



Bank of Russia



PATTERNS OF UTILISATION OF CORPORATE CREDIT LINES AND THEIR IMPLICATION FOR FINANCIAL STABILITY

WORKING PAPER SERIES

№ 158 / December 2025

A. Burova

D. Koshelev

I. Kozlovtsева

Anna Burova, Bank of Russia, Research and Forecasting Department
E-mail: burovaab@cbr.ru

Denis Koshelev, Bank of Russia, Research and Forecasting Department
E-mail: koshelevdm@cbr.ru

Irina Kozlovtceva, Bank of Russia, Research and Forecasting Department
E-mail: kozlovtseva@id@cbr.ru

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

All rights reserved. The views expressed in this paper are solely those of the authors and do not necessarily reflect the official position of the Bank of Russia. The Bank of Russia assumes no responsibility for the contents of the paper. Any reproduction of these materials is permitted only with the express consent of the authors.

Cover image: Shutterstock/FOTODOM
12 Neglinnaya street, Moscow, 107016
+7 495 771-91-00, +7 495 621-64-65 (fax)
Official web-site: www.cbr.ru

Contents

Abstract	4
1. Introduction	5
2. Credit lines in Russia.....	5
3. Literature review	10
4. Methodology.....	11
5. Data	12
6. Results	15
7. Discussion	17
8. Conclusion.....	19
References.....	21
Appendix	22

Abstract

Credit lines are an important source of financing for economic activities in different countries, including Russia. It is important to identify the factors affecting the utilisation of contingent loans in order to better understand the tendencies on the financial market and to identify possible risks for all participants in the loan market. We use credit registry data on all the credit on banks' balance sheets as of the beginning of 2017. We split our study into three parts: credit lines which have reached their limits, credit lines with the full limit still available and credit lines in the middle state.

For fully used credit lines, we show that a large share of them appear similar to regular loans (the company immediately uses the entire available limit and repays the funds when the loan matures). For two other groups we identify factors affecting the timing of the first credit line draw-down and the utilisation rate. For several factors we show that their impact coincides with what has been shown in other studies: dummy variable on the credit line issued by the company's main bank (credit lines obtained from the main bank are used more intensively), the age of credit line (the older the credit line, the less the utilisation rate), etc. Other variables in this study show the opposite effect compared to other papers. For example, the length of relationship with the bank in earlier studies negatively affects the utilisation rate of the credit line, while we can see that this factor has a positive impact in this study. We also show that lines with the fixed interest rate are used more intensively than those with floating rates. In cases of non-revolving credit lines this result is robust across all time sub-samples, both during tightening and easing of credit conditions. These findings may be significant for understanding the credit line utilisation process for the financial market participants as well as for monetary and prudential policies.

Keywords: Corporate credit, credit line utilisation, credit registry, micro-level data, bank lending, Russia

JEL-codes: G21, G32, D22.

1. Introduction

Contingent credit, or a credit line, is a widely used source of funding for companies. It helps companies overcome liquidity shocks, raise additional funds for different business purposes and maintain their current activities in the event of contingencies.

Nevertheless, despite the fact that contingent bank credit may be an important source of liquidity during crises, it might also be a source of inefficiency in the allocation of funds. For example, Greenwald et al., 2021 show that a considerable part of the unused limits on credit lines are assigned to the largest companies. This may cause an inefficient flow of funds to big companies instead of smaller firms regardless of actual their needs. Chodorow-Reich et al., 2022 prove that a major part of loans during COVID-19 is made up of withdrawals from the credit lines of large companies. This fact led to a decrease in the provision of even concessional credit to the firms most affected by the pandemic shock, particularly in banks with higher shares of credit line commitments. This effect is confirmed in the work of Kapan and Minoiu, 2021.

Although credit lines are commonly assumed to be motivated by precautionary motives, many papers show that volatile cash flow is associated with a lower level of utilisation of credit lines (see, for example, the works of Sufi, 2009 or Acharya et al., 2014). Other papers show a ‘flight to liquidity’ effect, in which companies withdraw the available limits on their credit lines to ensure the availability of the funds in the event that the bank refuses to provide them in the future as the negative effect of shocks worsen (Ivashina and Scharfstein, 2010; Bosshardt and Kakhbod, 2021).

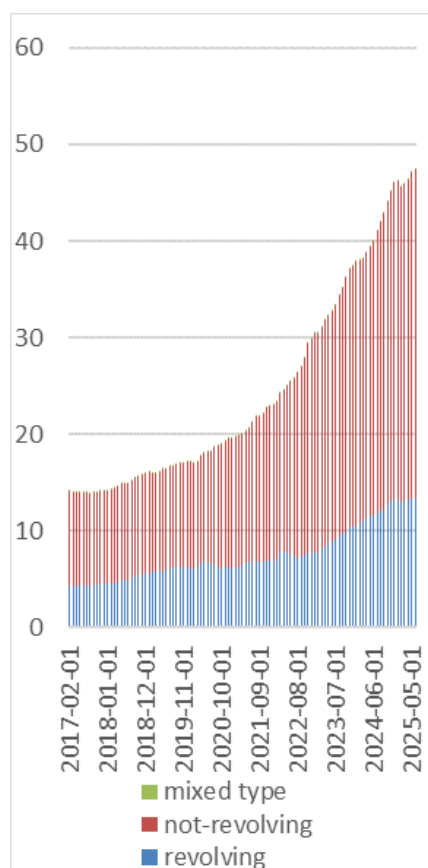
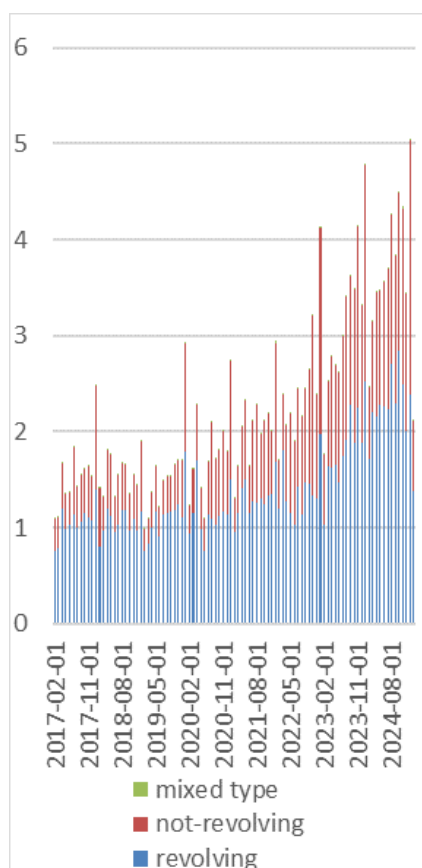
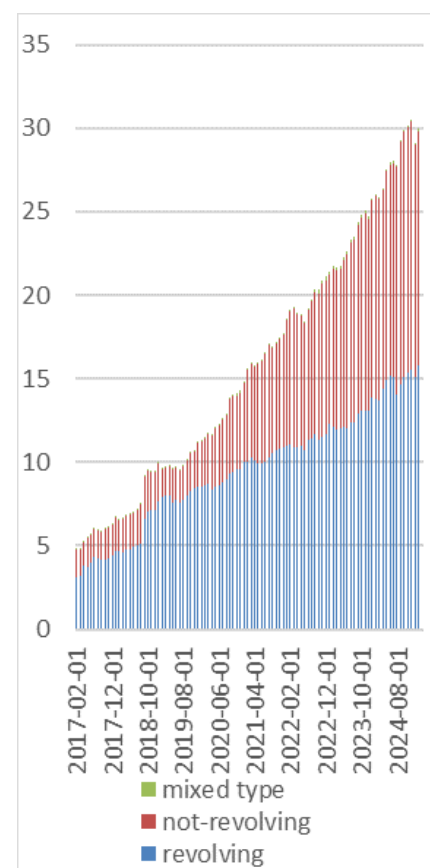
Our empirical exercise shows that a large amount of bank credit is attributable to credit lines. The volume of unused credit lines currently constitutes almost half of the total outstanding corporate credit portfolio, and this sum continues to grow. In this study, we reveal factors that affect the credit line utilisation patterns of non-financial corporate borrowers: firms tend to withdraw credit lines more intensively from their main bank (the bank providing the largest share of all the company’s borrowed funds), from smaller banks (significant in the case of revolving lines only), on recently opened credit lines, when there is collateral (for revolving lines only), or if the firm has a shorter history as a borrower and it has had no default on other loans (for non-revolving lines only).

2. Credit lines in Russia

In this Section, we briefly discuss the current situation with credit lines and their utilisation in Russia. In order to make the following study clearer and to arrive upon a common terminology, we begin with a few terms that will be used throughout the paper. In banking reports in Russia, all credit lines fall into three categories:

1. **Revolving credit lines.** In this case, the available limit on the credit line may be replenished. For example, a firm may have a credit line with an available commitment amount of 100 RUB. If the company has used 10 RUB in the previous month but paid them back, then it will have an available credit limit of 100 RUB.
2. **Non-revolving credit lines.** In this case, the available limit on the credit line cannot be replenished. In a case similar to the example above, after the repayment of the 10 RUB, the available limit will be only 90 RUB. This entails a non-decreasing utilisation rate for this type of credit line.
3. **Mixed-type credit lines.** In this case, the credit line has a structure combining features of both of the previous types of credit line. As the number of credit lines of this type is not significant, we remove them from our consideration.

For a first glimpse of credit lines, we study the dynamics of several key variables: the stock of debt on credit lines (Figure 1), the amount of funds issued each month on credit lines (Figure 2) and the stock of the unused limits on credit lines (Figure 3). We observe steady growth in the stock of debt on credit lines and in the unused limits. We also see an upward trend in the amount of funds issued each month on credit lines (Figure 2). All these graphs back up the importance of credit lines as a source of corporate financing.

