Who participates in the credit market during the COVID-19 pandemic? Evidence from the Consumer Expectations Survey[1]

Evangelos Charalambakis

(Bank of Greece)

Federica Teppa

(De Nederlandsche Bank and Netspar)

Athanasios Tsiortas

(European Central Bank)

This draft: 15 December 2021

Please do not quote without the authors' permission

Abstract

This paper provides new evidence on what determines the probability of the consumer's decision to apply for credit as well as the probability of the consumer credit being accepted by financial institutions. It also analyses whether and to what extent the COVID-19 pandemic impacts on consumers' borrowing behaviour. We use novel microdata between April 2020 and April 2021 obtained from the new ECB's Consumer Expectations Survey, a fully harmonized online survey measuring consumer expectations and behaviour. We find that age, education, household size, income, financial literacy, liquidity constraints and degree of urbanization significantly impact on both the application and the acceptance of credit. We also document that the probability for credit application and for the credit being accepted vary across countries. Finally, we find that there is heterogeneity in the type of credit and in particular for secured versus unsecured loans.

[1] Corresponding author: Federica Teppa, De Nederlandsche Bank, f.teppa@dnb.nl
Acknowledgments: The views expressed are those of the authors and do not necessarily reflect those of the Bank of Greece, De Nederlandsche Bank, the European Central Bank or the Eurosystem. Any remaining errors are the authors' own responsibility.

1. Introduction

Consumer finance has received wide attention in the academic literature as it plays an important role in the monetary policy transmission mechanism, through the so-called “credit channel”. The rationale behind it is that economic activity is affected by the amount of credit that consumers have access to in equilibrium. Factors that alter the availability of credit have an effect on consumers' spending and investment, which in turn leads to a change in economic growth. This paper focuses on consumers’ borrowing behaviour. In particular, it empirically investigates what drives consumers’ demand for credit applications and the probability that consumers’ demand for credit is accepted.

According to the traditional economic theory, based on the seminal work of Modigliani and Brumberg, (1954) and Friedman (1957), consumers have an expected optimal consumption level over the lifecycle that they should achieve through consumption smoothing. If income levels vary over time, consumption smoothing can be implemented by borrowing, provided that borrowing is temporary and sustainable (see e.g. Bagliano and Bertola, 2004). Therefore, credit access becomes a good indicator of financial wellbeing: the more sources to borrow from, the greater the opportunity to consume, the higher the level of utility consumers can reach. However, borrowing cannot go beyond a certain limit, otherwise consumers will face heavy financial burdens that will lead them, in the worst case, to financial insolvency and bankruptcy ultimately.

When tested empirically this standard model needs to incorporate two additional sets of variables that affect the demand and the supply of the credit market. Individual, socio-demographic and economic factors, on the one hand, and institutional factors, on the other hand; see, for example, Ando and Modigliani (1957), Modigliani et al. (1985); Modigliani (1988); Deaton (1992), Alessie et al. (1997) and Attanasio (1999), among others. Therefore, the empirical models described in the above studies take into account that (i) households demand for debt is subject to factors other than income and wealth (like age, size and composition of the household, education, employment status, financial/real assets) and that (ii) households may face liquidity constraints on their ability to borrow. This is due to the existence of asymmetric information between borrowers and lenders, the justice system, and the presence of informal credit circuits, like borrowing from relatives and friends.

The existence of borrowing constraints plays a crucial role in consumer finance. Borrowing constrained households should consider that their future consumption is not only affected by their current level of wealth and investment opportunities but also by their net future income. The impact of liquidity constraints on the excess sensitivity of consumption to transitory income shocks is a long-standing empirical question of major importance; see, for example, Hall and Mishkin (1982), Zeldes (1989), Jappelli (1990), Jappelli, Piske and Souleles (1998), Gross and Souleles (2002), Leth-Petersen (2010) and Crossley and Low (2014), among others.

There is a considerable debate about the incidence of borrowing constraints and whether the low borrowing in some groups of the population is due to the low demand for loans or to the denial of credit. Grant (2007) using data from the Consumer Expenditure Survey for 1988-1993 period documents that 31 percent of US households are constrained with young college educated households being the most constrained. He also shows that the low level of borrowing observed among black households is more likely to be a demand rather than a supply effect.

Our paper makes two main contributions to the literature. First, it offers new evidence on what determines the probability of a consumer to apply for a loan and the probability of the consumer credit being accepted by financial institutions in the six largest Euro area countries. Second, it provides unique evidence on whether and to what extent the COVID-19 pandemic impacts on consumers' borrowing behaviour.

The paper uses novel microdata from the ECB's Consumer Expectations Survey (CES), a new high-frequency and fully harmonized online survey measuring consumer expectations and behaviour in Germany, France, Italy, Spain, Belgium and the Netherlands. The CES was launched in a pilot phase in January 2020 and quickly achieved its target sample size of approximately 10,000 households since April 2020. One of the strong features of CES is its panel dimension that allows for an assessment of how consumer behaviour changes over time and how consumers respond to critical economic shocks[2]. In this paper we use quarterly data, from April 2020 to April 2021,[3] enabling us to investigate in depth the consumer borrowing behaviour throughout the COVID-19 pandemic.

We use a probit model to estimate the consumer's probability to apply for credit for the six Euro area economies. The results show that younger, more educated, male and high-risk

[2] Georgarakos and Kenny (2021) provide a more detailed description of the CES and ECB (2021) contains a first evaluation of the survey.
[3] This time span covers the full set of quarterly waves in the pilot phase of the survey.

consumers as well as consumers with high level of income, high number of children, hard access to credit, liquidity constraints, mortgage loan on their home residence and major concerns about their financial situation due to the COVID-19 pandemic tend to apply for credit more. In addition, we disclose the role of financial literacy in credit applications. We find that financial literacy is negatively related to the probability to apply for credit. However, this negative association is entirely driven by consumers who do not face any liquidity constraints. Finally, we show that the degree of urbanization matters and is positively associated with the probability to apply for credit.

As for the decision to apply for credit, we also use a probit model to estimate the probability of consumer loan to be accepted. We find that older consumers and consumers with high level of financial literacy are more likely to be accepted for credit. However, unemployed consumers, consumers with low level of income, missed payments on loans and consumers that live in suburbs and mid-cities are more likely to be denied for credit. Finally, we estimate the probability to apply for a loan focusing on each type of credit application. We find that age, education, household size, income, financial literacy, liquidity constraints and degree of urbanization are significant determinants of both the application and the acceptance credit rate.

This paper documents significant country and time fixed effects, too. More specifically, in all countries the probability to apply for credit is significantly lower than in Germany, with the only exception of Italy. We also find that the probability to get credit approval is significantly higher than in Germany in all countries but the Netherlands, for which the difference is not significant. In addition, the probability to apply for credit is significantly lower in January 2021 and April 2021 than in April 2020, whereas the probability of credit acceptance is significantly lower after the onset of the COVID-19 pandemic, likely reflecting the banks' increased risk aversion towards the household sector during the pandemic.

The analysis by type of credit application shows that there are heterogenous effects with respect to secured and unsecured credit. In particular, we find that the probability to apply for the secured credit is significantly higher in the presence of a partner and lower for the bottom income quintiles, whereas these variables are not significant for the probability of unsecured credit application. Being financially concerned due to the pandemic as well as being liquidity constrained are significant determinants of the application for unsecured credit, but not at all of the secured credit application. Overall, we show that the participation in the credit market is heterogenous across households, which may have substantial implications for the efficacy of monetary and fiscal policy.

The rest of the paper is organized as follows. Section 2 describes the empirical design and models to be estimated. Section 3 provides a description of the sample and the data used for the empirical analysis, that is reported in Section 4. Section 5 concludes the paper.

2. Empirical Design

Two methodologies are typically used to measure household access to credit and credit constraints in the literature. The first method infers the presence of credit constraints from violations of the assumptions of the life-cycle/permanent income hypothesis. More precisely, the method uses household consumption and income data to look for a significant dependence (or "excess sensitivity") of consumption on transitory income. Empirical evidence of significant dependence is taken as an indication of borrowing or liquidity constraint.[4] The second method directly uses information on consumers' participation and their experiences in the credit market to classify them as credit constrained or not. The classification is then used in reduced form regression equations to analyse the determinants of a household being credit constrained.[5]

Following the second approach, we use novel panel data from CES that measures consumer borrowing behaviour on a high frequency. In CES, households are interviewed on a monthly basis in the six largest economies in the euro area, i.e., Germany, France, Italy, Spain, Belgium and the Netherlands. The sample consists of anonymized household-level responses from approximately 2,000 households in Germany, France, Italy and Spain and 1,000 households in Belgium and the Netherlands. Respondents are invited to answer online questionnaires every month and typically exit the panel between 12 and 18 months after their entrance. Each respondent completes a background questionnaire upon survey recruitment providing important information on household characteristics that hardly change on a monthly frequency,

[4] For an extensive review, see Besley (1995) and Browning and Lusardi (1996), among others.
[5] See Jappelli (1990), among others.

such as age, gender, education, family status, employment status, annual household income. Consumer perceptions and expectations, which are more time-sensitive, are collected in a series of monthly and quarterly questionnaires. In particular, questions related to whether the household has applied for a loan and the outcome of the application or to whether it has any missed payments on a loan are collected on a quarterly basis. Consumer perceptions and expectations on credit access or whether the household is subject to liquidity constraints are collected on a monthly basis.[6]

Our main econometric approach is a binary probit model to estimate the probability P of a household to apply for a loan and has the following form:

$$P(Apply_{h,c}=1|a_c,X_{h,c})=\Phi(a_c + \beta X_{h,c}) \ , \qquad (1)$$

where $Apply_{h,c}$ is a dummy variable that denotes the binary outcome, i.e., whether the household has applied for a loan during the last 3 months, Φ is the cumulative distribution function of a standard normal distribution, a_c is a vector of country-level fixed effects,, β is the slope for household level demographics and socio-economic variables that is common across countries. In the set of the household-level variables X, we incorporate time dummies to account for time effects. The probit model is estimated using pooled and weighted quarterly CES data from April 2020 to April 2021. Likewise, we make use of a probit model to estimate the probability P of a household's credit application being accepted as follows:

$$P(Approval\_full_{h,c}=1|a_c,X_{h,c})=\Phi(a_c + \beta X_{h,c}) \ , \qquad (2)$$

where $Approval\_full_{h,c}$ is a dummy variable that denotes whether the household's credit application has been fully accepted. All the cases where the outcome of the credit application is not known, have been excluded. Also, we consider the credit applications that have been accepted but only part of the amount applied for was granted, as being rejected. For a more meaningful and direct interpretation we report the marginal effects from the probit models. Survey weights are employed to ensure population representativity.

