Time to Extend Credit?

Bank Credit Lines During the COVID-19 Pandemic in Russia

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ABSTRACT

This study focuses on the COVID-19 effect on the drawdown on bank credit lines in Russia. Using the bank-level data for all Russian banks for 2017-2020 we document that the first quarter of the pandemic witnesses a significant increase in probability for banks to demonstrate positive loans granted within the credit lines, which – given that banks are not prone to extend credit limits at the beginning of the economic crisis – could signal that the borrowers drawdown funds within the existing credit limits where possible, increasing the overall credit risk of the banking sector. The following quarters show the gradual decrease in the inability of pre-pandemic models to estimate the probability of granting lines of credit, meaning that the banks adapt to new economic reality. This is the first study examining the COVID-19 shock in credit lines draw dawns using publicly available bank-level data.

INTRODUCTION

A credit line (or a permitted overdraft), aiming mostly to smooth the financing of the borrower's business processes, is also an important tool that allows a firm to be insured against a liquidity shock, causing a certain deterioration in its performance (Holmström and Tirole, 1998; Sufi, 2009; Acharya *et al.*, 2021). A considerable amount of valuable work on the corporate sector's liquidity provision addressed by banks has been performed to provide a solid grounding for explaining the mechanism of credit lines and confirming their efficiency both theoretically and empirically. However, from a bank's point of view, efficiency is reached when liquidity shocks faced by borrowers are independently distributed. A systemic shock, making them widespread and simultaneous, may result in the need for banks to extend credit within the limits of the credit lines of numerous borrowers, increasing bank credit risk (Holmström & Tirole, 1998, Almeida, 2021). The credit line drawdowns may be caused by both current and potential liquidity shocks. The firms facing the current liquidity shocks withdraw the funds to cover it to support the business process financing. However even those firms that do not face the shock may still borrow more within the limit, expecting further shocks accompanied by future limits reduction. In this case the firms may not just withdraw the funds but also transfer them to the current accounts or deposits.

Quite a few papers have examined the determinants of the loan volumes granted within credit lines on both the demand and supply sides. The key predictor is the borrower's expected credit quality; thus, larger and more reliable firms seem to use more bank credit lines than firms with low credit quality and profit (Acharya et al., 2014; Sufi, 2009). Other factors, such as firm liquidity, age, risk premium, and industry, were found to be significant for the volumes of credit lines for firms (Jiménez, Lopez and Saurina, 2009). Companies that violate credit line contracts face negative restrictions such as a reduction in the credit line limit or its maturity, an increase in interest spreads, and the introduction of collateral requirements (Acharya et al., 2014, 2020, 2021). Acharya et al. 2021, concluded that credit lines are cyclical, which indicates the importance of macroeconomic conditions for both credit line supply and demand. For instance, during recessions, companies prefer to draw on their credit lines rather than other sources of external financing (Jiménez, Lopez and Saurina, 2009). Deterioration of banks' financial performance, especially in the case of global crises and other significant financial shocks, leads to a reduction in loans and credit lines granted (Acharya *et al.*, 2021). This means that the bank's capitalization or liquidity could also be considered determinants of the credit lines provided (Acharya et al., 2020; Almeida, 2021).

The ongoing COVID-19 pandemic of 2020-2021 is a perfect example of an external systemic shock that influences most businesses. The existing literature documents an increase in the usage of lines of credit by large companies, especially in the USA, at the beginning of the crisis in 2020 since they expected tightening of loan conditions (Acharya et al., 2021; Acharya & Steffen, 2020; Berger & Demirgüç-Kunt, 2021). Almeida, 2021, demonstrated that the situation caused by COVID-19 is an excellent example of the liquidity insurance provided by lines of credit since the predefined conditions allow companies to borrow at lower interest rates than would have been in the market at that time. In addition, (Javadi *et al.*, 2021) and (Acharya and Steffen, 2020) stated that in cases of financial and policy uncertainty, credit line usage by firms increases, which is explained by precautionary motives. These findings are based on the analysis of 19 non-U.S. countries, not only at the beginning of the COVID-19 crisis but also more than 20 years beforehand. On the other hand, Acharya & Steffen, 2020, concluded that during the COVID-19 pandemic, US firms drew down credit lines in favour of long-term debt and equity issuance.

The aim of this paper is to document and examine the drawdown of credit lines by Russian borrowers during the first wave of the pandemic in 2020. Identifying the influence of external shocks – including COVID-19 – is a complicated task, as the available data, if any, usually show the amount of loans granted: an increase could be either because of a line extension or increased use of the existing credit limit. More detailed data are either regulatory (e.g., Greenwald, Krainer, & Paul, 2020) or proprietary (e.g., Almeida, 2021). In this paper, we make the first attempt to estimate the influence of the COVID-19 shock using an alternative approach allowing publicly available bank-level data to be used. This paper is based on the assumption that an initial increase in volumes should be short term and that banks adapt to the shock by correcting credit limits according to standard credit risk estimation models, which capture an increase in borrower credit risks. Therefore, the study will test the following hypotheses:

Hypothesis 1: At the beginning of the COVID-19 pandemic, an increase in the probability of granting loans within credit lines is not fully explained by the factors significant pre-pandemic.

Hypothesis 2: The initial unexplained jump in credit line loan provision gradually smooths over time, meaning that the banking sector corrects the risk perception within the existing credit risk estimation models.