Figure 1. Stock of debt by type of credit lines**Figure 2.** Loans issued by type of credit lines**Figure 3.** Unused limits by type of credit lines

Credit lines represent the vast majority of the total loans provided by banks to companies in Russia (see Figures 4 for the stock of debt and Figure 5 for the monthly issuance of loans).

To study the share of credit lines in the banking portfolio more precisely, we show the distribution of the shares of revolving credit lines (Figure 6) and of non-revolving credit lines (Figure 7¹) among the banks. We observe that the median share stays near 30% for non-revolving credit lines. As for revolving credit lines, their median share in the banking portfolio rises from 30% in the beginning of 2017 to 40% in the beginning of 2025. The weighted average share, by contrast, is significantly higher for non-revolving credit lines (around 60%) than for revolving lines (around 25%). This difference reflects the fact that the debt on non-revolving credit lines is approximately two times greater than the debt on revolving lines (see Figure 1).

Coming back to unused credit lines, their volume constitutes almost half of the current portfolio of corporate bank loans. Figure 3 shows that the total unused credit line limits amounted to 30 trillion rubles in the end of 2024. The total amount of debt owed by non-financial corporations (NFCs) to Russian banks was approximately 65 trillion rubles by the end of 2024.² This high ratio of unused limits on credit lines to the total volume of banks' corporate portfolio may cause financial stability concerns if many companies decide to withdraw funds from their credit lines simultaneously.

To study this question more precisely, we build the distribution of the ratio of the unused limits on credit lines to the total corporate portfolio among banks. The distribution for revolving credit lines is

¹These graphs show a set of box plots for each observed month. The box is drawn from the 25th to the 75th percentiles. The whiskers reflect the 5th and the 95th percentiles for each month. The red triangles represent the weighted average share of credit lines of the corresponding type. It is calculated as the total debt on credit lines of one type in all the banks divided by the total debt in all the banks. The black rectangles are the median value of shares of credit lines in the portfolio.

²Data on loans is available at: https://www.cbr.ru/eng/statistics/bank_sector/sors/

Figure 4. Shares of debt on revolving and non-revolving credit lines in corporate loan portfolio

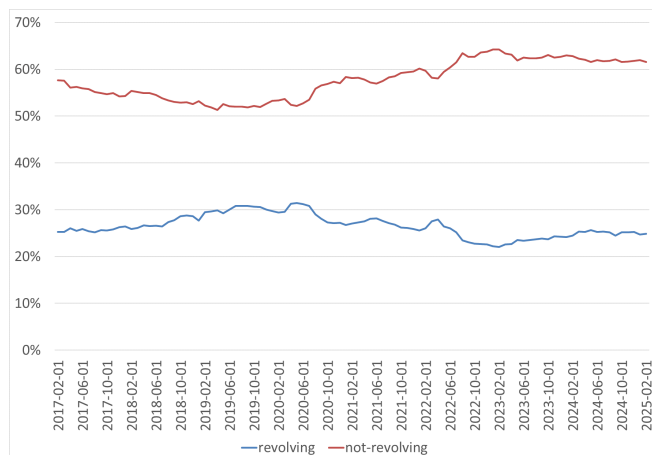


Figure 6. Distribution of the share of revolving credit lines in the banking portfolio

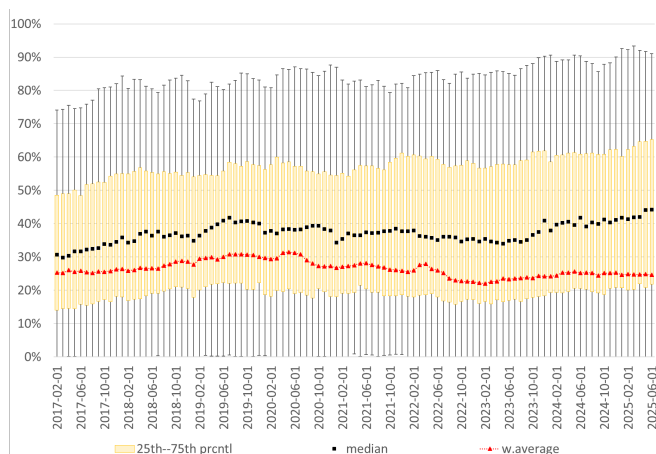


Figure 5. Shares of revolving and non-revolving credit lines in the loans issued by banks

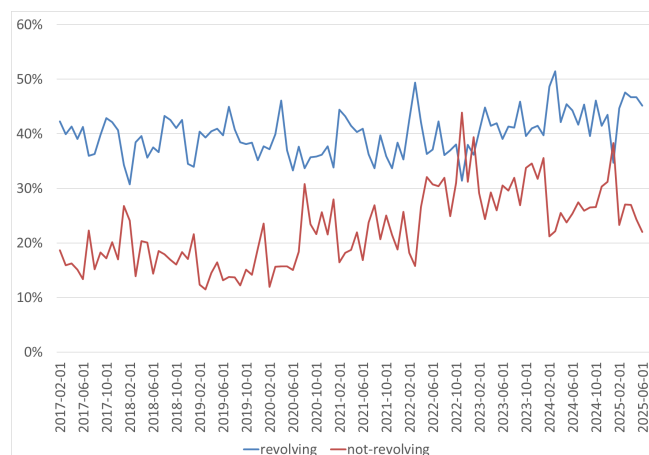
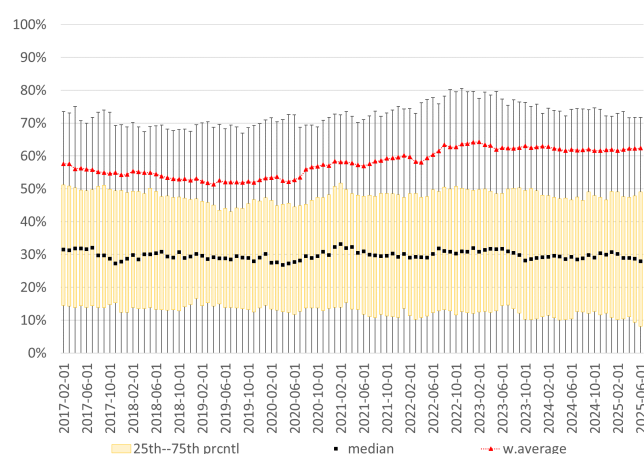


Figure 7. Distribution of the share of non-revolving credit lines in the banking portfolio



presented in Figure 8, and the distribution for non-revolving credit lines is presented in Figure 9.³ It can be seen that 75% of banks have shares of unused limits on revolving credit lines below 30%, while the share of the unused limits on non-revolving credit lines at the 75th percentile does not exceed 5%. The median share of revolving credit lines varies around 10%, while the median share of non-revolving lines remains close to zero throughout the time period considered. The whiskers of the box plots in Figure 8 suggest that there are banks that have amounts of unused limits on credit lines exceeding their corporate debt portfolios.

The literature suggests that the size of the company is a significant factor determining the utilisation rate of its credit lines (see, for example, the work of Chodorow-Reich et al., 2022). We can see that large entities account for almost 90% of all commitment amounts on revolving credit lines (see Figures 10) and 70–80% of non-revolving lines (see Figure 11). A similar case is presented in Figures 12 and 13, which illustrate the distribution of the stock of debt on revolving and non-revolving credit lines for SMEs and large entities separately. The ratio of the credit lines used by companies of different sizes suggests that a sudden increase in the utilisation rate of larger companies would be more significant for banks than the same increase in utilisation rate for SMEs.

The type of interest rate (fixed or floating) specified in the credit line agreement could also be a point of interest in the case of the Russian economy. It may be especially important in the case of an unexpected and enormous change in market interest rates: if a company has credit lines with both fixed

³These box plots are built in a similar way to Figures 6 and 7, described above.

Figure 8. Distribution of the ratio of the unused limits on revolving credit lines to the size of the banking portfolio

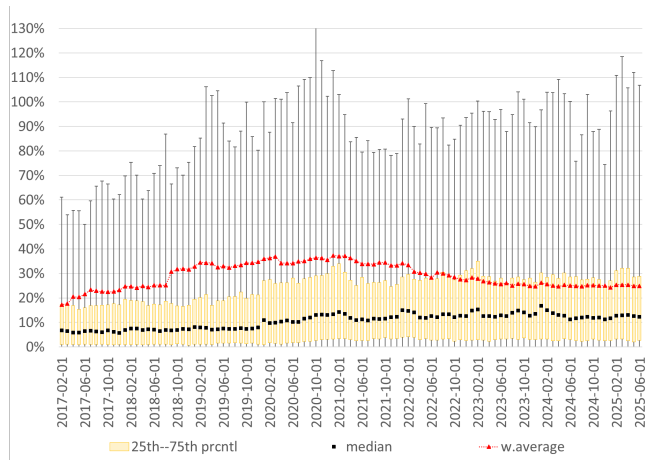


Figure 9. Distribution of the share of the unused limits on non-revolving credit lines to the size of the banking portfolio