[6] For a more extensive description of the CES see Georgarakos and Kenny (2021) and ECB (2021)

3. Sample and Data

Table 1 reports the summary statistics of the outcome variables along with the explanatory variables used in the empirical specifications. All these variables are described in the remainder of this section.

Our dataset consists of 18,610 households and of 50,744 observations. Weights are assigned only to respondents who completed the core and the quarterly modules. In this paper we use five quarterly waves: April, July, October 2020 and January, April 2021. For some variables, the number of available observations is lower due to (i) non-response (e.g. the credit application rate) or selection processes (e.g. the acceptance rate is conditional on having applied for credit) (ii) missing values in some steps of the data collection process (e.g. the risk aversion indicators suffer from some respondents skipping this information in the background module) and (iii) the different frequency in which some variables have been collected. In particular, some variables have been collected only once and not repeatedly (e.g. degree of urbanization has been collected only in November 2020) or in the core questionnaire (e.g. financial concern), which can be left uncompleted in some waves whereas the background module must be completed in order to become a panel member.

Table 1 about here

3.1. The dependent variables

The CES asks several questions about **credit applications** to eight categories every quarter, both with respect to the past 3 months and the future 12 months. The categories consist of a mortgage to purchase a house or other real estate or a housing loan for home renovation; a loan to purchase a car, motorbike or other vehicle; another type of consumer loan or instalment debt; a leasing contract (e.g. on a car); a credit card or an account with an overdraft facility with a financial institution; a loan for education purposes; an increase in the limit of an existing loan; refinancing of your current mortgage. From these questions, the total **credit application rate in the past 3 months**, defined as the percentage of respondents who applied for credit, is computed. This rate is the sum of the respondents who applied and (i) had their application approved; (ii) had their application rejected; and (iii) do not yet know the outcome of their application. For the period between April 2020 and April 2021, the average total application rate has been 15.3 percent (see Table 1). The top panel of Table 2 shows how the application rate varies over time and across countries. We observe that the application rate in the Euro area in July 2020 relatively decreased on average.[7] This is possibly attributed to the lower consumer confidence and decreased spending on durables triggered by the strict lockdown period of the COVID-19 pandemic. In particular, the application rate in the Euro area dropped from 15.8 percent in April 2020 to 15.3 percent in July 2020. However, in October 2020 the application rate increased significantly from 15.3 to 16.9 percent, reaching its peak, and reflecting a strong rebound in the demand for loans after the lockdown period in the second quarter. There is a decrease in the application rate from 16.9 percent in the last 2020 quarter to 13.7 percent in January 2021, which is possibly attributed to the lower consumer confidence in the Euro area at that period. Finally, there is an increase of the application rate amounting to 14.8 percent in April 2021 reflecting the improvement in consumer confidence. A cross-country comparison shows that all countries but Netherlands exhibit the highest application rates in October 2020, in line with the application rate in the overall Euro area in the same period. Germany, Spain and France exhibit the lowest application rates in January 2021 whereas Belgium, Italy and Netherlands have the lowest application rates in July 2020, April 2021 and January 2021, respectively.

The **acceptance credit rate** is defined as the percentage of the respondents who applied for credit and had their amount granted in full.[8] Between April 2020 and June 2021 the average acceptance rate has been 71 percent (see Table 1). In the bottom panel of Table 2 we observe that the average acceptance rate in the six Euro area countries has monotonically decreased until the third quarter 2020, from a maximum of 81.7 percent in April 2020 to a minimum of 66.8 percent in October 2020. Based on the euro area bank lending survey (BLS), this is mainly due to the tightening of credit standards for housing loans and consumer credit as a consequence of the deterioration of the economic outlook and worsened credit worthiness of consumers affected by the pandemic[9]. It remained unaltered in January 2021 and relatively increased in April 2021. This is possibly due to the fact that banks have eased the terms and

[7] Similar to ECB (2021), we define as Euro area numbers pooled results across the main six CES countries.

[8] The applications that were only partially accepted are treated as zero's. The observations with unknown outcome are treated as missing. Shares are conditional on having applied for credit.

[9] For more details, see, the ECB's website for the euro area bank lending survey, https://www.ecb.europa.eu/stats/ecb_surveys/bank_lending_survey/html/index.en.html

conditions of loans to households for house purchases by narrowing the margins on average loans (see the BLS report for the third quarter 2020). Looking at the acceptance rates across countries and in line with the average acceptance rate in the six countries surveyed, it dropped in all countries from April to October 2020. The largest declines are observed in Germany and France. According to BLS this is due to the net tightening of terms and conditions for housing loans for both German and French banks. In particular, German banks reported wider margins on both average and riskier loans and collateral requirements whereas French banks reported wider margins for riskier loans and stricter collateral requirements.

Table 2 about here

3.2. The main explanatory variables

The main consumer demographic and socio-economic characteristics are collected from the CES background module that respondents answer the first time they joined the panel. For our analysis we use **age** in dummies: 18-34 years, 35-49 years, 50-55 years, 56-60 years, 61-65 years and 66+ years. To capture **gender** and **education** we use a female indicator (females represent 51.1 percent) and a high-education indicator (highly educated respondents represent 54.4 percent), respectively[10]. We also control for **household size[11]** (on average households consist of slightly more than 2 members), the **presence of a partner** (64.3 percent) and **number of children[12]**, being **unemployed** (10.5 percent), **net income quintiles** (values are imputed) and being **mortgage holders** (30.1 percent)**.**

Financial literacy is asked both in subjective terms - respondents had to self-assess their level of financial literacy - and more objectively – respondents had to answer questions about compound interest (2 questions), real rates and risk diversification. We construct an index that consists of the total number of correct answers given to those questions. The index ranges between 0 and 4. On average our respondent gave the correct answer to 2.4 questions.

[10] The high-education indicator includes short-cycle tertiary education, bachelor or equivalent, master or equivalent and doctoral or equivalent.
[11] This variable is truncated at 5+. Households with more than 5 members represent less than 10 percent.
[12] Children are defined as “My child or step child” and include both dependent and adult children. This variable is truncated at 3+. Households with more than 3 children represent about 5 percent.

Risk is elicited through the following question asked in the background module:

"*Imagine you are playing a game of chance by flipping a coin. If the coin comes up heads, you win €60, but if it comes up tails you win nothing. Would you rather play this game or alternatively receive the amount shown below for sure?*"

The amount shown consists of 10 euros in the first place, 20 euros if the respondent chose to play the game further, and so on up to 60 euros. This way we build three levels of risk : low (if respondents choose up to 20 euros), medium (if respondents choose 30 euros), high (if respondents choose 40 euros and above). Slightly less than half of the sample falls into the low risk group (47.9 percent); the remaining half is evenly distributed between the medium and the high risk groups (22.8 and 29.3 percent, respectively).

Concern about the financial situation of the respondent's household due to COVID-19 is derived from a question that explicitly asks how concerned the respondent is about the impact of the COVID-19 on the financial situation of his/her household. In this question an ordered scale is used, from 0, not concerned, to 10, extremely concerned. The sample mean of this variable is 6.17 with a standard deviation of 2.7 (see Table 1).

The CES also asks whether the respondent thinks that it is generally harder or easier these days, compared to 12 months earlier, for his/her household to obtain credit or loans (including credit and retail cards, auto loans, student loans, and mortgages). We build an indicator for **credit being harder than 12 months earlier** if the respondent reported it to be much harder or somewhat harder.[13] Slightly less than one third of our respondents reported that it was indeed the case. The perceptions of consumers about their access to credit can impact on their decision to apply for credit.

Respondents who face **insufficient liquidity** are identified among those who report that -- when thinking about their available financial resources, including access to credit, savings, loans from relatives or friends, etc. – they would not have sufficient financial resources to pay for an unexpected payment equal to one month of their household income. Also for this variable, slightly less than one third reported to have not enough liquidity. Consumers that face liquidity constraints are more likely to apply for loans to meet their financing needs.

[13] The remaining options are "Equally easy/hard", "Somewhat easier" and "Much easier". In the indicator these options are set equal to 0.

Apart from the main empirical specification we include some additional variables that could be associated with either consumers' decision to apply for credit or credit of consumers being accepted. These variables are as follows:

The **degree of urbanization** is captured by means of a set of indicators about: "A big city with more than 500,000 inhabitants"; "A suburb or outskirts of a big city"; "A city with 100,000 to 500,000 inhabitants"; "A small city with less than 100,000 inhabitants"; "A village or rural area". This question is asked in an ad-hoc module fielded in November 2020. Only respondents who were in the panel at that point could answer this question, therefore the lower number of observations when this variable is included in the regressions.

Expected net total household income growth in the following 12 months is captured by the reported expected change in percentage terms. The variable is winsorized at 2 percent.

Home ownership is an indicator for home owners. The dataset consists of 64.3 percent of home owners (see Table 1).

CES data collects quarterly data on late payments on debt and non-debt obligations. **At least one past late payment** in the past 12 months is an indicator taking value 1 if the respondent reports to have had difficulty making payments on time for at least one of the following: rent, mortgage, other loans, utility bills. About 11 percent of the respondents reported to have had at least one missed payment in the past 12 months (see Table 1).

3.3. Univariate analysis

Table 3 reports some simple univariate analysis about the average value of the credit application rate (Panel A) and the credit acceptance rate (Panel B) with respect to the regressors that we will use in the multivariate analysis.

Table 3 about here

The univariate results suggest that the credit application rate decreases with age. In particular, the application rate drops from 20.7 percent for consumers aged 18-34 to 8.1 percent for consumers being more than 65 years old. A clear gradient for the credit application rate is observed with respect to household size: the higher the number of household members the higher the application rate, that almost doubles from 11.1 percent for the single-member households to 20.4 percent for the households with 5 or more components. A very similar gradient is observed with respect to the number of children: the credit application rate ranges between 13.1 percent for the households with no children to 21.7 percent for the households with 4 or more children. In addition, the consumers with an outstanding mortgage on their home residence, hard access to credit, liquidity constraints and missed payments on debt or non-debt obligations have higher application rates.