EMPIRICAL STRATEGY

To test our hypotheses, we pursue the following empirical strategy. Using quarterly bank-level data for all Russian banks for the period 2017-2020, covering the shock from the financial crisis in 2018 as well as both pre-pandemic and first wave quarters, we examine the factors influencing the probability of granting positive credit lines. For each quarter of our study, we estimate the Probit models regressing the probability of positive banks' overdrafts on the banks' financial characteristics, controlling the region of banks' registration for each quarter in the data, using the following approach:

$$y_{b,r,t} = \begin{cases} 1, & bank\ has\ positive\ credit\ lines\ granted \\ 0, & bank\ has\ zero\ credit\ lines\ granted \end{cases}, \quad (1)$$

$$P(y_{b,r,t} = 1) = F(Z_{b,r,t}) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{Z_{b,r,t}} e^{-\frac{u^2}{2}} du \text{ – Probit-model,} \quad (2)$$

where b indicates the Russian banks, r — the Russian regions, and t — the quarter.

The list of banks' financial characteristics ($Z_{b,r,t}$) includes the following:

- $ca_{b,r,t}$ is the ratio of a bank's capital to its assets (Acharya *et al.*, 2020). For the robustness check, we replace it by $n1_{b,r,t}$, which is the capital adequacy ratio. The minimum level of this ratio is 10% set by the Central Bank of Russian Federation (CBR). This parameter is computed as the ratio of the bank's capital base to the bank's assets weighted by risk and shows the banking soundness.
- $nplt_{b,r,(t-1)}$ is the ratio of nonperforming loans to the total gross loans of banks, taken with a lag to allow a bank to include the previous period of credit risks in the current strategy (Acharya et al., 2020, Jiménez et al., 2009).
- $roa_{b,r,(t-1)}$ is the lagged return on assets, calculated as net income divided by the total assets (Greenwald, Krainer, & Paul, 2020). According to (Sufi, 2009), we expect to find negative correlation with credit line usage.
- $\log\_assets_{b,r,t}$ is the natural logarithm of bank assets as a proxy for bank size (Acharya et al., 2020; Greenwald, Krainer, & Paul, 2020).

In addition, Russian region fixed effects – introduced according to the region where the ban is registered - are used to control for regional differences.

After estimating the Probit regressions, we predict the probabilities of positive lines of credit using the models for each quarter correspondingly. To trace the sustainability of the models over time, we re-estimate the predicted probabilities by the model of the previous quarter. Using the t-tests we determine whether there are statistically significant differences in probabilities predicted by the previous quarter model and the probabilities calculated using the model for the current quarter. If the model is quite sustainable, the differences should be statistically insignificant.

To examine the COVID-19 period adjustment process from another point of view, we use the pre-pandemic model of the 4th quarter of 2019 (pre-COVID-19 quarter) to determine how correctly it predicts the results for the first three pandemic quarters. When the difference between these probabilities is statistically significant, we can report the demand-side effect of COVID-19 on the credit lines provided by Russian banks according to *H1*. We expect the effect to be smoothed over time, signalling that the supply effect begins to prevail and that the banks correct the credit limits within the opened credit lines according to increased credit risks, according to *H2*.

The data on bank characteristics and the lines of credit considered in this study are gathered from bank financial statements provided by the Bank of Russia (CBR). The initial sample contains 617 unique banks and more than 7,100 observations[1].

The descriptive statistics are presented in Table 1. The banks where the borrowers use the credit line to draw funds are rather numerous. Table 2 shows that the proportion of those banks in the sample varies from 56% to 60%, meaning that slightly more than half of the banks provided funds within the credit line instrument.

Table 1. Descriptive statistics

Variable	N	Mean	Standard deviation	Min	Max
y	6786	0.589	0.492	0.000	1.000
ca	6786	0.249	0.161	0.002	0.996
$nplt_{t-1}$ (%)	6786	7.386	8.617	0.000	49.930
roa_{t-1} (%)	6776	2.713	6.968	-79.070	188.290
$Ln(assets)$	6786	6.949	0.896	4.102	10.545
$n1$	6786	29.014	19.350	0.000	99.990

Table 2. Banks with credit lines granted

T	N	Share of banks with positive credit lines granted
2q 2017	525	0.5600
3q 2017	527	0.5750
4q 2017	504	0.5734
1q 2018	509	0.5639
2q 2018	471	0.5966
3q 2018	469	0.5672
4q 2018	435	0.5816
1q 2019	436	0.5551
2q 2019	430	0.5698
3q 2019	407	0.5749
4q 2019	406	0.5542
1q 2020	388	0.5825
2q 2020	389	0.5758
3q 2020	372	0.5753
4q 2020	371	0.5849

[1] We cleaned the data, removing observations where the share of nonperforming loans exceeds 50% or the capital to assets ratio or N1 ratio does not fall between 0 and 1.

Figure 1 depicts the dynamics of this share around the COVID-19 shock (corrected for the seasonality): the three quarter moving average significantly jumps in the first quarter of 2020, becoming much more flat in the consequent quarters, and comparing the share against the one of the last year demonstrates a peak in the first quarter of 2020 and a decrease to near zero difference in the consequent quarters. Therefore we document some evidence that supports our hypotheses.

