008) and R. N. Banerjee and Kharroubi (2020)). Consequently, the support for such firms may have slowed down ’creative destruction’ with negative effects on the productivity growth of the economy.

This raises the issue of the efficiency of the programmes and the lenders involved in providing funds. For example, more incentives may be created for banks to identify the most efficient companies to fund. All the costs and benefits of this shift in the programme must be carefully considered. On the one hand, when banks monitor their borrowers more efficiently, the problem of ’free-riding’ companies might be reduced, and only firms with stronger financial fundamentals will survive during the crisis, allowing the economy to grow more rapidly in the future. On the other hand, banks will have to expend more resources on monitoring. This entails an increase in the cost of the credit. Additionally, the probable increase in unemployment and the corresponding drop in consumer spending, leading to a decline in aggregate demand, must be taken into account.

Current PD model does not take into account the fact that all industries are interconnected through the supply chains. It means that if one sector suffer any negative shock, then some other companies from other industries might become affected, but not directly. However, this influence may be sufficient

[2] The conditions for a loan under ’FOT 2.0’ mean that if a firm retains employment ex post, the borrower need not pay the loan back to the bank, but that the government will do so. If the firm does not retain employment ex post, it must pay the loan back to the bank. However, if such a borrower defaults, the government will compensate the loss to the bank anyway.

and consequently cause change in the probability of default of companies that were not affected by shock directly. This idea is very important for the sake of country financial stability and should be taken into account in further researches.

The second issue is the utilisation of credit lines which were approved before the pandemic but activated during the pandemic. We measure the share of the total lending to firms comprised of loan tranches that borrowers received during the pandemic from credit lines approved before the pandemic. Kapan and Minoiu (2021) use credit-level and bank-level data to show that banks with higher shares of previously approved credit lines had to restrict their stand-alone lending during the crisis. This also negatively affected banks' activity in offering new credit under the Paycheck Protection Program (PPP) in the US.

We find higher utilisation of credit lines during the pandemic compared to previous periods. However, the increase is weaker for companies with high PDs, i.e., riskier borrowers relied on credit lines less compared to safer ones (or banks encouraged safer borrowers to use credit lines). In addition, we find higher utilisation of ex ante credit lines during the pandemic, but only among companies not affected by the COVID crisis. For exposed companies, we find a decrease in the utilisation of credit lines which were opened before the pandemic.

As far as we know, this is the first study of corporate credit lines using granular credit registry data (in Russia). We believe that even the descriptive analysis we have done shows that credit lines were important in supporting the corporate sector during the pandemic as a kind of automatic stabiliser.

Finally, we study which banks provided a higher share of ex ante credit lines during the pandemic: those with larger or smaller shares of non-performing loans (NPLs) in their corporate loan portfolios? In a similar study, Li and Strahan (2021) use data on the PPP to study bank characteristics which may help explain loan dynamics. They conclude that a higher share of these loans was provided by small banks with more prior experience in providing loans on the local market (relationship lending) and higher shares of core deposits. We focus on only one characteristic of a bank prior the pandemics (the share of NPLs on its balance-sheet) as it is an aggregate measure of performance and risk-attitude (see Jiménez et al. (2014)).

We find that banks with more NPLs in their portfolios had higher shares of new lending through credit line utilisation. This means, on the one hand, that credit line utilisation (especially in a crisis) may pose more constraints for such banks, as compared to healthier banks. The constraint is the reduced ability to increase lending in the form of new stand-alone loans when such lending may be most in demand (Kapan and Minoiu (2021)). On the other hand, weaker banks have a chance of failing when providing loan supply through the activation of credit lines. Both considerations mean that regulation may need to account for whether weaker banks have high shares of credit lines that may be activated.

In this paper, we use loan-level data from the credit registry (report 303 in bank statements) and companies' financial statements. To assess corporate credit risks, we assign the probability of default (PD) to each company using the standard simple model based on financial indicators from Burova et al. (2021). Based on the distribution of PD estimates across corporate entities, we divide the companies into deciles, where the first decile includes the companies with the lowest probabilities of default and the tenth includes those with the highest PDs. This procedure allows us identify sets of 'weak' and 'strong' borrowers. We apply a similar procedure to banks, dividing them into quartiles using the share of loans of categories IV and V in their credit portfolios.

To compare loan issuance to the period before the pandemic, we use data for the same period of each year before the pandemic. Since the peak of the pandemic period and the restrictions was approximately March 2020 to August 2020, we use information about loans for the same months (March–August) for the years 2017–2019. We include dummy variables for the pandemic year and for the industries exposed using the list approved by the Russian authorities (No. 434, 03.04.2020).

Unfortunately, we have no granular data on corporate loan applications (as in Jiménez et al. (2014) and Ioannidou et al. (2015)), which means we cannot identify the supply or demand factors behind the changes in loan composition during the pandemic.

The paper is organised as follows: in the next section, we describe the relevant literature and outline our contribution to it. Next, we describe the data and the methodology used. Finally, we present and discuss our results, make conclusions, and identify possible policy implications.

2. Literature review

Our paper is connected with two strands in the existing literature. First, we contribute to the work studying the borrower risk composition of loans issued during the pandemic.

Such papers mostly focus on evaluating the performance of government support programmes during the pandemic. One dimension of such performance is the risk profile of the borrowers in these programmes. In particular, Granja et al. (2020) evaluate the effects of the Paycheck Protection Program (PPP) and find that bank intermediation helps to explain the mismatch between the strength of the adverse pandemic effects on a region and the size of the programme: they conclude that greater bank capacity to process lending or bank relationships with the programme's administration affected the distribution of funds. Thus, if the banks operating in a region were more effective, the local companies got easier access to PPP funding.[3]

In addition, Duignan, McGeever, et al. (2020) use loan-level data from largest Irish banks and find that small- and medium-sized entrepreneurs defaulted on their payments more frequently. They also note that companies with low credit quality defaulted more often, despite the fact that they did not do so before the pandemic crisis. Kozeniauskas et al. (2020) use Portuguese data and show that companies with higher productivity were more likely to stay open, less likely to reduce employment, less likely to have large sales declines, and less likely to use government support.

We examine similar questions in this study and identify whether the credit quality composition of new loans changed during the pandemic if credit risks are measured before the pandemic. The answer is that it did worsen. We also argue that the design of the government support programmes may be responsible for this effect. Another relevant question is whether banks with more NPLs provided more lending to companies with poor financial states. We do not find support for the hypothesis: all banks appear to have been more engaged in lending to lower-quality borrowers during the pandemic.

Second, we contribute to studies of credit line utilisation during the pandemic. Credit lines are a widespread form of financing in many countries. Shockley and Thakor (1997)) show that over 80% of all lending in the USA is provided using loan commitments. A recent paper by Greenwald et al. (2021) shows that 53% of the total financing provided through credit before the pandemic involved credit lines. When combined with the unused limits on credit lines, this share increases to 78%. The role of credit lines extended to companies especially increases during financial crises. Thus, Holmström and Tirole (1998) argue that credit lines help companies overcome financing shortages and maintain investments. This theoretical reasoning is supported empirically in many subsequent papers. For example, Campello et al. (2012) show that, during the Global Financial Crisis, European companies with limited access to credit used existing credit lines more intensively. There is also a precautionary explanation for the use of credit lines during crises: companies choose to use their credit lines as much as possible in case the creditor is not able to provide funds later (Ivashina and Scharfstein (2010); Bosshardt and Kakhbod (2021)). Greenwald et al. (2021) show that credit line drawdowns increase during negative economic shocks.

The study of credit lines is also important for understanding monetary policy transmission. Greenwald et al. (2021) show that credit line utilisation increases in periods of restrictive monetary policy (the same pattern is revealed in other papers, such as those of Kashyap and Stein (1995) and Den Haan et al. (2007)). Using micro-level supervisory data, the authors prove that this increase appears to be due to credit lines draw down, while term loans decrease.

Bosshardt and Kakhbod (2021) consider the use of funds received on credit and conclude that most companies use this money precautionarily to retain additional liquidity on their balance sheets. However, if a company operates in industry that was less affected by shutdown, it is more likely

[3]Li and Strahan (2021) also take the PPP programme as the main scope of their study, and they conclude that relationship lending helps in issuing loans more easily and quickly. Minoiu et al. (2021) look at the Main Street Lending Program (MSLP), which was mainly intended to support SMEs.

to have spent the money on investment. Chodorow-Reich et al. (2022) use US supervisory data and draw several conclusions. First, small firms open credit lines more frequently, and they provide more collateral, have higher utilisation rates, and pay higher spreads. During the COVID period, a major part of the increase in lending was due to credit line withdrawals by large companies, whereas small companies had no net withdrawal. Another interesting fact is that large companies show greater sensitivity to industry-level measures of exposure to the COVID recession. Greenwald et al. (2021) prove that the majority of unused credit line limits are assigned to the largest companies. Acharya and Steffen (2020) also show an increase in credit line withdrawals. Our study shows the same result: the share of ex-ante credit lines used grew significantly during the pandemic period.

As far as we know, ours is the first paper that measures credit line utilisation for the Russian corporate sector (using granular credit registry data). In contrast to the existing papers, we analyse credit line utilisation during the pandemic along three dimensions:

– Borrower's credit quality at levels fixed before the pandemic. We find that riskier borrowers relied on credit lines less in comparison with safer borrowers (or banks preferred for safer borrowers to use credit lines).
– Sectoral heterogeneity of credit line utilisation. The pandemic shock had a significant negative effect on most industries (del Rio-Chanona et al. (2020); Kozlowski et al. (2020)). We find higher utilisation of ex ante credit lines during the pandemic, but only among companies not affected by the COVID crisis. For exposed companies, we find a decrease in the utilisation of credit lines which were open before the pandemic.
– Bank heterogeneity in the use of credit lines compared to the quality the bank's corporate portfolio. We find that banks with higher NPLs in their portfolios had higher shares of new lending through credit lines utilization during the pandemic.

Despite this paper the first one studying credit line utilisation, in Bessonova et al. (2022) author used similar dataset to examine the subsidised credit during pandemic. Among other conclusion, we should mention a pair relevant to our study. In particular authors show that zombie and financially unstable firms are less likely to use subsidised credits. This result seems contradictory to our finding that banks increased the share of credits to risky firms. However this difference may be consequence of different model specification. In Bessonova et al. (2022) probability of obtaining subsidised credit by a company were used as dependent variable. We, in turn, applied share of loans provided to companies from three upped deciles of PD distribution. Moreover, explanatory variable is different either. Zombie firms are identified with the use of interest coverage ration which should be lower than 1 during three years. Probability of default, in contrast, were determined by a set of financial variables (like growth of sales, liquidity ratio, etc). However, one more result from the same regression shows that companies from ”Followers” and ”Laggards” group obtained subsidised credits with higher probability in comparison with leading firms. All these differences should be extensively studied in following researches.

Our analysis is descriptive and does not address the issue of banks' or borrowers' reaction to credit line withdrawals. Kapan and Minoiu (2021) consider the influence of the pre-pandemic share of credit lines on the credit activity of banks during the crisis. They conclude that the more credit lines a bank had approved ex ante (before the COVID crisis), the more restricted it was in providing loans (including PPP). Greenwald et al. (2021) find a similar result. In the empirical part of their study, the authors use loan-level data and conclude that credit lines allow firms to gain liquidity during adverse shocks. Thus, the utilisation of credit lines by such firms crowds out lending to more liquidity-constrained companies, as banks have fewer funds to provide term loans since they must fulfil their obligations on credit lines.

3. Data

Our main source of data is the credit registry for Russian corporates, i.e., the loan-level data collected by reporting form No. 303.[4] The data contain detailed information about each loan tranche issued by a bank to a firm on monthly basis: names and IDs of the creditor and borrower, the type of credit, the currency, the size of the loan, the credit limit, etc.