The acceptance rate is greater for the older households being more than 65 years old compared to younger households being between 18-34 years old. In particular, the acceptance rate increases from 60.7 to 81.6 percent. The acceptance rate is higher for the non-single respondents (73 percent versus 66.7 percent), and monotonically increasing with income, from 57.6 percent for the bottom income quintile to 82 percent for the top income quintile. Similarly, the acceptance rate is monotonically increasing with financial literacy, ranging from 50.3 percent for the lowest financial literacy score to 85.2 percent for the highest one.

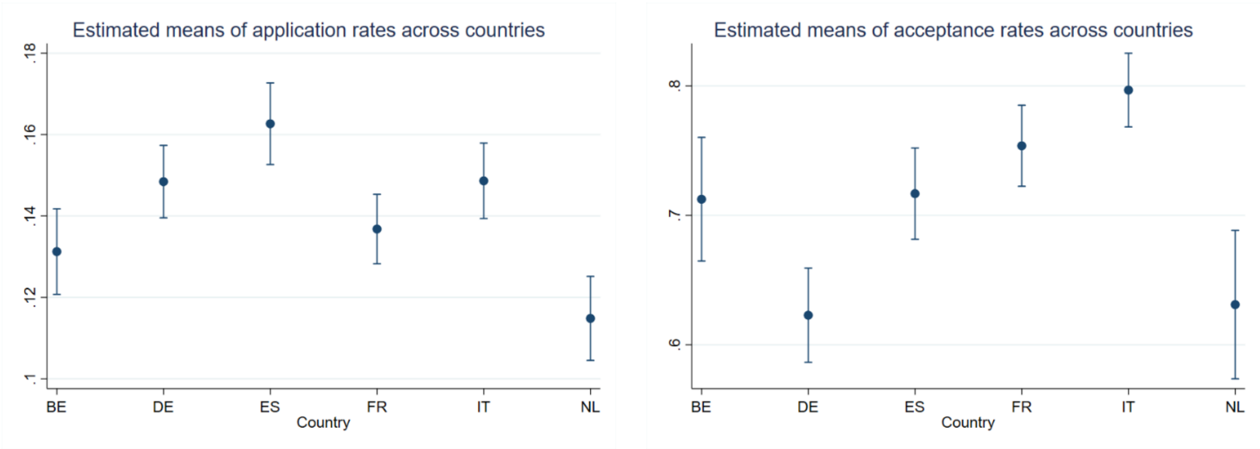
Being unemployed is associated to a lower application rate (15 percent versus 17 percent), and to a higher acceptance rate (73 percent versus 53.8 percent).

The respondents who reported to have had at least one late payment in the past 12 months have a higher application rate (35 percent versus 12.9 percent), and a lower acceptance rate (48.5 percent versus 79.8 percent).

Figure 1 Panel A shows that the average credit application rate is highest in Spain in Italy (17.4 and 16.8 respectively) and lowest in the Netherlands (10.5 percent). This is possibly due to the fact that Italian and Spanish consumers express the highest concerns about the financial consequences of COVID-19 whereas the Dutch are the least concerned. These differences are significantly different at the 5-percent level. The average acceptance rate is highest in Italy (80.5 percent) and lowest in Germany (62.6 percent), as shown in Figure 1 Panel B. This may reflect the tightened of credit standards of loans to households in Germany compared to Italy.

Figure 1 about here

Figure 1: Credit application rates and acceptance rates across countries



Notes: Figure 1 shows the estimated means of the application rates at the 95% confidence interval for the six Euro area countries surveyed in the CES, e.g. Belgium, Germany, Spain, France, Italy and the Netherlands.

4. Empirical results

We empirically investigate what types of households participate in the credit market. In particular, we explore what factors are associated with the probability of a household to apply for a loan and the probability of a household's loan to be accepted.

4.1. Determinants of credit applications

Table 4 reports the estimated marginal effects and standard errors derived from the probit model (1) that shows the probability of credit application. Two specifications are considered, all of which account for country and time fixed effects. *Specification (1)* is the baseline specification and is based on 14,995 households who respond the survey repeatedly over time.

Table 4 about here

Age dummies are jointly significant at the 1-percent level. The applications rate is monotonically decreasing with age. The probability to apply for credit is 10 percentage points higher for the youngest cohorts (18-34 years old) than the oldest cohorts (65+ years old) that serves as the reference group. The marginal effects are always positive when moving along the age dimension, but reduced in their magnitude, which implies that the application rate is always higher, but less intense for the respondents below 65 years if compared to the respondents aged 65 or more. This age profile is consistent with the lifecycle model of consumption and with some of the existing literature: young people are more likely to borrow than members of older age groups as they have lower level of current income and savings (Crook 2006; Fabbri and Padula 2004, among others).

Females are significantly less likely to apply for credit than males (the marginal effect equals 3.7 percentage points). This is may be due to their lower level of expected future income, as well as their higher level of risk aversion (see Jappelli, 1990).

Education is another significant (at the 1-percent level) determinant of credit applications. The highly educated are 2 percentage points more likely to apply. This finding is consistent with Grant (2007) and Del Rio and Young (2005), who find that having higher educational qualifications is associated with a higher probability of having unsecured debt. The empirical literature suggests that higher levels of education are a robust proxy of rising future earnings and greater information-processing skills, that make the participation in the credit market more profitable.

Neither household size nor the presence of a partner is a significant determinant of credit applications, but the number of children is significant (at the 5-percent level) and has a positive marginal effect. These findings stress the role of the dependent children as the main household members responsible for credit applications.

Income quintiles are jointly significant (at the 1-percent level): the people who belong to the two lowest quintiles are significantly less likely to apply for credit than the ones who belong to the top quintile. Being unemployed is negatively correlated to credit applications, but its effect is not significant, likely due to the typical collinearity with income. Our findings on income are consistent with Fabbri and Padula (2004) who find a positive relation between levels of debt and current income. Del Rio and Young (2005a) and Magri (2007) show that for middle-range levels of income, the marginal utility of consumption is high and income rises can generate higher spending and subsequent increased demand for credit. Crook (2006) also shows that high-income individuals have a greater probability of having debt also due to the probability of facing fewer supply side constraints.

Risk aversion is negatively correlated to credit application: being risk averse or risk neutral significantly reduces the application rate if compared to being risk seeking.

Having an outstanding mortgage, being financially concerned due to COVID-19, reporting that credit is harder than 12 months prior, and being liquidity constrained are positively and significantly associated with the probability to apply for credit (at the 1-percent level) . Financial literacy is another significant (at the 1-percent level) determinant, but it takes a negative sign, which is a bit puzzling and needs further investigation.

We also provide evidence that financial literacy has a negative and statistically significant impact on the probability of financial distress. In order to better understand how financial literacy affects the decision to apply for credit, we split the sample into liquidity constrained and liquidity unconstrained consumers and we separately estimate the probit model of credit application for the two sub-samples. The results, reported in the Appendix, show that the estimated marginal effect of financial literacy for the unconstrained group is negative and significant in line with our basic specification reported in Table 4. However, the estimated marginal effect of financial literacy for the liquidity constrained sample is very low in magnitude and statistically insignificant. This suggests that the negative marginal effect of financial literacy is solely attributed to consumers that are not subject to liquidity constraints, who represent 73 percent of the sample.

Some literature analyses the effect of town and city size on indebtedness. Fabbri and Padula (2004) and Magri (2002), for example, report that residents in smaller towns have a lower probability of having debt. The authors propose the greater presence of informal credit circuits in these contexts as an explanation. We control for degree of urbanization in *Specification (2)*. The number of households drops from 14,995 to 9,709 because this information is collected in a non-regular module fielded in November 2020. Only respondents who were in the panel at that point could answer this question, therefore the lower number of observations when this variable is included in this specification. We find that, compared to rural areas, households living in large cities, suburban areas and medium-size towns are significantly (at the 1-percent level) more likely to apply for credit.

Among economic determinants, income growth is also included in specification (2). Demand for credit is positively influenced by expectations of increased future receipts, as posited by the life-cycle theory: if there were no expectations of increased income in the future, there would be no need to advance spending via debt (Cox and Jappelli 1993, among others). In our analysis, the estimated marginal effect for income growth is positive but insignificant.

To check whether these results are robust across time, we re-estimate the same model specifications in two separate subperiods: from April 2020 to October 2020, and from January 2021 to April 2021. The results are presented in the Appendix (Table A.3) and are qualitatively similar to those of Table 4..

4.2. Determinants of credit acceptances

Table 5 reports the estimated marginal effects along with the corresponding standard errors, derived from the probit model (2). It shows the probability of credit acceptance with respect to the respondents who applied for credit and had their amount granted either in full or in part. Three specifications are considered, where country and time fixed effects are always included. *Specification (1)* is the baseline specification and is based on 3,502 households. The much lower number of households if compared to the application rate is due to the fact that (i) we look at the subsample of respondents who applied for credit and that (ii) for many respondents the outcome of their application is still unknown, which makes it impossible to identify whether the credit application is approved or not.

Table 5 about here

Age is jointly significant (at the 1-percent level). The age function is concave with the middle-aged households (aged 50-55 years old) having the highest probability to get their credit application approved if compared with the oldest old (66 plus). It seems that lenders prefer to grant loans to consumers of this age group due to their higher ability to service their debt.

Larger households are significantly (at the 5-percent level) less likely to have their application approved (the marginal effect equals 2.7 percentage points).

The applicant’s income is a major factor when it comes to being approved for a loan. Lenders prefer borrowers who have a stable, predictable income to those who do not. While they look at the applicant’s income from any work, additional income (such as that from investments) is included in their assessment. We find that income quintiles are jointly significant (at the 1-percent level): compared to the highest income quintile, the households belonging to any of the lower quintiles are less likely to get approval. The magnitude of the marginal effects is higher for the households in the two bottom quintiles (13.5 and 8.3 percentage points, respectively), followed by the ones in the fourth and third quintiles (5.4 and 3.4 percentage points, respectively.