Figure 1 Share of banks with positive credit lines granted

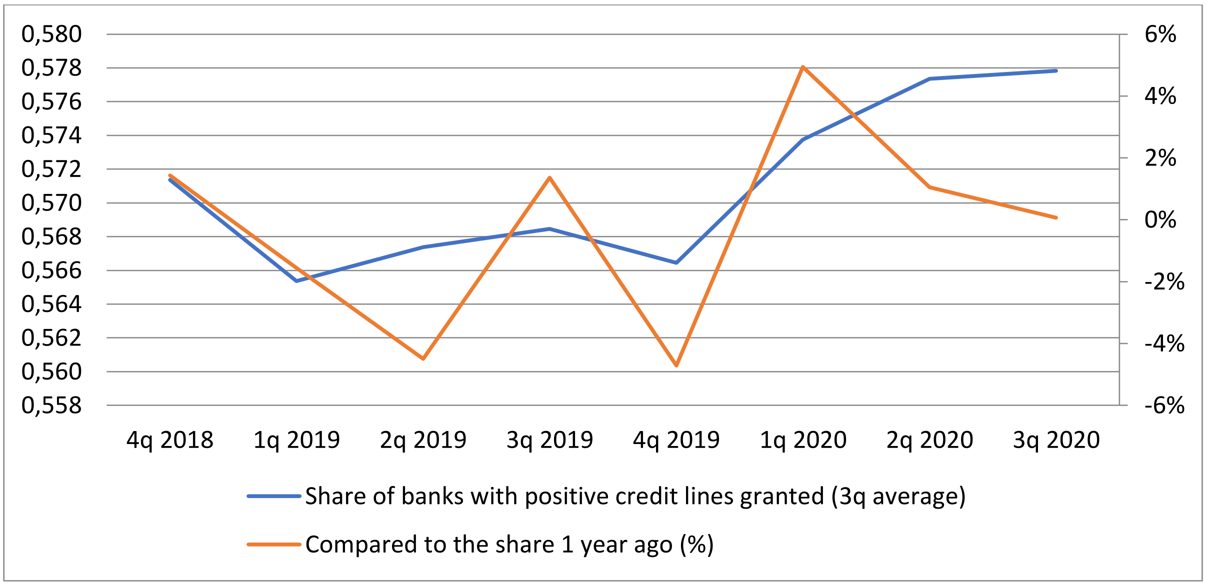
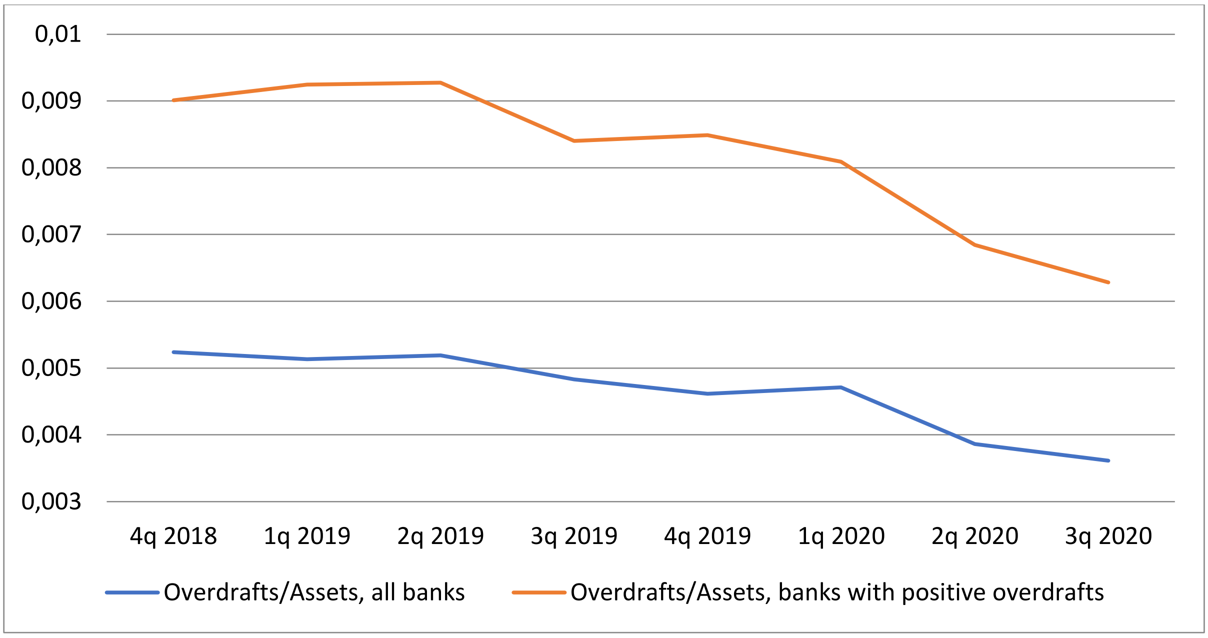


Figure 2 Overdrafts/Assets



Before we proceed with the result discussion, an important methodological issue should be mentioned. In this study we focus on comparing the banks with and without credit lines granted instead of analysing the overall amount of those credit lines. The reason for that lies in the fact, that the period under consideration witnessed a gradual decrease in the volumes of the granted credit lines with no jumps under the first COVID-19 wave Figure 2 shows that trend for the average ratio of the overall granted credit lines to total assets for both all the banks in the sample and the banks having positive granted credit lines. The dynamics of both demonstrate no increases around first quarters of 2020 meaning that the focus of the analysis should be done not on the size of the exposure but on the banks changing their position from zero lenders in this respect to those providing the funds within the credit lines.

RESULTS

The results of the baseline models' estimation are presented in Table A. 1 in Appendix, and all the models are statistically significant at a 1% significance level.

Table 3 shows the results of the *t-test*s for the differences between the predicted probabilities of granting the loans within the credit lines for the consequent quarters. We obtain the statistically significant difference in probabilities in the beginning of the first COVID-19 wave in early 2020, which does not allow us to reject *H1*. After several quarters of the almost similar overestimation of the probability to observe loan granting by the previous quarter models we witness a significant underestimation in the first and second quarters of 2020. This could signal the evidence that the borrowers withdrew the funds from the credit lines hurrying up to manage before the banks change the limits. The overestimation, however, is gradually decreasing in the next quarters meaning that the banks step into the game and - where possible – changed the credit line granting policies to incorporate the COVID crisis effect.

