DNB Working Paper
No 759/ December 2022

Who participates in the credit market during the COVID-19 pandemic?

Evangelos Charalambakis, Federica Teppa and Athanasios Tsiortas

DeNederlandscheBank
EUROSYSTEEM

Who participates in the credit market during the COVID-19 pandemic?
Evangelos Charalambakis, Federica Teppa and Athanasios Tsiortas*

* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

Working Paper No. 759

De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

December 2022

Who participates in the credit market during the COVID-19 pandemic?

Evidence from the Consumer Expectations Survey[1]

Evangelos Charalambakis

(European Central Bank, Frankfurt, Germany)

Federica Teppa

(De Nederlandsche Bank and Netspar, Amsterdam, Netherlands)

Athanasios Tsiortas

(European Central Bank, Frankfurt, Germany)

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 during the COVID-19 pandemic. The empirical analysis is based on microdata collected between April 2020 and January 2022 as part of the ECB Consumer Expectations Survey, a new online survey panel of Euro area consumers. We find that age, financial literacy, unemployment and degree of urbanization significantly affect both the application and the acceptance of credit, albeit in the opposite direction. We also document that the probability for credit application increases whereas the probability of credit approval decreases during the COVID-19 outbreak. Finally, we find that there is heterogeneity in the type of credit, particularly between secured and unsecured loans.

JEL classification: C23; D12; D14; G51

Keywords: Consumer debt; Liquidity constraints; COVID-19 pandemic; Consumer Expectations Survey

Acknowledgments: The views expressed in this paper 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. The paper benefited from useful feedback from seminars at the European Central Bank, De Nederlandsche Bank, Society for Economic Measurement, and Netspar Pension Day. Any remaining errors are the authors' own responsibility.

[1] Corresponding author: Federica Teppa, Economics and Research Division, De Nederlandsche Bank, Amsterdam, The Netherlands (f.teppa@dnb.nl).
Postal address: Spaklerweg 4, 1096 BA Amsterdam; Postbus 98, 1000 AB Amsterdam.
Telephone number: +31205245184

1. Introduction

The participation of households in the credit market receives wide attention in the consumer finance literature because consumer credit enters in the monetary policy transmission mechanism through the so-called “credit channel”: the amount of credit that consumers have access to in equilibrium can influence the economic activity. Changes of credit demand and supply have an effect on consumers' spending and investment, which in turn affect economic growth. This paper provides an extension to the empirical findings on what drives consumers’ demand for credit applications and the probability of credit acceptance using a new online survey panel of euro area consumers.

Our paper is related to a large number of empirical studies that focus on consumer behaviour and on the existence of borrowing constraints. Many studies explore the main implication of the permanent income / life cycle hypothesis of consumer behaviour, which states that individual consumption depends on the resources available to the consumer over her entire lifetime, under the assumption of complete capital markets. However, when capital markets are incomplete, consumers face borrowing constraints. Such 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 *et al.* (1998), Gross and Souleles (2002), Leth-Petersen (2010) and Crossley and Low (2014), among others.

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. See, among others, Agarwal et al. (2006), Campbell (2006), Gabaix and Laibson (2006), Lusardi and Tufano (2007a, 2007b), , Stango and Zinman (2009), Tufano (2009), Meier and Sprenger (2010), Stango and Zinman (2011) and Disney and Gathergood (2013). Our results are also associated with the 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; see, for example, Grant (2007). The second contribution of this paper is that it provides unique evidence on whether household borrowing behaviour. The analysis of the demand for credit along with the credit approval is of major importance given that the nature of the pandemic shock has generated high heterogeneity in financial needs not only across specific population groups but also across countries.

The paper uses novel microdata from the ECB's Consumer Expectations Survey (CES), a high-frequency and fully harmonized online survey that measures consumer expectations and behaviour in Germany, France, Italy, Spain, Belgium and the Netherlands. One of the strong features of the 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 focus on an unbalanced panel based on quarterly data, collected from April 2020 to January 2022, a period that saw the outbreak of the COVID-19 pandemic in the euro area.

We formulate and test four hypotheses for age, unemployment, financial literacy and the degree of urbanization that can impact the probability to apply for a loan and the probability of the loan to be approved. In particular, we test that age, unemployment and the degree of urbanization are positively related to the probability to apply for credit but negatively related to the probability of the loan to be accepted. In addition, we test that financial literacy is negatively correlated with the likelihood to apply for credit and positively with the likelihood of credit acceptance.

