PUBLISHED BY
VOPROSY EKONOMIKI N. P.

Russian Journal of Economics 11 (2025) 47–75
DOI 10.32609/j.ruje.11.145314
Publication date: 25 March 2025

Russian Journal of Economics

www.rujec.org

Demand for consumer loans in Russia: How strong is the interest rate channel of monetary policy?☆

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Abstract

The booming retail trade and the above-target consumer prices inflation in 2023–2024 in Russia, amid tightening monetary policy stance, raise an issue of the strength of the monetary policy interest rate channel. The focus of our paper is the interest rate elasticity (given inflation expectations) of a household's loan request probability. We argue that a household, rather than an individual consumer, is the appropriate unit of study. We use unique data on households' loan applications obtained from the *All-Russian survey of consumer finances*, which contains information on more than 6,000 households in Russia. Actual loan applications cover the period of 2020–2022, and the survey also includes information on households' borrowing intentions as of late spring–summer 2022. The interest rate channel of monetary policy, with regard to unsecured loans, although statistically significant and working in the right direction, does not appear to be economically significant from a microeconomic perspective. This suggests that the Bank of Russia, in relying on this channel for this type of credit, might have to increase the key rate significantly to cool down consumer demand and bring retail inflation to the target. We find that higher households' inflation expectations positively correlate with the loan demand, thus, households' inflation expectations do have real effect. Thus, anchoring inflation expectations is important for achieving macroeconomic stability. We empirically identify a set of Russian households' characteristics that are key drivers of households' requests for credit. Demographics is an important factor of the demand.

Keywords: household finances survey, survey of consumer finances, demand for credit, probability of requesting loans, elasticity of demand, credit demand drivers, interest rate, interest rate channel, monetary policy.
JEL classification: D12, D14, G21, G51.

☆ The content and results of this research should not be considered or referred to in any publications as the Bank of Russia's official position, official policy, or decisions. Any errors in this paper are the responsibility of the authors.

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1. Introduction

Household spending usually accounts for about 70% of total spending in the economy, and Russia is no exception, with unsecured consumer lending financing around 5–10% of retail turnover. Understanding the drivers and dynamics of a household demand for consumer loans helps central banks make better monetary policy decisions and formulate policies aimed at financial stability, financial market development, and better financial inclusion.

Empirical research on loan demand is complicated by the fact that most spending and financing decisions are made at the household level rather than by individual consumers. This means that the "household" is the appropriate object to investigate loan demand, not an individual consumer. However, data availability from this perspective is quite limited (this is especially relevant for commercial banks or credit bureaus, which lack such information as they deal with individuals only).

In 2022, the Bank of Russia conducted the fifth wave of the longitudinal *All-Russian survey of consumer finances*. This survey contains a detailed questionnaire about loan demand at the household level, loan application rejections, and actual loans issued by commercial banks to households, with many measured characteristics of such loans.[1] These unique data, covering more than 6,000 households, lay the groundwork for deep insights into credit demand.[2]

The focus of the paper is to assess the interest rates elasticity of credit demand — an indicator that features prominently in monetary policy decisions.[3] We operate data from the household finance survey on households' loan applications (past and planned).[4] When a household decides on whether to apply for a consumer loan, it may observe some public (advertised by lenders) information on interest rates — which, according to the interest rate channel of monetary policy

[1] Information about the survey as well as its microdata base is available on the Bank of Russia webpage http://www.cbr.ru/eng/ec_research/vserossiyskoe-obsledovanie-domokhozyaystv-po-potrebitel-skim-finansam/

[2] Demand for loans was measured using responses to two questions in the individual questionnaire with aggregation of the responses up to a household level. Question C1.1 establishes the fact of requesting a loan in the past (in the two years before the last survey wave): "*Let me ask you a few questions about loans. Have you personally applied for a loan in the last two years?*." The second question (C1.26) indicates the intention to apply for a loan in the future: "*Are you currently thinking about taking out a loan?*," which is complemented with Question C1.27 ("*What type of loan do you intend to take out?*") to distinguish between demand for a consumer loan including an emergency loan or a credit card.

[3] This study is split into two parts owing to the large volume of material. In the follow-up research, we plan to use data on actual issuance of unsecured loans to households (including credit cards) and interest rates on such loans. There are several selection stages in bank–borrower interactions that introduce selection bias and have to be taken into account: a loan application stage (in this paper), a stage for the bank to approve the application, and a final decision stage — when the household agrees to take the loan on the bank's terms (which could have changed at the second stage), see Duca and Rosenthal (1993).

[4] The data characteristics make it impossible to differentiate loan types (auto, mortgage, etc.), but taking into account the credit structure in the data we operate, the results mainly relate to unsecured loans (including credit cards). Therefore, credit is hereinafter understood as unsecured consumer credit. Demand for credit in the two years before this wave of the survey does not differentiate loan types; according to the latest survey of consumer finances, unsecured loans (excluding microloans) account for about $^2/_3$ of the total household debt burden (across all loan types) in the lowest income decile and about $^1/_2$ in other groups. It is only natural to expect the results to be closer to the demand model for this type of credit. Future or planned demand contains information on a loan type. It is also considered to pertain to unsecured loans (including credit cards).

hypothesis, should influence its decision. With the development of financial marketplaces and financial aggregators, the household may observe a targeted interest rate, set by a potential lender. When banks set such a targeted interest rate based on borrower characteristics, an endogeneity problem arises that challenges the estimation of the interest rate elasticity of demand.[5] To collect the data on interest rates advertised by the banks and address endogeneity, we use additional data-source. We collect data from an aggregator website for banking services on loan rates in the regions of households' residence. Using interest rates available in the area of households' residence, based on aggregator website data, helps identify the interest rate variation that is exogenous to a specific household. This approach is similar to Magri (2007).[6]

According to economic theory, it is the *real interest rate,* not the *nominal* rate that is important for households' saving and borrowing decisions. For this reason, we control for cross-sectional variation in inflation expectations in regressions with nominal interest rates.[7]

To our knowledge, we are the first to obtain estimates for the elasticity of the loan application probability (unsecured loans) in relation to the interest rate, based on microdata from Russian households (not individual consumers). We find that a 1 percentage point (p.p.) increase in the interest rate from the average level lowers the loan request probability by 1.5–2.3%.[8] That is, the sensitivity of the probability to small changes in the interest rate is relatively low. Nevertheless, this is notable compared to the average loan request probability of 0.27. A significant change in loan interest rates (for example, due to the profound tightening of monetary policy in 2023–2024) has a tangible impact on the probability. A 10 p.p. rate increase from its average level reduces the probability by at least half its average level, potentially to zero.

These results seem consistent with those in the literature and the nature of unsecured loans. The elasticity obtained in Magri (2007) for Italy is statistically insignificant. In practice, the level of interest rates on unsecured loans significantly exceeds the key rate, which suggests a lower role of the price factor relative to other loan types.[9] As Fig. 1 shows, the interest rate spread reaches 10 p.p. above the key policy rate of the Bank of Russia. Only very high interest rates (more than 20%) correspond to a reduction of unsecured consumer lending.

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[5] As the personally advertised interest rate may be set at a level to become attractive to the borrower, and increasing probability of demanding a loan.

[6] To eliminate the endogeneity, interest rates on loans offered by banks may be also instrumented with the characteristics of the banking system in the place of residence of households. Such characteristics reflect the supply-side of the loans and do not depend on the characteristics of specific borrowers but may be important for bank rates in the region.

[7] With the measure of inflation expectations being categorical in nature, in the current dataset it is impossible to compare the elasticity of demand relative to the nominal rate with given expectations and the elasticity of demand relative to inflation expectations with a given nominal rate. In accordance with the hypothesis about the demand response to real, rather than nominal, rates, these elasticities should coincide.

[8] Unfortunately, the effect of the variation in the interest rates on the demand for loans cannot be identified after controlling for the locality specific variation in the regressions.

[9] Furthermore, the type of unsecured loans, such as credit cards, is characterized not only by high interest rates, but also by a strong variation of interest rates even if adjusted for borrower and credit card characteristics. In other words, when there is a choice, borrowers tend to choose cards with higher interest rates, which indicates the importance of non-price demand factors, see Galenianos and Gavazza (2022). For other types of credit, a stronger response should be expected.

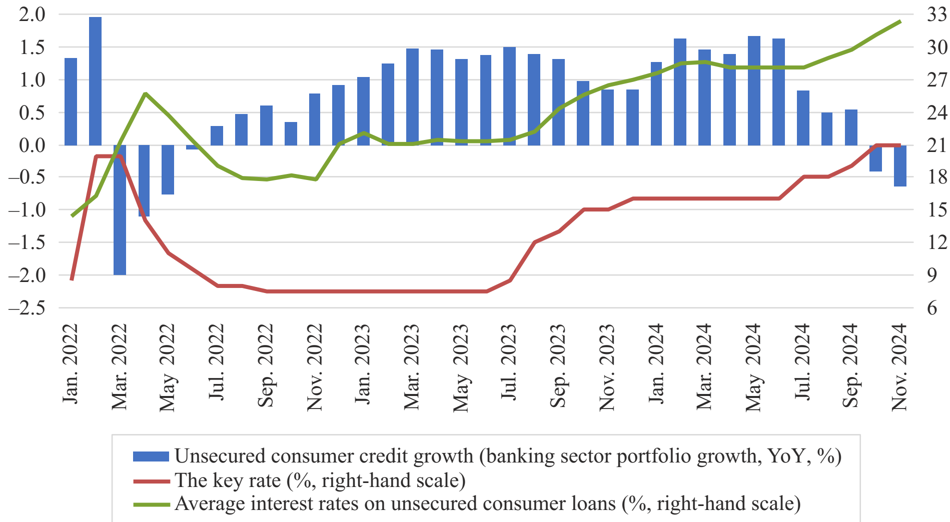

Fig. 1. Growth of unsecured consumer loans, average interest rates offered by banks, and the key rate, %, monthly.