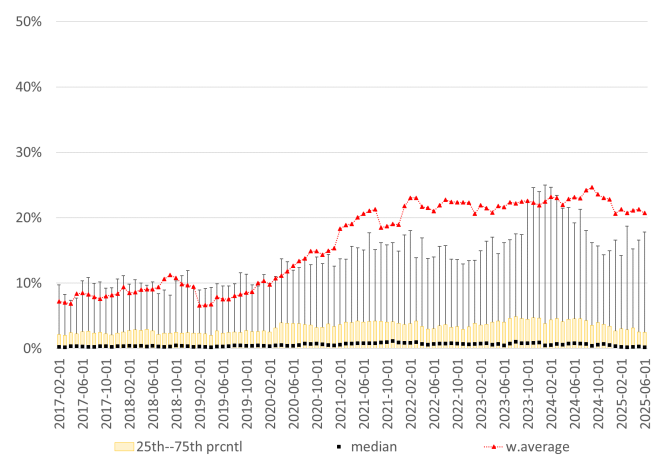


Figure 10. Revolving credit lines: commitment amount

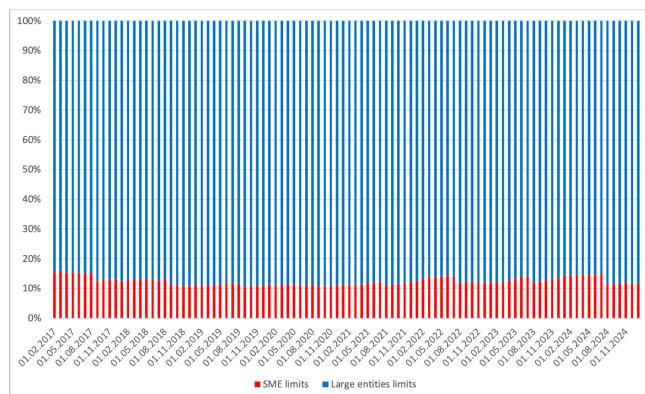


Figure 11. Non-revolving credit lines: commitment amount

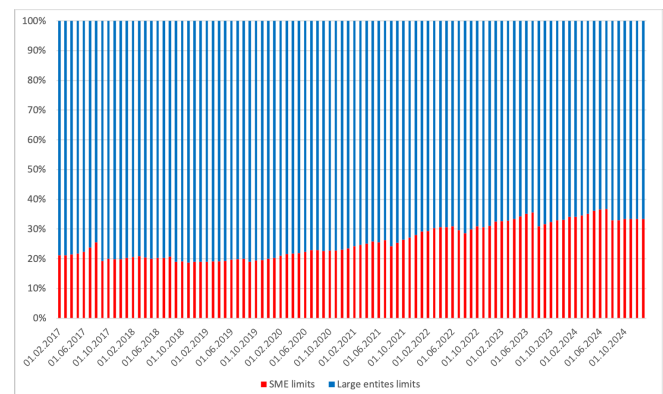


Figure 12. Revolving credit lines: debt

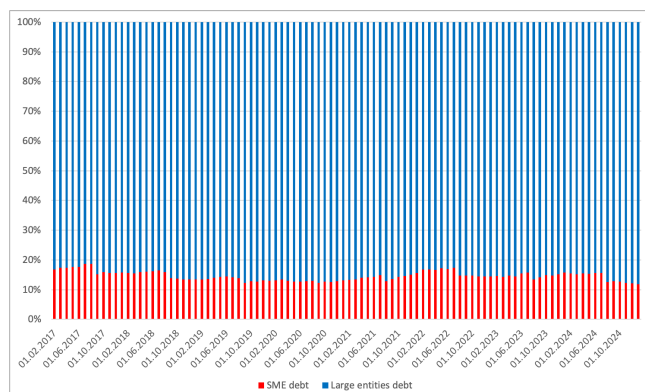


Figure 13. Non-revolving credit lines: debt

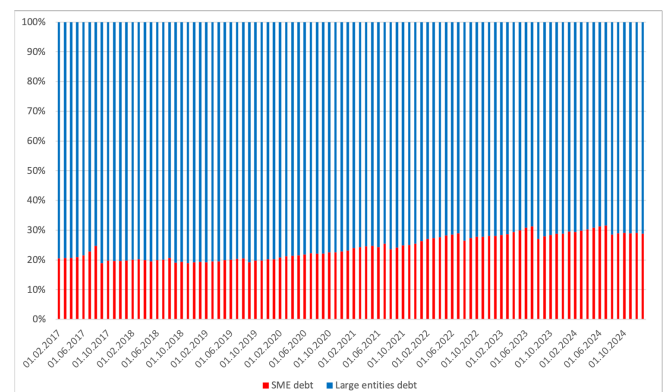
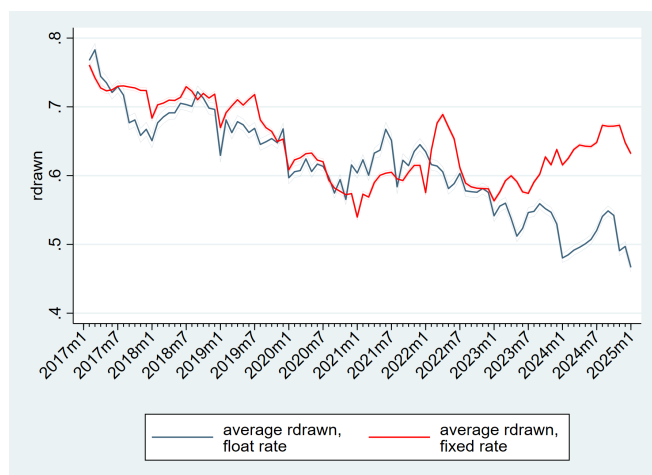
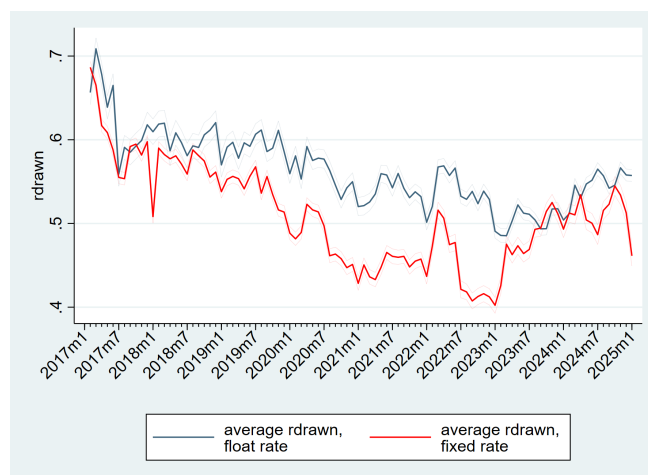
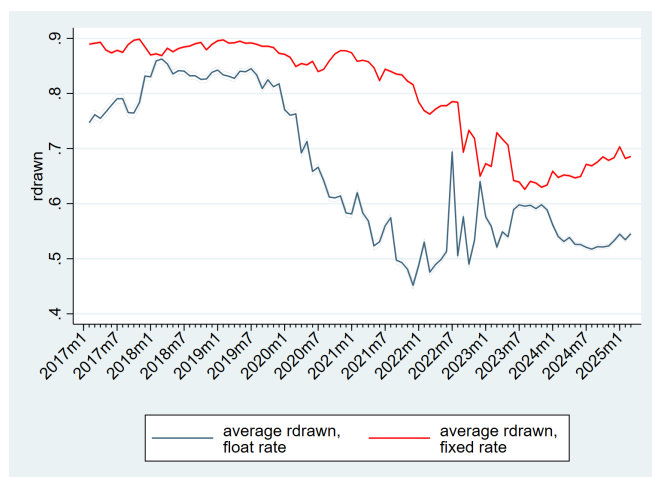
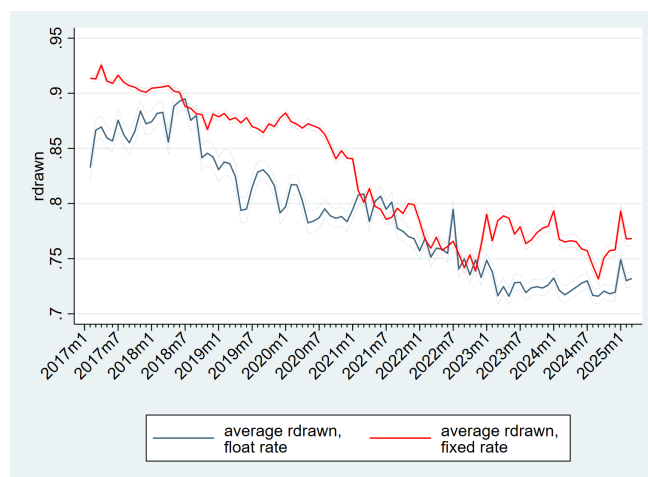


Figure 14. Revolving credit lines: utilisation rate for SMEs**Figure 15.** Revolving credit lines: utilisation rate for large companies**Figure 16.** Non-revolving credit lines: utilisation rate for SMEs**Figure 17.** Non-revolving credit lines: utilisation rate for large companies

interest rates and floating interest rates, then, in the event of a rise in the key rate, credit lines with fixed rates will become more preferable for the borrower and less preferable for the bank. To study this aspect in detail, we look at the dynamics of credit line utilisation rates disaggregated by company size and type of interest rate.

In the case of revolving credit lines, SMEs tend to use their lines more intensively on average (see Figure 14) compared to large companies (see Figure 15). If we look at the disaggregated dynamics of the utilisation rate of credit lines with fixed interest rates (red line) and floating interest rates (blue line) during 2024, we can see a divergence in the utilisation rates of credit lines for SMEs and convergence for large companies. The increasing utilisation rate of credit lines with fixed interest rates could not be profitable for banks in an environment of higher cost of deposits and squeezed margins. Implicitly, this could reflect the limited power of the banks to curtail companies' withdrawals on credit lines.