We use a probit model to estimate the consumer's probability to apply for credit. We provide evidence that supports our hypotheses. Younger and unemployed consumers as well as consumers that live in urban areas are more likely to apply for credit whereas financially literate consumers apply less for credit. However, this latter negative association is entirely driven by consumers who do not face any liquidity constraints. Also, more educated, male and risk-loving consumers as well as consumers with high level of income, high number of children, hard perceived 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. The latter factor reflects how COVID-19 pandemic has increased consumers' demand for loans.

We also use a probit model to estimate the probability of consumer loan to be accepted. In line with our hypothesis, we find that adult consumers (aged 50-55 years old) and consumers with high level of financial literacy are more likely to have their credit accepted whereas unemployed people and consumers living in suburbs and mid-sized cities are more likely to have their credit denied. In addition, the probability of credit being rejected increases for consumers with low level of income and missed payments on loans.

[2] ECB (2021) contains a first evaluation of the survey and Georgarakos and Kenny (2022) provide a detailed description of the CES.

This paper documents significant evidence on the impact of COVID-19 pandemic on the participation of euro area consumers in the credit market. We show that the probability to apply for credit is significantly lower in January 2021 and January 2022 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 of applying for unsecured credit is significantly higher for the unemployed, whereas being unemployed is not a significant determinant of secured credit applications. We also find that being financially concerned due to the pandemic as well as being liquidity constrained are significant determinants of unsecured credit applications, but not at all of secured credit applications. 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 and Hypotheses Testing

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 constraints.[3] 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 (where the

[3] For an extensive review, see Besley (1995) and Browning and Lusardi (1996), among others.

endogenous variables are expressed as functions of the exogenous variables) to analyse the determinants of a household being credit constrained.[4]

We adopt the second approach and we use novel panel data from the CES. Respondents are invited to answer online questionnaires every month.[5] Each respondent completes a background questionnaire upon survey recruitment providing important information on individual or household characteristics, such as age, gender, education, family status, employment status, annual household income. Consumer perceptions and expectations, which are more time-varying, are collected in 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.

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

$$P(Apply_{h,t}=1|a_t, X_{1h,t})=\Phi(a_t + \beta' X_{1h,t}) + \varepsilon_{1h,t} , \qquad (1)$$

where $Apply_{h,t}$ is a dummy variable that denotes whether the household *h* has applied for a loan during the last 3 months with respect to the date of interview t, Φ is the cumulative distribution function of a standard normal distribution, a_t is a vector of time fixed effects, β is the slope vector for household level demographics and socio-economic variables that is common across countries. In the set of the household-level variables X, we incorporate country dummies to account for country fixed effects[6]. The probit model is estimated using pooled quarterly CES data from April 2020 to January 2022. Likewise, we make use of a probit model to estimate the probability P of a household's credit application being accepted as follows:

$$P(Approval\_full_{h,t}=1|a_t, X_{2h,t})=\Phi(a_t + \beta' X_{2h,t}) + \varepsilon_{2h,t} , \qquad (2)$$

[4] See Jappelli (1990), among others.

[5] The sample consists of anonymized household-level responses with a monthly target sample size of approximately 2,000 households in Germany, France, Italy and Spain and 1,000 households in Belgium and the Netherlands until June 2021. As of July 2021, the target sample size has been increased to 3,000 households in Germany, France, Italy and Spain. The sample size gradually reached the new target by September 2021.

[6] We do not use individual fixed effects to avoid the incidental parameter problem in non-linear panel data models. The problem with individual fixed effects in non-linear panel data models, especially when the number of periods is relatively small, is that the number of parameters grows with the number of observations. Therefore, the parameter estimates cannot converge to a true value, leading inevitably to biased standard errors.

where $Approval\_full_{h,t}$ is a dummy variable that denotes whether the household's credit application has been fully accepted. Moreover, $\varepsilon_{1h,t}$ and $\varepsilon_{2h,t}$ are the error terms of equation (1) and (2) respectively which capture unobserved household characteristics. In our analysis, survey weights are employed to ensure population representativity.