Sources: Bank of Russia; banki.ru

In interpreting the results, it is important to consider that the *All-Russian survey of consumer finances* was conducted between March and September 2022, covering the past two years. The results may reflect 2020–2022 — a time marked by macroeconomic shocks and structural changes in the economy, rather than a universal pattern typical of calmer periods. In particular, these two years include both short-term episodes of feverish demand for consumer goods and real estate, as well as longer-term episodes of demand contraction, including for loans, and subsidized lending programs during the pandemic (see Bank of Russia, 2022a, 2022b, 2022c, 2023). This variation in loan demand in the sample may influence estimated sensitivity of demand to the interest rate. We assume that elasticity may be underestimated: during the period of feverish demand in March 2022, interest rates rose sharply amid high consumer goods demand. Subsequently, moderate consumer activity driven by uncertainty and supply-side restrictions coincided with the period of interest rate cuts; see the Bank of Russia (2022b, 2022c). The observed reduction in unsecured consumer credit stock in the autumn of 2024 (see Fig. 1) occurred at much higher *nominal* interest rates than in the 2022 episode. The difference may be partially explained by comparable *real* interest rates (amid higher inflation in 2024) and by other strong factors influencing borrowing and consumer demand in 2024 in the opposite direction, such as very high growth of salaries in real terms (around 9% year-on-year).

We also analyze the role of households' other characteristics. These explanatory variables cover households' socio-demographic, economic, and financial characteristics, regional factors, as well as their sentiments and expectations. In the literature, these characteristics are often the focus of loan demand studies. In this context, we supplement the previously made findings based on surveys of consumer finances or credit register data regarding the role of such drivers, see Crook (2001) for the United States, Chen and Chivakul (2008) for Bosnia, and Herzegovina et al. (2023) for Colombia.

Compared to the studies of loan demand based on microdata of Russian households, such as Sabelnikova (2017), our research is grounded in a new and more detailed source of granular data (compared to RLMS data or Rosstat's survey of households).[10]

The paper is structured as follows. Section 2 provides an overview of the relevant literature and our contribution to it. In Section 3, we describe the data and the regression variables. Section 4 presents the loan request probability model, considering the limitations we faced regarding data availability. Section 5 presents extensive results with some robustness checks. In the Conclusion, we present our key findings and policy implications.

2. Literature review

Our work is related to empirical research on household loan demand based on microdata — data from surveys of consumer finances or credit bureaus.

The theoretical foundations of households' decisions to enter the credit market are described in Bertola et al. (2006) and Magri (2007). Two dominant theories of credit demand stand out in the literature: the permanent income hypothesis and the life cycle hypothesis, which complement each other. Both theories assume that households solve the problem of maximizing consumption given intertemporal budget constraints. In the first case, demand for credit arises when income temporarily deviates from the permanent level (which may also be a steady level in the future). In the second, demand for credit is typical of younger ages, when actual income is small and future income (which may be considered as permanent) is higher. As a result, demand for credit theoretically depends on interest rates, intertemporal preferences (discount rates), current and expected incomes, uncertainty about future income flows, risk appetite, and life cycle indicators, i.e., social and demographic characteristics of households.

Chen and Chivakul (2008) offer an overview of empirical evidence for loan demand (loan applications) presented by several researchers on data from six countries. Loan request drivers include income and wealth, education, employment status, and socio-demographic characteristics. The studies find that the loan request probability depends quadratically on age (inverted U-shaped) and peaks in around 30–35 years. The probability increases as income increases (some studies show the quadratic dependence; demand begins to decline starting from a certain level of income). The wealth effect reduces the loan request probability; however, several studies find that this dependence is quadratic and peaks midway. A higher level of education and skills increases the loan demand probability, whereas unemployment reduces it. Other factors of interest to researchers include geographical variation (locality: rural or urban), see Magri (2007), indicators of risk appetite and household expectations or sentiment; see Duca and Rosenthal (1993).

Our research belongs to the strand of the literature that aims to estimate the elasticity of credit demand in relation to the interest rate.[11]

[10] Household finances survey data enable more accurate estimates of financial variables (more accurate measurements of net wealth, financial literacy, and financial inclusion). For Russia, there are also studies of demand based on aggregate data, for example, Mishura (2021), a work dedicated to the housing market.

[11] A number of empirical studies fail to account for the price of credit, which, according to microeconomic theory, has a key role to play in shaping credit demand.

All such studies are divided into two groups depending on the type of data used:

- experimental (manipulated) data, based on randomized experiments (the RCT approach) in which potential borrowers are offered random interest rates that do not depend on borrower characteristics, see Karlan and Zinman (2005, 2019), Alan et al. (2013);
- observational (actual) data, of which there are two types. The first type is loan applications, i.e. actual data on credit demand. Qualitative data on loan application are more commonly available (and show the number of consumers applying or planning to apply for a loan); less common are quantitative data on volumes of planned credit demand, as in Alessie et al. (2005). The second type is the actual amounts of loans (or the number of households to whom loans were extended). These data are more easily obtainable.

Both types of actual data are available for our analysis from the survey, but we use those data that require fewer identifying assumptions — directly observed data on loan demand.[12] In the case of loan application data, we observe the fact of applying for a loan in the past as well as the intention to apply for one in the future. Regarding the interest rates data that are observed and used by households when making decisions about applying for a loan, Alan et al. (2013) show that the bias resulting from the misalignment between the interest rates banks offer and the variation in interest rates exogenous to credit demand may be large. Magri (2007) suggests treating the actual loan rates offered by banks in the place of household residence (which are then the same for all households in the same place) as interest rates on the supply side, which in this case are exogenous to a specific borrower.

Our contribution to this literature is the application of the Bank of Italy's methodology, consistent with Magri (2007), to Russian loan request data (for the past two years before the survey and future intentions) and data on interest rates offered by banks. Ultimately, of all the published works we know, ours is the first to obtain estimates for the elasticity of the loan request probability in relation to the interest rate, based on microdata of Russian households. We also add to the empirical literature that uses survey or credit bureaus' data results regarding the role of credit demand factors other than interest rates.

3. Data

3.1. All-Russian survey of consumer finances

Regarding data on loan demand the study is based on data obtained from Wave 5 of the *All-Russian survey of consumer finances*, a project under way

[12] When actual transaction data are used to estimate the demand function, it is important, first, to identify the exogenous variation in the actual interest rate unrelated to demand for credit. It is often achieved through the method of instrumental variables. Second, it is equally important to adjust for non-random borrower selection. This is implemented through the Heckman's selection model, see Cox and Jappelli (1993), Duca and Rosenthal (1993). Identification that uses this approach see in Attanasio et al. (2008), Alessie et al. (2005), Gross and Souleles (2002). Gross and Souleles (2002) use credit register data unadjusted for non-random selection. Lukas (2017) uses data on actual loan issuance, but in the actual rate offering is universal across all borrowers (does not depend on the borrower and is specific to the loan type). This is how the author addresses the problem of endogeneity pertaining to the rate.

since 2013.[13] This survey is a globally standard approach to obtaining representative data on household income, consumption, financial and non-financial assets, and financial liabilities. The survey also includes detailed information on the socio-demographic characteristics of households. Survey questionnaires consist of a large number of questions about household sentiment and expectations. Wave 5 covered 6,082 households, including 12,162 respondents residing in 32 constituent entities of the Russian Federation (38 localities). This longitudinal survey is run every two years.

The survey contains qualitative data on loan demand: the facts of loan requests. There are two types of such data:

- actual demand for credit in the past two years (relative to the survey time);
- planned demand for credit in the future relative to the survey time.

Data on actual demand for credit are valuable in reflecting credit demand as a fact, whereas planned demand data are information about intentions, and such data can reflect nothing more than household sentiment at a certain point in time when surveyed. Such sentiment is prone to change even in a close temporal neighborhood of the survey. Thus, demand for loans is directly observable, at least at a qualitative level, considering that researchers often have to identify demand through the volume of actual loans issued by banks.

Unfortunately, the type of loan households requested in the previous two years before the survey is unknown. Thus, our demand model's estimates will be composed of mixed estimates from models for different loan types.[14] For future demand, however, a breakdown by loan type is possible. Here we focus on demand for unsecured loans (including for credit cards), which are the most representative in the sample.

Regarding alternative sources of data that exist in Russia credit bureau data may be one such alternative source of credit demand data. The advantage of a credit bureau data is that they cover the whole population, rather than a sample. Nevertheless, survey data have the advantage of representing household-level information and containing much more borrower characteristics. It is the household, rather than the individual, that is the right object to study the patterns of decisions in the lending market. Households' demand for loans is formed at the household level and under the influence of family factors. Indeed, loans are serviced out of household income, not individual income.

Apart from surveys, there are other sources of information on demand for loans in Russia. Incidentally, two other surveys of Russian households (RLMS and data from Rosstat's survey of households) include a question to establish the fact of household demand for credit (and planned demand in the RLMS survey). However, the alternative surveys fail to provide full information on household

[13] Details of the survey description, its methodology and questionnaires (individual and for the household as a whole), as well as the data we use, are available on the survey webpage: https://www.cbr.ru/eng/ec_research/vserossiyskoe-obsledovanie-domokhozyaystv-po-potrebitel-skim-finansam/, as well as in Bessonova and Tsvetkova (2022, 2023a), and Bank of Russia (2023). Data from the previous waves of the survey of consumer finances have been used in a number of studies. These data and their key characteristics are described in Artemova et al. (2018), Mamedli and Sinyakov (2017, 2018), Sinyakov and Ushakova (2018), Tishin (2020), Bessonova and Tsvetkova (2023b).