Table 3. Results of t-tests for the difference in the predictive probabilities for different quarters

	N	Mean	Standard Errors	P-value
deltaQ3-2017	481	0.0019564	0.0024044	0.4162
deltaQ4-2017	461	-0.0158788***	0.003177	0.0000
deltaQ1-2018	462	-0.0095691***	0.0018595	0.0000
deltaQ2-2018	415	**0.0583951*** **	0.0040213	0.0000
deltaQ3-2018	415	**-0.0360731*** **	0.0036464	0.0000
deltaQ4-2018	388	0.0029802	0.0037118	0.4225
deltaQ1-2019	390	-0.0243942***	0.0028777	0.0000
deltaQ2-2019	314	-0.0184887*	0.0109479	0.0923
deltaQ3-2019	321	-0.0091338*	0.0051954	0.0797
deltaQ4-2019	330	-0.0218997***	0.0022519	0.0000
deltaQ1-2020	319	**0.0226966*** **	0.0028632	0.0000
deltaQ2-2020	321	**0.0109648*** **	0.0052767	0.0022
deltaQ3-2020	307	**-0.0032034*** **	0.004955	0.0000
deltaQ4-2020	299	0.0040672	0.0058789	0.2836

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

Note: deltaQ3-2017-deltaQ4-2020 represent the differences in probabilities estimated by the models of the current and the previous quarter.

Our data also shows that such an increase in credit lines provided by the banks during COVID-19 is not the only case of such a reaction to external shocks. The results also show the similar positive effect in the second quarter of 2018, however we cannot be sure that the nature of this jump is mostly demand side: although additional sanctions on Russia were introduced before that period, the Bank of Russia decreased the key rate in March 2018, which could also lead to growth of banks' generosity in credit lines granting, demonstrating the supply-side effect. The latter is supported by the fact, that the banks quickly adopted their credit line loan granting when the key rate was increased again in September 2018, and continued growing in December 2018 - that can be seen from the drawdown of the third quarter of 2018.

To trace the adjustment of credit lines after the jump in the beginning of 2020 we fix the model of the fourth quarter in 2019 as the last pre-COVID quarter to predict the results for the first pandemic wave and then compare those probabilities with the ones predicted by the respective quarter model. Table 4 shows that this comparison allows to see even quicker – almost as in mid-2018 – banks' adjustment after the jump of credit lines in the beginning of 2020. After the drawdown of the second quarter of 2020, the models seem to return to sustainability, and – as far as the data allow us to conclude – we document statistically significant differences in predicted probabilities when comparing those for the current period model and the ones predicted using the pre-pandemic model of the 4th quarter of 2019. This result again suggests that our second hypothesis, *H2*, cannot be rejected.

Table 4. Results of t-tests for the difference in the predictive probabilities for the first pandemic wave

	N	Mean	Standard Errors	P-value
deltaQ1-2020	319	**0.0226966*** **	0.0028632	0.0000
deltaQ2-2020	318	**-0.016825** **	0.0054616	0.0385
deltaQ3-2020	309	-0.0127463	0.0029719	0.5184
deltaQ4-2020	297	0.0030015	0.0027939	0.4896

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

Note: deltaQ2-2020 – deltaQ4-2020 represent the differences between probabilities estimated by the models of the current quarter and by the model of the pre-pandemic 4th quarter of 2019.

At the next step we check the obtained results for the stochastic dominance, implementing the Fisher-Pittman test. This test could provide an additional insight to the nature of the probabilities comparison, allowing weakening the assumptions of the t-test. In terms of the current investigation the null hypothesis of Fisher-Pittman's test claims that there are no statistically significant differences in probabilities predicted by different quarter models (Kaiser, 2007). Table 5 shows the critical values of the Fisher-Pittman's test accompanied by the p-values by the differences in probability means. The test confirms the results described above, in terms of stochastic dominance. The positive statistically significant value in the second quarter of 2018 might be explained by both supply-side and demand-side reasons, while the similar result in the first quarter of 2020 is characterized by the COVID-19 outbreak — a non-financial shock. The subsequent quarters after these periods could be characterized as the adjustment made by the banks in terms of their provision of credit lines.

Table 5. Results of Fisher-Pittman test

	Mean	Critical Value	P-value
3q 2017	0.0019564	-0.9410	0.4192
4q 2017	-0.0158788***	7.3201	0.0000
1q 2018	-0.0095691***	4.4209	0.0000
2q 2018	**0.0583951*** **	-24.2340	0.0000
3q 2018	**-0.0360731*** **	14.9703	0.0000
4q 2018	0.0029802	-1.1563	0.4233
1q 2019	-0.0243942***	9.5137	0.0000
2q 2019	-0.0184887*	5.8054	0.0919
3q 2019	-0.0091338*	2.9319	0.0800
4q 2019	-0.0218997***	7.2269	0.0000
1q 2020	**0.0226966*** **	-7.2402	0.0000
2q 2020	**0.0109648*** **	5.3503	0.0019
3q 2020	**-0.0032034*** **	3.9386	0.0000
4q 2020	0.0040672	-0.8915	0.2876

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

Table 6 shows the results of Fisher-Pittman's test, when the model of the fourth quarter of 2019 is fixed for further comparisons. Again, the second quarter of 2020 indicates the drawdown of the use of credit lines provided, while in the subsequent quarters the situation tends to normalize.