Our empirical design enables us to formulate some testable hypotheses that clearly state how some common factors can affect both the probability to apply for a loan and the probability of a household's credit application being fully accepted but not in the same way. In particular, we make four hypotheses as follows[7]:

H1: Younger respondents are more likely to apply for a loan, but it is less likely their application to be fully accepted.

Young people are more likely to borrow than members of older age groups as they have lower level of current income and savings. In addition, they have longer life prospects that enable them to repay their loans. This is consistent with the life-cycle model of consumption and is documented in previous studies (Crook 2006; Fabbri and Padula 2004, among others). On the other hand, older respondents are more likely to obtain credit from banks as they have accumulated more income and wealth and are less subject to unemployment risk. However, they have shorter life prospects that may impair them repay their loans.

H2: Unemployed individuals are more likely to apply for a loan, but their application is less likely to be accepted.

According to the permanent income hypothesis, people temporarily without a job should increase their demand for credit. Unemployed consumers are more likely to face liquidity constraints and therefore they should apply more for loans to meet their financing needs without cutting on their consumption. However, employment status is a key criterion that lenders consider when they make their decisions on credit approval. Banks are reluctant to provide loans to the unemployed as this specific group may be less likely to service debt payments. Crossley and Low (2014) finds that one quarter of job-losers could not borrow to raise current consumption.

H3: Financial literacy negatively affects the likelihood to apply for a loan whereas it positively affects the probability of credit acceptance.

Households with high level of financial literacy are less likely to face liquidity constraints and therefore less willing to apply for credit. Clark, Lusardi and Mitchell (2021) show that being financially knowledgeable lessens the chance of being financially fragile. Moreover, financial literacy is positively associated with wealth

[7] All our hypotheses concern credit application and credit acceptance and we test them separately as described in equation (1) and equation (2) respectively. For all hypotheses we test against the null defined as the absence of any significant effect.

accumulation; see, among others, Lusardi and Mitchell (2007a, 2007b, 2011a, 2011b). In addition, Lusardi and Tufano (2009a, 2009b) show that financially literate people understand better interest compounding along with the terms and conditions of consumer loans and mortgages. Therefore, financially literate households are more likely to obtain credit from the bank as they have higher level of income and wealth and are more capable of debt management, enabling them to service their debt payments effectively.

H4: Households living in urban areas are more likely to apply for credit but their loan application is less likely to be accepted.

Households in urban areas are more willing to apply for credit as there are more financial intermediaries than in rural areas, making it easier for them to apply for a loan. Fabbri and Padula (2004) and Magri (2002) find that Italian households living in smaller towns show a lower demand for loans because of higher entry costs in the debt market. However, living in non-urban areas households are more likely to obtain credit because borrowers can develop a closer and long-standing relationship with their lenders.

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.

In this paper we use eight quarterly waves, from April 2020 to January 2022. Our dataset consists of 22,462 households and of 90,900 observations. Around 30 percent of households replied to at least seven out of these eight waves, while close to 50 percent replied only to one or two quarterly survey waves. Weights are assigned only to respondents who completed the core and the quarterly modules. The main analysis is based on an unbalanced panel, and for robustness checks we use a balanced panel of respondents who participated in at least any 2, 3, 4, 5, 6 or 7 quarterly waves. In all regressions we cluster standard errors at the respondent's level. For some variables, the number of available observations is lower due to (i) item 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 irregularly in November 2020 and in May 2021 as well as in the background questionnaire as of November 2021) 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 since the interview date. 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 any type of 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 January 2022, the average total application rate has been 15 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 compared to April 2020 slightly decreased on average.[8] However, in October 2020 the application rate increased significantly from 14.7 to 16.3 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 16.3 percent in the last 2020 quarter to 12.8 percent in January 2021, which is possibly attributed to the lower consumer confidence in the euro area at that period, along with the surge of Covid cases in the winter 2020 that led to a second lockdown. Finally, there is an increase of the application rate amounting to 14 percent in April 2021 reflecting the improvement in consumer confidence. Since then, the application rate remained relatively stable up to July 2021 when we observe another rebound to 14.4 percent in October 2021 and a drop to 13.7 percent in January 2022. A cross-country comparison shows that all countries

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

but the Netherlands exhibit the highest application rates in October 2020, in line with the application rate in the overall euro area in the same period.