[14] Since the survey shows that most borrowing households have liabilities under unsecured loans, it is only natural to expect that the resulting estimates will better reflect demand for unsecured loans.

assets and liabilities, which makes it difficult to measure a number of explanatory variables in the demand models.

3.2. Description of the variables

Supplementary material 1: Appendix A lists the variables used in the regressions, along with their description and code designations.[15] All variables are marked with the year of the corresponding survey wave (“20” or “22”) to which the data belong. This is needed for data on credit demand for the past two years. Most potentially endogenous explanatory variables were taken with a lag — from the previous wave of the survey to exclude endogeneity due to the contemporary impact of some third variable on the variable of interest and regressors.

The descriptive statistics are shown in Table B.1, and empirical distributions of some key variables are provided in Figs. B.1–B.15 (Supplementary material 1: Appendix B).

To estimate the loan application probability model (Model 4 in the following section), two key dependent variables are considered: “loan request for two years before the survey” and “planned demand for credit.”

The first dependent variable is a “loan request for two years before the survey.” The variable *Credit_demand_hh_corr2DSTI* is generated on the basis of responses to question C1.1 of the questionnaire: “*Have you personally applied for a loan in the last two years?*.” If at least one member of a given household answers “yes,” the variable is assigned “1,” otherwise, it is zero.[16]

Unfortunately, the questionnaire does not contain a question specifying the type of loan the individual applied for in the past two years.[17] This complicates the estimation of the demand models, and the estimates will reflect average demand for all loan types. Table B.1 in Supplementary material 1: Appendix B shows that only 27% of households have applied for a loan in the previous two years. The focus is on the significantly higher average loan request probability in Russia, at 0.27, compared to 0.057 in Italy, according to Magri (2007).

Fig. 2 presents a breakdown of loan-requesting households by income group. The reasons for not requesting a loan, according to the survey data, are distributed as shown in Fig. 3. As follows from the figure, about 80% of respondents have the potential to apply for a loan.[18]

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[15] The data underpinning the analysis reported in this paper see in Supplementary material 2.

[16] Additionally, two adjustments have been made. Adjustment 1: some individuals have not requested a loan in the previous two years: they are either still repaying outstanding loans or they are declared bankrupt. Such individuals were assigned “1,” and the variable *Credit_demand_hh_corr* was obtained for them. Adjustment 2: some of the households who have not requested loans in *Credit_demand_hh_corr* have a non-zero debt burden (debt service-to-income — DSTI > 0). Such households were also assigned “1,” and *Credit_demand_hh_corr2DSTI* was obtained.

[17] This information can be restored only for the following household members: (a) those who applied and received approval, if the loan was outstanding at the time of the survey, and (b) those who applied but were rejected. In the latter case, few responses specify the type of loan that was rejected.

[18] Those who have not previously planned purchases needing a loan can in principle change their mind in the future. Only those taking a negative view of loans, or whose income is enough to finance their expenses, are unlikely to change their decision.

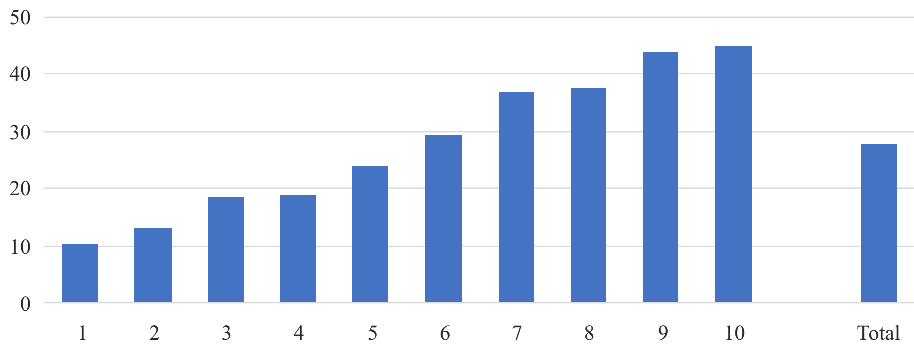

Fig. 2. Proportion of households requesting loans by income group (10 decile groups), share of all household in the group (%).

Sources: All-Russian survey of consumer finances 2022; authors' calculations.

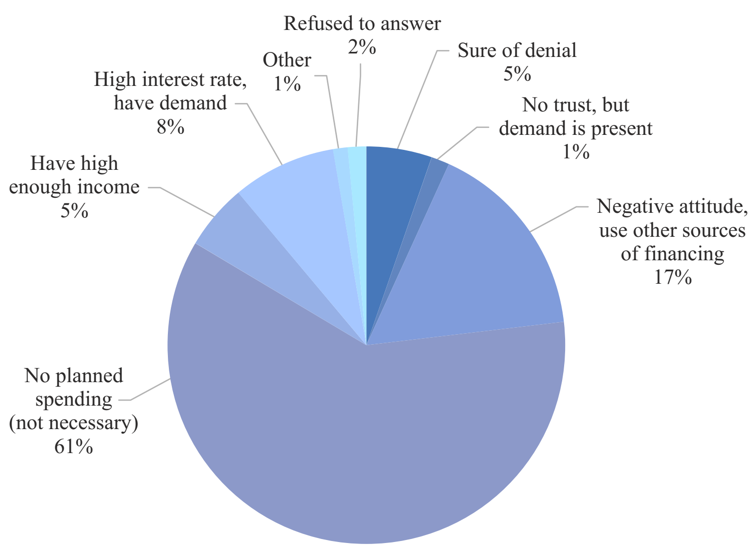

Fig. 3. Reasons to opt out of requesting a loan in two years before survey.

Sources: All-Russian survey of consumer finances 2022; authors' calculations.

The second dependent variable — "*planned demand for credit*" — (coded as *fut_credit_demand_consume*) is generated on the basis of responses to question C1.26. *"Are you currently considering taking a loan?*" *Credit_demand_hh* = 1 if at least one household member answers "Yes" and the question *"What type of loan are you going to take?*" was answered with "consumer loan," including "emergency loan" or "credit card."[19]

Fig. 4 shows that planned demand grows as the level of wealth increases (measured by the level of spending).[20]

[19] Other response options include: "mortgage loan," "construction loan," "repair loan," "auto loan," "education loan," "business development loan," and "microloan."

[20] This approach to measuring wealth by spending rather than income is used, for example, in Bessonova and Tsvetkova (2023a). The reason behind the substitution is that households are less likely to disclose their incomes than spending. However, household spending can be financed through loans, which is set to result in distortions.

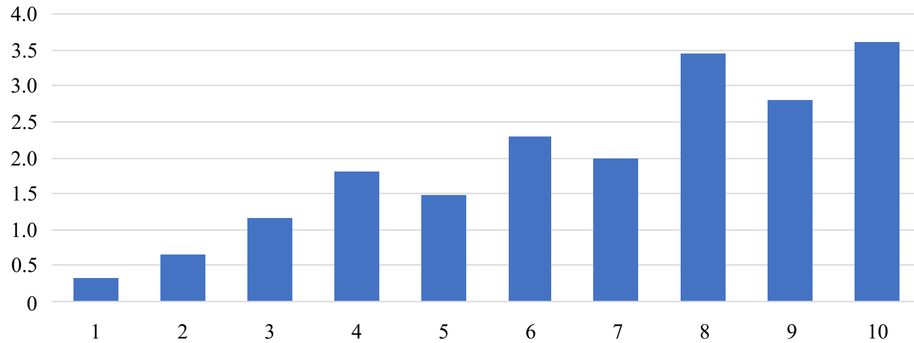

Fig. 4. Breakdown of planned demand for unsecured loans by wealth deciles (by per capita spending, % of number of households in the decile).

Sources: All-Russian survey of consumer finances 2022; authors' calculations.

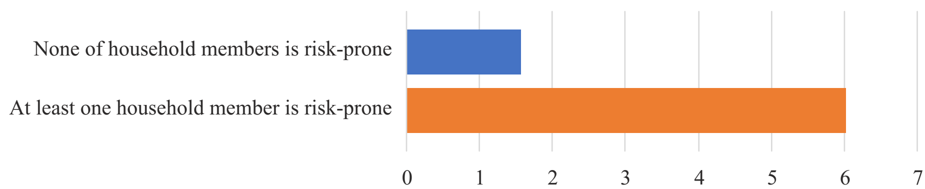

Fig. 5. Planned household demand breakdown by risk appetite group (% of the number of households in the group).

Sources: All-Russian survey of consumer finances 2022; authors' calculations.

Interestingly, an important factor in planned demand for loans is the attitude of household members to risk.[21] The higher the risk appetite, the higher the planned demand, as shown in Fig. 5. It shows percentage of households intending to request a loan, of respective group, in relation to risk.

Planned demand is nearly evenly distributed by the household deciles according to the level of their debt load, as shown in Fig. 6.[22] Therefore, unlike the level of income, outstanding debt does not seem to be a significant loan planning factor.

Fig. 7 shows that the group of households planning to request a loan and having a debt burden at the time of the survey of 2022 has a higher debt burden indicator (debt in the upper percentiles) than those who do not plan to request a loan. The debt-laden households (the top 10%) who, at the time of the 2022 survey, planned to take an unsecured loan show a significantly higher level of debt burden than the top 10% of those who did not plan to apply for a loan: 58% vs. 44% of their spending.