Table 6. Results of Fisher-Pittman test for the first pandemic wave

	Mean	Critical Value	P-value
1q 2020	**0.0226966*** **	-7.2402	0.0000
2q 2020	**-0.016825** **	-3.5196	.03877
3q 2020	-0.0127463	0.9835	.51947
4q 2020	0.0030015	-1.2161	.49107

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

ROBUSTESS CHECKS

To check these results for stability, we perform several robustness checks. First of all, we use an alternative test for the stochastic dominance of the probabilities' distribution — the Dunn's test (Dinno, 2015). The approach is similar to the mentioned above: Table 7 shows the results for the whole period analysed, while Table 8 shows the difference among quarters started from the fourth quarter of 2019. The results of the Dunn's test confirm those obtained before: the first quarter of 2020 – as well as the second quarter of 2018 - witnessed the increase in probability of granting loans within the credit lines, while the reduction in probabilities of further quarters is a signal of the adjustments in the credit policies of both of banks and borrowers.

Table 7. Results of Dunn's test

	Mean	z-statistic	p-value
3q 2017	0.0019564	0.2842	0.3881
4q 2017	-0.0158788	0.5138	0.3037
1q 2018	-0.0095691	0.4625	0.3219
2q 2018	**0.0583951*** **	-3.2741	0.0005
3q 2018	**-0.0360731*** **	3.0522	0.0011
4q 2018	0.0029802	-0.2110	0.4164
1q 2019	-0.0243942	1.1789	0.1192
2q 2019	-0.0184887**	1.6979	0.0448
3q 2019	-0.0091338	-0.9035	0.1831
4q 2019	-0.0218997	0.9592	0.1687
1q 2020	**0.0226966*** **	-1.2859	0.0992
2q 2020	0.0109648	1.0205	0.1538
3q 2020	-0.0032034	0.2353	0.4070
4q 2020	0.0040672	-0.0231	0.4908

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

Table 8. Results of Dunn's test for the first pandemic wave

	Mean	z-statistic	p-value
1q 2020	**0.0226966*** **	-1.285895	0.0992
2q 2020	0.0114942	1.0205	0.1538
3q 2020	0.000462	0.2353	0.4070
4q 2020	0.0095359	-0.0231	0.4908

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

Table 9. Results of t-tests for the difference in the predictive probabilities, N1 instead CA

	N	Mean	Standard Errors	P-value
deltaQ3-2017	474	0.0004126	0.0025968	0.8738
deltaQ4-2017	461	-0.0128499***	0.0033243	0.0001
deltaQ1-2018	462	-0.0032896	0.0022374	0.1422
deltaQ2-2018	406	**0.0756446*** **	0.0044537	0.0000
deltaQ3-2018	410	**-0.0423738*** **	0.0039955	0.0000
deltaQ4-2018	377	-0.0046816	0.0039617	0.2381
deltaQ1-2019	380	-0.0235669***	0.0031491	0.0000
deltaQ2-2019	300	-0.0020274	0.0123056	0.8692
deltaQ3-2019	314	-0.0213953***	0.004819	0.0000
deltaQ4-2019	324	**-0.0200471*** **	0.0023525	0.0000
deltaQ1-2020	304	**0.0365393*** **	0.0027895	0.0000
deltaQ2-2020	308	**0.0163417*** **	0.0057374	0.0001
deltaQ3-2020	294	**0.0024053*** **	0.0050519	0.0000
deltaQ4-2020	284	0.0131108	0.0054656	0.0727

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

Secondly, we re-estimate the models using the regulatory capital adequacy ratio (*n1*) instead of the ratio of the bank's capital over its assets (*ca*) (the results are presented in **Ошибка! Источник ссылки не найден.** in Appendix). Table 9 shows that our results are confirmed, with an alternative measure of bank stability. In this specification, the results for the second and third quarters of 2018 are similar to the abovementioned, while the smoothing effect appears to be more gradual, as the second quarter of 2020 also witnesses the statistically significant underestimation of the probability of granting loans within credit lines by the pre-pandemic model.

Furthermore, Table 10 demonstrates the adjustments in credit line loan provision already in the second quarter of 2020.

Table 10. Results of t-tests for the difference in the predictive probabilities for the first pandemic wave (compared to the 4q2019 model), N1 instead CA

	N	Mean	Standard Errors	P-value
deltaQ1-2020	304	**0.0365393*** **	0.0027895	0.0000
deltaQ2-2020	318	**-0.016825** **	0.0054616	0.0385
deltaQ3-2020	309	-0.0127463	0.0029719	0.5184
deltaQ4-2020	297	0.0030015	0.0027939	0.4896

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

Thirdly we estimate the baseline Probit models without region fixed effects (the results are presented in **Ошибка! Источник ссылки не найден.** in Appendix). Many Russian banks have offices outside the region where they are registered, so regional fixed effects may slightly blur the influence of bank fundamentals. Table 11 contains the results for this specification. In general, they are virtually the same as those in the previous robustness check. However, it should be noted that the pre-pandemic quarters demonstrate sustainability in the results (in other words, the estimated probabilities do not differ much regardless of the quarter model we use or the probability is overestimated), and with the start of the first wave of COVID-19, the pre-pandemic model starts underestimating the probability significantly. This could signal that the borrowers drawdown funds within the existing credit limits where possible, expecting worse times to come, both in terms of their own business financial struggling with the pandemic and the banks tightening credit conditions and freezing credit lines.