As for non-revolving credit lines, SMEs tend to use them less actively (see Figure 16) compared to larger entities (see Figure 17). The increase in the utilisation rate of credit lines with fixed interest rates for large companies is less apparent than it is for revolving lines. For large companies, we see a decline in the utilisation rate from the pandemic in 2020 until the beginning of 2023. Since that period, the utilisation rate of non-revolving credit lines with any type of interest rate (fixed or floating) has remained quite stable. Thus, for non-revolving credit lines, we also cannot see signs of widespread practice of curtailing the withdrawals of credit lines.

3. Literature review

Corporate credit lines (or revolving credit) are a crucial part of corporate liquidity management. The utilisation of credit lines has been extensively studied in the academic literature. In the context of this study, we are most interested in the literature which considers the determinants of credit line utilisation, their patterns, and their implications for firm performance and financial stability.

Why do companies want to have credit lines available and why do banks want to provide them? These questions have been intensively investigated in the academic literature for many years. Acharya et al., 2024 present a detailed review of the literature on these topics.

Credit lines can be seen as option contracts in which the firm has the opportunity to receive additional liquidity if it is necessary. Using this approach, Berg et al., 2016 show that firms are more likely to use credit lines when commitment and facility fees are higher and spreads are lower. Moreover, the choice of contract type (with a higher commitment fee or a higher spread) can be a signal of the likelihood of future credit line use. Amberg et al., 2023 show a similar result: when uncertainty increases, companies tend to use credit lines less. The authors prove this both theoretically and empirically. This signalling process helps banks identify borrowers' risk profiles and minimise the information asymmetry problem. Gatev and Strahan, 2006 show that banks can provide companies with protection against liquidity shocks since they usually have deposit inflows in times of economic instability.

Companies have their motives to use contingent credit facilities. They can provide protection against liquidity shocks (this motive has been mentioned frequently starting with Campbell, 1978) and economic downturns (Boot et al., 1987). It may seem that credit lines could be a substitute for liquidity reserves, however, different papers suggest that this is not always the case. Credit lines usually have covenants that are tied to cash flow. For example, Sufi, 2009 shows that utilisation depends on the company's cash flow and its volatility: the higher the cash flow and its volatility, the less likely it is that the credit line will be used. Acharya et al., 2014 show the same result. Lins et al., 2010 suggest that, although both cash reserves and credit lines can be explained with precautionary motives, firms think of their inherent risks differently. Cash serves as a cushion during periods of decrease in cash flows, while contingent credits are viewed as a source for seizing business opportunities. Additionally, Martínez-Sola et al., 2024 show that the appearance of company vulnerability (lower turnover, decreased profits, higher interest expenses and higher debt-to-assets ratio) has been associated with the use of credit lines or overdraft financing since the peak of the Global Financial Crisis. This effect can be explained by additional risks or as a signal of the existence of financial constraints.

Thus, macroeconomic conditions may affect the utilisation rate of previously issued credit lines. The literature provides extensive evidence of precautionary motives. Ivashina and Scharfstein, 2010 show a so-called 'flight to liquidity' during the Global Financial Crisis. A similar effect has been demonstrated for the COVID-19 pandemic (see, for example, the work of Bosshardt and Kakhbod, 2021). In most cases, companies draw on their credit lines to accumulate liquidity in their accounts. However, Liu et al., 2022 show that for SMEs in China, demand for credit lines decreased more severely for companies from the provinces that were most affected by the COVID-19 shock. This may be explained by the fact that the authors estimate demand for credit lines using the number of applications, and this decline may thus be part of the overall decline in the demand for credit due to the shortage of production activity.

Several variables can be identified among the drivers of credit line utilisation, including the characteristics of firms, banks and credit lines in addition to the economic shocks already mentioned. One of the most notable papers here is the work of Jiménez et al., 2009. They find that a company's probability of default is strongly positively correlated with credit line utilisation. Credit line age, the quantity and length of relationships with banks, and macroeconomic conditions also have significant effects on the use of credit lines.

Chodorow-Reich et al., 2022 look at loan-level data and show that small and medium-sized entities have higher utilisation rates in normal times but tend to use credit lines less during periods of negative shocks.

Profitability and cash flow volatility are also key determinants. Firms with volatile cash flows are more likely to rely on credit lines to smooth liquidity needs (Acharya et al., 2014). Additionally, firms

with greater growth opportunities often utilise credit lines to finance investments quickly, avoiding the delays associated with external capital markets (Campello et al., 2010).

4. Methodology

In this study, we are trying to identify factors that influence the utilisation rate (r_{drawn}). Figures 18 and 19 in Section 5 show that the distribution of r_{drawn} does not fit the normal distribution and does not follow the distribution of Jiménez et al., 2009, whose methodology we use as a baseline specification. This is one of the major obstacles to the direct application of the casual regression model to our dataset.

Thus, we split our analysis of both **revolving credit lines** and **non-revolving credit lines** into several parts. First, we study how long the company has a zero utilisation rate from the date the credit is assigned (contract date) to the first tranche. Second, we analyse what determines the credit line utilisation rate when it stays between 0 and 1. Finally, we study the behaviour of credit lines with exhausted limits ($r_{drawn} = 1$). This last approach is applicable to **revolving credit lines** only. In the case of **non-revolving credit lines** (the second type of credit lines that we study), if all of the committed amount is used (r_{drawn} reaches 1), the company will not be able to use the line again even in the case of the repayment of part of the debt. This is because the available limit cannot be replenished for non-revolving credit lines. On the contrary, the utilisation rate of **revolving credit lines** can decline after it reaches $r_{drawn} = 1$. Thus, if we wish to see the behaviour of the utilisation rate after a line is depleted, we can use information about **revolving credit lines** only. We use different analytical approaches for each of the three parts, which will be discussed further.

4.1 $0.01 < r_{drawn} < 0.99$

To study utilisation rates in the range between 0.01 and 0.99, we follow the methodology of Jiménez et al., 2009 for the complete CIR sample. Thus, we do not use supplementary firm-level financial variables except those that are already available in our dataset. This allows us to retain more observations, especially for small and medium-sized enterprises, which do not often have full sets of financial variables in their financial statements.

In this part, we define the regression model and briefly describe the variables. More detailed definitions of the variables and how they are calculated are presented in Section 5 below.

The baseline regression is the following:

$$RDRAWN_{ijkt} = \beta_0 + \beta_1 credit_line_{it} + \beta_2 firm_{jt} + \beta_3 bank_{kt} + \beta_4 cycle_t + \eta_{ijk} + \varepsilon_{it} \quad (1)$$

where $RDRAWN_{ijkt}$ is calculated as the total debt on credit line i of company j to bank k in period t divided by the initial limit on the credit line; $credit_line_{it}$ ⁴ is a set of variables with credit line characteristics (indicator of previous defaults, age, conditions, etc.); $firm_{jt}$ is a set of variables with company characteristics (age of the firm as a borrower, how many banks have provided loans to the company, etc.); $bank_{kt}$ is a set of variables with different bank characteristics (bank share, the quality of the bank's portfolio, an indicator for the bank that has provided the largest share of a firm's loans).

Jiménez et al., 2009 apply three estimators: simple OLS model estimation (or a pooled model), within-group estimation (or a fixed effect panel model) and a Tobit model. In our study, we focus on a fixed effect model and a probit model for the shares (which is described as a 'quasi-MLE approach with fixed effects' by Papke and Wooldridge, 2008). We prefer the last method over the Tobit model as it allows us to work with a bounded dependent variable that represents the share of the overall commitment amount. The Tobit method, in turn, assumes that the dependent variable is censored, meaning the values less than 0 and more than 1 exist but that we simply do not observe them. In our case, however, these values are not feasible.

⁴We use index i to indicate credit lines on the basis of continuous numbering throughout the whole database. This means that each credit line indicator is assigned to a credit line of one particular company provided by one particular bank.

4.2 $rdrawn = 0$

In this case, we are considering lines with zero utilisation. For the sake of simplicity of interpretation, we narrow the question and focus on new credit lines and identify the factors that influence the beginning of credit line withdrawals. We use the survival analysis technique to do this. Martínez-Sola et al., 2024 use a similar approach to study the impact of credit lines on the vulnerability of companies. Following this research, we use the Weibull proportional hazard model. The hazard function for observation j takes the following form in this case:

$$h_j(t) = p \cdot \exp(x_j \beta) \cdot t^{p-1} \quad (2)$$

where p is the estimated parameter of the function; x_j is the set of explanatory variables, and β is estimated coefficients representing the intensity of each variable's impact on the hazard ratio. The set of explanatory variables is almost the same as the set we use in the panel regression model. We exclude the variables that identify default on the credit line and the time passed since the default, since it is not possible to default if there have been no withdrawals on the credit line.

4.3 $rdrawn = 1$

In this case, we do not apply any econometric methods and use descriptive graphical analysis. We split all the credit lines with depleted limits into three groups at each reporting date:

- ‘Credit’: this group includes all lines for which there is no change in the utilisation rate during the three months following the reporting date. As their behaviour is more similar to that of regular credit (when all funds are withdrawn and the loan is repaid by a certain date) than to credit lines (when the company sometimes uses money when it is needed and then repays the debt in a short period of time).
- ‘Volatile lines’: this group includes lines for which $rdrawn$ changes by more than 50% during the three months following the reporting date.
- ‘Non-volatile lines’: this group includes lines for which $rdrawn$ changes by less than 50% during the three months following the reporting date.

5. Data

Our main source of data is the credit registry for Russian legal entities, collected by reporting form No. 0409303⁵ (the ‘credit registry’). This dataset contains comprehensive information on every loan provided by each bank: borrowers’ ID, type of credit, loan volume, interest rate, maturity, etc. The data are provided monthly.