The main explanatory variables in this work are standard for estimating credit demand models, see Magri (2007), Arango and Cardona-Sosa (2023), Crook (2001), Chen and Chivakul (2008). The explanatory variables are grouped in

[21] Responses of each member to the question "Which of the statements best describes you personally?" Options: "I am ready to take significant financial risks to make a high profit," "I am ready to take rather strong risks to make a fairly high profit," "I am ready to take moderate financial risks to make a moderate profit," and "I am not ready to take any financial risks." The first option has the value "1"; the rest, "0." The household-level aggregation follows. Accordingly, the greater the indicator, the greater the risk appetite.

[22] The measurement approach to the debt burden indicator is explained in Supplementary material 1: Appendix A.

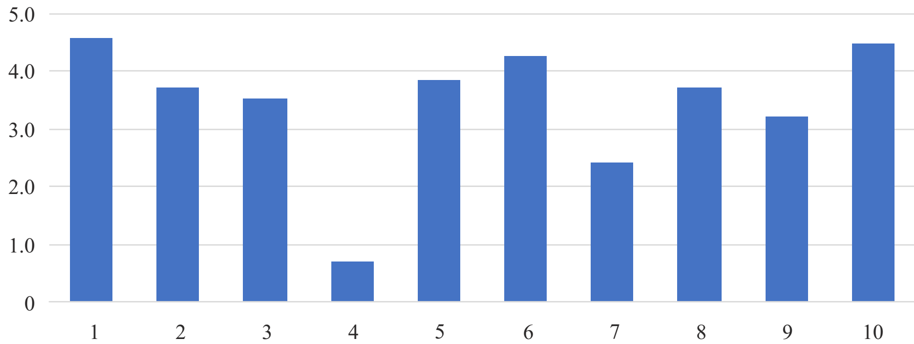

Fig. 6. Breakdown of planned demand for unsecured loans by debt burden decile (% of the number of households in decile).

Sources: All-Russian survey of consumer finances 2022; authors' calculations.

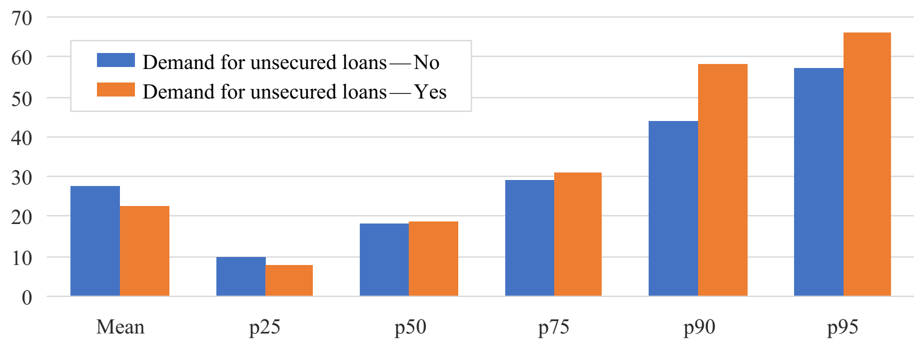

Fig. 7. Debt burden percentiles in planned demand subgroups (debt-to-income ratio, %).

Sources: All-Russian survey of consumer finances 2022; authors' calculations.

the following way (the full description is provided in Supplementary material 1: Appendix A):

- Interest rate. In theory, the *real* interest rate (i.e., the *nominal* rate adjusted for expected inflation) affects households' decisions. As a result, inflation expected by a household should be considered — included on the list of explanatory variables.
- Financial variables. Income and spending, wealth (volumes of non-financial and financial assets, total assets), financial liabilities, and debt burden (debt service-to-income, DSTI).[23]
- Demographic variables. The number of household members aged under 18, the average age of adult household members, and the average age and gender of the head of the household.
- Social variables. Household size, marital status of the head of the household, the level of education of members (higher educational attainment of at least one member), the share of employed members, and the employment status of the head of the household.

[23] Financial indicators were included in the logarithms to analyze the relationship between such indicators and the loan application probability in order to interpret such changes in the indicators as interest rate changes, rather than changes in absolute values (rubles).

- Spatial variables. Urban or rural area, settlement size, macro region of residence (one of the four), and federal district of residence.
- Subjective variables. Risk appetite, expectations regarding future financial position, expectations regarding future economic conditions in the country, and financial literacy.
- Assessment of financial inclusion.

The key variable of demand for loans we are interested in is the interest rate.[24] Following Magri (2007), we use the nominal interest rates that individuals could observe in the local market (their place of residence). These are proxy for bank rate offerings at the time of deciding to request a loan in the past two years (between the 2020 and 2022 surveys). One of the sources of information on banks' rates offered to borrowers is the website banki.ru. This resource provided data on banks' interest rates, which were downloaded and broken down into 38 residential localities of respondents as of 10 February 2023.[25] As the website lacks data on loan rates offered by banks to borrowers in rural settlements, their residents were equated with residents of an administrative center of the relevant district or region to which the rural settlement belongs.

Measured in this way, the interest rates reflect only geographical variation and do not change from household to household within one place of residence of such households. Thus, the role of the variation in the interest rates on the demand for loans cannot be identified after controlling for the locality specific variation in the regression.

Unfortunately, the resource does not contain historical data on rates to ensure that the downloaded data are aligned with the survey dates. The absence of historical data will not prevent the use of data on interest rates if the geographical ranking of the rates persists over time. In other words, if the interest rates in locality "A" are invariably higher than in locality "B," the rates observed by households over the last two years can be substituted with the available breakdown of interest rates of a later period. To verify this, we repeatedly downloaded data as of May 30, 2023 and compared them to those of February 10, 2023. Fig. 8 shows that the distribution of rates across the residential areas is stable in time (we see a decrease in the level of loan rates offered in all localities in the five-month period, with the rate line running below 45 degrees).

In addition to nominal rates, the model includes inflation expectations to account for variation in the *real* interest rate. It is important to consider that not only nominal, but also real interest rates should be exogenous to a household's decision to request a loan. Let us imagine that a third variable (for example, information about a planned change in the central bank rate) influenced both inflation expectations and the decision of households to request a loan. Then the data will show a correlation between inflation expectations (real interest rates) with the decision to request a loan. This would lead the researcher to make incorrect conclusions about the role of inflation expectations in a household's decision to request a loan. To correct for such endogeneity, we use inflation expectations

[24] While for households who expressed demand, the interest rate on offer can be "restored" in the survey from the data on actual loan disbursements, it is not possible for those whose applications were rejected or who did not express demand.

[25] The residential areas' names are not publicly known, but are known to the Bank of Russia, which commissions the survey.

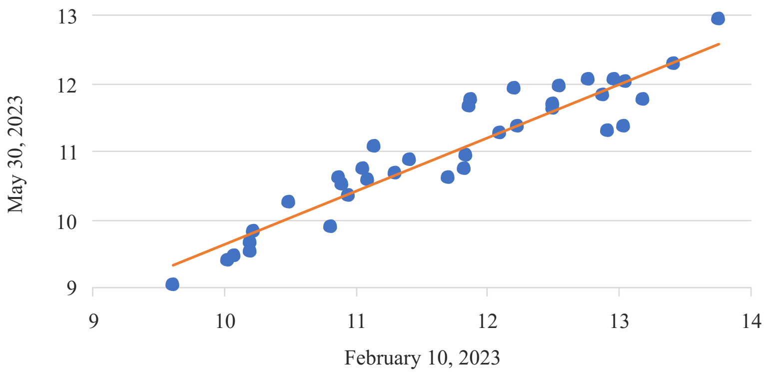

Fig. 8. Interest rates on unsecured loans in survey localities for two data download dates (% per annum).

Sources: banki.ru; authors' calculations.

observed in the 2020 survey — *before* households decided to request a loan (in the subsequent two years), and even before they announced their plans to request a loan in the 2022 survey. The response to the question of the 2020 questionnaire was used to capture the heterogeneity of households by inflation expectations.[26]

The descriptive statistics of all variables, as well as the distribution of key variables, including analysis of possible outliers in the data, are provided in Supplementary material 1: Appendix B.

4. The model

We follow the strategies by Magri (2007), Chen and Chivakul (2008), and Arango and Cardona-Sosa (2023) to estimate the loan application (demand) probability. In general, this approach is standard and based on Probit model estimation.

Suppose each of N households makes a loan request based on the implicit demand[27] function:

$$D_j^* = \alpha + \beta_1' X_j + \beta_2 i_j + \varepsilon_j, \tag{1}$$

where: D_j^* is the desired demand volume for credit of household j; i_j is the nominal interest rate observed by household j. In practice, this may be the average or

[26] The dummy variable is equal to one if at least one household member says in response to question M14 "What is your personal greatest concern in the current situation?" (2020 questionnaire): "rising prices for goods and services." This aids in dividing all households into two groups: those considering price growth harmful and those giving other response options. Unfortunately, this was the best measurement technique for inflation expectations in the 2020 survey at our disposal.