Table 11. Results of t tests for the difference in the predictive probabilities, No region FEs

	N	Mean	Standard Errors	P-value
deltaQ3-2017	527	0.0089784***	0.000522	0.0000
deltaQ4-2017	504	-0.011588***	0.001354	0.0000
deltaQ1-2018	507	-0.0108409***	0.0006358	0.0000
deltaQ2-2018	470	**0.0550147*** **	0.0021073	0.0000

deltaQ3-2018	468	**-0.0333655*****	0.0028815	0.0000
deltaQ4-2018	434	-0.0003095	0.0012204	0.7999
deltaQ1-2019	436	-0.0274393***	0.0010539	0.0000
deltaQ2-2019	427	0.0686071	0.0049515	0.0000
deltaQ3-2019	407	-0.0066109**	0.0025867	0.0110
deltaQ4-2019	405	-0.0297913***	0.0005824	0.0000
deltaQ1-2020	388	**0.0184247*****	0.0011388	0.0000
deltaQ2-2020	388	**0.0109266*****	0.0025036	0.0000
deltaQ3-2020	372	**0.0008037*****	0.001512	0.0000
deltaQ4-2020	371	0.008073	0.0020869	0.0000

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

Table 12 shows the stability of the results since they are similar to the specification with the regulatory capital adequacy ratio instead of the ratio of the bank's capital over its assets.

Table 12. Results of t-tests for the difference in the predictive probabilities for the first pandemic wave (compared to the 4q2019 model), No region FEs

	N	Mean	Standard Errors	P-value
deltaQ1-2020	388	**0.0184247*****	0.0011388	0.0000
deltaQ2-2020	388	**-0.0080702*****	0.0019454	0.0000
deltaQ3-2020	372	-0.0089605	0.0012385	0.5954
deltaQ4-2020	371	**0.0066519*****	0.0012005	0.0001

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

Table 13. Results of t-tests for the difference in the predictive probabilities for the first pandemic wave (compared to the 2019 panel model), No region FEs

	N	Mean	Standard Errors	P-value
deltaQ1-2020	388	**0.0184247*****	0.0011388	0.0000
deltaQ2-2020	388	**-0.0080702*****	0.0019454	0.0000
deltaQ3-2020	372	-0.0089605	0.0012385	0.5954
deltaQ4-2020	371	**0.0066519*****	0.0012005	0.0001

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

Finally we turned to the panel data analysis, estimating (2) on the whole sample. This approach does not allow us to trace the changes in the models' predictive power from quarter to quarter, but it can shed some light on how the significance of the bank fundamentals vary over time, which could also signal the changes in the determinants of the probability of positive credit lines. To account for the time influence we introduce the binary variables for all the quarters and we also include the multiplied variables for each bank fundamental:

$$P(y_{b,r,t} = 1) = F(Quarter_t + Z_{b,r,t} + Quarter_t * Z_{b,r,t}) \quad (3)$$

Ошибка! Источник ссылки не найден. in Appendix demonstrates the results of the panel Probit model estimations, showing that many coefficients are insignificant. This confirms that the models vary from quarter to quarter. However there are some important observations in these results. On the one hand during the first quarter of 2020, which welcomed the first wave of

COVID-19, we observe that the growth trend, existing for all the quarters before 2020, disappears, meaning that on average the probability of being involved into credit lines granting banks does not increase during all the 2020 quarters. On the other hand, however, the results provide some evidence that this increase may appear for banks with certain characteristics. Under the first wave of COVID-19 larger banks (in terms of assets) with higher capital adequacy seem to appear among those who grant the credit lines more frequently compared to the quarter before 2020 under consideration. This result supports the idea that at least some banks – generally more reliable ones – face credit lines drawdowns.

CONCLUSION

Our findings allow us to believe that both hypotheses related to the COVID-19 reaction of the bank credit lines should not be rejected. The simultaneous (potential) liquidity shock that Russian borrowers faced in the first quarter of 2020 makes them drawdown existing credit lines, as new loans became extremely difficult to obtain, and economic expectations turned to be extremely pessimistic. This effect is qualitatively the same as one observed in the second quarter of 2018, but the reasoning for the 2020 comes more pronouncedly from the demand side, allowing us to suppose the prevailing credit lines drawdown strategy. However, the jump in credit line use gradually disappeared, as the banks seemed to adapt to new economic reality by correcting the limits within the credit lines according to the increased credit risk of their borrowers. Importantly, the results are obtained from publicly available bank-level data, meaning that we reduce the severity of the identification problem caused by difficulties in separating the supply and demand sides and determining the final amount of loans granted within a credit line.

REFERENCES

Acharya, V. *et al.* (2014) ‘Credit lines as monitored liquidity insurance: Theory and evidence’, *Journal of Financial Economics*. Elsevier, 112(3), pp. 287–319. doi: 10.1016/j.jfineco.2014.02.001.

Acharya, V. *et al.* (2020) ‘Bank lines of credit as contingent liquidity: Covenant violations and their implications’, *Journal of Financial Intermediation*. Elsevier, 44(April 2019), p. 100817. doi: 10.1016/j.jfi.2019.03.004.

Acharya, V. V. *et al.* (2021) ‘Credit Lines and the Liquidity Insurance Channel’, *Journal of Money, Credit and Banking*, 53(5), pp. 901–938. doi: 10.1111/jmcb.12821.

Acharya, V. V. and Steffen, S. (2020) ‘The Risk of Being a Fallen Angel and the Corporate Dash for Cash in the Midst of COVID’, *SSRN Electronic Journal*. doi: 10.2139/ssrn.3704158.

Almeida, H. (2021) ‘Liquidity Management During the Covid- 19 Pandemic*’, *Asia-Pacific Journal of Financial Studies*. John Wiley & Sons, Ltd, 50(1), pp. 7–24. doi: 10.1111/ajfs.12322.

Berger, A. N. and Demirgüç-Kunt, A. (2021) ‘Banking research in the time of COVID-19’, *Journal of Financial Stability*. Elsevier B.V., 57(July), p. 100939. doi: 10.1016/j.jfs.2021.100939.

Dinno, A. (2015) ‘Nonparametric pairwise multiple comparisons in independent groups using Dunn’s test’, *Stata Journal*, 15(1), pp. 292–300. doi: 10.1177/1536867x1501500117.