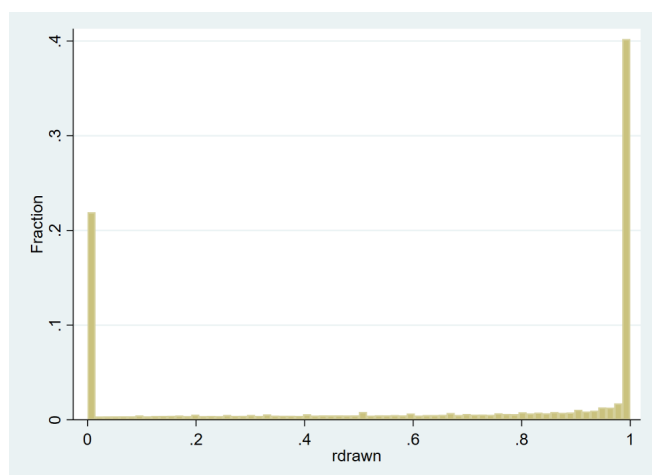
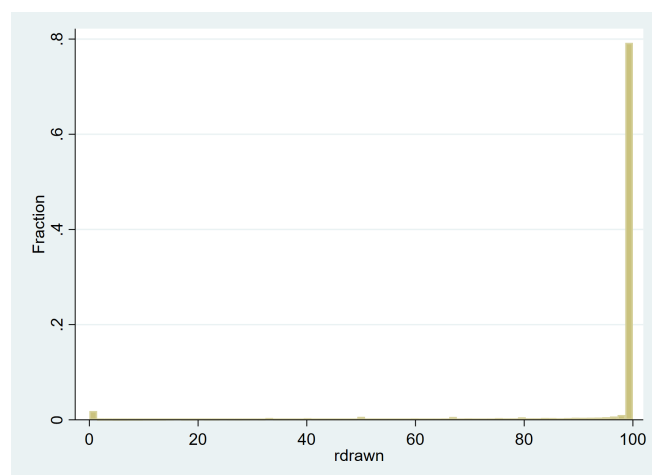
Loans provided to companies can be one of several types: loans, overdrafts, or credit lines with different types of limits (maximum size of debt (or revolving credit line), maximum size of total withdrawals (non-revolving credit line), or mixed type). In this study, we are interested only in credit lines. Moreover, we exclude mixed-type credit lines from consideration as there are too few observations (xxx out of yyy for the study period). Thus, we focus on revolving and non-revolving credit lines. Since in the second case, the utilisation rate is a non-decreasing function of time, we study the different types of credit lines separately.

The main variable of interest is the rate of credit line utilisation $RDRAW_{ijkt}$. It is calculated as the total debt on credit line i of company j to bank k in period t divided by the amount committed. The distributions of this variable for revolving and non-revolving credit lines are presented in Figure 18 and Figure 19, respectively.

Now, we will have a closer look at each explanatory variable and briefly discuss how we achieve the final versions of the variables included in the regression.

1. Characteristics of credit lines.

⁵Banks submit this form to the Bank of Russia on a monthly basis. We refer to it as the ‘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/ and Instruction of the Bank of Russia No. 6406, dated 10 April 2023.

Figure 18. Distribution of utilisation of revolving credit lines**Figure 19.** Distribution of utilisation of non-revolving credit lines

- **Dummy variable for defaulted credit lines.** This variable equals 1 in the case the company has defaulted on credit line i . In our paper, we define default as being overdue for over 90 days. Jiménez et al., 2009 define this variable as default during the available subsample. In our dataset, we have information about credit lines provided before the start date of the sample period, so we can look at credit lines that originated before 2017 with the use of information about overdue length and the number of restructurings.
 - **Months from default** is used in interaction with the indicator for credit line default. It shows the long-run effect of default on credit line utilisation. It is calculated as the number of months since default.
 - **Credit line age** is calculated as the difference between reporting date t and the date of the credit line's origination (contract date).
 - **Dummy for long-term credit lines.** This variable is equal to 1 if the maturity exceeds one year. Most credit lines are comprised of multiple tranches, which can have different maturities. To define the overall maturity of the whole credit line, we weight the tranche maturity by the volume of debt on each tranche.
 - **Dummy for collateralised loans.** This variable is equal to 1 if there is any collateral on at least one tranche of the credit line.
 - **Type of interest rate.** We use the information about the type of interest rate and define whether it is fixed or floating. This variable is equal to 1 if the interest rate is fixed.
2. Characteristics of companies.
- **Age as a borrower.** Jiménez et al., 2009 use the age only within the available database (so the age of borrowers does not exceed the time span of the database). However, in our database, we have information about credit lines that originated before 2017 if they still existed as of January 2017. Measured in months.
 - **Firm risk.** This is a dummy variable that shows whether a company had a default on any credit facility in previous years (*default_inn*). Similar to credit line default, we define default on any loan as being overdue for over 90 days.
 - **Time with the bank.** Calculated as the difference between the reporting date and the contract date of the oldest known credit contract. To define this variable, we use information about all types of loans (not only credit lines). Measured in months. This variable is added to regression in logarithm form $\ln_with_bank = \ln(1 + month_with_bank)$.
 - **Number of credit relationships with banks.** This variable shows the number of banks with which firm j has contracts as of reporting date t .
 - **Size of the company.** This variable represents the size of the company: is it a micro, small, or medium-sized enterprise or a large firm. This variable equals 1 if the company is large, and 0 otherwise. Chodorow-Reich et al., 2022 show that SME companies have higher utilisation

Table 1. Description statistics of main variables used for revolving credit lines

Variable	Observations	Mean	Std.Dev.	Min	Max
rdrawn	7,476,967	64.183	41.097	0	100
main bank	7,476,967	0.840	0.367	0	1
bank share	7,476,967	0.177	0.163	0	0.378
bank npl share	7,476,255	-0.058	0.059	-0.130	0.919
infl	7,476,967	0.587	0.816	-0.54	7.61
ind	7,476,967	103.273	3.694	92.3	112.9
default cl	7,476,967	0.0034	0.0578	0	1
months default cl	7,476,967	0.0080	0.5258	0	95
line age	7,476,967	11.894	11.923	0	214
collateral	7,476,967	0.414	0.493	0	1
fix	7,476,967	0.808	0.394	0	1
long term	5,913,367	0.634	0.482	0	1
ln age bor	7,476,843	3.513	0.9424	0	5.697
big corp	7,476,967	0.199	0.399	0	1
ln with bank	7,476,967	3.111	0.999	0	5.537
default inn	7,476,967	0.0060	0.0771	0	1
month default inn	7,476,967	1.0733	5.8780	0	97
ln count bank	7,476,967	0.334	0.492	0	3.045

Table 2. Description statistics of main variables used for non-revolving credit lines

Variable	Observations	Mean	Std.Dev.	Min	Max
rdrawn	14,726,646	90.744	22.985	0	100
main bank	14,726,646	0.911	0.284	0	1
bank share	14,726,646	0.218	0.161	0	0.378
bank npl share	14,725,964	-0.065	0.045	-0.130	0.919
infl	14,726,646	0.587	0.816	-0.54	7.61
ind	14,726,646	103.273	3.694	92.3	112.9
default cl	14,726,646	0.0041	0.0642	0	1
months default cl	14,726,646	0.0624	1.7396	0	95
line age	14,726,646	16.110	18.716	0	272
collateral	14,726,646	0.372	0.483	0	1
fix	14,726,646	0.864	0.343	0	1
long term	13,428,025	0.858	0.349	0	1
ln age bor	14,726,646	3.519	1.085	0	5.759
big corp	14,726,646	0.132	0.339	0	1
ln with bank	14,726,646	3.247	1.112	0	5.759
default inn	14,726,646	0.0138	0.1165	0	1
month default inn	14,726,646	1.080	6.0340	0	97
ln count bank	14,726,646	0.215	0.397	0	3.045

rates.

- **Age of the company.** This variable shows the number of months passed since the date of firm's registration with Federal Tax Service (the date it obtained a tax ID).

3. Characteristics of banks.

- **Bank share.** This variable is calculated as the ratio of the size of each bank's portfolio to the total market size of corporate borrowings. The size of each bank's portfolio of corporate loans is calculated as the total debt of all borrowers using the information from the credit registry. These portfolios include only loans given to residents of the Russian Federation in domestic currency.
- **Bank NPL ratio.** This variable is calculated as the deviation of each bank's share of non-performing loans (NPL) from the average NPL share among all banks. The NPL share for each bank is calculated as the ratio of overdue debt to the sum of overdue and term debt. Non-performing loans are those overdue for 90 days or more. Information on the length of the overdue period is obtained from the credit registry.
- **Main bank.** This variable is an indicator for the main banks. For each company, we calculate how much it owes to all its creditors (banks) and to each bank separately. Using this information, we identify bank \bar{k} to which company j is indebted the most. This bank \bar{k} is marked as the main bank for company j in period t and it receives the value $main_bank_{j\bar{k}t} = 1$. Other banks that provided loans to firm j receive $main_bank_{jkt} = 0$.

4. Characteristics of macroeconomic conditions.

- **Inflation**, measured as the percent change in the seasonally adjusted consumer price index (CPI) from the end of the previous month (taken from Rosstat).
- **Growth of production**, measured as the Industrial Production Index (taken from Rosstat).

6. Results

6.1 Regression analysis.

The results for both types of credit lines (revolving and not-revolving) and two cases of $rdrawn$ values ($0 < rdrawn < 1$ and $rdrawn = 0$) are presented in Table 3.

The left part of this table represents the analysis for revolving lines. For the range $0 < rdrawn < 1$ estimations of marginal effects for fractional probit model are presented. For $rdrawn = 0$ coefficients survival regression model are presented.

The right part of the table represents the same two models for not-revolving credit lines. FE model estimations of the full sample and results for the analysis of the subsamples (performed for time periods and companies' size) can be found in the Appendix (see Tables 4–8).