Detailed descriptions of this dataset, with a discussion of the important features of the data, are given by Bessonova et al. (2021), Goncharenko et al. (2021) and Burova (2022). One dimension of the data is useful for our study: the identification of stand-alone loans vs. credit lines (the main difference is that credit lines can be withdrawn later in time as needed, while stand-alone loans usually have predefined withdrawal schemes).

We match the dataset with information on certain characteristics of banks and firms. Regarding banks, we use the share of loans of quality categories IV and V from bank reporting form No. 115 to measure the quality of banks' portfolios. A higher share indicates poorer *realised* credit quality in the bank portfolio. These data are available on a monthly basis.

For firms, we use information about companies' financial statements from SPARK. A detailed description of the SPARK data is provided by Bessonova et al. (2021). Since this dataset is combined with corporate financial statements, the information has a yearly frequency.

When we combine all these data, we have a matched loan-firm-bank level dataset. Table 1 in Appendix summarises information on all the data used in this study.

The overall time period that we consider covers the years 2017–2020. This time span is the maximum possible period for which micro-level data on credit are available. As we focus on the credit structure (credit line utilisation vs. new stand-alone loans) during the COVID-19 crisis, we restrict the sample to those credit tranches that were provided in March–August 2020, the period of the most acute pandemic-related restrictions. To be able to compare the pandemic period to a 'normal' time, we do the same for the data from previous years, i.e., we consider March–August 2019, and so on. To take the effect of pandemic into account, we also generate a dummy variable ($pandemic$) that equals 1 in 2020 and 0 in the previous years.

Due to the specificity of our study design, we do not need monthly credit data. Since credit provided is a flow variable, we can sum up all the tranches issued by a bank or all the tranches received by a company during a given period of time. A PD is assigned to each company using information from the previous year financial statement and is considered a stock variable at the beginning of March of each year (this means that PD is an ex ante variable for each year). Similarly, the share of loans of quality categories IV and V is also a stock variable, and thus we use information at the beginning of March of each year (this share is also an ex ante variable).

Next, we reduce the original sample in two steps to get the sample we use in the regressions. As the first step, we exclude all data on 'loans with overdraft', leaving only information on stand-alone loans and credit lines. We do this to narrow the focus of our study. This step decreases our sample by almost 25% of loans. As the second step, we exclude observations on small and medium enterprises (SMEs), because we have no information about their financial statements. This action decreases the sample by an additional 35% of observations. At each step, we calculate several key characteristics of the data sample. A comparison is presented in Table 2 in Appendix. We can conclude that the variables in the sample retain the same (increasing) trend, which means that structural changes related to the issuance of overdraft loans or loans to SMEs, if any exist, are not strong enough to reduce the representativeness of the data.

Using the resulting sample, for a given time period, we assign each bank a number from 1 to 4 depending on the share of low-quality loans (quality categories IV and V according to bank reporting form No. 115) on its balance-sheet *before the period starts*. The bank is assigned a 1 if its share of

[4]Referred to hereinafter as credit registry Form No. 0409303 (Russian). Banks submit it to the Bank of Russia on a monthly basis. We refer to it as a 'credit registry', although it is not data from credit registry bureaus. For the methodology and a detailed description of the form, see http://www.cbr.ru/eng/statistics/pdko/sors/summary_methodology/

low-quality loans falls into the first quartile of the low-quality loan distribution constructed for all banks in the sample. Thus, this variable measures the relative risk of the bank's portfolio for each year and is used as the Bank Strength (BS) variable in the regressions. We focus on this relative measure to exclude the common trend effect from the consideration, i.e., to analyse the relative performance of banks, not their absolute performance.

We should make several remarks concerning the volume of credits from quality categories IV and V. First, this variable is known as rather volatile. However, since we use it as a state variable on the same day of each year, this problem should not lead to a sufficient change in results. Second, this variable represents the cumulative effects of banks' credit policy (whether it was more or less risky) and this is the crucial feature that we tried to cover with the use of this variable. However, there are obviously some other options to evaluate risk aversion of banks.

SPARK data are used to construct a measure of borrower quality. We use information from each borrower's financial statement to assign it a probability of default (PD). To do so, we apply the model provided by Burova et al. (2021) paper and use the data from companies' financial statements for year t to make a prediction of probability of default. This PD is treated as an indicator of the financial strength of each company in year $t + 1$, which means, for example, that the PD in the pandemic year of 2020 is determined by variables from 2019, and the pandemic shock thus has no effect on companies' estimated sustainability. Thus, the methodology above allows us to predict the financial condition of the company on the basis of previous information and eliminate endogeneity problem, that may influence the results, especially in crisis period of time.

There are several reasons why we do not use the data from the bank reports directly (i.e., information on the quality category of a particular loan from the credit registry). First, we would like to rely on common information about borrowers, since different banks might have different information about the same borrower and thus assign the same borrower different quality rates in the reporting forms. Second, the majority of loans in the credit registry fall into the second quality category, which means low variance in a borrower quality measure constructed this way. Third, a borrower may be assigned different quality characteristics for different types of loans, which is an unpleasant feature for a borrower quality measure: a company may, for example, have high quality as a new borrower on a stand-alone loan but low quality as a borrower on a credit line.

After assigning quality measures to each of the borrowers (firms) in the sample, we split our sample into deciles on the basis of this estimated PD (the 1st group contains the firms with the lowest PDs, and the 10th group contains the firms with the highest PDs). Thus, we assign each firm a number from one to ten, a measure of the firm's relative quality. Again, our focus is on relative performance (differentiation), not on absolute performance. Summary statistics for these variables are presented in Table 3 in Appendix, and the distributions used to construct the measures of firm and bank quality are presented in Figures 1 and 2.

Using the information about which decile each company belongs to, we can calculate the volume of loans each bank issued to the companies in each decile. As the dependent variable for studying our first issue, we find the share of loans to the companies with the highest PDs. In the benchmark model, we use the share of credits provided to the companies in the 8th to 10th deciles.

Figure 1 reveals a notable difference between the 9th and 10th deciles and between the 9th decile and all preceding deciles. This means that the PD distribution is skewed to the left. The difference in thresholds implies that the companies in the two upper deciles have fundamentals that are significantly different from those in the lower deciles. The same is true of Figure 2 and the bank quartiles.

We use this distribution among deciles as the explanatory variable in the study of one of our issues: the decile number represents Firm Strength, or the quality of the firm. However, the significant difference in thresholds is eliminated if we use only decile numbers.[5]. For the robustness check, therefore, we use a continuous PD variable instead of decile number to take this non-uniform distribution into account. The same robustness check is used in the case of Bank Strength.

[5]The numbers increase linearly, but PD itself can vary significantly even between companies in neighbouring deciles.

Figure 1. Thresholds of deciles for probability of corporate default by year (PD)

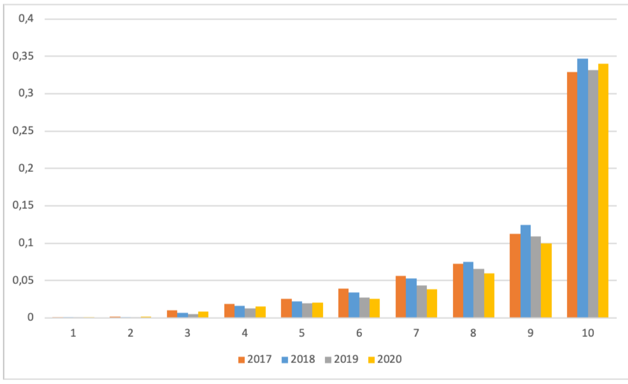
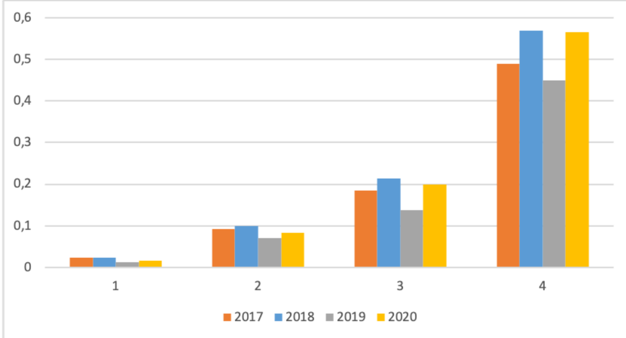


Figure 2. Thresholds of quartiles for share of risky loans by year



We need a good measure to study credit line utilisation. Kapan and Minoiu (2021) use information about the share of credit lines approved. They show that if a bank issues more credit lines, it has a higher probability of facing new limits on extending stand-alone loans in a time of crisis due to the utilisation of previously approved credit lines by borrowers. To measure credit line utilisation in the pandemic and compare it with that before the pandemic (a 'normal' time), we must identify whether a particular loan in the credit registry (tranche) was provided as a part of a credit line opened before the time period under consideration or as a new stand-alone loan.

As the result of the sample reduction in the first step (see above), all the tranches left in our sample are of two types: either new stand-alone loans or credit lines (we take this information from the 'Loan type' field in the report).

For every tranche, we observe two loan characteristics: the date of contract agreement and the date of money transfer. These dates are equal (or rather close to one another) for all stand-alone loans, and so these are all classified as 'new' loans in our study. For credit lines, the contract date may be any number of days before the money was actually transferred and the tranche was generated. Using these two loan characteristics, we divide the credit lines into two categories: 1) the contract date and the credit tranche date took place during the crisis (from March to August 2020) and 2) the tranche was provided during the crisis but the contract was signed before the start of the pandemic (March 2020). Credit lines of the first type are treated in our analysis as new stand-alone loans (so we expand the category of true stand-alone loans with such credit lines), while tranches of the second type are treated as 'ex ante credit lines'.

Using this procedure, we identify whether a tranche was provided as part of a credit line opened before the crisis period or not. We then total these tranches for each company and calculate the share they represent in the overall loans each firm took during the given period. We can calculate this share not only for firms but also for banks, finding the share of credit lines in the overall volume of money provided by each bank.

For example, consider company A during March–August 2020. It has a credit line opened in 2019 in bank B and has not used the available credit limit. During the pandemic, it received \$100 from bank B as a tranche of the credit line and \$100 from bank B as a new loan. In addition, it received \$200 from bank C as another new loan (for example, bank C signed a credit line arrangement with company A in June 2020). Thus, we see that the overall utilisation rate of ex ante credit lines is 25% ($\frac{100}{(100+100+200)}$), however, if we calculate utilisation rate of company A per bank, we get 50% for bank B ($\frac{100}{(100+100)}$) and 0% for bank C ($\frac{0}{200}$). Thus, although the \$200 from bank C was received as a credit line, the amount is treated as new credit since it was arranged during the pandemic, i.e., it was not an ex ante credit line.

One more important firm characteristic is exposure to the COVID-19 restrictions. To take this information into account, we add dummy variables for susceptible industries using the industry list approved by the Russian authorities (Russian Federation Government Resolution No. 434, dated 3 April 2020,'On the List of Sectors of the Russian Economy Most Affected by the Deterioration of the Situation Resulting from the Coronavirus Pandemic'). This Resolution provides a list of codes of industries that are considered exposed to the pandemic shock. Summary statistics for the variables used in this part of the study are presented in Table4 in Appendix.

4. Methodology

We focus on three issues in this paper:

- The credit quality of the borrowers in banks' portfolios of corporate loans issued during the pandemic.
- The utilisation of credit lines which were approved before the pandemic but activated during the pandemic.
- The bank-side determination of lending composition (whether banks with stronger fundamentals provided more loans to lower quality borrowers during the pandemic period).

We formulate a number of hypotheses and estimate several regressions to address these issues. Our analysis is descriptive in nature and is not causal inference. As we have no data on loan applications, we cannot identify the demand (and, correspondingly, supply) factors behind the observed conditional correlations as, for example, Jiménez et al. (2014) and Cuciniello and Di Iasio (2021) do.

Regression 1.