Greenwald, D. L., Krainer, J. and Paul, P. (2020) ‘The Credit Line Channel’, *Federal Reserve Bank of San Francisco, Working Paper Series*, pp. 1.000-96.000. doi: 10.24148/wp2020-26.

Holmström, B. and Tirole, J. (1998) ‘Private and public supply of liquidity’, *Journal of Political Economy*, 106(1), pp. 1–40. doi: 10.1086/250001.

Javadi, S. *et al.* (2021) ‘Corporate cash holdings, agency problems, and economic policy uncertainty’, *International Review of Financial Analysis*. Elsevier Inc., 77(February), p. 101859. doi: 10.1016/j.irfa.2021.101859.

Jiménez, G., Lopez, J. A. and Saurina, J. (2009) ‘Empirical analysis of corporate credit lines’, *Review of Financial Studies*, 22(12), pp. 5069–5098. doi: 10.1093/rfs/hhp061.

Kaiser, J. (2007) ‘An exact and a Monte Carlo proposal to the Fisher-Pitman permutation tests for paired replicates and for independent samples’, *Stata Journal*, 7(3), pp. 402–412. doi: 10.1177/1536867x0700700307.

Sufi, A. (2009) ‘Bank lines of credit in corporate finance: An empirical analysis’, *Review of Financial Studies*, 22(3), pp. 1057–1088. doi: 10.1093/revfin/hhm007.

APPENDIX

Table A. 1 Basic models: average marginal effects

VARIABLES	3q 2017	4q 2017	1q 2018	2q 2018	3q 2018	4q 2018	1q 2019
ca_t	-0.65430***	-0.74709***	-0.74800***	-0.70858***	-0.49170***	-0.50877***	-0.63513***
	(0.14694)	(0.15344)	(0.13910)	(0.16058)	(0.15108)	(0.16024)	(0.16281)
log_assets_t	0.08465***	0.08057***	0.08185***	0.05971**	0.06943**	0.07995***	0.06061**
	(0.02717)	(0.02705)	(0.02625)	(0.02918)	(0.02894)	(0.02996)	(0.02986)
$nplt_{t-1}$	-0.00202	-0.00234	-0.00174	0.00005	-0.00209	0.00005	-0.00070
	(0.00252)	(0.00255)	(0.00238)	(0.00264)	(0.00250)	(0.00261)	(0.00245)
roa_{t-1}	-0.01136**	-0.01717**	-0.02147***	-0.01288***	-0.02394***	-0.01471**	-0.02354***
	(0.00457)	(0.00677)	(0.00714)	(0.00375)	(0.00656)	(0.00691)	(0.00766)
Region FE	+	+	+	+	+	+	+
Observations	483	461	464	421	423	397	390

Standard errors are shown in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	2q 2019	3q 2019	4q 2019	1q 2020	2q 2020	3q 2020	4q 2020
ca_t	-0.52335***	-0.62655***	-0.59195***	-0.54143***	-0.40309**	-0.44826**	-0.25249
	(0.17217)	(0.17707)	(0.18664)	(0.18983)	(0.18125)	(0.17712)	(0.19255)
log_assets_t	0.10689***	0.14084***	0.13931***	0.15886***	0.17218***	0.17086***	0.19445***
	(0.03088)	(0.03057)	(0.03045)	(0.03198)	(0.03097)	(0.03029)	(0.03119)
$nplt_{t-1}$	-0.00059	0.00311	0.00381	0.00368	0.00405	0.00490*	0.00600**
	(0.00256)	(0.00254)	(0.00268)	(0.00277)	(0.00279)	(0.00276)	(0.00268)
roa_{t-1}	-0.00258*	-0.00773*	-0.01112**	-0.01444**	-0.00231	-0.00682*	-0.00809*
	(0.00140)	(0.00404)	(0.00464)	(0.00603)	(0.00256)	(0.00386)	(0.00420)
Region FE	+	+	+	+	+	+	+
Observations	345	333	336	321	323	309	302

Standard errors are shown in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A. 2 Models with capital adequacy ratio: average marginal effects

VARIABLES	3q 2017	4q 2017	1q 2018	2q 2018	3q 2018	4q 2018	1q 2019
$n1_t$	-0.00457***	-0.00512***	-0.00485***	-0.00504***	-0.00379***	-0.00429***	-0.00355***
	(0.00108)	(0.00110)	(0.00100)	(0.00114)	(0.00092)	(0.00116)	(0.00110)
log_assets_t	0.09943***	0.09469***	0.09587***	0.06890**	0.06933**	0.06749**	0.07766***
	(0.02705)	(0.02681)	(0.02674)	(0.02893)	(0.02725)	(0.02982)	(0.02821)
$nplt_{t-1}$	-0.00211	-0.00277	-0.00186	-0.00122	-0.00228	-0.00289	-0.00295
	(0.00273)	(0.00254)	(0.00237)	(0.00264)	(0.00248)	(0.00278)	(0.00276)
roa_{t-1}	-0.01419***	-0.02191***	-0.02760***	-0.01412***	-0.03080***	-0.02011**	-0.03263***
	(0.00451)	(0.00652)	(0.00693)	(0.00425)	(0.00703)	(0.00830)	(0.00914)
Region FE	+	+	+	+	+	+	+
Observations	476	461	464	412	418	386	380