If we take a look on the results, we can see that some coefficients have the same sign for all four models:

- *main bank*: if the credit line is granted by the main bank, its utilization rate will be higher and withdrawals will begin sooner in comparison to lines provided by other banks. The difference is 6.2 p.p. for not revolving credit lines and 9.1 p.p. for revolving lines. This result is in line with Jiménez et al., 2009.
- *line age*: the older is the credit line, the lower is the utilization rate and the lower is the probability that the withdrawals begin. The utilization rate is lower by $0.0026 \cdot 12 = 3.12p.p.$ for not-revolving lines and by $0.00093 \cdot 12 = 1.11p.p.$ for revolving lines when the lifetime of the line increases by one year (12 months). This result is in line with Jiménez et al., 2009
- *firm's age as a borrower*: the older is the borrowing firm, the lower is the utilization rate and the lower is the probability that the withdrawals begin sooner.
- *number of the banks*: the larger is the number of banks that have contracts with the company, the higher is the credit line utilization rate for this company and the higher is the probability that the withdrawals begin sooner. The only exception is the utilization rate of not-revolving credit lines, where the coefficient is insignificant.

Table 3. Regression estimation results. Marginal effects for fractional probit estimation and coefficients for survival regression model for revolving and not-revolving credit lines.

	Revolving lines		Not-revolving lines	
	Probit, ME	Survival	Probit, ME	Survival
	($0 < rdrawn < 1$)	($rdrawn = 0$)	($0 < rdrawn < 1$)	($rdrawn = 0$)
main bank	0.091***	0.079***	0.062***	0.046**
bank share	-0.728***	0.061*	-0.064	0.217***
bank npl share	-0.426***	0.128	0.158***	0.120
prod.index	-0.00069***	0.0029**	-0.0035***	0.015***
inflation	0.00053***	-0.016***	-0.0013***	-0.153***
line age	-0.00093***	-1.210***	-0.0026***	-1.701***
collateral	0.021***	0.115***	-0.011***	-0.098***
fix rate	0.0018***	-0.0003	0.041***	0.037***
long term	0.039***	0.296***	-0.0037***	0.012
ln age bor	-0.026***	0.002	-0.015***	-0.012**
large enterprises	-0.031***	-0.034***	-0.046***	-0.253***
ln with bank	0.0130***	-0.048***	0.055***	-0.036***
default inn	0.066***	0.150	-0.028***	0.125**
default inn x months	0.0035***	0.003***	0.0014***	0.0015*
ln count bank	0.0059***	0.108***	0.0035	0.050***
default cl	0.025**		0.038***	
default cl x months	-0.0162***		-0.0042	
default cl x months sq	0.00010		0.00013**	
trend			0.000053	
N	2,618,507	99,738	2,229,240	111,387
pseudo R^2	0.0068		0.0061	
ln_p		1.485		1.809
Wald test	14421.22	38604.95	14198.77	50095.64

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

- *fixed interest rate*: if the interest rate on the credit line is fixed, then the utilization rate of the credit line is higher and it is being utilized sooner.
- *large companies*: utilization rate for large firms is lower, and the company start to withdraw the credit line lately.
- *default of credit line*: the utilization rate of both revolving and not-revolving credit lines is higher on average for defaulted credit lines.

Then we also have a set of variables with different signs for fractional probit model and survival model meaning the factor is associated with higher utilisation rate and longer period of zero utilization of the same line, and vice versa. Those signs are the same for both revolving and not-revolving lines:

- *bank share*: the larger is the market share of the bank, the lower will be the utilization rate of the credit lines provided by this bank. But withdrawals for such lines begin sooner.
- *production index*: if the growth rate of the output in the economy increases, the utilization rate slightly decreases. At the same time, new credit lines are being used sooner.
- *time spent with the bank*: the longer are the relationships of the firm with the bank, the higher will be the utilization rate and the longer will be the period before the first withdrawal on the new line.
- *default of credit line*: the utilization rate of both revolving and not-revolving credit lines is higher on average for defaulted credit lines. This variable was not used in the survival regression, as was discussed above.

We can see that in several cases the results coincide with those in Jimenez et al. (2009). Firms tend to withdraw credit line more intensively from the main bank, from the smaller bank (significant in case of revolving lines only), on the recently opened credit lines, with the collateral (for the revolving lines only), if a firm has shorter history as a borrower and it had no default on other loans (for non-revolving lines only).

To study more precisely the differences in the behaviour of credit lines utilization rates between large companies and SMEs we estimated our regressions on subsamples. You can find results in the Table 5 for revolving and not-revolving credit lines separately. The only difference that appears for both revolving and not-revolving lines is the significance of credit line default indicator: utilization rate of defaulted credit lines is higher for SMEs and remains the same for large entities.

We also estimate regressions on subsamples by the periods of time:

- Pre-covid period of time: since January, 2017 until February, 2020.
- COVID-19 crisis period: since March, 2020 until February, 2021
- Post COVID-19 period: since March, 2021 until February, 2022
- Geopolitical tensions: since March, 2022 until August, 2024
- Period of key interest rate acceleration: since September, 2024.

We can barely identify some stable and significant differences in the effects of explanatory variables depending on whether during normal times or crisis periods (see Table 6 for revolving credit lines and Table 7 for not-revolving credit lines). One of the few exceptions is the change in the sign of the *fix rate* variable and only for revolving lines. During pre-covid period (2017—2020) the utilization rate of credit lines with the fixed interest rate was lower than in case of floating rate. During this period we can see relatively calm economic conditions and gradually declining key interest rate. Positive and significant coefficient appears only for the period starting with the March 2022 until August 2024 where we can see significant economic fluctuations and large changes in the key rate. This pattern does not appear for not-revolving credit lines (the coefficients of the *fix rate* variable are positive and significant for all the time sub-samples).

Moreover, if we look at the coefficients of the *large enterprise* variables, we can see that they are all negative. It means that our results for the large companies contradicts the Chodorow-Reich et al., 2022 paper: we see no increase in the utilization rate for large companies during crisis.

6.2 The case of fully used credit lines.

The analysis of the fully used credit lines shows that almost 60% of those lines as of the beginning of the month remain in the same condition (*rdrawn* = 1) during the following 3 months (see Fig. 20). In fact, these lines have more common with regular loans (thus they are labeled as “credit” on the graph). The remaining 40% have some volatility in their utilization rates:

- in half of the cases the rate did not fall below 50% (thus they can be treated as not volatile lines and they are labeled as “cl_not_vol” on the graph)
- in other half of the cases their utilization rate fell below 50% (meaning they are volatile and thus they are labeled as “cl_vol” on the graph).

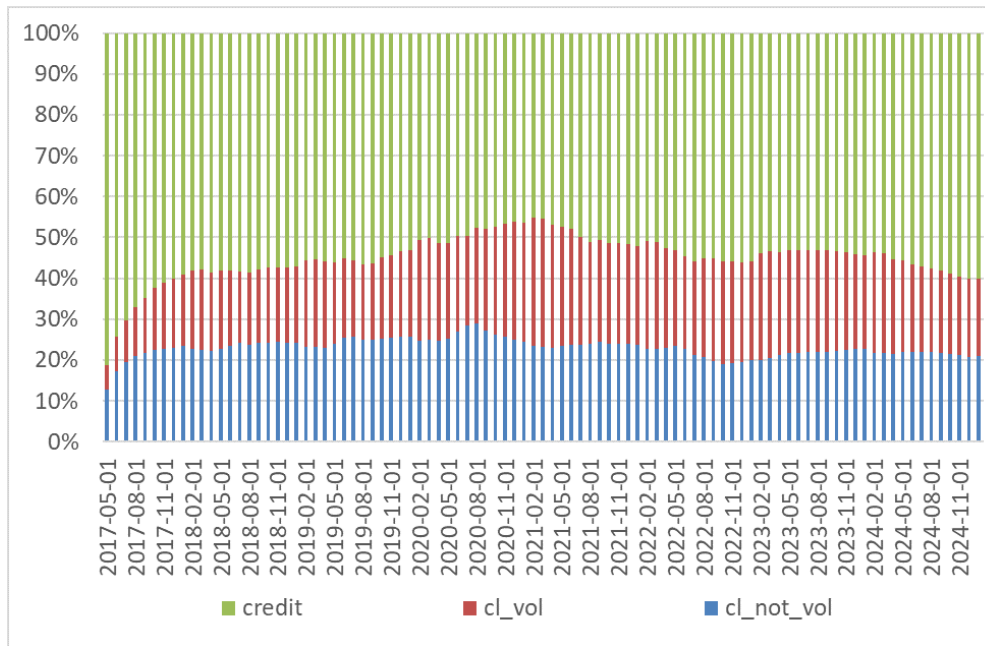
It is worth noting that in the latter case there are instances of repayment of loans due to maturity.

We can conclude that the majority of credit lines that reached their limit remains quite stable until they mature. And the remaining share is relatively small and these credit lines show a significant volatility, meaning they could be withdrawn again lately after they were partially repaid. Thus, these credit lines will unlikely to create an additional uncertainty regarding the flow of funds for their banks.

7. Discussion

First thing that we should emphasize is that we actually cannot observe demand and supply sides of the credit lines utilization. For example, banks may more or less freely refuse to provide new tranches, depending on the terms of the contract. However, we are not able to find a reliable indicator for this feature. Thus, in each case we see the decline in the credit line utilization, we can not say with confidence

Figure 20. Distribution of fully used credit lines with respect to their behavior in the following 3 months.



is this happening because a company is not willing to use the available limit or because a bank refuses to provide funds.