This regression addresses the first and third issues. Here, we estimate regression:

$$Y_{b,t} = \beta_0 + \beta_1 i_{pandemic,t} + \beta_2 BS_{b,t} + \beta_3 i_{pandemic,t} \cdot BS_{b,t} + \epsilon_{b,t} \qquad (1)$$

where, $Y_{b,t}$ is the share of loans issued by bank b during period t to firms with the highest probability of default (the three upper deciles) in all loans to all firms during the period, $i_{pandemic,t}$ is a dummy variable which equals 1 if the data are from March–August 2020 and equals 0 otherwise, $BS_{b,t}$ is the strength variable of bank b as measured before the pandemic period, which, since it is a number that represents the bank's quartile distribution, is treated as one of three dummy variables in the regression

The estimation results help us to test three hypotheses.

Hypothesis 1. During the pandemic in 2020, the share of loans issued to riskier firms[6] increased compared to what was observed before the pandemic. If β_1 is positive and significant, then the risk composition of new loans during the pandemic is skewed to loans given to the riskiest firms compared to the risk composition of new loans during pre-pandemic times.

Hypothesis 2. Riskier/weaker banks on average issue more loans to riskier firms compared to banks with healthier fundamentals (those with smaller shares of bad loans in their portfolios). A positive β_2 means that the corresponding group of banks issues more loans to risky borrowers compared to the reference group.[7] This may have adverse consequences on the stability of such banks.

Hypothesis 3. Riskier/weaker banks (as measured before the pandemic) increased their share of riskier loans during the pandemic to a higher degree compared to stronger banks. β_3 has a similar meaning to β_2, but regarding the pandemic period. If β_3 is positive and significant, then we cannot reject the hypothesis that banks from a given quartile increased their shares of loans provided to risky borrowers more in comparison with banks from the 1st (benchmark) quartile.

In the robustness check section, we study the sensitivity of the results to the choice of different measures on the left-hand side of regression 1: the difference between the share of loans provided

[6] As discussed in Section 3, these firms are from the three upper deciles with the highest estimated PD coefficients. For each year, PD is estimated using the previous year's values for financial variables.

[7] In our case, the 1st quartile of banks is treated as a benchmark., and thus a positive and significant coefficient β_2 means that banks with risky portfolios issued more risky loans compared to the banks in the reference group.

to the companies with highest PDs (the 8th to 10th deciles) and the share of loans provided to the companies with the lowest PDs (the 1st to 3rd deciles). On the application of alternative measures, see the work of Burova et al. (2022), in which the authors use the difference between percentile groups as an alternative measure for the variable.

Regressions 2 and 3.

The next two models address the second issue of loan composition in terms of credit line utilisation vs. new stand-alone loans. In the second regression, we examine how the share of a company's ex-ante credit lines changed during the pandemic depending on its financial soundness indicators.

Initially, we estimate the following regression:

$$Y_{f,t} = \beta_0 + \beta_1 i_{pandemic,t} + \beta_2 FS_{f,t} + \beta_3 FS_{f,t} \cdot i_{pandemic,t} + \epsilon_{f,t} \tag{2}$$

where $Y_{f,t}$ is the share of ex ante (issued before the period of reference) credit lines of firm f in the total funds borrowed during period of time, $i_{pandemic,t}$ is a dummy variable which equals 1 if the data are from 2020, $FS_{f,t}$ is the strength variable of firm f.

Here, we can check two more hypotheses that are relevant to our study.

Hypothesis 4: The share of ex ante credit line utilisation increased during the pandemic. In this case, we must pay attention to coefficient β_1. If β_1 is positive and significant, then the share of ex ante credit lines increased during pandemic, in which case we cannot reject Hypothesis 4.

Hypothesis 5: The share of ex ante credit line utilisation was, on average, higher for companies with higher probabilities of default (worse fundamentals). In this case, we look at β_2. If this coefficient is positive, it means that companies from the 2nd to 10th deciles used ex ante credit lines more intensively in comparison with companies from the 1st decile.[8] This means that more financially stable companies were less willing to use credit lines and preferred newly issued loans, thus if β_2 is positive and significant, we cannot reject Hypothesis 5.

β_3 provides an estimation of interaction term effects, meaning whether the utilisation of credit lines changed for different companies significantly during the pandemic. If β_3 is positive, then there was an increase in credit line utilisation among firms in the given decile during the COVID-19 period.

In the third regression, we expand the previous model by adding information about companies' vulnerability to the pandemic restrictions: the industry in which a company operates. The modified regression is:

$$\begin{aligned} Y_{f,t} = \beta_0 + \beta_1 i_{pandemic,t} + \beta_2 FS_{f,t} + \beta_3 i_{exposed,f} + \beta_4 FS_{f,t} \cdot i_{pandemic,t} + \\ + \beta_5 i_{exposed,f} \cdot i_{pandemic,t} + \beta_6 FS_{f,t} \cdot i_{exposed,f} + \beta_7 FS_{f,t} \cdot i_{pandemic,t} \cdot i_{exposed,f} + \epsilon_{f,t} \end{aligned} \tag{3}$$

where $Y_{f,t}$is the share of ex ante (issued before the period of reference) credit lines of firm f in the total funds borrowed during period of time t, $i_{pandemic,t}$ is a dummy variable that equals 1 if the data are from March–August 2020, $FS_{f,t}$ is the strength variable of firm f, and $i_{exposed,f}$ is a dummy variable that equals 1 if the main activity of firm f is in a sector of industry identified by the government as exposed to the pandemic.

Here, we are interested in testing two more hypotheses.

Hypothesis 6: Companies from exposed sectors had higher credit line utilisation during the pandemic compared to non-exposed companies. To check this statement, we look at coefficient β_5. If it is positive, this means that companies in the exposed industries had a higher rate of ex ante credit line utilisation during pandemic in comparison with non-exposed industries. Thus, if β_5 is positive and significant, we cannot reject Hypothesis 6.

[8] The 1st decile is chosen as the benchmark for the estimations. The lower the decile number, the better the financial condition of the firms, and thus the lower the estimated PD.

Hypothesis 7: Stronger companies in the exposed sectors had higher credit line utilisation during the pandemic compared to weaker companies in the exposed sectors. To verify this hypothesis, we look at coefficient β_7. If it is positive, then exposed companies in worse financial condition relied on ex ante credit lines more than companies in good financial standing. Here, the first decile is chosen as a benchmark. Companies are distributed by their estimated PD coefficients.[9]

Coefficients β_1, β_2, and β_4 have the same interpretation as coefficients β_1, β_2, and β_3 in Regression 2, respectively.

Regression 4.

Finally, to deepen our understanding of the third issue, we account for the bank-side determinants of lending composition in Regression 3. We add a new dimension to Regression 3 to examine how the share of a company's ex-ante credit lines provided by each separate bank changed during the pandemic period and how the changes are correlated with the financial strength of the bank that issued loans to or opened credit lines for the firm. We estimate the following regression:

$$Y_{f,b,t} = \beta_0 + \beta_1 i_{pandemic,t} + \beta_2 FS_{f,t} + \beta_3 BS_{b,t} + \beta_4 i_{exposed,f} + (interactions) + \epsilon_{f,t} \tag{4}$$

where $Y_{f,b,t}$ is the share of ex ante (issued before the period of reference) credit lines of firm f in the total funds borrowed by the firm from bank b during period of time t, $i_{pandemic,t}$ is a dummy variable that equals 1 if the data are from 2020, $FS_{f,t}$ is the strength variable of firm f, $i_{exposed,f}$ is a dummy variable that equals 1 if the main activity of firm f is in a sector of industry identified by the government as exposed to the pandemic, $BS_{b,t}$ is the strength variable of bank b as measured before the pandemic period, and $interactions$ is the set of all possible variables cross-effects by two ($i_{pandemic,t} \cdot i_{exposed,f}$, $i_{pandemic,t} \cdot FS_{f,t}$, etc), three (for example, $i_{pandemic,t} \cdot i_{exposed,f} \cdot FS_{f,t}$), or all four variables together ($i_{pandemic,t} \cdot i_{exposed,f} \cdot FS_{f,t} \cdot BS_{b,t}$).

Regression 4 helps us to test the following hypothesis:

Hypothesis 8: Credit line utilisation increased for firms with weaker fundamentals during the pandemic, and, in addition, the utilization rate was higher for the riskier banks for companies in the same decile. This means that the coefficient of double interaction for the pandemic dummy and firm strength ($i_{pandemic,t} \cdot FS_{f,t}$) is positive and the coefficient of triple interaction for pandemic, firm strength, and bank strength ($i_{pandemic,t} \cdot FS_{f,t} \cdot BS_{b,t}$) is also positive. In the first case, firms in poor financial condition are in higher deciles and thus have higher estimated coefficients for double interaction, which means that they have higher credit line utilisation rates in comparison with the 1st (benchmark) decile. A positive second coefficient shows that, for the same type of firms, banks with higher shares of risky loans provide higher shares of credit lines (in comparison with banks in the 1st quartile).

General approach to estimation

We estimate a fixed-effect model for our main results. The results are described in the following section.

We make this choice for several reasons. The first is to incorporate the information about banks more efficiently. A fixed-effect model allows us to consider the dynamic structure of the dataset and eliminate individual effects, and the statistical tests support this decision in all cases. Additionally, in Regressions 2–4, a comparison of the estimations of pooled and fixed-effect models proves the appearance of Simpson's paradox (we see opposite signs for pandemic coefficient estimations). In this case, a fixed-effect estimation is preferable, because it takes into account information about the model structure.

We note that in none of these specifications do we use bank characteristics or bank control variables as is done, for example, by Kapan and Minoiu (2021). Controls are not always used in empirical studies (see, for example, the work of Granja et al. (2020) where industry controls are not always

[9] A detailed description of this can be found in Section 3

used for estimations). The main reason for using such variables is to exclude the individual effects of banks on the results, but these individual effects are already taken into account with the use of fixed-effect model estimations.

We also implicitly assume that the trends are parallel for all groups, i.e., that absent the pandemic, we would observe the same differences between the different groups of firms and banks (those in exposed and non-exposed sectors, and those with strong and weak fundamentals). We do not check this explicitly, however the summary statistics by year and the graphs presented in Appendix, combined with the graphs of the regression results, show little evidence for non-parallel trends. The thresholds for the groups are rather stable over time, and the tendency changed significantly only in 2020. For example, if we look at Figure 3, we notice that the share of loans issued to firms with high PDs differs insignificantly among groups both before and after the pandemic.

5. Results

In this section we present results of estimating regressions 1–4. As the robustness check we provide results of the same regressions but with alternative specifications of right-hand side variables, i.e. continuous variables for Firm Strength (probability of default) and for Bank Strength (share of loans with credit quality IV and V in bank's portfolio).

Regression 1.

Detailed results of the estimation of Regression 1 are presented in Table 5 in the Appendix. Figure 3 illustrates these results graphically. The blue dots show the pre-pandemic level of the share of risky loans and their values, calculated as constant β_0 for the 1st quartile (this group is the benchmark), and the constant with the effect of bank group $\beta_0 + \beta_2$ for the rest of the banks. Similarly, we calculate values for the share of risky loans for the pandemic period: we take the constant and pandemic dummy effect $\beta_0 + \beta_1$ for the 1st quartile of banks and $\beta_0 + \beta_1 + \beta_2 + \beta_3$ for the rest of the banks. Thus, the difference between the pandemic and non-pandemic periods is equal to β_1 or $\beta_1 + \beta_3$ for different types of banks.

Hypotheses 1 and 2 can be illustrated with the use of the graphical representations in Figure 3: β_1 is the difference between the red and the blue points for the 1st bucket, and β_2 is difference among all the blue points for the 2nd to 4th buckets and the 1st. Hypothesis 3 is not evident in this graph. All the statistical tests for Hypotheses 1–3 can be found in Table 5. From both the graph and the table, it can be seen that β_1 is positive and significant, while β_2 and β_3 are not significant.

These results support *Hypothesis 1*. During the pandemic, the share of loans issued to riskier firms (when measured riskiness is fixed at levels from before the pandemic started) increased compared to what was observed in 'normal times' irrespective of bank-fundamentals (the positive and significant estimation of β_1). This share is higher by approximately 10pp compared to the almost 30% level before the pandemic.