[27] In our case of demand for credit for the past two years, it is "any credit," while in the case of planned demand, it is unsecured credit (including credit cards). At the same time, loan request decisions as regards some loan types may not be independent. For example, demand for mortgage loans can influence demand for unsecured loans for down payments (usually at least 20% of the mortgage value). This leads to the demand model receiving the demand variable for another loan type. To estimate such models a good sample with several loan types is needed. Household finances survey data we operate cannot aid in the estimation since they provide a small number of observations for several loan types. Nevertheless, implicitly — through household characteristics and without explicitly including the demand variables related to other loan types — we take into account the chances of some households (with certain characteristics) requesting both the type of loan in question and other types (which are unconsidered). Still, there is no clear division by loan type in this work.

minimum interest rate of a set of the available (observable) bank rates.[28] X_j is a set of measurable factors that households consider in decision making, in addition to the interest rate, including households' inflation expectations, financial inclusion indicators (internet availability to household j, web-based loan request, etc.). Unobservable decision factors are accumulated in variable ε_j. In what follows, it is assumed that the aggregate effect of these unobservable factors relative to the utility of credit, conditionally relative to X_j and i_j has a normal distribution with zero mean and some variation.[29]

Given the availability of data, only a binary fact (intention) of applying for a loan is observed for each household. Thus, there is an observable binary variable:

$$D_j = 1, \text{ if } D_j^* > 0, \tag{2}$$

$$D_j = 0, \text{ if } D_j^* \leq 0, \tag{3}$$

where $D_j = 1$ is household j that has requested a loan (or intends to do so). Further, a standard Probit model is estimated for this binary variable as follows:

$$\Pr(D_j = 1 | X_j, i_j) = \Pr(D_j^* > 0 | X_j, i_j) = \Pr(\varepsilon_j > -(\alpha + \beta_1' X_j + \beta_2 i_j) | X_j, i_j), \tag{4}$$

where: $\Pr(X < x) = F(x)$ is the integral function of the normal distribution of random value X (its role is played by ε_j) with zero mathematical expectation and a certain variance. Our goal is to assess the elasticity of demand for credit in relation to the interest rate, which is estimating coefficient β_2. It is also of interest to understand the role of demographic factors such as income, expected income and the level of wealth of individuals in the decision to request a loan.

For the actual demand model (loan requests for the past two years), in order to avoid endogeneity, we ensure the variables that can bring such endogeneity are taken with lags (according to the previous wave of the survey, held in 2020).

To eliminate the problem of endogeneity arising when interest rate offerings reflect unobservable household characteristics (which affect both the bank's rate offering and the potential borrower's desire to apply for a loan), instead of equation 4, we estimate model

$$\Pr(D_j = 1 | X_j, \bar{i}_l) = \Pr(D_j^* > 0 | X_j, \bar{i}_l) = \Pr(\varepsilon_j > -(\alpha + \beta_1' X_j + \beta_2 \bar{i}_l) | X_j, \bar{i}_l), \tag{4'}$$

where $\bar{i}_l$ is the average interest rate of loans offered by banks in locality l; l is one of the 38 localities (district or regional centers including districts, St. Petersburg and Moscow) of the place of residence of household j.

In this case, interest rates are not specific to a particular borrower, that is, they are exogenous to the borrower's decision to apply for a loan.

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[28] Since we abstract from the demand for a loan from a particular bank and describe the loan decision in terms of yes or no in principle, this decision should depend on the level of rates in the lending market as a whole (rather than in a particular bank).

[29] As regards the effect of future interest rate expectations on credit demand, we note that interest rates are a cyclical variable: they rise at a time of high inflation and fall when inflation is low. Accordingly, current high rates should assume expectations of lower rates in the future, which should reduce the utility of loan requests.

The problem of such identification may arise if the ranking of interest rates reflects not only supply-side but also demand-side factors. That is, banks in a locality can set rates at a certain level due to the nature of demand in this locality as a whole. Specifically, it is natural to assume that the higher the average demand, the higher the average loan rates on offer. In this case, if a negative, rather than positive, correlation is discovered between the rates and demand (loan request probability), it will act as indirect evidence of the dominance of supply-side factors for rate variation by locality.[30]

The actual loan application probability model uses data on facts of loan requests in the two years before the survey. In this context, for the actual demand model (loan requests for the past two years), in order to avoid endogeneity, we ensure there are lags with the variables that can bring such endogeneity (according to the previous wave of the survey held in 2020). Potentially endogenous variables include financial variables (the loan may have increased the size of assets; an education loan may have helped boost education and thus income), as well as the subjective variables related to future expectations, including inflation expectations. For example, the average age of household members is obviously not affected by the fact that the household applied for a loan over the previous two years. There are three ways to measure the explanatory variables over which the fact of applying for a loan has no influence. Such household characteristics can be measured either as of the 2020 or 2022 survey date or as the average for the period between these survey dates. Since the exact date of the household's loan request in the previous two years is unknown, it is more logical to use the average values of such characteristics for the inter-wave period. For example, the age of household members is taken as the average for the period between the survey dates. This was the basic calculation principle.

5. Results

Section 5.1 starts with the estimates of the loan application model for (any) loan demand in the two years before the survey. Section 5.2 presents the estimates of the model for perspective loan demand on unsecured loans (including credit cards).

5.1. Results for loan demand in the past

Table 1 summarizes estimated marginal effects determinants in equation (4′) on the loan demand in different specifications. Each cell contains statistically significant at 5% minimum and maximum values of marginal effects of the variable in the row on loan demand for set of models represented in the column. Each value in a cell is the marginal effects evaluated at average values of regressors and expressed in decimal quantity in points (0.01 points = 1%).

[30] Current rates in the decision model i_j will therefore reflect not only the effect of the current rate itself but also the combined effect on demand of currently high but expectedly lower rates (conditional expectation of future rates at given current rates). Then, given this cyclic nature of rates, ε_j will not reflect the expectations of future rates, but rather their deviation from the conditional mathematical expectation relative to given actual observed rates. In this context, the assumption that such a deviation is distributed normally with zero mathematical expectation will be justified.

Column 1 presents the results of estimating equation (4) in its baseline version: some of the potentially endogenous variables are measured as of the 2020 survey and others are measured based on the average for the period between the survey dates. The model estimates are provided in Supplementary material 1: Appendix C. In each case, 11 models were estimated, with the dependent variable being a discrete variable of the fact of a loan request in the previous two years. In each case, the first model contains a minimum set of regressors commonly used in such studies. Additional factors are then added one-by-one to the baseline regression in subsequent regressions up to the eleventh (not an expanding set of regressors). This one-by-one method helps avoid a strong reduction in the sample size caused by the lack of data on some variables for some households.

Column 2 presents the results of regressions in Supplementary material 1: Appendix D. There we consider Supplementary material 1: Appendix C's models, but strip out the measure of inflation expectations and keep only the nominal rates.

Column 3 presents result of robustness-check calculations made for the values of exogenous explanatory variables as of the 2020 survey (i.e. when all the regressors characterize households as of the 2020 survey). The results are shown in Supplementary material 1: Appendix E. Column 4 presents results of calculations made for the values of exogenous explanatory variables as of the 2022 survey (i.e. when all the regressors characterize households as of the 2022 survey). The results are shown in Supplementary material 1: Appendix F.

Supplementary material 1: Appendices C–F present estimated marginal effects at the average values of regressors.

In Column 5 of Table 1, we provide estimates of marginal effects in the 11 models, obtained by sequentially expanding the number of regressors (Supplementary material 1: Appendix G). Because of the expanding set of regressors, the number of observations from 3,733 in the baseline model is reduced to 1,690 in the 11th model.[31] Clearly, the addition of regressors instead with replacement as in models from Supplementary material 1: Appendices C–F does not result in the sample size reduction.[32]

Additionally, in Supplementary material 1: Appendix I, we repeat the calculations of 11 models without extreme income values, i.e. excluding the "outliers" (limiting the monthly income of households in the 2020 survey to the 99% quantile, which corresponds to 114,155 rubles). In Supplementary material 1: Appendix J, all the specifications take into account the additional factor of survey month (it proved insignificant and therefore from now onwards these results are ignored). The survey was conducted between May and September 2022.

[31] The reduction in observations in the baseline model from 6,081 to 3,733 households is due, first, to the fact that 20% (1,200) of households were added to the 2022 wave, but were absent from the 2020 wave (the wave is the source of income and financial position data). The rest is the product of incomplete data for a number of households (unfilled indicators of assets or liabilities) In particular, the use of asset size logarithms strips out households whose asset sizes are zero.

[32] An additional calculation is presented in Supplementary material 1: Appendix H. It shows that the inclusion of a dummy variable for 37 localities (+one taken as baseline, which is not in the regression to exclude multicollinearity) controls for all locality level variation thus making impossible to identify particular effect of interest rates variation, when such variation is locality-measured only.

Table 1
Minimum and maximum statistically significant marginal effects (point estimation) evaluated at average values of regressors, from 11 models calculated in different ways, decimal quantity (0.01 points = 1%).