Being unemployed significantly (at the 1-percent level) reduces the probability to obtain credit (the marginal effect equals 15.2 percentage points). This finding, consistent with Del Rio and Young (2005a), is not conforming to the Permanent Income theory that postulates that those temporarily without a job should increase their demand for credit. Instead, it is consistent with the fact that banks and lenders often review their applicants' employment histories. Lenders want to ensure that borrowers can afford to make regular mortgage payments, and applicants often need to prove that they have a steady source of income. On the contrary, being a home owner and having higher financial literacy significantly (at the 5-percent and 1-percent level, respectively) increases the probability to obtain credit (the marginal effects equal 4.4 and 7.1 percentage points, respectively). These results may be explained by the role of collaterals and of the ability to better judge the chances to successfully apply for credit. In fact, according to the theoretical models, uncertainty about future income is a factor that reduces borrowing. The empirical evidence shows indeed that demand for personal loans is higher for the employed than for the self-employed, who are subject to greater uncertainty in their future income (Crook 2006; Magri 2007). The unemployed not having as much credit as they should can be explained by their pessimism about their future work chances and by supply-side restrictions. Individuals who are already retired have a lower probability of holding debt due to their advanced age that does not allow further expectations of rising future income.

In *Specification (2)* we use an indicator for having at least one late payment in the past 12 months as a proxy for the personal credit score. It is normal practice, in fact, that lenders look at the applicant's credit score and credit history in order to get a sense of how the applicant's manage money and the likelihood that he/she will be able to pay back the requested loan. In addition, lenders also check to see if there are any dispute statements or pending disputes on the applicant credit report, and may look upon them negatively. The estimated marginal effect is strongly significant (at the 1-percent level) and negative. As expected, past delinquencies affect credit approvals adversely and quite strongly: the marginal effect is 28.2 percentage points and significant at the 1-percent level.

Finally, in *Specification (3)* we control for degree of urbanization and find that, if compared to rural areas, all other areas are negatively associated to credit acceptance. More precisely, living in sub-urban and medium-sized towns significantly reduces credit approvals. If combined with the finding for the application rate, we conclude that living is non-rural areas significantly increases the probability to apply for credit, but it decreases the probability to actually obtain the demanded credit. A potential explanation of this duality is the fact that in larger cities the supply of credit is larger, so that the households are in general more willing to demand credit, also those who do not have a lot of chances to obtain it. In rural areas, instead, the formal credit channel is less pronounced, possibly competing with informal channels from family and friends. Households who live in rural areas are less encouraged to apply for credit, but once they do, they have better chances to get it, likely reflecting also closer relationships between the lender and the borrower.

As for the credit applications, we perform a robustness check for the credit acceptance by splitting the data between April-October 2020 and January-April 2021. Our results are confirmed in both subperiods, as shown in Table A.3 in the Appendix.

4.3. Role of country and time in credit applications and in credit acceptances

Cross-country analyses can reveal the effect of institutional factors on individual behaviour. Even if the set of individual variables influencing demand for credit are common across countries, significant differences may emerge regarding how individuals respond to certain adverse events. These differences cannot be explained solely on the basis of individuals' deviant behaviour with regard to debt, but also on the basis of differences in the efficiency and effectiveness of institutional factors (Crook 2006; Bianco et al. 2007).

Table 6 reports the results related to the country and time dummies that were included in Table 4. Germany and April 2020 serve as the reference groups in the three specifications. In all specifications, both the country and the time dummies are jointly significant at the 1-percent level.

Table 6 about here

In all countries but Italy, the probability to apply for credit is significantly (at the 1-percent level) lower than in Germany. This result is robust across the three model specifications. The marginal effect is highest for the Netherlands, where the probability to apply for credit is lower by 5.2-5.8 percentage points than in Germany. This is also linked to the lowest application rate in the Netherlands observed in Table 1. The second highest marginal effect is found for Belgium (3.7-4.1 percentage points) in line with the lower application rate compared to that of Germany, as seen from Table 1. Italy exhibits the lowest marginal effect (0.6-1.3 percentage points) and it is statistically insignificant.

The probability to apply for credit is significantly (at the 1-percent level) lower in January 2021 and April 2021 than in April 2020. This result is robust across the two empirical specifications. In particular, the marginal effect for January 2021 are 2.8 and 2.7 percentage points wherea for April 20211.4 and 1.5 percentage points, respectively. are 2.8 and 2.7 percentage points. Two plausible reasons could explain this pattern. Households might be applying in order to overcome the adverse effect of the lockdown measures put in place in the summer 2020 to contrast the COVID-19 pandemic. The demand for credit might have had the primary need to ease liquidity problems, as also confirmed by the significant role of the liquidity constrained indicator. The second explanation might be that the financial support measures promised by the national governments were received later in time, likely as of the start of 2021 and throughout that year. In this respect, the financial support measures might have served as substitute of the more traditional demand for credit during the pandemic. Finally, the probability is higher in July 2020 and October 2020, but insignificant.

Table 7 reports the results related to the country and time dummies that were included in the probit model of credit acceptance (2). Germany and April 2020 serve as the reference groups in the three specifications.

Table 7 about here

In Spain, France and Italy the probability to get credit approval is significantly (at the 1-percent level) higher than in Germany. In Belgium the probability to get credit approval is significantly (at the 5 -percent level) higher than in Germany. In the Netherlands the probability is still higher than in Germany, but insignificant. This result is robust across the three model specifications. The marginal effect is highest for Italy, where the probability to get credit approval is higher by 14.1-15.3 percentage points than in Germany. The other countries are rather homogeneous in terms of magnitude of the marginal effects. The results suggest that the credit standards of loans to households during the COVID-19 pandemic have been significantly less tightened in Italy, France, Spain and Belgium compared to Germany. This is consistent with the lowest acceptance rate in Germany reported in Table 1. Finally, in favour of our evidence, results from the BLS shows that Germany exhibits the highest rejection rate for loans to households for house purchase compared to France, Spain and Italy from June 2020 to April 2021.

The probability of credit acceptance is significantly (at the 1-percent level) lower in all quarters than in April 2020. In other words, obtaining credit becomes significantly less likely after the onset of the COVID-19 pandemic, and monotonically worse in two model specifications out of three (in specification (2) and (3)). The marginal effects are rather large and range between 5.6 and 15.7 percentage points. A plausible explanation of this finding is the increased risk aversion of the banking sector to lend to the household sector during the pandemic, due to the high uncertainty that would go along with it. This is in line with BLS documenting that since the second quarter of 2020 banks have tightened the credit standards of the loans to the households reflecting their strongly increased risk perceptions with respect to the deterioration of the economic outlook and the worsened creditworthiness of the household sector.

4.4. Credit applications by type of credit

The CES collects information about eight types of credit: mortgage to purchase a house or other real estate or a housing loan for home renovation mortgage; a loan to purchase a car, motorbike or other vehicle; another type of consumer loan or instalment debt; a leasing contract (e.g. on a car); a credit card or an account with an overdraft facility with a financial institution; a loan for education purposes; an increase in the limit of an existing loan; refinancing of current mortgage. Table 8 collects the credit application rates for each of these types by country and over time. We observe that the application rates for other types of consumer loan or instalment debt as well as for a credit card or an account with an overdraft facility with a financial institution are more common in Spain and Italy in all quarters. The maximum application rates in Spain are 6.92 percent for the former type and 3.95 percent for the latter type, both in April 2020; in Italy the corresponding figures are 6.61 in April 2020 and 4 percent in October 2020. Leasing contracts, on the contrary, are most common in Germany, peaking at 3.63 percent in April 2021. Loans for educational purposes are most popular in the Netherlands (where they reach the maximum value of 1.58 percent in July 2020) and in Spain (where they represent 1.33 percent in October 2020).

Table 8 about here

We further investigate the probability of a consumer to apply for credit focusing on specific categories of credit. The analysis by type of credit is reported in Table 9. The regression analysis for secured and unsecured credit (columns 1 and 2) is based on specification (3) from Table 4 and it aims to identify whether these two groups of credit differ in some respect.[14] We find that the probability of the secured credit application rate is significantly (at the 10-percent level) higher in the presence of a partner and lower for the bottom income quintiles, whereas these variables are not significant for the unsecured credit application rate. This finding can be explained by the fact that lenders typically want the applicant to put money down on a home so he/she has some equity in the house. This practice protects the lender because the lender wants to recoup all the funds they have loaned if the applicant does not pay.

We also find that being financially concerned due to the pandemic as well as being liquidity constrained are significant (at the 1-percent level) determinants of the unsecured credit, but not at all of the secured credit. This suggests that consumer confidence, proxied by the financial concerns due to COVID-19 pandemic and the liquidity constraints, affects to a major extent the probability to apply for non-collateralized loans. Highly educated households are more significantly likely to apply for secured vis-à-vis unsecured credit (1-percent level versus 5-percent level) and display a higher marginal coefficient (13 percentage points versus 10 percentage points). In the literature there is some evidence that education levels affects secured debt and less so for the unsecured debt (see e.g. Grant 2007; Del Rio and Young 2005a). Levels of education in general can reasonably be seen to have a positive impact on the household's ability to access and assess financial products and services. This aspect should logically play an important role in the presence of complex products or large loan amounts, such as mortgages. In fact, educational qualifications appear to be a less important factor for simple, easy-to-understand small loan packages, which are distributed not only by lenders over-the-counter, but also directly by retail stores. Ferri and Simon (2000) use the ratio between cash and financial instruments as a proxy for individuals' educational levels and report that the lower

[14] Secured credit includes mortgage to purchase a house or other real estate or a housing loan for home renovation mortgage, refinancing of current mortgage, a credit card or an account with an overdraft facility with a financial institution; unsecured credit includes a loan to purchase a car, motorbike or other vehicle, another type of consumer loan or instalment debt, a leasing contract (e.g. on a car), a loan for education purposes, an increase in the limit of an existing loan.

the ratio, the higher the level of financial expertise which, in turn, raises awareness regarding the decision to borrow.