The insignificance of coefficient β_2 does not support *Hypothesis 2*. Riskier/weaker banks on average did not issue more or less credit to riskier firms in comparison with banks with healthier fundamentals (with smaller shares of bad loans in their portfolios).

Finally, looking at the value of β_3 and its standard error, we can conclude that, for the size of the test, we do not find support for *Hypothesis 3* either. Riskier/weaker banks (when bank weakness is measured before the pandemic) did not change their share of riskier loans during the pandemic to a larger (or smaller) degree in comparison with stronger banks.

To put it briefly, we can see that the share of loans provided to firms with high probabilities of default became significantly larger during the pandemic period. Meanwhile, the difference between the groups of banks was insignificant both during the pandemic and the non-pandemic periods. We conclude that during the pandemic, banks reallocated loans to firms that had worse risk-profiles even before the crisis. We discuss the possible explanations of these results in the Concluding section.

Regression 2.

We present detailed results of the estimation of Regression 2 in Table 7 in the Appendix. Figure 4 illustrates these results graphically. The blue dots show the pre-pandemic level of ex ante credit line

Figure 3. Predicted values and confidence intervals for share of loans to firms with high PDs. The blue points show the predicted values in the non-pandemic period, and the red points show the predicted values in the pandemic period. Bank strength is described in Section 4. Higher values correspond to a higher share of NPLs on banks' balance sheets. The estimations are from a bank-level regression.

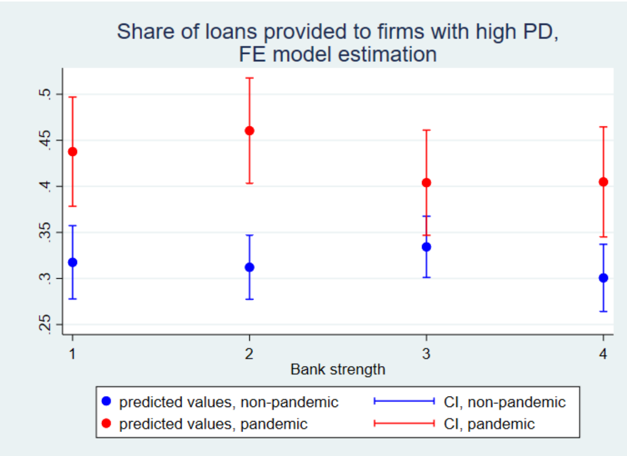
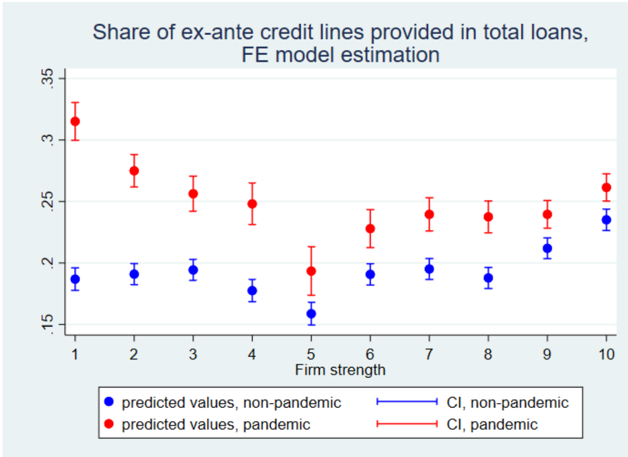


Figure 4. Predicted values and confidence intervals for share of ex ante credit lines in total loans. The blue points show the predicted values in the non-pandemic period, and the red points show the predicted values in the pandemic period. Firm strength is described in Section 4. Higher values correspond to a higher estimation of the PD coefficient (lower financial fundamentals for the firm). The estimations are from a firm-level regression.



utilisation and their values, calculated as constant β_0 for the 1st decile (this group is treated as the benchmark) and as constant together with effect of the company's PD decile $\beta_0 + \beta_2$ for the rest of the firms. Similarly, we calculate the values for the share of ex ante credit lines in the pandemic period: we take constant and pandemic dummy effect $\beta_0+\beta_1$ for the 1st decile of companies and $\beta_0+\beta_1+\beta_2+\beta_3$ for the rest of the firms. Thus, the difference between the non-pandemic and the pandemic periods is equal to β_1 or $\beta_1 + \beta_3$ depending on the company's PD group.

Hypotheses 4 and 5 can be illustrated with the graphical representations in Figure 4: β_1 is the difference between the red and the blue points for the 1st decile, and β_2 is the difference among all the blue points for the 2nd to 10th buckets and the 1st. All the statistical tests for Hypotheses 4 and 5 can be found in Table 7. From both the graph and the table, it can be seen that β_1 is positive and significant, but the β_2 coefficients are not significant in most cases. This coefficient is negative and significant for companies in the 5th decile and positive and significant for companies in the 9th and 10th deciles.

These results support *Hypothesis 4*. We notice that β_1 is statistically significant, which means that we observe an increase in the ex ante credit line utilisation rate during the pandemic. The share increased from approximately 20 percent before the pandemic period to almost 30 percent in 2020.

Considering *Hypothesis 5*, we find that the firms with the highest probabilities of default (the firms in the 9th and 10th deciles) on average attracted higher share of loans through the utilisation of previously opened credit lines (or banks supplied such firms more through credit lines). This result supports Hypothesis 5, although the difference is not very large from the point of view of economic significance.

If we take into account the interaction term of the pandemic dummy and the firm strength dummies, it can be seen that all the estimated coefficients are negative and significant. Moreover, these coefficients tend to increase in absolute values with increases in PD decile (Firm Strength), though this does not mean that weaker firms relied on ex ante credit lines less in comparison with the pre-pandemic period. It means, rather, that they used credit lines less in comparison with the most financially strong firms. Adding β_1 and β_3 for each decile shows the overall pandemic effect. This pandemic effect for each PD decile is presented in Figure4. This difference is statistically significant in all cases, but the effect is small in size for higher PD deciles (6–8% for the 2nd to 4th deciles in comparison with 2–4% for the 5th to 10th deciles). They cannot therefore be thought of as economically significant for companies in deciles higher than the 5th.

To sum up the results from Regression 2, the utilisation of previously approved credit lines increased significantly during the pandemic period, but it did so less for weaker firms. The increase is especially significant for less risky firms (as judged by their performance before the pandemic). This result may be explained both by supply and demand factors, and we discuss this issue in Section 6. In the non-pandemic period, we notice a tendency of growth in credit line utilisation with the increase of PD. This means that firms in worse financial condition used ex ante credit lines more. This may be due to the fact that banks are reluctant to provide new credit to companies with high PDs, and thus such firms have to use existing lending facilities (such as ex ante credit lines). This tendency has disappeared during the pandemic.

Regression 3.

In Regression 3, we take into account the variation from industry exposure to the pandemic shock. The results of the estimation of Regression 3 are presented in more detail in Table 8 in the Appendix. A graphical illustration of these results is presented in Figures 5 and 6.

In this case, each graph is built the same way as for Regression 2, but we also take the exposure dummy into account. β_0 is visualised as the blue point for the 1st decile of PD in Figure 5. The same blue point for the 1st decile in Figure 6 is equal to $\beta_0 + \beta_3$. The rest of the blue points (the pre-pandemic level of credit line utilisation) are calculated as $\beta_0 + \beta_2$ for non-exposed firms (Figure 5) and as $\beta_0 + \beta_2 + \beta_3 + \beta_6$ for exposed firms (Figure 6). In the pandemic period, visualised with the red points on both graphs, the level of credit line utilisation is $\beta_0 + \beta_1$ for the 1st decile of PD and $\beta_0 + \beta_1 + \beta_2 + \beta_4$ for the 2nd to 10th deciles of PD for non-exposed companies (Figure 5), and it is $\beta_0 + \beta_1 + \beta_3 + \beta_5$ for the 1st decile of PD and $\beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 + \beta_7$ for the 2nd to 10th deciles of PD for exposed companies (Figure 6).

First, we do not find a significant difference in the credit line utilisation of exposed and non-exposed companies on average in normal times (β_3 is insignificant). In the pandemic period, we do notice a significant difference between exposed and non-exposed entities. Firms in non-exposed industries began to use credit lines significantly more in 2020 ($beta_1 = 13.8$% and is positive and significant). This value is also economically significant.

To test *Hypothesis 6*, we look at coefficient β_5, which shows whether exposed companies used credit lines more or less in comparison with non-exposed companies in the pandemic period. From Table 8, it can be seen that $\beta_5 = -19.2$% and is significant. This means that exposed companies in the 1st decile had lower ex ante credit line utilisation rates in comparison with non-exposed firms, and so Hypothesis 6 should be rejected.

If we compare the utilisation rates of exposed companies before and after the onset of the pandemic (Figure 6), we notice that the firms in several PD decile buckets used credit lines to the same extent (1st to 4th and 8th deciles) or less in comparison with non-pandemic times. This occurred due to the fact that the initial effect of the pandemic shock on utilisation rates (β_1) was offset by opposite side effects for the exposed group (β_5), i.e., β_1 is positive while β_5 is negative, and their values are rather close, meaning that the overall effect is insignificant. The overall results for the 2nd to 10th PD deciles also depend on the individual coefficients for each decile (coefficients β_2, β_4, β_6 and β_7 should be taken into account). This difference may be attributable to supply and demand side factors. Unfortunately, due to a lack of data, we cannot identify their importance quantitatively (see Jiménez et al. (2014)). We elaborate on this in the concluding remarks.

To test *Hypothesis 7*, we take a closer look at the set of coefficients of β_7. They are insignificant in almost all cases (excluding the 8th decile of PD), meaning the hypothesis should be rejected: stronger companies in exposed sectors did not have higher ex ante credit line utilisation rates during the pandemic in comparison with firms with weaker fundamentals.

Figure 5. Predicted values and confidence intervals for share of ex ante credit lines in total loans. The blue points show the predicted values for the non-pandemic period, and the red points show the predicted values for the pandemic period. Firm strength is described in Section 4. Higher values correspond to higher estimations of the PD coefficient (lower financial fundamentals of the firm). The estimations for the non-exposed firms are from a firm-level regression.

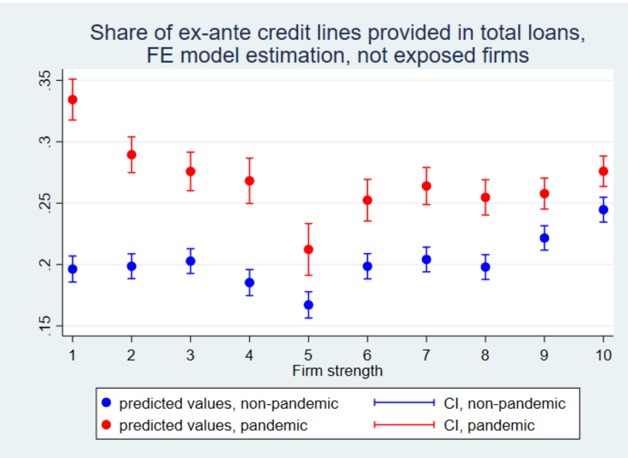
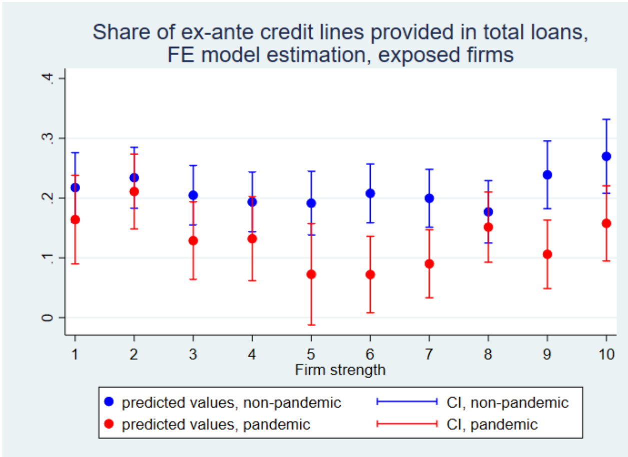


Figure 6. Predicted values and confidence intervals for share of ex ante credit lines in total loans. The blue points show the predicted values for the non-pandemic period, and the red points show the predicted values for the pandemic period. Firm strength is described in Section4. Higher values correspond to higher estimations of the PD coefficient (lower financial fundamentals of the firm). The estimations for the exposed firms are from a firm-level regression.