Variable	Marginal effect	Models of				
		Appendix C	Appendix D	Appendix E	Appendix F	Appendix G
		(1)	(2)	(3)	(4)	(5)
Average loan rate offered by banks in the locality of household residence	Min	–0.022	–0.021	–0.023	–0.019	–0.023
	Max	–0.016	–0.015	–0.016	–0.015	–0.015
Measure of inflation expectations	Min	0.022	–	–	–	–
	Max	0.028				
Logarithm of monthly income of a household	Min	0.018	0.017	0.020	0.017	0.018
	Max	0.036	0.035	0.035	0.020	0.038
Logarithm of total liabilities of a household	Min	0.004	0.004	0.004	0.004	0.005
	Max	0.005	0.005	0.006	0.005	0.006
Logarithm of total assets of a household	Min					
	Max	NS	NS	NS	NS	NS
Mean number of members aged under 18	Min	0.015	0.015	0.015	0.014	0.015
	Max	0.039	0.038	0.038	0.025	0.043
Marital status of household head	Min	NS	NS	NS	0.035	NS
	Max				0.047	
Average age of adult household members	Min	0.009	0.005	0.010	0.009	0.006
	Max	0.012	0.012	0.012	0.014	0.010
Average age of adult household members squared		–0.0001	–0.0001	–0.0001	–0.0001	–0.0001
Average share of employed household Members	Min	0.063	0.060	0.060	0.073	0.081
	Max	0.115	0.109	0.082	0.101	0.148
Higher educational attainment of at least one household member		NS	NS	NS	NS	NS
Willingness to take financial risks	Min	0.035	0.035	0.035	0.036	0.036
	Max	0.053	0.053	0.055	0.042	0.051
Reside in Southern or North Caucasian Federal District		NS	NS	NS	NS	NS
Reside in Volga, Urals or Siberian Federal District	Min	0.045	0.048	0.050	0.048	0.053
	Max	0.058	0.061	0.063	0.060	0.068
Reside in Far Eastern Federal District	Min		–0.015	–0.016		
	Max	0.113	0.100	0.122	0.116	NS
Household head's expectations of positive economic developments for next 12 months	Min					
	Max	–0.053	–0.053	–0.053	–0.058	–0.053

(continued on next page)

Table 1 *(continued)*

Variable	Marginal effect	Models of				
		Appendix C	Appendix D	Appendix E	Appendix F	Appendix G
		(1)	(2)	(3)	(4)	(5)
Household head's expectations of negative economic developments for next 12 months		NS	NS	NS	NS	NS
Propensity to save	Min					–0.065
	Max	–0.039	–0.040	–0.041	–0.030	–0.038
Expectations of improvements in financial position, average for a household	Min					
	Max	NS	NS	NS	NS	NS
Expectations of deterioration in financial position, average for a household	Min					
	Max	NS	NS	NS	NS	NS
Financial inclusion index, average for Household	Min					0.163
	Max	0.094	0.092	0.086	0.100	0.216
Financial literacy index, average for household	Min					
	Max	0.001	0.001	0.001	0.001	NS
Financial literacy index of household head	Min					
	Max	0.001	0.001	0.001	0.001	NS
City residence		NS	NS	NS	NS	–0.120
Higher educational attainment of household head		NS	NS	NS	NS	NS
Number of household members		–0.024	–0.022	–0.022	NS	–0.022
Effect of interest rate and income interaction		NS	NS	NS	NS	NS

Note: Appendix C: regressors added with replacement; the exogenous regressors are average values for 2020–2022; Appendix D: models of Appendix C but without measure of inflation expectations. Regressors added with replacement; the exogenous regressors are average values for 2020–2022; Appendix E: regressors added with replacement; the exogenous regressors are at 2020 values; Appendix F: regressors added with replacement; the exogenous regressors are at 2022 values; Appendix G: expanding set of regressors; the exogenous regressors are average for 2020–2022. All Appendices are in Supplementary material 1. In some cases minimum and maximum values coincide (due to limited number of digits after the decimal point) in the table. Min and max are not mentioned in this case as well as in the case of statistical insignificance of the estimated coefficients. NS — not significant.
Source: Authors' own calculations.

Adjustments for the survey month are intended to reflect macroeconomic changes over the turbulent period, which could affect responses (households demand for loans as of the date of the survey).

As can be seen from Table 1, the nominal interest rate offered by banks in a household locality is statistically significant and negatively correlates with the loan application probability, controlling for household's inflation expectations. The result is not robust if controls for localities are included.

In the models where the interest rate is significant, a 1 p.p. increase in the interest rate from the average level lowers the loan request probability by 1.5–2.3% (0.015–0.023). Therefore, the sensitivity of demand to small changes in the interest rate is very weak. This elasticity obtained in Magri (2009) for Italy is statistically insignificant. With the vast majority of loans in the sample being unsecured loans or credit cards, this result can be said to characterize exactly the demand for unsecured loans.

By contrast, a significant change in the interest rate (for example, the profound tightening of monetary policy in 2013–2024) has a tangible impact on the probability. Thus, a 10 p.p. rate increase from its average level (from the Supplementary material 1: Table B.1 of descriptive statistics, the average level is 11.7% per annum in February 2023) will reduce the loan request probability by 15–23% (0.15–0.23 in terms of fractions of probability). With the average loan request probability at 0.27, this rate increase reduces the probability by at least half its average level and all the way to the point of a zero probability.

The measure of inflation expectations (households' fear of rising prices in the 2020 survey) is statistically significant in certain specifications. A household whose members note a high risk of inflation is more likely to request a loan. However, the effect is economically weak: for a household whose one member at least notes such risks, the probability demanding a loan is only 3% higher compared to a household whose members do not see such risks. In general, it is difficult to reach a clear interpretation of the positive correlation of this measure of inflation expectations with credit demand. It can be attributable to the effect of lower real rates for given nominal rates or to the effect of expectations for higher real rates (following monetary tightening), as well as fears of a crisis, as long as, historically, crises in Russia have been related to spikes in inflation.

Accordingly, the interest rate channel of monetary policy is quite weak in terms of sensitivity of the number of households requesting a loan (i.e., extensive growth, not growth in the amount of loans) to the interest rate, when the rate change is small. Therefore, for the channel to make a visible impact, a drastic change in interest rates is required. As can be seen from Fig. 9, two episodes of strong reduction in loan issuance over the past five years stand out: one in early 2020 and one in the first quarter of 2022. Both episodes came with unfavorable exchange rate developments, increased volatility in the financial market and growing uncertainty about business conditions. In the course of the latter episode, the Bank of Russia significantly increased the key rate. Its statistics show an increase in 2022 in rates on loans for 1–3 years from a peak of 13.8% p.a. in December 2021 to 21.3% in April 2022, which is a 7.5 p.p. increase. As follows from Fig. 9, loan disbursements over the period declined from the seasonal reading of 120 to 60 (in terms of January disbursements), that is by half. Doubtless, it would be a mistake to attribute all the reduction to the rise in loan rates over the period, given the concurrent impact of many other factors on the side of demand (including those that our model cannot capture) and supply.

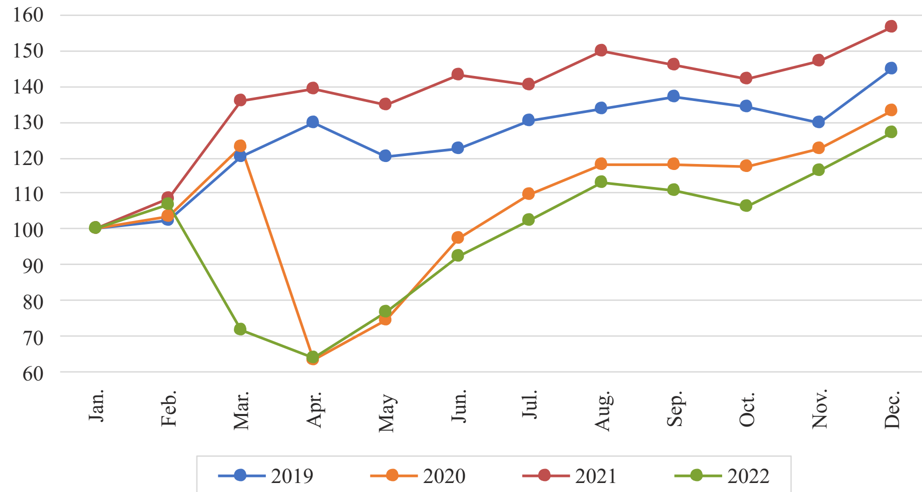

Fig. 9. Disbursements of unsecured loans by year, 2019–2023 (January of corresponding year = 100).

Sources: Bank of Russia; authors' calculations.

A number of other variables help explain the loan request variation (over the previous two years), which are as follows (based on results from Table 1).

- Household income, according to the 2020 survey, which increases a loan request probability over the following two years; 10% growth in income from the average level in 2020 increases the loan request probability by about 0.3 points in terms of fractional values or by 30%. The economic significance is quite high.
- The higher level of financial liabilities according to the 2020 survey also increases demand for loans. This may reflect the demand for refinancing of previously taken loans. The marginal effect of a 10% increase in liabilities from the average level is a tenth of the same 10% change in revenues — only about 0.04 points. Therefore, only households with a strong deviation in the level of liabilities from the average level show an economically significant deviation in credit demand.
- Households with a large number of adults have a lower loan request probability (families with adult children), while the presence of children increases the demand for credit. A married head of the household is more likely to apply for a loan.
- The average age of adult members is modelled non-linearly, and its impact is described in detail below.
- The share of employed household members has a positive impact on credit demand. The economic effect is significant: a household with employed members is about 10% more likely to request a loan, relative to a household of unemployed members (all other things being equal and at the average level, in particular, with the same age characteristics).[33]
- Risk appetite positively correlates with demand for loans: households with a high level of credit risk are more willing to apply for a loan.

[33] Therefore, the inclusion of the age variable makes it possible to control for households' age differences, in particular, for the fact that the oldest households are most likely unemployed. Thus, this variable reflects differences in employment status of households of the average age.

- Families residing in the Volga, Urals, and Siberian Federal Districts are marked by higher demand for loans relative to residents in the Central or North Western Federal Districts.
- Expectations of positive economic developments in the country reduce demand for loans. Importantly, we consider expectations according to the 2020 survey and demand between the two surveys, regardless of actual changes over this period.
- The propensity to save, according to the 2020 survey, reduces the loan request probability in the subsequent two years.
- Financial inclusion has positive and economically significant effects: the opportunity to take a loan online or offline adds 10–20% to the loan request probability.
- Financial literacy also increases the loan request probability in the future, but with a low economic significance.