When looking at single credit types, we notice that the age effect is significant for mortgage to purchase a house or other real estate or a housing loan for home renovation mortgage, and for a loan to purchase a car, motorbike or other vehicle, whereas it is not for neither a credit card or an account with an overdraft facility with a financial institution nor for refinancing of current mortgage and consumer credit (see columns 3-7 of Table 9). Being highly educated is a significant (at the 1-percent level) determinant of holding a mortgage to purchase a house or other real estate or a housing loan for home renovation mortgage, and for a credit card or an account with an overdraft facility with a financial institution. The number of children is significantly (at the 1-percent level) increasing the probability to apply for a credit card or an account with an overdraft facility with a financial institution (the marginal effect is 0.5 percentage points), likely reflecting the relatively higher need of liquidity in the household for daily activities. We provide evidence that low income consumers are negatively and significantly (at the 5-percent level) associated with the probability of applying for mortgage to purchase a house or other real estate or a housing loan for home renovation mortgage. In addition, we find that middle-income consumers are more likely to apply for consumer credit.

Table 9 about here

5. Concluding remarks

This paper focuses on the household participation in the credit market in the Euro area at the onset of the COVID-19 pandemic. The empirical analysis of the determinants of the credit applications and those of the credit acceptances is based on the novel data collected in the Consumer Expectations Survey between April 2020 and April 2021 in the six largest Euro area countries. The main findings of our study are summarized as follows.

The credit application rate is monotonically decreasing with age, so that, consistently with the lifecycle model of consumption, the probability to apply for credit is higher for the youngest cohorts. Females are significantly less likely to apply for credit than males. Education is another significant determinant of credit applications: higher levels of education are associated to higher probability to apply for a loan, as being a robust proxy of rising future earnings and greater information-processing skills. In addition, the number of children is significantly and positively correlated with the probability to apply for credit. We also find that the households who belong to the two lowest income quintiles are significantly less likely to apply for credit than the ones who belong to the top quintile. Low risk aversion, having an outstanding mortgage, being financially concerned due to COVID-19, reporting that credit is harder than 12 months prior, and being liquidity constrained are positively and significantly associated with the probability to apply for credit. In addition, being financially literate decreases the probability to apply for credit for the consumers who are not subject to liquidity constraints. Finally, compared to rural areas, households living in large cities, suburban areas and medium-size towns are significantly more likely to apply for credit.

The credit acceptance rate is significantly affected by the applicant's age (the age function is concave with the middle-aged households -- aged 50-55 years old -- having the highest probability to get their credit application approved if compared with the oldest old -- 66 plus), the household size (larger households are less likely to have their application approved), the applicant's income (compared to the highest income quintile, the households belonging to any of the lower quintiles are less likely to get approval), the applicant's employment status (being unemployed reduces the probability of credit acceptance), as well as home ownership and financial literacy. In addition, having past delinquencies affects credit approvals adversely, and if compared to rural areas, all other areas are negatively associated to credit acceptance. More precisely, living in sub-urban and medium-sized towns significantly reduces credit approvals.

The analysis of the country effect shows that in all countries the probability to apply for credit is significantly lower than in Germany, with the only exception of Italy. We also find that the probability to get credit approval is significantly higher than in Germany in all countries but the Netherlands, for which the difference is not significant. The results suggest that the credit standards of loans to households during the COVID-19 pandemic have been significantly less tightened in Italy, France, Spain and Belgium vis a vis Germany.

Our results also suggest that the timing of the credit application is important. The probability to apply for credit is significantly lower in January 2021 and April 2021 than in April 2020. This suggests that the demand for credit was higher for the first lockdown period of the COVID-19 pandemic. In addition, the probability of credit acceptance is significantly lower in all quarters than in April 2020. In other words, obtaining credit becomes significantly less likely after the onset of the COVID-19 pandemic. We rationalize this finding by the increased risk aversion of the banking sector to lend to the household sector during the pandemic, due to the high uncertainty that would go along with it, also confirmed by BLS data.

Finally, the analysis by type of credit shows that the secured credit has different determinants from the unsecured credit. In particular, the probability of the secured credit application rate is significantly higher in the presence of a partner and lower for the bottom income quintiles, whereas these variables are not significant for the unsecured credit application rate. We also find that being financially concerned due to the pandemic as well as being liquidity constrained are significant determinants of the unsecured credit, but not at all of the secured credit.

This paper has potentially important implications for monetary and fiscal policy and more broadly for welfare and growth. Our findings highlight which specific population groups need more credit such as young, liquidity constrained and low-income households. Reflecting this heterogeneity, our results suggest that monetary policy and fiscal measure will be most effective in ensuring financial stability if they focus on such vulnerable groups. In addition, we document which groups of consumers are more likely to be dropped out of the credit market, such as unemployed, financially illiterate and low-income consumers and consumers that have delinquencies on their payments and no home ownership. Therefore, economic measures that could minimize the share of consumers being credit constrained, for example a tax cut should target these groups of consumers.

Bibliographic references

Alessie, R., Kapteyn, A. and Klijn, F. (1997). Mandatory pensions and personal savings in the Netherlands. *De Economist* 145(3), 291-324.

Ando, A. and Modigliani, F. (1957). Tests of the life-cycle hypothesis of savings: Comments and suggestions. *Bulletin of the Oxford Institute of Statistics* 19, 99-124.

Attanasio, O. P. (1999). Consumption. Handbook of Macroeconomics. In: J. B. Taylor & M. Woodford (ed.), Handbook of Macroeconomics, edition 1, volume 1, chapter 11, 741-812, Elsevier.

Bagliano, F.C. and Bertola, G. (2004). Models for Dynamic Macroeconomics. Oxford University Press.

Besley, T. (1995). Savings, credit and insurance. *Handbook of Development Economics*, III, ed. J. Behrman and T. N. Srinivasan. Amsterdam and New York: Elsevier.

Bianco, M., Giacomelli, S., Giorgiantonio, C., Palumbo, G. and Szego, B. (2007). La durata (eccessiva) dei procedimenti civili in Italia: offerta, domanda o rito? *Rivista di Politica Economica*, 97(3), fascicolo IX-X.

Browning, M., and Lusardi A. (1996). Household saving: Micro theories and micro facts. *Journal of Economic Literature* 4, 1797–1855.

Cox, D. and Jappelli, T. (1993). The effect of borrowing constraints on consumer liabilities. *Journal of Money Credit and Banking* 25, 197–213.

Crook, J. (2006). The demand and supply of household debt: A cross country comparison. In Bertola, G., Disney, R. and Grant, C. eds. (2006). The Economics of Consumer Credit. Cambridge MA: MIT Press.

Crossley, T.F. and Low, H.W. (2014). Job loss, credit constraints, and consumption growth. *The Review of Economics and Statistics* 96(5), 876–884.

Deaton, A. (1992). Understanding consumption. Oxford: Oxford University Press.

Del-Rio, A. and Young, G. (2005). The determinants of unsecured borrowing: Evidence from the British Household Panel Survey. Bank of England Working Paper No. 263, Available at SSRN: https://ssrn.com/abstract=824164 or http://dx.doi.org/10.2139/ssrn.824164

ECB (2021). The ECB’s Consumer Expectations Survey: An overview and first evaluation, forthcoming, ECB Occasional Paper Series.

Fabbri, D., and Padula, M. (2004). Does poor judicial enforcement make households credit-constrained?. *Journal of Banking & Finance* 28, 2369-2397.

Ferri, G. and Simon, P. (2000). Constrained consumer lending: Methods using the Survey of Consumer Finances.

Friedman, M. (1957). A theory of the consumption function. NBER Books, National Bureau of Economic Research, Inc, number 57-1, November.

Georgarakos, D. and Kenny, G. (2021) Euro Area Household Sector Adjustment during the Global Pandemic: Insights from a New Consumer Survey," mimeo, European Central Bank.

Grant, C. (2007). Estimating credit constraints among US households. *Oxford Economic Papers* 59, 583-605.

Gross, D. and Souleles N. (2002). Do liquidity constraints and interest rates matter for consumer behaviour? Evidence from credit card data. *Quarterly Journal of Economics*, 117(1),149-85

Hall, R.E. and Mishkin, F.S. (1982). The sensitivity of consumption to transitory income: Estimates from panel data on households. *Econometrica* 50(2), 461-481.

Jappelli, T., Piske J-S. and Souleles, N. (1998). Testing for liquidity constraints in Euler equations with complementary data sources. *Review of Economics and Statistics*, 80(2), 251-262.

Jappelli, T. (1990). Who is credit constrained in the U.S. economy? *The Quarterly Journal of Economics* 40(1), 219–234.

Leth-Petersen, S. (2010). Intertemporal consumption and credit constraints: Does consumption respond to an exogenous shock to credit? *American Economic Review*100(3), 1080-1103

Magri, S. (2002). Italian household debt: Determinants of demand and supply. Banca d'Italia, Temi di discussione del Servizio Studi, 454.

Magri, S. (2007). Italian households' debt: The participation to the debt market and the size of the loan. *Empirical Economics* 33, 401–426.

Modigliani, F. (1988). The role of intergenerational transfers and life cycle saving in the accumulation of wealth. *Journal of Economic Perspectives* 2, 15-40.

Modigliani, F., Jappelli, T. and Pagano, M. (1985). The impact of fiscal policy and inflation on national saving: the Italian case. *Banca Nazionale del Lavoro Quarterly Review* 153, 91-126.

Modigliani, F. and Brumberg, R.H. (1954). Utility Analysis and the Consumption Function: An Interpretation of Cross-Section Data. In: Kurihara, K.K., Ed., Post-Keynesian Economics, Rutgers University Press, New Brunswick, 388-436.

Tufano, P. (2009). Consumer finance. *Annual Review Financial Economics*, 1(1), 227-247.

Xiao, J. and Tao, C. (2020). Consumer finance / household finance: the definition and scope. *China Finance Review International*, 11(1), 1-25.

Zeldes, S. P. (1989). Consumption and liquidity constraints: An empirical investigation. *Journal of Political Economy* 97(2), 305-346.