Regression 4.

The estimation results are presented in more detail in Table 9 in the Appendix. Figure 7 presents the calculated values for the share of ex ante credit lines in total loans as a heat map. These calculations are based on the estimated coefficients of Regression 4 at the firm-bank level. The Bank Strength variable is on the horizontal axis and the Firm Strength variable is on the vertical axis.

The main idea for the calculation of each value is very similar to those presented in the previous regressions. For example, the value in Table 9 for $Not\ exposed$ companies with $Firm\ Strength = 1$ during the $Non-pandemic$ period and for banks with $Bank\ Strength = 1$ is equal to β_0 from the regression. The same coefficient for $Exposed$ companies is equal to $\beta_0 + \beta_4$. Within each of the four panels, moving along the 1st row means moving from Bank Strength bucket 1 to Bank Strength bucket 4 (adding β_3 to β_0). Similarly, moving along the 1st column means moving from $FirmStrength = 10$ to $FirmStrength = 10$ (adding β_2 to β_0). When moving both row and column, we add not only β_2 and β_3, but also the interaction of the Bank Strength and Firm Strength variables. When switching from one panel to another, we take into account whether the period is $Pandemic$ or $Non-pandemic$ (β_1) and whether the companies are $Exposed$ or $Not\ exposed$ (β_4), including all the necessary interactions. If more than one parameter is changed, additional interactions should also be added.[10].

This regression allows the testing of *Hypothesis 8*. As discussed in Section 4, two sets of coefficients must be examined: the interaction of the pandemic dummy and *Firm Strength* and the triple interaction of *Pandemic*, *Firm strength* and *Bank strength*. All these coefficients can be found in Table 9. The coefficients for the double interaction $pandemic \times Firm\ Strength$ are all significant and negative. In addition, they tend to rise in absolute value with an increase in PD decile from the 1st to the 10th. This means that weaker firms had lower credit line utilisation rates during the pandemic.

[10]For example, if we move from the coefficient for non-exposed firms during the non-pandemic period for which $FS = 1$ and $BS = 1$ to exposed firms in the pandemic period with $FS = 1$ and $BS = 1$, we add both both β_1 and β_4 and the interaction term

Looking at the triple interaction $pandemic \times Firm\ Strength \times Bank\ Strength$, the coefficients are insignificant in almost all cases. This means that Hypothesis 8 is rejected: credit line utilisation decreased for weaker firms, and this result is the same for all banks.

Additional interactions must be considered for exposed companies (e.g., the triple interaction of $pandemic$ with the $exposure$ dummy and $Firm\ Strength$h). However, most of these coefficients are insignificant.

Among the significant variables and interaction terms, we note the positive influence of $pandemic$, the negative influence of $pandemic \times exposed$, the positive influence of $Firm\ Strength$ (especially for deciles higher than the 6th), the negative influence of $pandenic \times Firm\ Strength$, the positive influence of $Bank\ Strength$, the two positive coefficients out of three for $pandemic \times exposed \times Bank\ Strength$, and the several negative coefficients for $Firm\ Strength \times Bank\ Strength$ (in most cases, they apply to the 4th quartile of $Bank\ Strength$).

Thus, we can conclude that banks with higher shares of non-performing loans had relatively more ex ante credit lines drawn up. All the other relations are non-monotonic (U-shaped): for example, in Bank Strength buckets 3 and 4 (banks with the highest shares of low-quality loans in their portfolios), in the non-pandemic period, non-exposed companies (the last column in the upper right panel) show decreasing utilisation of credit lines with increasing PD up to the 5th PD decile. This relationship is reversed at higher PD levels.

This tendency holds for exposed companies during the non-pandemic period (the upper left panel) and for banks with high shares of low-quality loans in their portfolios, and this tendency is preserved for non-exposed companies during the pandemic period (the lower right panel).

The conclusion from Regression 3 also holds here: non-exposed firms began to use more ex ante credit lines during the pandemic (compare the values in the upper right panel and the lower right panel for each group). This is not the case for highly exposed companies (compare the values in the upper left panel and the lower left panel), especially for exposed companies with lower PDs and loans from stronger banks (those in Bank Strength buckets 1 or 2). We discuss this result in the Concluding section.

6. Conclusion

We have used loan-level supervisory data on corporate loans to test several hypotheses about the descriptive characteristics of corporate lending in Russia during the COVID-19 pandemic.

First, we studied how the credit quality composition of new loans issued during the pandemic changed compared to what was observed in normal times if the credit quality of borrowers is fixed at the levels observed before the pandemic (ex ante PDs). We fixed credit quality to exclude the effects of the pandemic on firm performance. We have found that the share of loans provided by banks to firms with the highest ex ante PD levels increased during the pandemic compared to what was observed in 'normal' times, and this result is statistically and economically significant. It is uniformly observed for all groups of banks, as defined by the share of NPLs in their portfolios. Additionally, we have not found that riskier/weaker banks changed their shares of riskier loans during the pandemic to a larger or smaller degree compared to stronger banks, that is, the intensity of the change does not correlate with the share of NPLs on a bank's balance sheet. Thus, we have found that there was no concentration of these risks on the balance sheets of 'riskier' or 'weaker' banks.

As government support programmes became an important driver of corporate loan issuance during the pandemic, the design of these programmes may explain the results we have found.[11] In what follows, we present some explanations of the result on the supply and demand sides. Both are related to the presence of the government support programmes.

[11] Bessonova et al. (2021) describe main types of subsidised loans issued during the COVID-19 pandemic in Russia and show that the number of new loans increased by 65% in January–August 2020 compared to the same period of 2019, mostly due to subsidised loans.

Figure 7. Predicted values for share of ex ante credit lines in total loans estimated at firm-bank level for exposed (left panel) and non-exposed (right panel) firms. Presented separately for non-pandemic (upper panel) and pandemic (lower panel) periods.

Fixed Effect									
		Exposed				Not exposed			
		Bank strength				Bank strength			
	Firm strength	1	2	3	4	1	2	3	4
Non-pandemic	1	0,214731	0,199231	0,206387	0,380455	0,090003	0,171334	0,188687	0,270074
	2	0,19196	0,233014	0,251579	0,222951	0,115571	0,175664	0,199564	0,271536
	3	0,123414	0,263235	0,117202	0,163706	0,135797	0,186009	0,203484	0,243145
	4	0,141079	0,2232	0,202647	0,248509	0,114499	0,189805	0,171969	0,223556
	5	0,234395	0,223688	-0,00911	0,077786	0,078643	0,172735	0,155443	0,186068
	6	0,116518	0,247579	0,23217	0,182308	0,125802	0,180213	0,195084	0,262789
	7	0,180999	0,230647	0,079855	0,152092	0,157201	0,181352	0,187845	0,248463
	8	0,108819	0,225434	0,165109	0,082721	0,13303	0,184511	0,184286	0,234427
	9	0,184106	0,226002	0,182353	0,261474	0,140862	0,205574	0,224826	0,269782
	10	0,128943	0,301121	0,209816	0,211258	0,191114	0,213991	0,256162	0,317623
		Bank strength				Bank strength			
	Firm strength	1	2	3	4	1	2	3	4
Pandemic	1	0,002078	0,242681	0,461081	0,569804	0,370007	0,340598	0,49489	0,566952
	2	0,145366	0,267727	0,267356	0,22171	0,289351	0,30434	0,414726	0,46204
	3	0,118124	0,216664	0,221652	0,722824	0,299435	0,296236	0,365633	0,459908
	4	0,135547	0,242738	0,371412	0,32002	0,274307	0,293362	0,389133	0,407066
	5	0,163731	0,102521	0,203691	0,599842	0,217782	0,259006	0,294049	0,430058
	6	0,067622	0,192223	0,234674	0,024432	0,28213	0,26554	0,418348	0,413716
	7	0,086617	0,212509	0,38601	0,355644	0,293169	0,275689	0,384919	0,39652
	8	0,235494	0,252396	0,41529	0,433459	0,249326	0,282932	0,358576	0,417058
	9	0,150163	0,215741	0,192801	0,395573	0,256256	0,272277	0,398275	0,425369
	10	0,238491	0,267385	0,33085	0,51606	0,263851	0,304558	0,379229	0,430732

The government support programmes compensated banks for credit losses, which may have made banks less sensitive to borrower credit quality (especially in the case of the 'FOT 2.0' programme[12]). Banks issuing subsidised loans were promised compensation for all potential credit losses, irrespective of the risk profile of the potential borrower. Thus, the programme design did not select for healthier firms (judged, in particular, by firm performance before the pandemic).

There is extensive literature that shows that reduced stimulus for banks to monitor borrowers has unpleasant effects on financial stability and on the efficient allocation of financing.

The programmes may have had unpleasant effects on the supply side for loans. Firms that already had risky profiles before the pandemic were able to get financing during the pandemic due to banks' lower monitoring efforts, a problem known as 'moral hazard' (Repullo (2004); Boyd and De Nicolo (2005)). One supply-side consequence of this is 'zombification'. There are several studies (R. Banerjee and Hofmann (2020); Laeven et al. (2020); Altavilla et al. (2020); Caballero et al. (2008); R. N. Banerjee and Kharroubi (2020)) which show that government support programmes may explain the rise in zombie firms (due to lower rates). Thus, supply-side effects may have resulted in a higher share of loans to firms that were risky even before the pandemic.

There may also be unpleasant demand-side effects from the loan programmes. If they expect lower monitoring from banks, weaker or riskier potential borrowers may intensify their loan applications, causing adverse selection. As a result, banks may have attracted potential borrowers which knew even before applying for subsidised loans that they would not repay the debt (see, for example, Saito and Tsuruta (2018) or Burova et al. (2021)).

[12]The conditions of loans under 'FOT 2.0' mean that if a firm retains employment ex post, the borrower need not repay the loan to the bank, but that the government will do so. If the firm does not retain employment ex post, it must repay the loan to the bank. However, if such a borrower defaults, the government will compensate the loss to the bank anyway.

If our explanation is close to the truth, the higher share of new loans to the riskiest firms during the pandemic represents a decrease in the efficiency of allocation of financial resources in the economy. The cost of this loss falls on society in the form of higher government compensation to banks for borrowers that do not fulfil the ex post conditions of their loans.

Second, we studied how the share of credit line utilisation in total corporate borrowing changed during the pandemic depending on companies' financial state and their exposure to the negative effects of the COVID-19 pandemic.

We found a statistically and economically significant increase in the share of ex ante credit line utilisation during the pandemic. This result is expected, as the utilisation of previously approved credit lines is a primary defence for companies facing liquidity shocks. This result is not novel (see, for example, Greenwald et al. (2021), Campello et al. (2012) or Bosshardt and Kakhbod (2021)).

We also found that the firms with the highest probabilities of default on average attracted lower shares of loans through the utilisation of previously opened credit lines, i.e., such firms increased the share of new stand-alone loans in their external financing. This result may be explained by entrance of riskier firms to the credit market for subsidised loans, i.e., new stand-alone loans, rather than the activation of previously approved credit lines.

Finally, we studied whether banks with larger or smaller shares of NPLs in their portfolios (as measured before the pandemic) saw higher utilisation of ex ante credit lines during the pandemic. We found that financially weaker banks (with higher shares of NPLs) tended to have higher shares of credit lines utilisation during the pandemic. This is an important observation as it means, on the one hand, that credit line utilisation (especially in a crisis) may entail more constraints for such banks compared to healthier banks. The constraint is the reduced ability to increase lending in the form of new stand-alone loans when such lending may be most demanded (Kapan and Minoiu (2021)). On the other hand, weaker banks have a greater chance of failing to provide loan supply through credit lines when they are activated. Both considerations mean that regulators may need to pay attention to whether weaker banks have higher shares of credit lines that may be activated.