The **acceptance credit rate** is defined as the percentage of the respondents who applied for credit **in the past 3 months** and had their amount granted in full.[9] If the respondent has applied for more than one type of credit CES asks the respondent to think about the most recent credit application. Between April 2020 and January 2022, the average acceptance rate across survey waves has been 70.3 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 fourth quarter 2020, from a maximum of 82.8 percent in April 2020 to a minimum of 65.2 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.[10] The acceptance rate increased relatively in January 2021 and then slightly decreased in April 2021. In July 2021 there was a significant drop of the credit acceptance rate reaching its absolute minimum value (63,7 percent). This finding is consistent with the BLS report for the third quarter 2021. The acceptance rate substantially increased in October 2021 and January 2022, to 68.9 and 72.7 percent, respectively. This is in line with the BLS report for the last quarter of 2021, which states that banks have eased the credit standards for consumer credit and other lending to households during this period. Looking at the acceptance rates across countries, it dropped in all countries from April to October 2020, slightly rebounded thereafter before dropping again in July 2021. 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.

Table 2 about here

[9] The applications that were only partially accepted are treated as zeros. They represent about 21 percent of the applicants who know the outcome of their applications. The observations with unknown outcome are treated as missing. Shares are conditional on having applied for credit. We also experimented with an alternative definition of the acceptance rate where the partially accepted applications were coded as one's. The main findings remain robust.

[10] 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

3.2. The main explanatory variables

To test our empirical hypotheses, we use **age** in dummies: 18-34 years, 35-49 years, 50-55 years, 56-60 years, 61-65 years and 66+ years. **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. **Unemployment** is measured as a dummy variable that equals 1 if respondents are unemployed; zero otherwise. 9.1% of our sample are unemployed. 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”.

To capture **gender** and **education** we use a female indicator (women represent 50.7 percent) and a high-education indicator (highly educated respondents represent 54.6 percent), respectively.[11] We also control for **household size**[12] (on average households consist of slightly more than 2 members), the **presence of a partner** (64.4 percent) and **number of children**[13], a dummy indicator for **home ownership** (65 percent), **net income quintiles** (values are imputed) and being **mortgage holders** (29.9 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

[11] The high-education indicator includes short-cycle tertiary education, bachelor or equivalent, master or equivalent and doctoral or equivalent.

[12] This variable is truncated at 5+. Households with more than 5 members represent less than 10 percent.

[13] Children are defined as “My child or stepchild” and include both dependent and adult children. This variable is truncated at 3+. Households with more than 3 children represent about 5 percent.

of the sample falls into the low-risk group (48.6 percent); the remaining half is evenly distributed between the medium and the high risk groups (22.7 and 28.7 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 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 with a standard deviation of 2.7.

The CES also asks whether the respondent thinks that it is generally harder or easier these days, compared to 12 months earlier, for 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.[14] 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.

The CES also 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.

Expected net total household income growth in the following 12 months is captured by the reported expected change in percentage terms. The variable is winsorised at the 2nd and 98th percentile of the pooled distribution of responses to deal with extreme outliers.

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

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 3 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 21,192 households who respond to the survey repeatedly over time.

Table 3 about here

Age dummies are jointly significant at the 1-percent level. In line with our hypothesis H1, the probability to apply for credit is monotonically decreasing with age. The probability to apply for credit is 10.7 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.

The estimated coefficient for financial literacy is negative and significant (at the 1-percent level) which could be associated with our hypothesis H2 highlighting the role of liquidity constraints. 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 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 3. 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.

Also, unemployment is positively associated with the probability of credit applications, which is in line with our hypothesis H3.

To test our hypothesis H4, we control for the degree of urbanization in *Specification (2)*. 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, which confirms our hypothesis. A potential explanation for this finding is the fact that in rural areas there are larger credit supply issues due for example to the proximity of another bank.

In both specifications, we find that other socio-economic factors affect credit applications. Women are significantly less likely to apply for credit than men (the marginal effect equals 3.6 percentage points). This may be due to their lower level of expected future income, as well as their higher level of risk aversion, on average. (see Jappelli, 1990).

Education is another significant (at the 1-percent level) determinant of credit applications. The highly educated are 1.9 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 qualification 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 1-percent level) and has a positive marginal effect. These findings highlight that the households with dependent children are the ones mostly in need of financial help.