Second, we should mention that we partially depart from the methodology applied in Jiménez et al., 2009. For example, we use different approach to define the denominator in the *rdrawn*. As bank can change the commitment amount of funds, there is a choice: to apply initial limit or limit after the change. In Jiménez et al., 2009 authors use the following approach: they treat the increase of the commitment amount as creation of the new line of credit. In case of decrease in this amount, they keep the initial amount of funds. This approach creates a downward bias in the *rdrawn* levels, as stated in Jiménez et al., 2009. Thus, the authors conclude that if the coefficient is significant, then it will be even stronger if we have an unbiased utilization rate.

The treatment of the increase in the commitment amount as providing a new credit line instead of the old one implies that we create a new observation. This can be made in two ways. In the first case, the new observation will have new values in some explanatory variables (for example, the age of the credit line will start counting the life of this "new" credit line). The second approach supposes that we keep all variables unchanged (except commitment amount and *rdrawn*). But eventually it will be the same observation that we would have in case of using the new commitment amount as the denominator in *rdrawn*. As a result, the first approach will bring some additional noise in the explanatory variable. The second approach will affect the length of observation over one credit line into several peaces that will affect the estimations. Thus, creating a new line in case of increase in commitment amount add the new noise in the dataset instead of other source of noise (generated by changes in available limits). Moreover, the decline in commitment amount are ignored, however it might affect future decision of the company about the amount of funds they would like to withdraw.

We actually have some cases of change in the commitment amount, both upward and downward. But these cases are rare and most of them are relatively small. Thus, we decided to calculate *rdrawn* as the ratio to current level of commitment amount (i.e. with changes) for both increase and decrease in contract agreement amount without creating new observations. We suppose that this approach better reflects the actual utilization rate of the credit line.

The next topic for discussion is the choice of the *default* variables. In this paper, we use all the available information about defaults, whether they happened before or after 2017 (when our dataset begins). However, not all the cases of financial distress lead to the delinquencies on the loan. In many cases, companies prefer to restructure their credits if they understand that they are not able to pay on

all their debts. Thus, one of the interesting question for the future research may concern restructurings as the alternative variable to measure the financial quality of the firm.

The final consideration relates to the ability of banks to refuse to provide funds to companies on the opened credit lines. The bank's right to do this is usually stipulated by the contract, and may vary case by case depending on the conditions. Thus, in case of significant burden on the banking financial condition, it might be prudent to use this right. Thus, if companies overwhelmingly rely on credit lines and expect the usage of available limits, they might suffer the negative shock. It may threaten the liquidity position if they will not be able to get additional funds apart from credit lines.

Can these results be relevant for monetary and macroprudential policy? A precise answer to this question requires additional studies of the role of credit lines in the transmission mechanisms. However, this study allows to identify several hypothesis about which factors might be of particular interest.

A sufficient share of the committed limits on credit lines is provided to large companies. On the one hand, we can see no strong increase in the utilisation rate of credit line by large enterprises during crisis periods (Figures 14–17), which suggests a relatively stable lending structure in terms of fund distribution between large firms and SMEs. On the other hand, regression analysis (Table 5) shows that large companies have higher utilisation rate of both types of credit lines if inflation increases (this process is usually accompanied by key interest rate hike), while SMEs have mixed dynamics (revolving lines are used more intensively while non-revolving lines are used less intensively). This may indicate some decline in transmission efficiency, as large companies use their committed lines more actively while interest rates increase. However, inflation may be correlated with other other variables so these additional effects can compensate increase in the utilisation rate of large companies.

Additionally, we can see that the utilisation rate of credit lines with fixed interest rate is higher than those with floating rate. This effect is robust for non-revolving lines across all time sub-samples, both during monetary easing and tightening. This may weaken the interest rate channel of monetary transmission, as some loans are insensitive to rate changes. However, the scale of this reduction should be investigated more precisely. The difference in utilisation rates is about 4 percentage points for non-revolving lines and 0.1 percentage points for revolving lines.

we should also note that banks with a higher market share have lower utilisation rates of both types of credit lines among SMEs but higher utilisation rate of non-revolving lines for large firms. This dynamic may lead to the concentration of large enterprise loans with major banks and small enterprise loans with smaller banks. This could potentially create risk imbalances if a shock affects company of different sizes unequally (i.e., only large firms or only SMEs). Moreover, as it was discussed above, some banks have unused revolving credit limits that exceed their portfolio size. Therefore, in case of a significant increase in the demand for credit lines from these banks' borrowers, banks may need additional financing or they will have to deny the use of the lines. This can potentially lead to losses either for banks or borrowers. In the latter case, a second round effect may occur (insolvency of one borrower can affect all counterparties, including banks and other companies).

8. Conclusion

To conclude, credit lines are an important source of financing production activity in many countries, including Russia. It is crucial to identify factors affecting the utilization of contingent loans (i.e. credit lines) since the unexpected withdrawal of funds may lead to the additional burden on banking system. This burden may be especially significant if many companies simultaneously decide to use their available credit lines more intensively or in case the bank has a significant amount of unused limits on credit lines (exceeding the total corporate credit portfolio). Consequently, the banks might be able to refuse providing funds to their clients in order to maintain different requirements (capital, liquidity, etc.). Thus companies might face the liquidity shortage that can affect its activity.

In this paper we found several characteristics of banks, firms, credit lines and macroeconomic dynamics that are related to the utilization rate. We can identify several significant factors that have a robust effect on utilization rate of both revolving and not-revolving credit lines.

Firstly, if the credit line is assigned by the main bank of the firm (meaning that provide the majority of the company's loans), its utilization rate will be higher and withdrawals will begin sooner in comparison

to lines provided by other banks. We also see that if the time spent with the bank increase, the utilization rate gets higher. Both these results might be explained by the fact, that if the bank have a long story of relationships with the company, it knows better the necessary amount of funds and provide it to the firm. Consequently, this credit line will have higher utilization rate.

The age of credit line has a negative effect on the utilization rate. It might be explained with the maturity of the old credit lines and their replacement with the new lines. In case the credit line exists for a very long period of time, its conditions might become outdated. So the old credit line is gradually repaid while company actively use the new credit line.

Another significant factor is the indicator of the previous default on credit line and the time passed since the default. We can say that defaulted credit lines have a higher utilization rate, but this difference decline over the time passed. However, in this case we should mention, that these variables are significant only for subsample of SMEs. For large companies we see no difference in the utilization rate of credit lines with and without previous defaults.

One more significant variable is the type of interest rate: if an interest rate on the credit line is fixed, its utilization rate is higher. This might reflect the preference of the companies to have more predictable terms on the debt, especially if the market rate is quite volatile.

The last significant variable we would like to mention here is the indicator of large enterprises: we can see that utilization rate for large companies is lower than for SMEs. This result is generally in line with the literature. However, there are evidences of the increase in utilization of credit lines for large companies in the periods of crisis. Meanwhile, in our study, we see that indicator of large firms have negative coefficients on every time period we identified in our study.

Considering fully utilized credit line, we can conclude that the majority of credit lines that reached their limit remains quite stable untill they mature. Thus, such a behaviour of some credit lines lowers the uncertainty regarding the flow of funds for their banks.

References

- Acharya, V., Almeida, H., Ippolito, F., & Perez, A. (2014). Credit lines as monitored liquidity insurance: Theory and evidence. *Journal of financial economics*, 112(3), 287–319.
- Acharya, V., Jager, M., & Steffen, S. (2024). Contingent credit under stress. *Annual Review of Financial Economics*, 16.
- Amberg, N., Jacobson, T., Quadrini, V., & Rogantini Picco, A. (2023). *Dynamic credit constraints: Theory and evidence from credit lines* (tech. rep.). Sveriges Riksbank (Central Bank of Sweden).
- Berg, T., Saunders, A., & Steffen, S. (2016). The total cost of corporate borrowing in the loan market: Don't ignore the fees. *The Journal of Finance*, 71(3), 1357–1392.
- Boot, A., Thakor, A. V., & Udell, G. F. (1987). Competition, risk neutrality and loan commitments. *Journal of Banking & Finance*, 11(3), 449–471.
- Bosshardt, J., & Kakhbod, A. (2021). Why did firms draw down their credit lines during the covid-19 shutdown? Available at SSRN 3696981.
- Campbell, T. S. (1978). A model of the market for lines of credit. *The Journal of Finance*, 33(1), 231–244.
- Campello, M., Graham, J. R., & Harvey, C. R. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of financial Economics*, 97(3), 470–487.
- Chodorow-Reich, G., Darmouni, O., Luck, S., & Plosser, M. (2022). Bank liquidity provision across the firm size distribution. *Journal of Financial Economics*, 144(3), 908–932.
- Gatev, E., & Strahan, P. E. (2006). Banks' advantage in hedging liquidity risk: Theory and evidence from the commercial paper market. *The journal of finance*, 61(2), 867–892.
- Greenwald, D. L., Krainer, J., & Paul, P. (2021). The credit line channel.
- Ivashina, V., & Scharfstein, D. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial economics*, 97(3), 319–338.
- Jiménez, G., Lopez, J. A., & Saurina, J. (2009). Empirical analysis of corporate credit lines. *The Review of Financial Studies*, 22(12), 5069–5098.
- Kapan, T., & Minoiu, C. (2021). Liquidity insurance vs. credit provision: Evidence from the covid-19 crisis. *Credit Provision: Evidence from the COVID-19 Crisis (January 25, 2021)*.
- Lins, K. V., Servaes, H., & Tufano, P. (2010). What drives corporate liquidity? an international survey of cash holdings and lines of credit. *Journal of financial economics*, 98(1), 160–176.
- Liu, Y., Zhang, Y., Fang, H., & Chen, X. (2022). Smes' line of credit under the covid-19: Evidence from china. *Small Business Economics*, 58(2), 807–828.
- Martínez-Sola, C., Mol-Gómez-Vázquez, A., & Hernández-Cánovas, G. (2024). Lines of credit and vulnerability during the financial crisis: A survival analysis for european smes. *Applied Economics*, 1–13.
- Papke, L. E., & Wooldridge, J. M. (2008). Panel data methods for fractional response variables with an application to test pass rates. *Journal of econometrics*, 145(1-2), 121–133.
- Sufi, A. (2009). Bank lines of credit in corporate finance: An empirical analysis. *The Review of Financial Studies*, 22(3), 1057–1088.