We also studied the industry composition of credit lines before and during the pandemic. We found higher utilisation of ex ante credit lines during the pandemic, but only among companies that were less affected by the COVID-19 crisis. Exposed companies showed a decrease in the utilisation of existing credit lines.

As an explanation for this, we can propose both supply-side and demand-side factors. On the supply side, banks may have taken measures to reduce the availability of credit line utilisation to companies in exposed sectors to contain the elevated credit risk. [13] However, we believe that the main factors at play were on the demand side. Two groups of demand factors may have been important. First, as the demand for the output of the exposed sectors slumped during the pandemic, their demand for financing may have followed suit, especially that provided by credit lines. Second, firms in the exposed sectors that had not applied for loans before the pandemic may have entered the credit market demanding new subsidised loans. As a result, the share of activated credit lines in the total loans provided by banks declined for such firms. The arguments for the last explanation are presented by Bessonova et al. (2022).

To sum up, if our explanation is true and the government support programmes during the COVID-19 pandemic did indeed result in the observed unpleasant change in the structure of new loans, there is an avenue to improve the design of lending support schemes to better account for banks' monitoring stimulus.

For example, a support scheme may have two components. As its first component, the design should attract only those firms which intend to follow the 'rules of the game' (retain employment during the slump in demand amid the pandemic, etc.). For example, asking firms to provide some 'skin in the game' when applying for government subsidised loans may be a component of this design. As the second component, the government should not provide financing to a firm which is not ready to put 'skin in the game' when applying for a subsidised loan. Instead, it should support the employees

[13] We leave for future research the role of relationship lending in the observed difference. In this study we are not able to identify all relationship lending explicitly as our data has no such direct indicators.

of the firm by direct wage subsidies. Alternatively, the scheme could be designed such that it compensates banks only for realised losses exceeding a certain threshold level estimated based on the PD, LGD (loss given default), and EAD (exposure at default) components of the comprehensive risk assessment of borrowers eligible for the credit support scheme.

Concerning future research on this topic, we note that, first, we have considered the COVID-19 pandemic because it was an exogenous economic shock that occurred during a period of time for which data are available. Second, we examine only Russian banks and companies, as they represent the only granular data we have. However, it could be beneficial to use the same methodology on similar data from different countries and compare the results and provide meta-analysis. One more important issue concerns the use of different measures of banks' quality and corporate quality. In the first case, credits of IV and V quality category may be too volatile due to data specificity, and it would probably be better to use more stable variable, representing the riskiness of banks. In the second case, we should take the interconnection of different industries, leading to the higher probability of default.

Appendix

Summary statistics

Table 1. Data and sources

Variable	Units of measure	Description
Form No. 303. Detailed information about bank reporting form No. 303 can be found in Bank of Russia Ordinance No. 4927-U, dated 8 October 2018, 'On the List, Forms and Procedure for Compiling and Submitting Credit Institutions' Reporting Forms to the Central Bank of the Russian Federation', Appendix 1, Part 0409303 'Details of Loans Granted to Legal Entities'		
Tranche date	-	Field 5.1 of the form
Agreement date	-	Field 2.3 of the form
Debt repayment date	-	Field 3.8 of the form
Bank ID (REGN)	-	-
Company ID (INN)	-	Field 1.5 of the form
Agreement ID	-	Field 2.1 of the form
Type of loan	-	Field 3.1 of the form. 1 — credit (loans), 2 — overdraft credit, 3 — credit line with debt limit, 4 — credit line with issue limit, 5 — combined credit line with both debt and issue limits, 6 — credit cards
Special agreement terms	-	Field 3.15 of the form. 'T' is stated for credits with concessional interest rates
Total loans on agreement given the changes	RUB	Field 3.4 of the form. Loans in foreign currencies are presented in ruble equivalent
Total term debt outstand-ing	RUB	Field 6.3 of the form. Loans in foreign currencies are presented in ruble equivalent, and main and additional lines combined
Available unused credit limit	RUB	Field 8.1 of the form
Credit tranche volume	RUB	Field 5.3 of the form. Loans in foreign currencies are presented in ruble equivalent. Represented by tranche
Currency ID	-	Synthetic field in the report

Table 2. Summary statistics for subsamples

Overall sample

Year	2017	2018	2019	2020
Total credits, billion RUB	19,617.94	22,572.60	26,506.45	35,984.41
Observations	764,094.00	917,725.00	1,168,453.00	1,669,239.00
Number of unique IDs	115,057.00	146,244.00	183,057.00	350,425.00
Sub-sample, without overdrafts				
Year	2017	2018	2019	2020
Total credits, billion RUB	16,724.72	19,409.48	22,703.11	32,711.52
Observations	610,115.00	662,256.00	782,571.00	1,284,188.00
Number of unique IDs	89,950.00	97,181.00	109,125.00	281,678.00
Sub-sample, without overdrafts and with financial statement				
Year	2017	2018	2019	2020
Total credits, billion RUB	12,447.74	12,889.55	11,179.19	13,529.64
Observations	421,830.00	465,438.00	512,196.00	801,570.00
Number of unique IDs	44,669.00	47,561.00	51,744.00	138,762.00

Table 3. Summary statistics for regressions on bank-level data.
Note: The LC/TC variable represents the share of low-quality credits in the total credit portfolio.

Variable	mean	sd	count	min	max
2017					
Total credits (TC)	2.52E+10	1.63E+11	493	700,000	2.87E+12
Low-quality credits (LC)	7.42E+09	4.70E+10	493	0	7.71E+11
Share of category IV & V credits	0.1976071	0.2046711	493	0	0.9910293
LC/TC	0.3689322	0.2628493	493	0	1
2018					
Total credits (TC)	2.88E+10	2.09E+11	448	1,000,000	3.34E+12
Low-quality credits (LC)	8.73E+09	6.08E+10	448	0	8.82E+11
Share of category IV & V credits	0.2264603	0.2310415	448	0	1
LC/TC	0.3846213	0.2731901	448	0	1
2019					
Total credits (TC)	2.91E+10	1.64E+11	384	1,676,000	2.03E+12
Low-quality credits (LC)	9.30E+09	5.09E+10	384	0	5.82E+11
Share of category IV & V credits	0.2241562	0.2317299	384	0	1
LC/TC	0.3572287	0.2496626	384	0	1
2020					
Total credits (TC)	3.89E+10	2.25E+11	348	190,000	2.76E+12
Low-quality credits (LC)	1.99E+10	1.10E+11	348	0	1.22E+12
Share of category IV & V credits	0.2161275	0.2368818	348	0	0.9534884
LC/TC	0.442742	0.2599288	348	0	1

Table 4. Summary statistics for regressions on firm-level data

Variable	mean	sd	count	min	max
2017					
Total credits	2.79E+08	7.08E+09	44,669	1	8.77E+11
Ex ante credit lines	1.08E+08	3.21E+09	44,669	0	5.31E+11
PD	0.0664556	0.1097422	44,669	0	1
Share of ex ante credit lines	0.2947011	0.4255684	44,669	0	1
2018					
Total credits	2.71E+08	5.37E+09	47,561	1	5.24E+11
Ex ante credit lines	1.19E+08	3.08E+09	47,561	0	4.04E+11
PD	0.067936	0.1156658	47,561	0	1
Share of ex ante credit lines	0.3152794	0.4329423	47,561	0	1
2019					
Total credits	2.16E+08	4.43E+09	51,744	155.13	5.38E+11
Ex ante credit lines	1.10E+08	3.17E+09	51,744	0	5.38E+11
PD	0.0614362	0.1118705	51,744	0	1
Share of ex ante credit lines	0.3053399	0.4327039	51,744	0	1
2020					
Total credits	9.75E+07	4.38E+09	138,762	0.31	1.10E+12
Ex ante credit lines	4.67E+07	1.94E+09	138,762	0	3.65E+11
PD	0.0607798	0.1165458	138,762	0	1
Share of ex ante credit lines	0.1343297	0.322101	138,762	0	1

Histograms

Figure 8. Share of category IV & V credits in total loans provided by banks by year

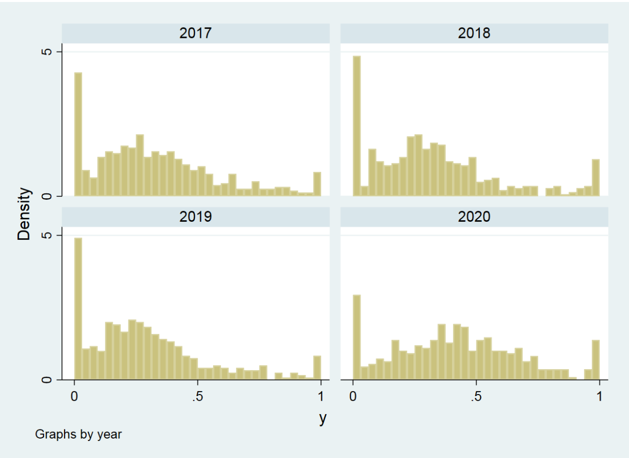
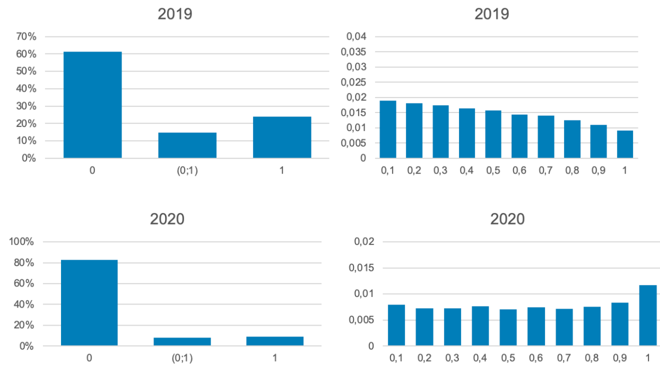


Figure 9. Share of ex ante credit line credit in total loans provided to companies in 2019 and 2020. Left graph in histogram by parts: 0, 1, and everything in between. Right graph presents part (0,1) in more detail.



Regression outputs

Figure 10. Predicted values and confidence intervals for share of loans to firms with high PDs. The blue points are the predicted values for the non-pandemic period, and the red points show the predicted values for the pandemic period. Bank strength is described in Section 4. Higher values correspond to a higher share of NPLs on banks' balance sheets. These are pooled estimations are from a bank-level regression.

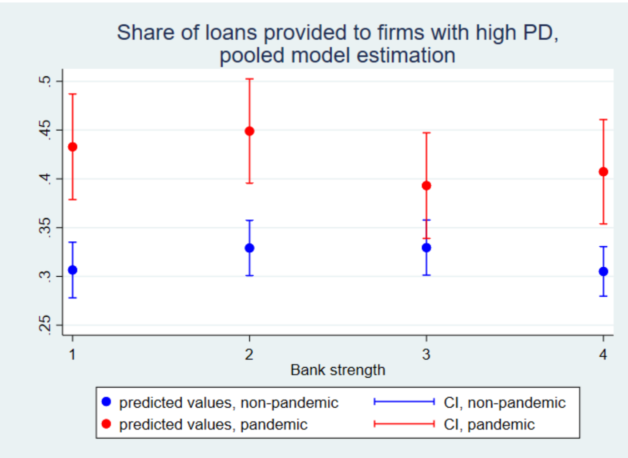


Figure 11. Predicted values and confidence intervals for share of ex ante credit lines in total loans. These are pooled estimations from a firm-level regression.