Tables and Figures

Table 1: Summary Statistics

VARIABLE	Mean	Min	Max	SD	N	HHs
Credit application rate	0.153	0	1	0.360	46788	15682
Credit acceptance rate	0.710	0	1	0.454	5019	3588
Age 18-34 years	0.234	0	1	0.423	50744	18610
Age 35-50 years	0.345	0	1	0.475	50744	18610
Age 50-55 years	0.136	0	1	0.343	50744	18610
Age 56-60 years	0.101	0	1	0.302	50744	18610
Age 61-65 years	0.090	0	1	0.286	50744	18610
Age over 65 years	0.094	0	1	0.292	50744	18610
Female	0.511	0	1	0.500	50717	18599
Higher education	0.544	0	1	0.498	50744	18610
HH size (truncated)	2.681	1	5	1.191	50744	18610
Presence of a partner	0.643	0	1	0.479	50744	18610
Number of children	0.707	0	3	0.931	50744	18610
Net income quintiles	2.976	1	5	1.409	50744	18610
Unemployed	0.105	0	1	0.306	50744	18610
Low risk	0.479	0	1	0.500	49775	18245
Medium risk	0.228	0	1	0.419	49775	18245
High risk	0.293	0	1	0.455	49775	18245
Mortgage holders	0.301	0	1	0.459	50744	18610
Financial concerns	6.172	0	10	2.703	50172	16606
Credit access harder than 12 months earlier	0.310	0	1	0.462	48521	16304
Insufficient liquidity	0.291	0	1	0.454	50740	16692
Financial literacy	2.423	0	4	1.133	50744	18610
Degree of urbanization (categorical)	3.209	1	5	1.426	41852	10093
Expected net total household income growth	0.141	-30	30	9.298	50740	16799
Home ownership	0.643	0	1	0.479	50744	18610
At least 1 past late payment	0.110	0	1	0.313	47497	15776

Notes: This table reports the basic summary statistics for each variable used in the study along with the number of households (HHs) that correspond to each variable.

Table 2: Application and Acceptance Rates across time and countries

Time Period	EA	BE	DE	ES	FR	IT	NL
Apr-20	15.8	13.5	15.0	19.6	15.8	16.8	11.3
Jul-20	15.3	10.8	15.8	16.6	15.1	17.5	12.2
Oct-20	16.9	15.9	16.2	18.5	17.3	20.0	8.8
Jan-21	13.7	12.7	14.0	15.1	11.9	15.3	10.8
Apr-21	14.8	12.3	16.4	17.5	14.6	14.3	9.4
Time Period	EA	BE	DE	ES	FR	IT	NL
Apr-20	81.7	79.3	79.6	77.1	86.5	85.8	80.3
Jul-20	74.0	77.0	64.3	68.9	83.9	79.0	75.6
Oct-20	66.8	63.8	60.5	64.8	63.1	80.5	69.6
Jan-21	66.8	73.1	58.8	69.7	63.4	77.9	53.4
Apr-21	67.5	71.6	56.8	72.0	63.4	79.3	62.3

Notes: This table reports the credit application and acceptance rates across time and countries.

Table 3: Heterogeneity in Credit Application and Credit Acceptance Rates

VARIABLES	Descriptive Statistics		
Panel A: Credit Application Rate			
	Mean	SD	N
Age group			
18-34 years	0.207	0.405	10309
35-49 years	0.171	0.376	16126
50-55 years	0.136	0.343	6546
56-60 years	0.12	0.325	4893
61-65 years	0.096	0.294	4361
Over 65 years	0.081	0.273	4574
HH Size			
1	0.111	0.315	8260
2	0.128	0.334	15416
3	0.182	0.386	10321
4	0.181	0.385	9534
5+	0.204	0.403	3278
No. children			
0	0.131	0.338	26620
1	0.18	0.384	9340
2	0.177	0.382	8534
3+	0.204	0.403	2315
Mortgage			
No	0.137	0.344	32479
Yes	0.189	0.391	14330
Hard past (credit access)			
No	0.14	0.347	30810
Yes	0.198	0.398	13947
Illiquid (unexpected payment)			
No	0.139	0.346	33697
Yes	0.189	0.392	13109
Panel B: Credit Acceptance Rate			
	Mean	SD	N
Age Group			
18-34 years	0.607	0.489	1318
35-49 years	0.729	0.444	1929
50-55 years	0.774	0.419	677
56-60 years	0.749	0.434	470
61-65 years	0.728	0.446	320
Over 65 years	0.816	0.338	309
Partner			
No	0.667	0.472	1569
Yes	0.73	0.444	3454

Income Quintile			
1	0.576	0.495	940
2	0.653	0.476	793
3	0.728	0.445	1128
4	0.74	0.439	1065
5	0.82	0.384	1097
Financial Literacy			
0	0.503	0.501	292
1	0.581	0.494	893
2	0.678	0.468	1325
3	0.767	0.423	1619
4	0.852	0.355	894
Unemployed			
Yes			4491
No			532
Past Late Payments			
No	0.798	0.401	3725
Yes	0.485	0.5	1085

Notes: This table reports heterogeneity in credit application and acceptance rates across specific groups of households. Credit application rates vary across age, household size, households with number of children, outstanding mortgage, hard access to credit and liquidity constraints. Credit acceptance rates vary across age, income quintiles, financial literacy, unemployed households and households with partner and liquidity constraints.

Table 4: Probit model of Credit Applications

	(1)	(2)
VARIABLES	Marg. Effects	Extra MEs
Age 18-34	0.104***	0.097***
	(0.010)	(0.011)
Age 35-49	0.054***	0.053***
	(0.009)	(0.010)
Age 50-55	0.037***	0.033***
	(0.010)	(0.011)
Age 56-60	0.026**	0.021*
	(0.011)	(0.011)
Age 61-65	0.016	0.018
	(0.011)	(0.012)
Age over 65 = o	-	-
Female	-0.037***	-0.032***
	(0.005)	(0.006)
High education	0.021***	0.020***
	(0.006)	(0.006)
Household size (censored)	0.006	0.004
	(0.004)	(0.004)
Partner	0.001	0.007
	(0.006)	(0.007)
Number of children (censored)	0.010**	0.012**
	(0.005)	(0.005)
1st income quintile	-0.032***	-0.037***
	(0.009)	(0.010)
2nd income quintile	-0.022**	-0.022**
	(0.009)	(0.010)
3rd income quintile	0.003	0.006
	(0.009)	(0.010)
4th income quintile	-0.006	-0.009
	(0.008)	(0.009)
Unemployed	-0.002	-0.002
	(0.008)	(0.009)
Risk averse	-0.009	-0.004
	(0.006)	(0.007)
Risk neutral	-0.018***	-0.015**
	(0.007)	(0.008)
Outstanding mortgage	0.045***	0.045***
	(0.007)	(0.007)
Financial concerns	0.003***	0.003***
	(0.001)	(0.001)
Credit harder than 12 months earlier	0.051***	0.056***

	(0.006)	(0.007)
Insufficient liquidity	0.031***	0.030***
	(0.007)	(0.007)
Financial literacy	-0.016***	-0.015***
	(0.003)	(0.003)
Big city (residence)		0.019**
		(0.009)
Suburb of big city (residence)		0.055***
		(0.011)
Mid-size city (residence)		0.042***
		(0.009)
Small city (residence)		0.005
		(0.008)
Rural area (residence) = o		-
Expected net total HH income growth		0.000
		(0.000)
Constant		
Observations	43,540	36,137
HHs (Cluster)	14995	9709
Pseudo R-squared	0.0443	0.0508
Joint Country (p-vauel)	0.00	0.00
Joint Wave (p-value)	0.00	0.00
Joint Age (p-value)	0.00	0.00
Joint Income (p-value)	0.00	0.00

Note: This table reports the probit marginal effects of credit applications. Data are drawn from April 2020 to April 2021 quarterly waves of CES. Time and country dummies are also included, ***, ** and * denote significance at 1%, 5% and 1% level. Robust standard errors in parentheses.

Table 5: Probit model of Credit Acceptance

	(1)	(2)	(3)
VARIABLES	Marg. Effs.	Extra MEs	Extra MEs
Age 18-34	-0.072*	-0.064	-0.053
	(0.040)	(0.040)	(0.045)
Age 35-49	-0.006	-0.008	0.012
	(0.038)	(0.038)	(0.043)
Age 50-55	0.064	0.061	0.085*
	(0.041)	(0.040)	(0.045)
Age 56-60	-0.031	-0.014	0.011
	(0.048)	(0.045)	(0.052)
Age 61-65	-0.042	-0.019	-0.003
	(0.048)	(0.047)	(0.053)
Age over 65 = o,	-	-	-
Female	0.005	0.002	-0.003
	(0.019)	(0.019)	(0.021)
High education	0.003	0.022	0.031
	(0.019)	(0.019)	(0.021)
Household size (censored)	-0.027**	-0.024*	-0.022
	(0.013)	(0.013)	(0.015)
Partner	0.000	-0.006	-0.015
	(0.022)	(0.022)	(0.024)
Number of children (censored)	-0.010	0.003	-0.004
	(0.016)	(0.016)	(0.018)
1st income quintile	-0.135***	-0.100***	-0.081**
	(0.033)	(0.033)	(0.038)
2nd income quintile	-0.083***	-0.059*	-0.039
	(0.031)	(0.030)	(0.035)
3rd income quintile	-0.034	-0.012	0.008
	(0.027)	(0.026)	(0.029)
4th income quintile	-0.054**	-0.049*	-0.032
	(0.028)	(0.028)	(0.031)
Unemployed	-0.152***	-0.098***	-0.085***
	(0.030)	(0.029)	(0.032)
Risk averse	0.031	0.030	0.022
	(0.021)	(0.021)	(0.024)
Risk neutral	0.013	-0.012	-0.018
	(0.025)	(0.025)	(0.028)
Home ownership	0.044**	0.024	0.024
	(0.020)	(0.020)	(0.022)
Financial literacy	0.071***	0.054***	0.056***
	(0.008)	(0.008)	(0.009)
At least 1 late payment		-0.282***	-0.254***

		(0.025)	(0.028)
Big city (residence)			-0.033
			(0.032)
Suburb of big city (residence)			-0.163***
			(0.033)
Mid-size city (residence)			-0.096***
			(0.029)
Small city (residence)			-0.023
			(0.029)
Rural area (residence) = o,			-
Constant			
Observations	4,904	4,699	3,809
HHs (Cluster)	3502	3361	2556
Pseudo R-squared	0.107	0.147	0.150
Joint Country (p-value)	0.00	0.00	0.00
Joint Wave (p-value)	0.00	0.00	0.00
Joint Age (p-value)	0.00	0.00	0.00
Joint Income (p-value)	0.00	0.01	0.10

Note: This table reports the probit marginal effects of credit acceptance. Data are drawn from April 2020 to April 2021 quarterly waves of CES. Time and country dummies are also included, ***, ** and * denote significance at 1%, 5% and 1% level. Robust standard errors in parentheses.