Statistically insignificant factors for loan requests include the fact of city residence (significant only in one specification), the level of education, and an assessment of the future personal financial position. The level of assets (financial and non-financial), according to the 2020 survey, of households with such assets is also not a statistically significant predictor of loan applications.

The results are overall consistent with those obtained in the studies of credit demand (loan request probability) for other countries. Chen and Chivakul (2008, p. 28) present a table with international comparisons of estimates obtained in loan application probability studies that are available at the time of writing. The results in terms of age effects are similar to ours.[34] The wealth effect is negative, which is consistent with our estimates bearing out that the effect of assets is not significant; the effect of liabilities is positive. Accordingly, the increase in liabilities means a reduction in net wealth, which increases the likelihood of applying for a loan. In other studies, demand for credit also increases with income growth. The effect of education is either insignificant or positive. Unemployed people are less likely to apply for loans, as in our study.

Next, we have a closer look at the elasticity of loan requests to the average age of adult household members. This variable is included in the quadratic expression in the regression equation. The dependence of the probability on age is represented in Fig. 10. It follows from the figure that the loan request probability peaks (55–65%) for 35-year- olds and thereafter declines by half by the age of about 70 years.[35] This time profile for the loan request probability is overall aligned with the lending penetration data in Fig. 11, see Bank of Russia (2022a).

Credit bureau data on actual loan disbursements (rather than applications) show that the penetration of lending is about 60% at its peak and coincides with the range of 35–40 years. In the loan application model, the peak of probability is similar at 60% for the average values of the other control variables.

[34] In the specifications that also include this variable in a quadratic representation.

[35] For comparison, Magri (2007) finds for Italy that the probability peaks at 30 years for the age of family heads and decreases by half for those aged about 55 years. The earlier peak and earlier decline in demand may be explained by the significant penetration of mortgage loans in Italy (and advanced economies in general). According to Magri (2007), the number of mortgage borrowers in Italy is approximately equal to the number of consumer loan borrowers. Speaking of individuals (not households), in Russia, there were 8 million borrowers with a mortgage or borrowers with both a mortgage and a loan in the second quarter of 2022 year (survey dates) against 34 million borrowers with other types of loans (mostly for consumption purposes).

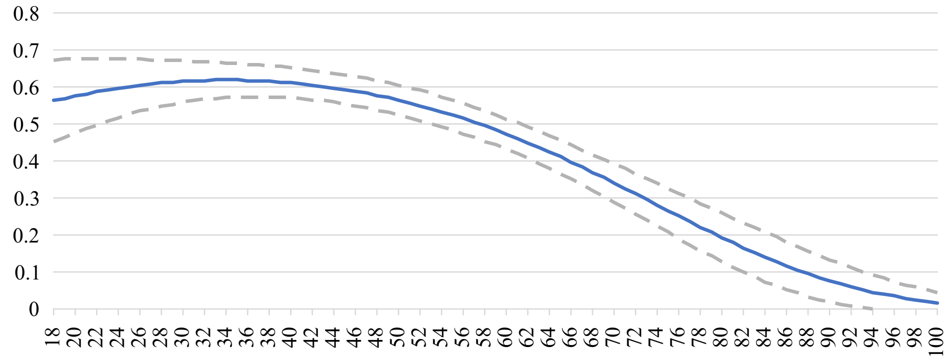

Fig. 10. Dependence of loan request probability on average age of adult household members.

Note: The results are based on regression coefficients whose ultimate effects are presented in Supplementary material 1: Appendix D (the Basic Regression column). The probability estimates are based on the average values of independent variables, with the exception of variable *average_adults_age_nw* and *average_adults_age_nw_srt*, in which the value *average_adults_age_nw* changes in increments of one year from 18 to 100. The calculation uses an asymptotic 95% confidence interval (+/–1.96* Standard error). The standard errors are obtained with the delta method.
Source: All-Russian survey of consumer finances 2022; authors' calculations.

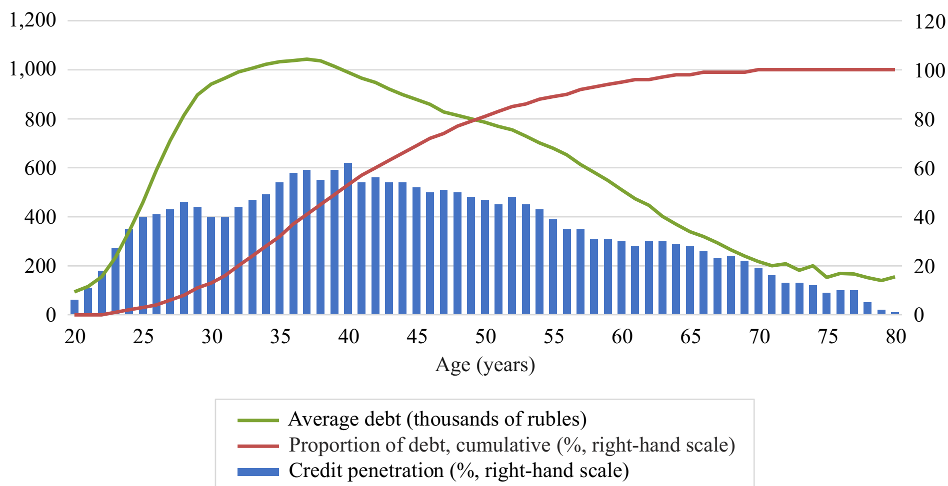

Fig. 11. Credit penetration, average debt, and the proportion of debt of individuals, by age group.

Source: Bank of Russia (2022a).

5.2. Results for planned loan demand

In this section, we describe results of estimating equation (4′) for the plans to apply for an unsecured loan in the survey of 2022. High uncertainty and structural shifts of 2022 makes the analysis especially valuable.

The results of the model estimation for the planned demand for consumer loans, including credit cards, according to the 2022 survey, are presented in Table 2.[36]

[36] Supplementary material 1: Appendix K shows the results excluding inflation expectations. The results in terms of interest rate elasticity are close to presented in Table 2.

It follows from the analysis of results that the elasticity of planned demand in relation to interest rates, while remaining statistically significant and negative, is economically very weak. The finding may partly be attributable to the fact that, unlike for past demand where consumer loans cannot be distinguished, the model in this case is built only for demand for consumer loans (including credit cards). These loans are marked in theory by lower interest rate elasticity. This is further explained by the fact that planned loan demand was observed only for 3% of the households surveyed, which means there may be few observations and variation in the data for good identification.

It is notable that the measure of inflation expectations according to the 2020 survey positively correlates with planned loan requests, which corresponds

Table 2
Estimated marginal effects: models of future demand as a dependent variable, decimal quantity (0.01 points = 1%)

Variable	Model						
	Baseline regression	+ risk appetite	+ macroregion of residence	+ expectations as to economic outlook	+ propensity to save	+ expectations of change in financial position	+ financial inclusion
	(1)	(2)	(3)	(4)	(4.1)	(4.2)	(5)
Average loan rate offered by banks in the locality of household residence	–0.006** (0.002)	–0.006*** (0.002)	–0.006*** (0.002)	–0.006** (0.002)	–0.008*** (0.003)	–0.006** (0.003)	–0.004 (0.004)
Measure of inflation expectations	0.013** (0.005)	0.014*** (0.005)	0.014*** (0.005)	0.015*** (0.005)	0.015** (0.006)	0.015*** (0.005)	0.024*** (0.008)
Logarithm of monthly income of a household	0.009*** (0.004)	0.007** (0.003)	0.009** (0.004)	0.008** (0.004)	0.010** (0.004)	0.010** (0.004)	0.008 (0.006)
Logarithm of total liabilities of a household	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Logarithm of total assets of a household	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000** (0.000)
Mean number of members aged under 18	–0.006* (0.003)	–0.004 (0.003)	–0.004 (0.003)	–0.004 (0.003)	–0.005 (0.003)	–0.004 (0.003)	–0.004 (0.005)
Marital status of household head	0.006 (0.005)	0.004 (0.005)	0.004 (0.005)	0.007 (0.006)	0.012* (0.006)	0.005 (0.006)	0.010 (0.008)
Average age of adult household members	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.002)
Average age of adult household members squared	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)
Average share of employed household members	0.011 (0.008)	0.015** (0.007)	0.016** (0.007)	0.015* (0.008)	0.015* (0.009)	0.018** (0.008)	0.012 (0.012)