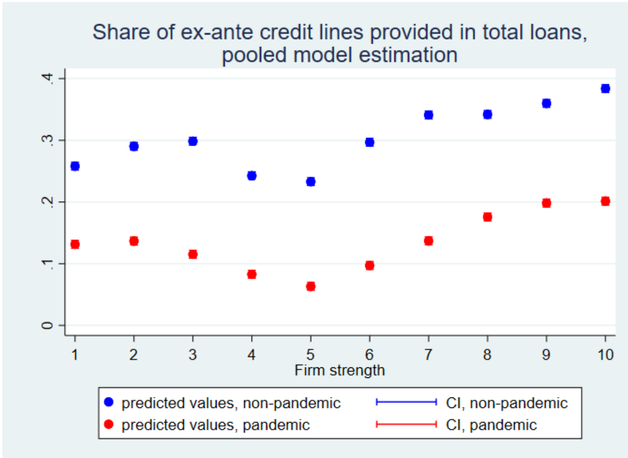


Figure 12. Predicted values and confidence intervals for share of ex ante credit lines in total loans. The blue points show the predicted values in the non-pandemic period, and the red points show the predicted values in the pandemic period. The estimations are from a bank-level regression. Firm strength is described in Section 4. Higher values correspond to higher estimations for the PD coefficient (lower financial fundamentals of the firm). The pooled model estimations are from a firm-level regression for non-exposed firms.

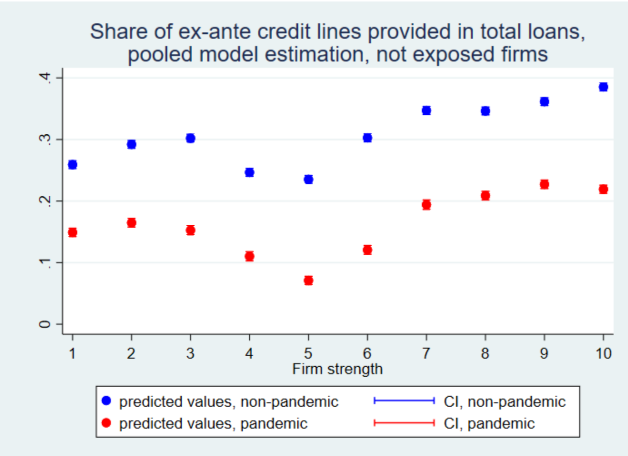


Figure 13. Predicted values and confidence intervals for share of ex ante credit lines in total loans. The blue points show the prediction values in the non-pandemic period, and the red points show the predicted values in the pandemic period. The estimations are from a bank-level regression. Firm strength is described in Section 4. Higher values correspond to higher estimations for the PD coefficient (lower financial fundamentals of the firm). The pooled model estimations are from a firm-level regression for exposed firms.

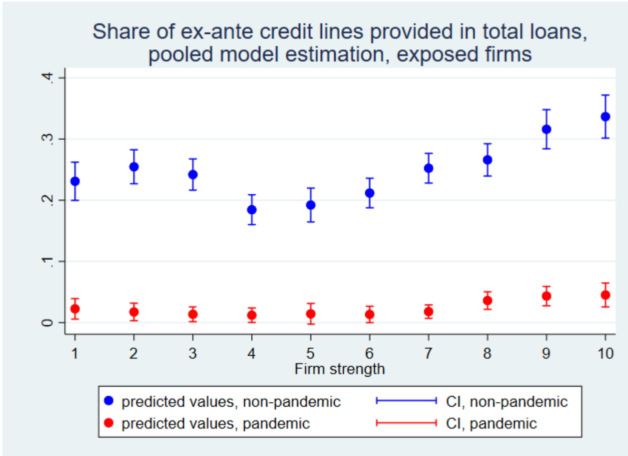


Table 5. Estimation of Regression 1. Regression by banks. Baseline model is presented in column (2).

VARIABLES	(1) pooled	(2) FE model	(3) pooled	(4) FE model
$pandemic = 1$	0.126***	0.120***	0.127***	0.142***
		$bank\ strength$		
$bs = 2$	0.023	-0.005		
$bs = 3$	0.023	0.017		
$bs = 4$	-0.001	-0.017		
$share$			-0.006	0.057
		$pandemic \times bank\ strength$		
$p = 1, bs = 2$	-0.006	0.028		
$p = 1, bs = 3$	-0.063	-0.050		
$p = 1, bs = 4$	-0.024	-0.016		
$p = 1, share$			-0.106	-0.144**
Constant	0.307***	0.318***	0.318***	0.303***
Observations	1,659	1,659	1,659	1,659
Groups		508		508
R^2_{overall}	0.030	0.029	0.029	0.027
R^2_{between}		0.0006		0.0008
R^2_{within}		0.051		0.051
F-stat	7.232	8.713	16.40	20.69
p-value	1.49e-08	1.86e-10	1.67e-10	0

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6. Estimation of Regression 1. Robustness check. Regression by banks with alternative dependent variable for robustness check. Baseline model is presented in column (2).

VARIABLES	(1) pooled	(2) FE model	(3) pooled	(4) FE model
$pandemic = 1$	0.127**	0.131**	0.140***	0.160***
	$bank\ strength$			
$bs = 2$	0.005	-0.019		
$bs = 3$	0.012	0.014		
$bs = 4$	-0.004	-0.028		
$share$			0.028	0.192*
	$pandemic \times bank\ strength$			
$p = 1, bs = 2$	0.032	0.057		
$p = 1, bs = 3$	-0.084	-0.089		
$p = 1, bs = 4$	0.021	-0.014		
$p = 1, share$			-0.090	-0.187
Constant	-0.003	0.009	-0.006	-0.041
Observations	1,659	1,659	1,659	1,659
Groups		508		508
R^2_{overall}	0.014	0.013	0.013	0.009
R^2_{between}		0.0013		0.00014
R^2_{within}		0.021		0.022
F-stat	3.433	3.505	7.136	8.512
p-value	0.001	0.001	9.23e-05	1.36e-05

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7. Estimation of Regression 2. Regressions by firms without exposure. Baseline model is presented in column (2).

VARIABLES	(1) pooled	(2) FE model	(3) pooled	(4) FE model
$pandemic = 1$	-0.127***	0.128***	-0.165***	0.065***
	$firm\ strength$			
$fs = 2$	0.032***	0.004		
$fs = 3$	0.040***	0.007		
$fs = 4$	-0.015***	-0.009		
$fs = 5$	-0.025***	-0.028***		
$fs = 6$	0.039***	0.004		
$fs = 7$	0.083***	0.008		
$fs = 8$	0.084***	0.001		
$fs = 9$	0.102***	0.025***		
$fs = 10$	0.126***	0.048***		
pd			0.246***	0.119***
	$pandemic \times firm\ strength$			
$p = 1, fs = 2$	-0.027***	-0.044***		
$p = 1, fs = 3$	-0.057***	-0.066***		
$p = 1, fs = 4$	-0.033***	-0.058***		
$p = 1, fs = 5$	-0.043***	-0.094***		
$p = 1, fs = 6$	-0.073***	-0.091***		
$p = 1, fs = 7$	-0.077***	-0.084***		
$p = 1, fs = 8$	-0.040***	-0.079***		
$p = 1, fs = 9$	-0.035***	-0.101***		
$p = 1, fs = 10$	-0.056***	-0.102***		
$p = 1, pd$			-0.073***	-0.099***
Constant	0.258***	0.187***	0.289***	0.184***
Observations	282,051	282,051	282,051	282,051
Groups		194,197		194,197
R^2_{overall}	0.062	0.0148	0.052	0.0360
R^2_{between}		0.0285		0.0753
R^2_{within}		0.011		0.008
F-stat	981.4	50.17	5120	249
p-value	0.000	0.000	0.000	0.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8. Estimation of Regression 3. Regressions by firms with exposure. Baseline model is presented in column (2).

VARIABLES	(1) pooled	(2) FE model	(3) pooled	(4) FE model
$pandemic = 1$	-0.110***	0.138***	-0.139***	0.076***
	$firm\ strength$			
$fs = 2$	0.033***	0.002		
$fs = 3$	0.043***	0.006		
$fs = 4$	-0.013***	-0.011		
$fs = 5$	-0.024***	-0.029***		
$fs = 6$	0.044***	0.002		
$fs = 7$	0.088***	0.008		
$fs = 8$	0.087***	0.002		
$fs = 9$	0.102***	0.025***		
$fs = 10$	0.126***	0.048***		
pd			0.242***	0.122***
	$pandemic \times firm\ strength$			
$p = 1, fs = 2$	-0.017***	-0.047***		
$p = 1, fs = 3$	-0.039***	-0.065***		
$p = 1, fs = 4$	-0.026***	-0.055***		
$p = 1, fs = 5$	-0.054***	-0.093***		
$p = 1, fs = 6$	-0.072***	-0.084***		
$p = 1, fs = 7$	-0.043***	-0.078***		
$p = 1, fs = 8$	-0.027***	-0.081***		
$p = 1, fs = 9$	-0.024***	-0.102***		
$p = 1, fs = 10$	-0.056***	-0.107***		
$p = 1, pd$			-0.093***	-0.116***
$exposed = 1$	-0.028*	0.021	-0.063***	0.010
$pandemic = 1, exposed = 1$	-0.099***	-0.192***	-0.071***	-0.153***
	$firm\ strength \times exposed$			
$fs = 2, e = 1$	-0.009	0.014		
$fs = 3, e = 1$	-0.032	-0.019		
$fs = 4, e = 1$	-0.034	-0.013		
$fs = 5, e = 1$	-0.015	0.003		
$fs = 6, e = 1$	-0.063***	-0.012		
$fs = 7, e = 1$	-0.067***	-0.026		
$fs = 8, e = 1$	-0.052**	-0.042		
$fs = 9, e = 1$	-0.017	-0.004		
$fs = 10, e = 1$	-0.021	0.004		
$pd, e = 1$			0.007	0.027
	$pandemic \times firm\ strength \times exposed$			
$p = 1, fs = 2, e = 1$	-0.011	0.078		
$p = 1, fs = 3, e = 1$	0.020	0.043		

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VARIABLES	(1) pooled	(2) FE model	(3) pooled	(4) FE model
$p = 1, fs = 4, e = 1$	0.062***	0.047		
$p = 1, fs = 5, e = 1$	0.085***	0.027		
$p = 1, fs = 6, e = 1$	0.082***	0.002		
$p = 1, fs = 7, e = 1$	0.017	0.022		
$p = 1, fs = 8, e = 1$	0.006	0.109**		
$p = 1, fs = 9, e = 1$	-0.040	0.023		
$p = 1, fs = 10, e = 1$	-0.027	0.048		
$p = 1, pd, e = 1$			-0.089	0.057
Constant	0.259***	0.196***	0.292***	0.193***
Observations	282,051	282,051	282,051	282,051
Groups		194,197		194,197
R^2_{overall}	0.073	0.001	0.062	0.0001
R^2_{between}		0.0003		0.0001
R^2_{within}		0.014		0.011
F-stat	570	31.56	2671	144.4
p-value	0.000	0.000	0.000	0.000

*** p<0.01, ** p<0.05, * p<0.1

Table 9. Estimation of Regression 4. Regressions by firms and banks combined. Baseline model is presented in column (2).