Standard errors are shown in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	2q 2019	3q 2019	4q 2019	1q 2020	2q 2020	3q 2020	4q 2020
$n1_t$	-0.00238**	-0.00241**	-0.00262**	-0.00265**	-0.00255**	-0.00249*	-0.00171
	(0.00109)	(0.00105)	(0.00125)	(0.00114)	(0.00125)	(0.00134)	(0.00120)
log_assets_t	0.14138***	0.18890***	0.17604***	0.18566***	0.18766***	0.19457***	0.20626***
	(0.02893)	(0.02490)	(0.02612)	(0.02946)	(0.02875)	(0.02859)	(0.02735)
$nplt_{t-1}$	0.00038	0.00239	0.00313	0.00262	0.00326	0.00391	0.00494*
	(0.00272)	(0.00256)	(0.00269)	(0.00279)	(0.00273)	(0.00272)	(0.00266)
roa_{t-1}	-0.00357*	-0.00928**	-0.01244***	-0.01353**	-0.00134	-0.00649*	-0.00816**
	(0.00183)	(0.00381)	(0.00472)	(0.00689)	(0.00331)	(0.00362)	(0.00401)
Region FE	+	+	+	+	+	+	+
Observations	330	328	330	309	313	299	290

Standard errors are shown in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A. 3 Models without region FEs: average marginal effects

VARIABLES	3q 2017	4q 2017	1q 2018	2q 2018	3q 2018	4q 2018	1q 2019
ca_t	0.09111***	0.08074***	0.08632***	0.06572**	0.07163**	0.08551***	0.06780**
	(0.02669)	(0.02746)	(0.02641)	(0.02869)	(0.02801)	(0.02890)	(0.02801)
log_assets_t	-0.00137	-0.00022	-0.00014	-0.00040	-0.00173	-0.00029	0.00025
	(0.00240)	(0.00252)	(0.00236)	(0.00246)	(0.00235)	(0.00243)	(0.00238)
$nplt_{t-1}$	-0.00765*	-0.01489**	-0.02002***	-0.01075***	-0.02607***	-0.01954***	-0.02242***
	(0.00423)	(0.00637)	(0.00649)	(0.00378)	(0.00582)	(0.00704)	(0.00672)
roa_{t-1}	-0.66904***	-0.77766***	-0.73070***	-0.69683***	-0.45878***	-0.47602***	-0.62455***
	(0.14193)	(0.15424)	(0.14246)	(0.15751)	(0.14525)	(0.15849)	(0.15762)
Observations	527	504	507	470	468	434	436

Standard errors are shown in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	2q 2019	3q 2019	4q 2019	1q 2020	2q 2020	3q 2020	4q 2020	2019 (panel)
ca_t	0.05857**	0.07596***	0.08028***	0.10531***	0.11610***	0.10470***	0.11760***	-4.17232***
	(0.02866)	(0.02945)	(0.02893)	(0.02982)	(0.02904)	(0.02909)	(0.03052)	0.33166
log_assets_t	-0.00038	0.00181	0.00188	0.00312	0.00416	0.00406	0.00378	0.53030***
	(0.00227)	(0.00235)	(0.00254)	(0.00262)	(0.00273)	(0.00267)	(0.00259)	0.06593
$nplt_{t-1}$	-0.00300*	-0.00695**	-0.00585*	-0.00628	-0.00182	-0.00403	-0.00447	0.00708
	(0.00155)	(0.00344)	(0.00343)	(0.00455)	(0.00206)	(0.00339)	(0.00364)	0.00501
roa_{t-1}	-0.64928***	-0.77915***	-0.81726***	-0.67707***	-0.57411***	-0.71401***	-0.54468***	-0.01126**
	(0.15114)	(0.15930)	(0.17401)	(0.17842)	(0.16920)	(0.17172)	(0.17700)	0.00545
Observations	427	407	405	388	388	372	371	1675

Standard errors are shown in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A. 4 Panel Probit model

	Quarter		ca_t		log_assets_t		$nplt_{t-1}$		roa_{t-1}	
*Quarter	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
			1.448	1.201	2.529***	0.302	-0.015	0.019	-0.002	0.035
2q2017	6.464***	2.488	-3.401**	1.403	-0.829**	0.331	-0.005	0.026	-0.010	0.038
3q2017	8.034***	2.529	-3.580**	1.424	-1.020***	0.334	0.001	0.025	-0.040	0.048
4q2017	7.526***	2.582	-4.700***	1.483	-0.860**	0.340	-0.034	0.025	-0.107	0.065
1q2018	5.979**	2.516	-3.740***	1.425	-0.706**	0.332	-0.008	0.023	-0.142*	0.078
2q2018	7.184***	2.547	-3.818***	1.454	-0.809**	0.331	-0.017	0.022	-0.072	0.046
3q2018	5.787**	2.569	-1.229	1.402	-0.751**	0.339	-0.037	0.023	-0.097*	0.054
4q2018	5.263**	2.599	-1.243	1.434	-0.696**	0.340	-0.021	0.023	-0.009	0.045
1q2019	7.379***	2.629	-2.016	1.482	-1.035***	0.344	-0.012	0.023	-0.031	0.064
2q2019	5.617**	2.360	-0.907	1.434	-0.798***	0.305	-0.005	0.022	0.013	0.037
3q2019	6.432**	2.601	-2.641*	1.547	-0.817**	0.336	-0.024	0.025	0.024	0.042
4q2019	6.112**	2.598	-2.762*	1.558	-0.812**	0.337	-0.020	0.024	0.013	0.043
1q2020	2.958	2.522	-2.624*	1.547	-0.307	0.324	-0.008	0.023	0.023	0.043
2q2020	0.276	2.402	-0.501	1.425	-0.026	0.312	0.011	0.022	-0.004	0.042
3q2020	1.775	2.397	-2.118	1.496	-0.193	0.311	0.004	0.024	-0.023	0.054
Region FEs	+	+								
cons	-14.31***	3.010								
Number of obs =	6453									
Number of banks =	557									

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