Table 6: Country and Time Marginal Effects of Credit Applications

	(1)	(2)
DUMMIES	Marg. Effects	Extra MEs
Belgium	-0.037***	-0.041***
	(0.009)	(0.010)
Spain	-0.023***	-0.024***
	(0.008)	(0.009)
France	-0.032***	-0.030***
	(0.008)	(0.008)
Italy	-0.013	-0.006
	(0.008)	(0.009)
Netherlands	-0.052***	-0.058***
	(0.009)	(0.011)
July 2020	0.004	0.007
	(0.007)	(0.007)
October 2020	0.008	0.009
	(0.006)	(0.007)
January 2021	-0.027***	-0.028***
	(0.006)	(0.007)
April 2021	-0.014**	-0.015**
	(0.007)	(0.007)
Constant		
Observations	43,540	36,137
HHs (Cluster)	14995	9709
Pseudo R-squared	0.0443	0.0508
Joint Country (p-value)	0.00	0.00
Joint Wave (p-value)	0.00	0.00

Note: This table reports the probit marginal effects of country and time dummies of credit application. Data are drawn from April 2020 to April 2021 quarterly waves of CES. Time and country dummies are also included, ***, ** and * denote significance at 1%, 5% and 1% level. Robust standard errors in parentheses.

Table 7: Country and Time Marginal Effects of Credit Acceptance

	(1)	(2)	(3)
DUMMIES	Marg. Effs.	Extra MEs	Extra MEs
Belgium	0.085**	0.092***	0.104**
	(0.035)	(0.035)	(0.042)
Spain	0.107***	0.081***	0.082***
	(0.028)	(0.028)	(0.031)
France	0.126***	0.078***	0.080***
	(0.026)	(0.027)	(0.030)
Italy	0.152***	0.153***	0.141***
	(0.027)	(0.027)	(0.030)
Netherlands	0.023	0.047	0.070
	(0.040)	(0.039)	(0.050)
July 2021	-0.092***	-0.062***	-0.056**
	(0.022)	(0.022)	(0.025)
October 2020	-0.149***	-0.127***	-0.115***
	(0.022)	(0.023)	(0.025)
January 2021	-0.138***	-0.134***	-0.130***
	(0.022)	(0.022)	(0.025)
April 2021	-0.157***	-0.139***	-0.149***
	(0.024)	(0.023)	(0.027)
Constant			
Observations	4,904	4,699	3,809
HHs (Cluster)	3502	3361	2556
Pseudo R-squared	0.107	0.147	0.150
Joint Country (p-value)	0.00	0.00	0.00
Joint Wave (p-value)	0.00	0.00	0.00

Note: This table reports the probit marginal effects of country and time dummies of credit acceptance. Data are drawn from April 2020 to April 2021 quarterly waves of CES. Time and country dummies are also included, ***, ** and * denote significance at 1%, 5% and 1% level. Robust standard errors in parentheses.

Table 8: Type of Credit Applications across Countries and Time

BE	Mortgage	Car loan	Consumer credit	Leasing contract	Credit card or overdraft	Student loan	Limit Increase in existing loan	Mortgage refinance
Apr20	2.74	2.81	2.66	0.68	2.20	0.76	0.76	1.52
Jul20	3.04	2.09	1.14	1.62	1.62	0.86	0.29	1.62
Oct20	3.12	4.39	3.21	1.60	2.62	1.35	1.01	1.27
Jan21	2.89	2.79	2.60	1.35	1.93	1.35	1.64	1.54
Apr21	3.30	2.32	2.32	1.43	2.05	0.71	0.89	1.43
DE	Mortgage	Car loan	Consumer credit	Leasing contract	Credit card or overdraft	Student loan	Limit Increase in existing loan	Mortgage refinance
Apr20	1.82	2.47	2.99	2.47	2.86	0.91	1.56	1.69
Jul20	2.34	2.90	2.85	3.26	2.75	1.48	1.07	1.53
Oct20	1.53	5.81	3.40	2.05	2.05	0.79	0.98	1.30
Jan21	1.53	3.15	3.58	3.29	2.58	0.62	1.00	0.57
Apr21	1.44	4.02	6.01	3.63	1.99	0.55	0.94	0.75
ES	Mortgage	Car loan	Consumer credit	Leasing contract	Credit card or overdraft	Student loan	Limit Increase in existing loan	Mortgage refinance
Apr20	2.23	3.37	6.92	1.14	3.95	1.09	2.40	1.20
Jul20	2.11	3.09	5.64	1.28	3.83	0.93	2.16	1.18
Oct20	2.34	3.98	6.10	1.55	3.01	1.33	1.90	0.71
Jan21	2.70	2.94	5.16	1.56	2.42	0.95	1.42	0.52
Apr21	3.11	4.24	6.46	1.08	3.30	1.04	1.68	0.94
FR	Mortgage	Car loan	Consumer credit	Leasing contract	Credit card or overdraft	Student loan	Limit Increase in existing loan	Mortgage refinance
Apr20	2.84	3.10	3.87	0.77	2.00	0.84	1.16	1.55
Jul20	2.67	3.48	4.09	1.21	2.17	0.91	1.21	0.71
Oct20	2.72	5.25	3.92	2.86	2.35	0.88	0.97	0.88
Jan21	2.75	3.45	3.75	1.65	1.70	0.65	0.75	0.65
Apr21	3.44	4.47	3.49	2.31	2.65	0.93	1.18	0.93
IT	Mortgage	Car loan	Consumer credit	Leasing contract	Credit card or overdraft	Student loan	Limit Increase in existing loan	Mortgage refinance
Apr20	1.70	3.36	6.61	0.46	3.87	0.41	0.88	1.60
Jul20	2.57	3.90	5.81	1.00	3.00	0.57	1.00	1.76
Oct20	3.62	4.33	6.28	1.33	4.00	0.57	1.19	1.95
Jan21	2.72	2.82	5.19	0.94	3.51	0.40	0.99	1.14
Apr21	2.99	3.84	4.48	0.75	2.99	0.95	0.85	1.10
NL	Mortgage	Car loan	Consumer credit	Leasing contract	Credit card or overdraft	Student loan	Limit Increase in existing loan	Mortgage refinance
Apr20	3.25	0.67	1.48	0.96	1.48	1.26	0.44	1.18
Jul20	3.63	1.30	1.40	1.30	1.77	1.58	0.56	1.30
Oct20	1.97	1.16	1.16	1.43	1.79	0.90	0.45	1.25
Jan21	1.66	1.66	1.37	2.44	1.17	1.46	1.17	1.46
Apr21	2.48	1.10	1.19	1.10	1.65	0.92	0.55	1.74

Note: This table reports the application rate for each type of credit application across countries and over time.

Table 9: Probit Model of Credit Applications, by Type of Credit

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Secured	Unsecured	Mortgage	Auto Loan	Consumer Credit	Credit Card
Age 18-34	0.049***	0.039***	0.026***	0.037***	0.010	0.020***
	(0.007)	(0.008)	(0.004)	(0.004)	(0.006)	(0.005)
Age 35-49	0.022***	0.018**	0.019***	0.022***	0.006	0.001
	(0.006)	(0.007)	(0.003)	(0.004)	(0.006)	(0.004)
Age 50-55	0.008	0.014	0.007***	0.013***	0.006	-0.002
	(0.006)	(0.009)	(0.003)	(0.004)	(0.007)	(0.005)
Age 56-60	0.003	0.010	0.008***	0.011***	0.003	-0.005
	(0.006)	(0.009)	(0.003)	(0.004)	(0.007)	(0.004)
Age 61-65	-0.002	0.012	0.005*	0.011***	0.005	-0.006
	(0.006)	(0.009)	(0.003)	(0.004)	(0.008)	(0.004)
Female	-0.010***	-0.018***	-0.000	-0.008***	-0.011***	-0.009***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
High education	0.013***	0.010**	0.006***	0.002	0.004	0.007***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
Household size (censored)	0.000	0.004	0.001	0.003**	0.002	0.000
	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)
Partner	0.008**	0.001	0.004	0.001	-0.002	0.001
	(0.004)	(0.005)	(0.002)	(0.003)	(0.004)	(0.003)
Number of children (censored)	0.006*	0.009**	-0.000	0.003	0.004	0.005***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
1st income quintle	-0.011*	-0.009	-0.009**	-0.006	0.001	-0.001
	(0.006)	(0.007)	(0.003)	(0.004)	(0.005)	(0.004)
2nd income quintile	-0.012**	-0.006	-0.007**	0.000	0.002	-0.005
	(0.005)	(0.007)	(0.003)	(0.004)	(0.005)	(0.004)
3rd income quintile	0.000	0.009	-0.004	-0.001	0.016***	0.002
	(0.005)	(0.007)	(0.003)	(0.004)	(0.006)	(0.004)
4th income quintile	-0.005	-0.004	-0.003	0.000	0.005	-0.001
	(0.005)	(0.006)	(0.003)	(0.004)	(0.005)	(0.004)
Unemployed	-0.006	-0.001	-0.006***	-0.002	-0.006	0.002
	(0.005)	(0.006)	(0.002)	(0.004)	(0.004)	(0.004)
Risk averse	-0.001	0.003	-0.001	-0.006**	0.005	0.000
	(0.004)	(0.005)	(0.002)	(0.003)	(0.004)	(0.003)
Risk neutral	-0.002	-0.007	-0.002	-0.009***	-0.007*	0.003
	(0.004)	(0.005)	(0.002)	(0.003)	(0.004)	(0.003)
Outstanding mortgage	0.034***	0.015***	0.017***	0.005*	0.012***	-0.005**
	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.002)
Financial concerns	0.000	0.003***	-0.001*	0.000	0.002***	0.001**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Credit harder than 12 months earlier	0.027***	0.023***	0.012***	0.020***	0.016***	0.012***

	(0.004)	(0.005)	(0.002)	(0.003)	(0.004)	(0.003)
Insufficient liquidity = 1	0.001	0.038***	-0.002	-0.007***	0.027***	0.000
	(0.004)	(0.006)	(0.002)	(0.003)	(0.004)	(0.003)
Financial literacy = 1	-0.004**	-0.007***	-0.001*	-0.006***	-0.001	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Big city (residence)	0.011**	0.013**	0.003	0.000	0.005	0.009**
	(0.005)	(0.006)	(0.003)	(0.003)	(0.005)	(0.004)
Suburb of big city (residence)	0.017***	0.025***	0.005	0.024***	0.003	0.008**
	(0.006)	(0.007)	(0.003)	(0.005)	(0.005)	(0.004)
Mid-size city (residence)	0.015***	0.022***	0.003	0.013***	0.010*	0.011***
	(0.005)	(0.007)	(0.003)	(0.004)	(0.005)	(0.004)
Small city (residence)	0.003	-0.000	0.001	0.002	-0.001	0.002
	(0.004)	(0.006)	(0.002)	(0.003)	(0.004)	(0.003)
Expected net total HH income growth	0.000	0.000	0.000*	-0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	36,137	36,137	36,137	36,137	36,137	36,137
HHs (Cluster)	9709	9709	9709	9709	9709	9709
Pseudo R-squared	0.0540	0.0446	0.0767	0.0608	0.0433	0.0420
Joint Country (p-value)	0.00	0.00	0.00	0.00	0.00	0.00
Joint Wave (p-value)	0.00	0.01	0.15	0.00	0.03	0.01

Note: This table reports the probit marginal effects of credit applications. Data are drawn from April 2020 to April 2021 quarterly waves of CES. Time and country dummies are also included, ***, ** and * denote significance at 1%, 5% and 1% level. Robust standard errors in parentheses.