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Table 2 *(continued)*

Variable	Model						
	Baseline regression	+ risk appetite	+ macroregion of residence	+ expectations as to economic outlook	+ propensity to save	+ expectations of change in financial position	+ financial inclusion
	(1)	(2)	(3)	(4)	(4.1)	(4.2)	(5)
Higher educational attainment of at least one household member	–0.003 (0.005)	–0.002 (0.005)	–0.002 (0.005)	–0.002 (0.005)	–0.001 (0.006)	–0.003 (0.005)	0.002 (0.007)
Willingness to take financial risks		0.026*** (0.006)	0.025*** (0.007)	0.026*** (0.007)	0.027*** (0.007)	0.024*** (0.007)	0.033*** (0.010)
Reside in Southern or North Caucasian Federal District			0.009 (0.008)	0.011 (0.008)	0.017* (0.010)	0.011 (0.009)	0.014 (0.012)
Reside in Volga, Urals or Siberian Federal District			0.010* (0.006)	0.012** (0.006)	0.015** (0.006)	0.011* (0.006)	0.017** (0.008)
Reside in Far Eastern Federal District			–0.013* (0.006)	–0.012* (0.007)	–0.011 (0.007)	–0.014** (0.006)	
Household head's expectations of positive economic developments for next 12 months				–0.007 (0.010)	–0.011 (0.010)		
Household head's expectations of negative economic developments for next 12 months				–0.000 (0.006)	–0.002 (0.006)		
Propensity to save					–0.013** (0.006)		
Expectations of improvements in financial position, average for a household						–0.001 (0.007)	
Expectations of deterioration in financial position, average for a household						0.008 (0.006)	
Financial inclusion index, average for household							0.042** (0.019)
Observations	3,740	3,740	3,740	3,467	3,090	3,416	2,073
Wald Chi^2	66.22	77.40	80.05	79.28	132.9	77.52	50.42
Prob > Chi^2	$6.36e^{-10}$	0	$6.83e^{-11}$	$5.14e^{-10}$	0	$1.05e^{-09}$	$1.03e^{-05}$
Pseudo R^2	0.0799	0.0996	0.109	0.115	0.141	0.110	0.0942
AIC	784.4	770	768.7	735.8	669.6	744.5	574.1
BIC	859.1	851	868.3	846.5	784.3	854.9	664.3

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Table 2 *(continued)*

Variable	Model					
	+ financial literacy, average household	+ financial literacy of head	+ locality type	+ higher educational attainment of household head	+ household size	+ effect of rate and income interaction
	(6)	(7)	(8)	(9)	(10)	(11)
Average loan rate offered by banks in the locality of household residence	–0.005** (0.002)	–0.006** (0.002)	–0.005** (0.002)	–0.006*** (0.002)	–0.006*** (0.002)	–0.004* (0.002)
Measure of inflation expectations	0.015*** (0.005)	0.015*** (0.005)	0.014*** (0.005)	0.013** (0.005)	0.013*** (0.005)	0.013*** (0.005)
Logarithm of monthly income of a household	0.008** (0.004)	0.009** (0.004)	0.008** (0.004)	0.008** (0.004)	0.006* (0.004)	0.030*** (0.011)
Logarithm of total liabilities of a household	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Logarithm of total assets of a household	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)
Mean number of members aged under 18	–0.004 (0.003)	–0.004 (0.003)	–0.004 (0.003)	–0.003 (0.003)	–0.007 (0.004)	–0.004 (0.003)
Marital status of household head	0.004 (0.005)	0.003 (0.005)	0.005 (0.005)	0.003 (0.005)	0.002 (0.005)	0.002 (0.005)
Average age of adult household members	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)
Average age of adult household members squared	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)
Average share of employed household members	0.013* (0.007)	0.014* (0.007)	0.015** (0.007)	0.016** (0.007)	0.019** (0.008)	0.013* (0.007)
Attainment of at least one household member	–0.006 (0.005)	–0.005 (0.005)	–0.003 (0.005)	0.011 (0.007)	–0.002 (0.005)	–0.002 (0.005)
Willingness to take financial risks	0.025*** (0.006)	0.026*** (0.006)	0.025*** (0.006)	0.025*** (0.007)	0.024*** (0.007)	0.026*** (0.007)
Reside in Southern or North Caucasian Federal District	0.011 (0.008)	0.014 (0.009)	0.012 (0.008)	0.009 (0.008)	0.008 (0.008)	0.008 (0.008)
Reside in Volga, Urals or Siberian Federal District	0.010* (0.006)	0.010* (0.005)	0.010* (0.005)	0.009 (0.006)	0.009 (0.006)	0.009 (0.006)
Reside in Far Eastern Federal District	–0.012* (0.006)	–0.013** (0.006)	–0.012* (0.007)	–0.013** (0.006)	–0.013** (0.006)	–0.013** (0.006)
Financial literacy index, average for household	0.000*** (0.000)					
Financial literacy index of household head		0.000*** (0.000)				

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Table 2 *(continued)*

Variable	Model					
	+ financial literacy, average household	+ financial literacy of head	+ locality type	+ higher educational attainment of household head	+ household size	+ effect of rate and income interaction
	(6)	(7)	(8)	(9)	(10)	(11)
Type of residence			0.005 (0.008)			
Higher educational attainment of household head				–0.018** (0.009)		
Number of household members					0.003 (0.004)	
Effect of interest rate and income interaction						0.000 (0.000)
Observations	3,740	3,740	3,740	3,740	3,740	3,740
Wald Chi^2	79.87	80.59	97.23	84.15	80.10	76.83
Prob > Chi^2	$1.75e^{-10}$	$1.30e^{-10}$	0	0	$1.59e^{-10}$	$6.18e^{-10}$
Pseudo R^2	0.119	0.127	0.111	0.115	0.110	0.115
AIC	762.4	755.8	768.8	765.2	769.5	765.0
BIC	868.2	861.6	874.7	871	875.3	870.9

Note: The standard errors in parentheses; *** $p < 0.1$, ** $p < 0.5$, * $p < 0.1$.
Source: Authors' calculations.

to the economic theory, as higher expected inflation means lower *real* interest rate.

Among other statistically significant loan application factors are household income and households' financial liabilities. The point marginal effect of household income by absolute value is three times weaker than for loan applications for the past two years. Households' financial liabilities growth increases the loan request probability, but the economic effect is very weak. The proportion of employed household members that has a positive impact on planned applications. Planned applications in some specifications demonstrate a non-linear quadratic age relationship and thus confirm the life cycle hypothesis. Risk attitude statistically significantly increases the loan request probability in all specifications. More financially literate households tend to more willingly plan to request loans in the future. Financial inclusion, as in the case of demand in the past, leads to more frequent plans to apply for loans in the future.

At the same time, compared to the demand for credit between summer 2020 and summer 2022, we do not find any critical differences in the role of abovementioned factors.[37]

[37] For another comparison, we made a calculation not for the planned consumer loan requests in the right side of the model, but for total planned loan requests (all types of loans). Supplementary material 1: Appendix L shows the results for planned demand for all loans, not only consumer loans. The results — in terms of their point estimates and significance — are overall close to those in Table 2. In addition, the amount of liabilities and the amount of assets are statistically significant.

6. Conclusion

Russian surveys of consumer finances provide data that enable analysis of households' loan requests. Given that loan request decisions are made not at the individual but at the household level, these data — unlike those usually available to banks or credit bureaus — contain reliable information to explore demand for credit and the elasticity of demand in relation to the interest rate.

This work presents an estimation of the decision-making model for households requesting loans. The key focus is to estimate the elasticity of the loan request probability in relation to the interest rate, accounting for inflation expectations. The main difficulty in understanding the role of the interest rate is the need to distinguish the interest rate variation, which is exogenous to credit demand. In this work, this is achieved through the use of interest rates on banks' consumer loans available in the place of residence of households (according to banki.ru). Such rates do not depend on borrower characteristics. Accordingly, their variation from one location to another reflects the variation on the credit supply side. The resulting estimates show that the loan request probability is lower in the place of residence of households marked with higher rates, other things being equal. In terms of economic significance, the elasticity of the probability is weak, that is, as the estimates show, the interest channel of monetary policy for minor rate changes is weak. For the channel to make a visible impact, a drastic change in interest rates is required. This can be attributed to the fact that the sample mainly includes consumer loans — already with rather high rates — for which an additional rate increase of 1 p.p., on a relative basis, is insignificant.

Concerns over high inflation correlate positively with loan requests (both for two years before the survey and in the future). The result increases priority of bringing inflation under control as it helps to cut a vicious circle from higher inflation expectations, to borrowing, to consumer expenditures and to higher inflation.

The results for the loan request probability model bear out the value and economic importance of the following characteristics: income (10% growth from the average level leads to a 0.3 p.p. increase in the probability), employment status, children under 18 years of age, risk appetite, and financial inclusion. The average age of adult household members, estimated in a non-linear way, confirms the dependence that is specific to the life cycle hypothesis and that the literature has previously explored.

The following attributes were of low economic significance but statistically significant: a rise in liabilities triggering an increase in the loan request probability and the level of financial literacy (measured on the basis of survey data by the authors) which, when growing, also increases the probability.

The significance of non-financial assets (mainly real estate) as an indicator was not found. This probably reflects the fact that Russian households making an unsecured loan application do not consider such assets as a factor (potential collateral). Statistically insignificant factors for loan requests include the fact of city residence (significant only in one specification), the level of education, and an assessment of the future personal financial position. Overall, the results match the results obtained in the studies of demand for loans (the loan request probability) for other countries.

Acknowledgments

The authors are grateful to Denis Shibitov and Sergey Seleznev for the data on interest rates from the banki.ru, as well as Anna Tsvetkova and Eugenia Bessonova for their data on income, non-financial and financial assets and liabilities, all calculated on the basis of the *All-Russian survey of consumer finances*. The authors are further grateful to Maria Lymar for her financial literacy index data calculated on the basis of the same survey. The authors also acknowledge Aleksey Egorov (Bank of Russia) and the participants of the Bank of Russia economic research workshop for their useful comments and suggestions.

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Supplementary material 1

Description of variables, descriptive statistics and model estimates

Authors: Andrey A. Sinyakov, Tatyana I. Shelovanova

Data type: Text

Explanation note: Appendixes.

Link: https://doi.org/10.32609/j.ruje.11.145314.suppl1

Supplementary material 2

Variables construction files using raw data and replication code

Authors: Andrey A. Sinyakov, Tatyana I. Shelovanova

Data type: Archive

Explanation note: The data underpinning the analysis reported in this paper and replication code.

Link: https://doi.org/10.32609/j.ruje.11.145314.suppl2