VARIABLES	(1) pooled	(2) FE model	(3) pooled	(4) FE model
$pandemic = 1$	-0.165***	0.276***	-.152***	0.116***
$exposed = 1$	-0.050	0.123	-0.082***	0.039
$pandemic = 1, exposed = 1$	-0.180***	-0.490***	-0.054***	-0.155***
$firm\ strength$				
$fs = 2$	0.030**	0.024		
$fs = 3$	0.070***	0.044***		
$fs = 4$	0.027**	0.021		
$fs = 5$	0.009	-0.013		
$fs = 6$	0.059***	0.034**		
$fs = 7$	0.070***	0.064***		
$fs = 8$	0.074***	0.040**		
$fs = 9$	0.080***	0.049***		
$fs = 10$	0.105***	0.099***		
pd			0.245***	0.121***
$pandemic \times firm\ strength$				
$p = 1, fs = 2$	-.020	-0.104***		
$p = 1, fs = 3$	-.049**	-0.114***		
$p = 1, fs = 4$	-.078***	-0.115***		
$p = 1, fs = 5$	-.136***	-0.144***		
$p = 1, fs = 6$	-.095***	-0.122***		
$p = 1, fs = 7$	.024	-0.140***		
$p = 1, fs = 8$	.008	-0.159***		
$p = 1, fs = 9$	.008	-0.161***		
$p = 1, fs = 10$	-.037**	-0.205***		
$p = 1, pd$			-0.136***	-0.092**
$firm\ strength \times exposed$				
$fs = 2, e = 1$	-.050	-0.042		
$fs = 3, e = 1$	-.020	-0.136		
$fs = 4, e = 1$	-.092	-0.096		
$fs = 5, e = 1$	.059	0.032		
$fs = 6, e = 1$	-.052	-0.132		
$fs = 7, e = 1$	-.051	-0.099		
$fs = 8, e = 1$	-.035	-0.146		
$fs = 9, e = 1$	-.018	-0.080		
$fs = 10, e = 1$	-.048	-0.185*		
$pd, e = 1$			0.015	-0.094
$pandemic \times firm\ strength \times exposed$				
$p = 1, fs = 2, e = 1$	0.036	0.266		
$p = 1, fs = 3, e = 1$	-.011	0.322		
$p = 1, fs = 4, e = 1$	.131*	0.323*		
$p = 1, fs = 5, e = 1$	.056	0.286		
$p = 1, fs = 6, e = 1$	.075	0.286		
$p = 1, fs = 7, e = 1$	-.055	0.260		
$p = 1, fs = 8, e = 1$	-.026	0.500***		
$p = 1, fs = 9, e = 1$	-.032	0.340*		

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VARIABLES	(1) pooled	(2) FE model	(3) pooled	(4) FE model
$p = 1, fs = 10, e = 1$	.017	0.529**		
$p = 1, pd, e = 1$			-0.090	0.336*
	$bank\ strength$			
$bs = 2$	-0.240***	0.081***		
$bs = 3$	-0.101***	0.099***		
$bs = 4$	-0.098***	0.181***		
$share$			0.132***	0.109***
	$pandemic \times bank\ strength$			
$p = 1, bs = 2$	0.088***	-0.108***		
$p = 1, bs = 3$	0.044***	-0.029		
$p = 1, bs = 4$	0.407***	0.019		
$p = 1, share$			0.152***	0.188***
	$exposed \times bank\ strength$			
$e = 1, bs = 2$	0.047	-0.097		
$e = 1, bs = 3$	0.049	-0.095		
$e = 1, bs = 4$	0.029	-0.047		
$e = 1, share$			0.126***	-0.125
	$pandemic \times exposed \times bank\ strength$			
$p = 1, e = 1, bs = 2$	0.085	0.364**		
$p = 1, e = 1, bs = 3$	0.065	0.423**		
$p = 1, e = 1, bs = 4$	-0.063	0.395		
$p = 1, e = 1, share$			-0.200***	0.309**
	$firm\ strength \times bank\ strength$			
$fs = 2, bs = 2$	0.012	-0.019		
$fs = 2, bs = 3$	-.013	-0.014		
$fs = 2, bs = 4$	.032*	-0.023		
$fs = 3, bs = 2$	-.019	-0.030		
$fs = 3, bs = 3$	-.042***	-0.029		
$fs = 3, bs = 4$	-.004	-0.071***		
$fs = 4, bs = 2$	-.022*	-0.002		
$fs = 4, bs = 3$	-.037**	-0.038		
$fs = 4, bs = 4$	-.009	-0.67**		
$fs = 5, bs = 2$	-.016	0.014		
$fs = 5, bs = 3$	-.007	-0.019		
$fs = 5, bs = 4$	-.032*	-0.071**		
$fs = 6, bs = 2$	0.006	-0.024		
$fs = 6, bs = 3$	-.047***	-0.028		
$fs = 6, bs = 4$	.006	-0.041		
$fs = 7, bs = 2$	.031**	-0.054***		
$fs = 7, bs = 3$	-.015	-0.065***		
$fs = 7, bs = 4$	.050***	-0.086***		
$fs = 8, bs = 2$	.019	-0.026		
$fs = 8, bs = 3$	-.015	-0.044*		
$fs = 8, bs = 4$	.017	-0.078***		
$fs = 9, bs = 2$	.041***	-0.015		
$fs = 9, bs = 3$	-.023	-0.016		
$fs = 9, bs = 4$	.019	-0.052**		
$fs = 10, bs = 2$	.017	-0.057***		
$fs = 10, bs = 3$	-.001	-0.032		
$fs = 10, bs = 4$	.014	-0.053**		

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VARIABLES	(1) pooled	(2) FE model	(3) pooled	(4) FE model
$pd{,}share$			-0.239***	0.059
$pandemic \times firm\ strength \times bank\ strength$				
$p = 1{,}fs = 2{,}bs = 2$	.006	0.063		
$p = 1{,}fs = 2{,}bs = 3$	.013	0.013		
$p = 1{,}fs = 2{,}bs = 4$	-.005	-0.002		
$p = 1{,}fs = 3{,}bs = 2$	.017	0.056		
$p = 1{,}fs = 3{,}bs = 3$	.006	-0.029		
$p = 1{,}fs = 3{,}bs = 4$	.039	0.038		
$p = 1{,}fs = 4{,}bs = 2$	.053**	0.050		
$p = 1{,}fs = 4{,}bs = 3$	.029	0.031		
$p = 1{,}fs = 4{,}bs = 4$	.066	0.003		
$p = 1{,}fs = 5{,}bs = 2$	.086***	0.061		
$p = 1{,}fs = 5{,}bs = 3$	.034	-0.026		
$p = 1{,}fs = 5{,}bs = 4$	.173***	0.094		
$p = 1{,}fs = 6{,}bs = 2$	.024	0.036		
$p = 1{,}fs = 6{,}bs = 3$	.055**	0.042		
$p = 1{,}fs = 6{,}bs = 4$	.026	-0.027		
$p = 1{,}fs = 7{,}bs = 2$	-.068***	0.065		
$p = 1{,}fs = 7{,}bs = 3$	-.028	0.032		
$p = 1{,}fs = 7{,}bs = 4$	-.129***	-0.007		
$p = 1{,}fs = 8{,}bs = 2$	-.035*	0.089**		
$p = 1{,}fs = 8{,}bs = 3$	.004	0.026		
$p = 1{,}fs = 8{,}bs = 4$	-.054	0.044		
$p = 1{,}fs = 9{,}bs = 2$	-.048**	0.058		
$p = 1{,}fs = 9{,}bs = 3$	.034	0.029		
$p = 1{,}fs = 9{,}bs = 4$	-.041	0.026		
$p = 1{,}fs = 10{,}bs = 2$	-.018	0.128***		
$p = 1{,}fs = 10{,}bs = 3$	.002	0.025		
$p = 1{,}fs = 10{,}bs = 4$	.015	0.025		
$p = 1{,}pd{,}share$			0.517***	-0.292
$exposed \times firm\ strength \times bank\ strength$				
$e = 1{,}fs = 2{,}bs = 2$	.027	0.070		
$e = 1{,}fs = 2{,}bs = 3$	.070	0.067		
$e = 1{,}fs = 2{,}bs = 4$	-.010	-0.088		
$e = 1{,}fs = 3{,}bs = 2$	-.040	0.185*		
$e = 1{,}fs = 3{,}bs = 3$	.031	0.018		
$e = 1{,}fs = 3{,}bs = 4$	.005	-0.026		
$e = 1{,}fs = 4{,}bs = 2$	.017	0.100		
$e = 1{,}fs = 4{,}bs = 3$	.105	0.94		
$e = 1{,}fs = 4{,}bs = 4$	.056	0.044		
$e = 1{,}fs = 5{,}bs = 2$	-.110	-0.010		
$e = 1{,}fs = 5{,}bs = 3$	-.100	-0.229		
$e = 1{,}fs = 5{,}bs = 4$	-.132	-0.221		
$e = 1{,}fs = 6{,}bs = 2$	-.058	0.173		
$e = 1{,}fs = 6{,}bs = 3$	.056	0.123		
$e = 1{,}fs = 6{,}bs = 4$	-.008	-0.016		
$e = 1{,}fs = 7{,}bs = 2$	-.044	0.118		
$e = 1{,}fs = 7{,}bs = 3$	.044	-0.040		
$e = 1{,}fs = 7{,}bs = 4$	-.015	-0.079		
$e = 1{,}fs = 8{,}bs = 2$	-.039	0.158		

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VARIABLES	(1) pooled	(2) FE model	(3) pooled	(4) FE model
$e = 1, fs = 8, bs = 3$	.037	0.094		
$e = 1, fs = 8, bs = 4$	-.038	-0.084		
$e = 1, fs = 9, bs = 2$	-.066	0.073		
$e = 1, fs = 9, bs = 3$	.088	0.009		
$e = 1, fs = 9, bs = 4$	.032	-0.006		
$e = 1, fs = 10, bs = 2$	-.005	0.245*		
$e = 1, fs = 10, bs = 3$	.096	0.109		
$e = 1, fs = 10, bs = 4$	-.064	0.001		
$e = 1, pd, share$			-0.024	0.208
$pandemic \times exposed \times firm\ strength \times bank\ strength$				
$p = 1, e = 1, fs = 2, bs = 2$	-.038	-0.233		
$p = 1, e = 1, fs = 2, bs = 3$	-.119	-0.401		
$p = 1, e = 1, fs = 2, bs = 4$	.088	-0.360		
$p = 1, e = 1, fs = 3, bs = 2$	.048	-0.354		
$p = 1, e = 1, fs = 3, bs = 3$	-.034	-0.314		
$p = 1, e = 1, fs = 3, bs = 4$	.206	0.113		
$p = 1, e = 1, fs = 4, bs = 2$	-.040	-0.281		
$p = 1, e = 1, fs = 4, bs = 3$	-.139	-0.309		
$p = 1, e = 1, fs = 4, bs = 4$	-.293	-0.342		
$p = 1, e = 1, fs = 5, bs = 2$	.050	-0.368		
$p = 1, e = 1, fs = 5, bs = 3$	.040	-0.144		
$p = 1, e = 1, fs = 5, bs = 4$	.008	0.092		
$p = 1, e = 1, fs = 6, bs = 2$	.039	-0.301		
$p = 1, e = 1, fs = 6, bs = 3$	-.107	-0.426*		
$p = 1, e = 1, fs = 6, bs = 4$	.261	-0.512		
$p = 1, e = 1, fs = 7, bs = 2$	.096	-0.244		
$p = 1, e = 1, fs = 7, bs = 3$	-.011	-0.133		
$p = 1, e = 1, fs = 7, bs = 4$	.337**	-0.109		
$p = 1, e = 1, fs = 8, bs = 2$	.048	-0.445**		
$p = 1, e = 1, fs = 8, bs = 3$	-.044	-0.354		
$p = 1, e = 1, fs = 8, bs = 4$	.481***	-0.233		
$p = 1, e = 1, fs = 9, bs = 2$	.055	-0.292		
$p = 1, e = 1, fs = 9, bs = 3$	-.103	-0.438*		
$p = 1, e = 1, fs = 9, bs = 4$	.208	-0.272		
$p = 1, e = 1, fs = 10, bs = 2$	-.014	-0.528**		
$p = 1, e = 1, fs = 10, bs = 3$	-.113	-0.474*		
$p = 1, e = 1, fs = 10, bs = 4$	.315*	-0.246		
$p = 1, pd, share$			0.267	-0.825
Constant	0.429***	0.092***	0.294***	0.167***
Observations	315,810	315,810	315,810	315,810
Groups		233,379		233,379
R^2_{adjusted}	0.109		0.060	
R^2_{overall}	0.109	0.006	0.060	0.011
R^2_{between}		0.016		0.027
R^2_{within}		0.037		0.031
F-stat	243.39	19.95	1,338.8	172.75
p-value	0.000	0.000	0.000	0.000

*** p<0.01, ** p<0.05, * p<0.1

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