Appendix Tables

Table A1: Credit application and acceptance -Summary Statistics by country and time

VARIABLES	Application Rate			Acceptance Rate		
	Mean	SD	N	Mean	SD	N
Country						
BE	0.1311	0.337545	4836	0.726582	0.446279	395
DE	0.155163	0.36208	9287	0.625795	0.484137	1101
ES	0.173867	0.379015	9513	0.702911	0.457172	1168
FR	0.149307	0.356411	8948	0.713389	0.452415	956
IT	0.167798	0.373706	9577	0.805477	0.39602	1059
NL	0.104991	0.306575	4648	0.686047	0.464774	344
Time						
Apr-20	0.157515	0.364308	8031	0.817073	0.386821	902
Jul-20	0.153483	0.360472	9330	0.740061	0.438825	981
Oct-20	0.16946	0.375176	10144	0.668359	0.471002	1182
Jan-21	0.136642	0.343487	9631	0.668383	0.471037	971
Apr-21	0.147627	0.354749	9673	0.674772	0.468697	987

Notes:

Table A2: Credit application regressions – split by liquidity constrained status

	(1)	(2)	(3)	(4)
VARIABLES	Liquid MEs	Liquid Extra MEs	Non-Liquid MEs	Non-Liquid Extra MEs
Age 18-34	0.101***	0.091***	0.103***	0.105***
	(0.011)	(0.012)	(0.022)	(0.024)
Age 35-49	0.058***	0.054***	0.042**	0.046**
	(0.010)	(0.010)	(0.020)	(0.022)
Age 50-55	0.038***	0.034***	0.034	0.030
	(0.011)	(0.012)	(0.024)	(0.027)
Age 56-60	0.022**	0.015	0.030	0.032
	(0.011)	(0.011)	(0.025)	(0.028)
Age 61-65	0.018	0.018	0.011	0.018
	(0.011)	(0.012)	(0.026)	(0.029)
Female	-0.032***	-0.028***	-0.051***	-0.046***

	(0.006)	(0.006)	(0.011)	(0.013)
High education	0.014**	0.014**	0.037***	0.034***
	(0.006)	(0.007)	(0.012)	(0.013)
Household size (censored)	0.004	0.003	0.005	0.003
	(0.004)	(0.005)	(0.007)	(0.008)
Partner	0.008	0.014*	-0.013	-0.009
	(0.007)	(0.007)	(0.013)	(0.015)
Number of children (censored)	0.008	0.010*	0.018**	0.022**
	(0.005)	(0.006)	(0.009)	(0.010)
1st income quintle	-0.016	-0.020*	-0.074***	-0.086***
	(0.010)	(0.011)	(0.023)	(0.025)
2nd income quintile	-0.025***	-0.023**	-0.042*	-0.050*
	(0.009)	(0.010)	(0.023)	(0.026)
3rd income quintile	-0.001	0.002	-0.015	-0.017
	(0.009)	(0.010)	(0.023)	(0.026)
4th income quintile	-0.008	-0.010	-0.014	-0.024
	(0.008)	(0.009)	(0.024)	(0.027)
Unemployed	0.025**	0.022*	-0.034***	-0.034**
	(0.011)	(0.012)	(0.012)	(0.013)
Risk averse	-0.015**	-0.010	0.008	0.012
	(0.007)	(0.008)	(0.013)	(0.014)
Risk neutral	-0.022***	-0.019**	-0.005	-0.005
	(0.007)	(0.008)	(0.015)	(0.016)
Outstanding mortgage	0.042***	0.043***	0.050***	0.043***
	(0.007)	(0.008)	(0.013)	(0.015)
Financial concerns	0.006***	0.006***	-0.007***	-0.008***
	(0.001)	(0.001)	(0.002)	(0.002)
Credit harder than 12 months earlier	0.061***	0.065***	0.036***	0.043***
	(0.008)	(0.008)	(0.010)	(0.011)
Financial literacy	-0.020***	-0.019***	-0.000	0.002
	(0.003)	(0.003)	(0.005)	(0.006)
Big city (residence)		0.009		0.043**

		(0.009)		(0.019)
Suburb of big city (residence)		0.039***		0.094***
		(0.011)		(0.021)
Mid-size city (residence)		0.034***		0.059***
		(0.010)		(0.018)
Small city (residence)		-0.002		0.025
		(0.008)		(0.016)
Expected net total HH income growth		0.000		-0.000
		(0.000)		(0.000)
Constant				
Observations	31,347	26,258	12,193	9,879
HHs (Cluster)	11640	7919	5673	3854
Pseudo R-squared	0.0500	0.0554	0.0420	0.0548
Joint Country (pval)	8.31e-08	3.21e-08	1.58e-07	2.80e-06
Joint Wave (pval)	7.23e-06	1.32e-06	0.000122	0.000148
Joint Age (pval)	0	0	2.63e-06	6.92e-05
Joint Income (pval)	0.0400	0.0381	0.000491	0.000309

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Incl. country and wave dummies

Table A3: Credit application and acceptance regressions – Year split

VARIABLES	(1) Applied 2020	(2) Applied 2021	(3) Acc 2020	(4) Acc 2021
Age 18-34	0.102***	0.089***	-0.052	-0.077
	(0.014)	(0.013)	(0.050)	(0.071)
Age 35-49	0.054***	0.051***	0.009	-0.002
	(0.013)	(0.012)	(0.047)	(0.069)
Age 50-55	0.032**	0.034***	0.074	0.077
	(0.015)	(0.013)	(0.049)	(0.071)
Age 56-60	0.011	0.033**	-0.033	0.057
	(0.014)	(0.014)	(0.061)	(0.073)
Age 61-65	0.018	0.018	-0.009	-0.014
	(0.015)	(0.013)	(0.059)	(0.085)
Female	-0.033***	-0.031***	0.002	-0.017
	(0.008)	(0.007)	(0.024)	(0.032)
High education	0.018**	0.022***	0.010	0.070**
	(0.008)	(0.007)	(0.024)	(0.034)
Household size (censored)	0.005	0.004	-0.024	-0.020
	(0.005)	(0.005)	(0.018)	(0.022)
Partner	0.006	0.009	-0.035	0.010
	(0.009)	(0.008)	(0.027)	(0.039)
Number of children (censored)	0.012*	0.012**	0.001	-0.011
	(0.006)	(0.006)	(0.021)	(0.026)
1st income quintle	-0.046***	-0.027**	-0.114**	-0.027
	(0.013)	(0.012)	(0.046)	(0.054)
2nd income quintile	-0.025*	-0.018	-0.030	-0.056
	(0.013)	(0.012)	(0.039)	(0.058)
3rd income quintile	0.007	0.005	-0.001	0.014
	(0.013)	(0.012)	(0.032)	(0.048)
4th income quintile	-0.007	-0.011	-0.031	-0.037
	(0.012)	(0.011)	(0.035)	(0.049)
Unemployed	-0.013	0.011	-0.034	-0.175***
	(0.011)	(0.012)	(0.036)	(0.057)
Risk averse	0.005	-0.016*	-0.014	0.079**
	(0.009)	(0.008)	(0.027)	(0.037)
Risk neutral	-0.009	-0.023**	-0.018	-0.027
	(0.010)	(0.009)	(0.031)	(0.045)
Outstanding mortgage	0.053***	0.035***		
	(0.009)	(0.009)		
Financial concerns	0.004***	0.002		
	(0.001)	(0.001)		
Credit harder than 12 months earlier	0.055***	0.058***		
	(0.009)	(0.009)		
Insufficient liquidity	0.036***	0.022**		

	(0.009)	(0.009)		
Financial literacy	-0.013***	-0.017***	0.049***	0.065***
	(0.004)	(0.004)	(0.011)	(0.014)
Big city (residence)	0.025**	0.013	-0.029	-0.031
	(0.011)	(0.011)	(0.037)	(0.048)
Suburb of big city (residence)	0.058***	0.051***	-0.151***	-0.193***
	(0.013)	(0.013)	(0.039)	(0.053)
Mid-size city (residence)	0.036***	0.049***	-0.091***	-0.105**
	(0.012)	(0.011)	(0.033)	(0.047)
Small city (residence)	0.008	0.002	-0.018	-0.042
	(0.010)	(0.009)	(0.032)	(0.047)
Expected net total HH income growth	0.000	-0.000		-
	(0.000)	(0.000)		
Home ownership			0.022	0.037
			(0.026)	(0.036)
At least 1 late payment			-0.253***	-0.250***
			(0.035)	(0.041)
Constant				
Observations	20,227	15,910	2,310	1,499
HHs (Cluster)	9329	8813	1814	1271
Pseudo R-squared	0.0459	0.0565	0.151	0.159
Joint Country (pval)	0.000116	4.46e-07	0.0314	6.22e-05
Joint Wave (pval)	0.432	0.0164	2.21e-05	0.577

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.; Incl. country and wave dummies