Appendix

Table 4. Regression estimation results. Comparison of FE and probit for share estimations for **revolving lines** for overall dataset and for subsample ($0.01 \leq rdrawn \leq 0.99$)

	All sample			Subsample		
	FE	probit	probit, ME	FE	probit	probit, ME
main bank	9.698***	0.250***	0.071***	14.559***	0.236***	0.092***
bank share	-139.786***	-7.224***	-1.915***	-144.824***	-1.908***	-0.728***
bank npl share	-50.159***	-1.559***	-0.413***	-51.043***	-1.116***	-0.426***
prod.index	-0.041***	-0.0028***	-0.0007***	-0.058***	-0.0018***	-0.0007***
inflation	0.221***	0.0074***	0.002***	0.142***	0.0014**	0.0005**
default of CL	0.938**	0.136***	0.034***	0.431	0.065**	0.025**
default of CL x month from default	-0.584***	-0.071***	-0.0189***	-1.360***	-0.042***	-0.016***
default of CL xmonth from default sq	0.002***	0.0006***	0.0002***	0.0044	0.0003	0.0001
line age	0.015***	0.004***	0.001***	-0.132***	-0.002***	-0.0009***
collateral	-1.445***	0.097***	0.025***	-0.145	0.055***	0.021***
fix rate	0.896*	0.053***	0.014***	-1.429***	0.0049*	0.0019*
long term	-0.952***	0.272***	0.075***	-1.206***	0.103***	0.039***
ln age bor	0.613***	0.043***	0.011***	-1.803***	-0.069***	-0.026***
large enterprises	-0.521***	-0.049***	-0.013***	-0.337***	-0.080***	-0.031***
ln with bank	1.372***	0.044***	0.012***	2.171***	0.034***	0.013***
default inn	-1.480***	0.273***	0.064***	-5.385***	0.178***	0.066***
months default inn	0.013**	0.005***	0.001***	0.167***	0.013***	0.005***
ln count bank	1.765***	0.022***	0.006***	1.872***	-0.007	-0.003
cons	88.351***	-0.934***		70.017***	-0.956***	
F-test	3827.24			2706.55		
Wald-test		45366.25			14421.22	
R^2	0.0136	0.0307		0.0214	0.0068	
N	5,488,900	5,488,900		2,618,507	2,618,507	

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 5. Regression estimation results. Marginal effects for fractional probit estimations for revolving and not-revolving credit lines for middle subsample ($0.01 \leq rdrawn \leq 0.99$) for groups of SME and large entities.

	Revolving lines		Not-revolving lines	
	(SME)	(large)	(SME)	(large)
main bank	0.094***	0.097***	0.071***	0.048***
bank share	-0.965***	-0.032	-1.141***	1.492***
bank npl share	-0.460***	-0.239***	0.153***	0.061
prod.index	-0.0008***	-0.0004***	-0.004***	-0.0001
inflation	0.0006**	0.0008*	-0.0014***	0.0002***
line age	-0.0009***	-0.0011***	-0.0038***	-0.0008***
collateral	0.016***	0.038***	-0.0186***	0.032***
fix rate	-0.0011***	0.0045***	0.047***	0.023***
long term	0.042***	0.030***	-0.0057***	0.018***
ln age bor	-0.027***	-0.024***	-0.015***	-0.0014***
ln with bank	0.014***	0.014***	0.060***	0.066***
default inn	0.063***	0.048***	-0.041***	0.0067***
default inn x months	0.0057***	0.0013**	0.0008**	0.0025***
ln count bank	-0.0004	-0.0001	0.0067***	0.0062
default cl	0.029**	0.014	0.059***	-0.016
default cl x months	-0.018***	-0.012	-0.007**	-0.0009
default cl x months sq	0.0001	0.0001	0.0002***	0.0001
trend			0.0003***	-0.001***
N	2,133,690	484,817	1,795,470	433,770
<i>pseudo R</i> ²	0.0072	0.0080	0.0074	0.0058
Wald test	12968.63	2801.35	16389.99	1342.82

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6. Regression estimation results. Comparison of marginal effects in different time periods for revolving lines for middle subsample ($0.01 \leq r_{drawn} \leq 0.99$). Fractional probit estimations.

	Jan'17—Mar'20	Apr'20—Mar'21	Apr'21—Feb'22	Mar'22—Aug'24	Sep'24—Dec'24
main bank	0.093***	0.115***	0.102***	0.085***	0.067***
bank share	−0.370***	0.069	−1.028***	−1.613***	−1.347***
bank npl share	−0.015	−0.952***	−0.373***	−0.283***	−0.702***
prod.index	0.00005	−0.0005***	−0.0003	−0.0010***	0.0003
inflation	0.015***	−0.048***	0.016***	0.0002	0.025***
default of CL	0.035	0.022	0.067**	0.073***	0.132***
default of CL x month from default	−0.021*	−0.010	0.006	−0.045***	0.065***
default of CL xmonth from default sq	0.0002	0.00008	−0.0003	0.0003***	
line age	−0.0013***	−0.0008***	−0.0019***	−0.0012***	0.0006
collateral	0.020***	0.020***	0.039***	0.021***	−0.006*
fix rate	−0.006***	−0.0003	−0.0003	0.003*	−0.001
long term	0.042***	0.030***	−0.0007	0.045***	0.041***
ln age bor	−0.010***	−0.022***	−0.052***	−0.045***	−0.045***
large enterprises	−0.028***	−0.029***	−0.032***	−0.032***	−0.030***
ln with bank	0.013***	0.005	0.013***	0.023***	0.0003
default inn	0.079***	0.092***	0.079***	0.032**	0.050**
months default inn	0.0039***	0.0017**	0.0063***	0.0094***	0.023***
ln count bank	−0.004	−0.002	−0.004	−0.005*	0.040***
N	689,292	287,406	286,528	1,158,374	196,907
<i>pseudo R</i> ²	0.0063	0.0085	0.0132	0.0089	0.0138
Wald test	4026.32	3204.27	3680.03	26572.89	1479416.24

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7. Regression estimation results. Comparison of marginal effects in different time periods for **not-revolving lines** for middle subsample ($0.01 \leq r_{drawn} \leq 0.99$). Fractional probit estimations.

	Jan'17—Mar'20	Apr'20—Mar'21	Apr'21—Feb'22	Mar'22—Aug'24	Sep'24—Dec'24
main bank	0.062***	0.065***	0.056***	0.053***	0.048***
bank share	−0.343*	−3.210***	2.464***	0.657***	−1.767***
bank npl share	0.280***	0.313***	−0.177***	0.0069	0.302**
prod.index	−0.0004***	−0.0041***	−0.0018***	−0.0000	−0.0004***
inflation	0.037***	−0.136***	−0.015***	−0.0003	0.002
default of CL	0.049***	0.105***	0.087***	0.043**	0.080**
default of CL x month from default	−0.0042	0.0057	−0.0015	−0.0013	0.015***
default of CL xmonth from default sq	0.00004	−0.0002	−0.0001	0.00005	
line age	−0.0042***	0.0006***	−0.0049***	−0.0033***	−0.00001
collateral	0.0086***	−0.0069***	0.0196***	−0.028***	−0.047***
fix rate	0.011***	0.042***	0.048***	0.041***	0.042***
long term	0.024***	0.0003	0.016***	0.009***	−0.013***
ln age bor	−0.003	−0.022***	0.028***	0.003	−0.0002
large enterprises	−0.028***	−0.023***	−0.047***	−0.070***	−0.061***
ln with bank	0.053***	0.085***	0.069***	0.062***	0.036***
default inn	−0.019*	−0.106***	−0.058***	0.003	0.023*
months default inn	0.0019***	−0.0017**	0.0025***	0.0062***	0.035***
ln count bank	0.004	0.011**	−0.016***	−0.003	−0.008
trend	0.0015***	0.0040***	−0.0005**	0.00002	0.0026***
N	448,064	615,406	262,743	766,696	136,331
<i>pseudo R</i> ²	0.0092	0.017	0.0109	0.0090	0.0100
Wald test	2308.49	25659.91	2497.45	4010.45	1691.47

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8. Regression estimation results. Survival analysis for the length of the period before the first utilization.

	Revolving lines (length $rdrawn = 0$)	Not-revolving lines (length $rdrawn = 0$)
main bank	0.079***	0.046**
bank share	0.061*	0.217***
bank npl share	0.128	0.120
prod.index	0.0029**	0.015***
inflation	-0.016***	-0.153***
line age	-1.210***	-1.701***
collateral	0.115***	-0.098***
fix rate	-0.0003	0.037***
long term	0.296***	0.012
large enterprises	-0.034***	-0.253***
ln age bor	0.002	-0.012**
ln with bank	-0.048***	-0.036***
default inn	0.150	0.125**
months default inn	0.003***	0.0015*
ln count bank	0.108***	0.050***
cons	-0.306***	1.551***
ln_p	1.485	1.803
LR test	1169.77	6335.65
Wald test	38705.61	51600.38
N obs	99,743	111,387

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.