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 positively and significantly (at the 1-percent level) correlated to credit applications. 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 (2005) 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 loving. Financial concerns due to COVID-19 significantly increase the probability to apply for credit. This provides useful insights into how COVID-19 pandemic has affected consumers' demand for credit. Having an outstanding mortgage, 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).

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 January 2022. The results, available upon request, are qualitatively similar to those reported in Table 3.

4.2. Determinants of credit acceptances

Table 4 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 in full. Three specifications are considered, where country and time fixed effects are always included. *Specification (1)* is the baseline specification and is based on 5,251 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 4 about here

Age is jointly statistically significant (at the 1-percent level). The age function is concave with the mid-aged young adult respondents (aged 50-55 years old) having the highest probability to get their credit application approved if compared with those in retirement age (66 plus). It seems that lenders prefer to grant loans to consumers of this age group likely due to their higher ability to service their debt. The youngest respondents, aged below 35 years old, are the ones with the highest negative marginal effect (10.8 percentage points). This finding confirms our hypothesis H1.

Being unemployed significantly (at the 1-percent level) reduces the probability to obtain credit (the marginal effect equals 26.2 percentage points). This finding is consistent with our hypothesis H2 that banks and lenders often review their applicants' employment histories. Lenders want to ensure that borrowers can afford to make regular debt repayments, and applicants often need to prove that they have a steady source of income. The unemployed not having as much credit as they would like to, can be explained also by their pessimism about their future work chances and by supply-side restrictions.

On the contrary, having higher financial literacy increases the probability to obtain credit. The marginal effect is significant at the 1-percent level and is equal to 6.7 percentage points. This can be linked to the ability to better judge the circumstances to successfully apply for credit, supporting our hypothesis H3.

In *Specification (3)* we control for the degree of urbanization to test our hypothesis H4. We find that, if compared to rural areas, all the other areas are negatively associated to credit acceptance. This is in line with our hypothesis. 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 in 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.

We also find that other factors affect the probability for a loan to be granted. 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 (10.5 and 8 percentage points, respectively), followed by the ones in the fourth and third quintiles (5.2 and 2.3 percentage points, respectively).

Home ownership is positively related to the probability of credit approval (the marginal effect equal 4.1 percentage points). This is possibly attributed to the role of collaterals. 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). 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 manages 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 of late payments 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 26.4 percentage points and significant at the 1-percent level.

As for the credit applications, we perform a robustness check for the credit acceptance by splitting the data between years, i.e. April-October 2020 and January-November 2021. Our results, available upon request, are confirmed in both subperiods.

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 5 reports the results related to the country and time dummies that were included in the regressions in Table 3. 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 5 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 two model specifications. The marginal effect is highest for the Netherlands, where the probability to apply for credit is lower by 4.8-5.2 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 (4.1-4.1 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 (0.6-0.7 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 January 2022 than in April 2020. This result is robust across the two empirical specifications. In particular, the marginal effects for January 2021 are 2.5 and 2.7 percentage points, respectively, whereas for January 2022 they are somewhat lower at 1.6 and 2.1 percentage points, respectively. 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 and in the fall 2021 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. We also observe a negative and significant (but at the 10-percent level only) probability to apply for credit in April and July 2021. Finally, the probability is higher in July 2020 and October 2020, but insignificant.

Table 6 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 6 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 13.3-14.1 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 show that Germany exhibits the highest rejection rate for loans to households for house purchases 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. The marginal effects are rather large and range between 5.1 and 16.4 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

As explained in Section 3.1. the CES collects information about eight types of credit. Table 7 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 7.69 percent for the former type and 4.16 percent for the latter type, both taking place in April 2020; in Italy the corresponding figures are 6.06 in April 2020 and 4.08 percent in July 2021. On the other hand, leasing contracts, compared to other countries, are most common in Germany, peaking at 3.61 percent in April 2021. Loans for educational purposes are most popular in the Netherlands (where they reach the maximum value of 2.33 percent in July 2020) and in Germany (where they represent 1.75 percent in July 2020).

Table 7 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 8. The regression analysis for secured and unsecured credit (columns 1 and 2) is based on specification (3) from Table 3 and it aims to identify whether these two groups of credit differ in some respect.[15] We find that the probability of the unsecured credit application is significantly (at

[15] 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 1-percent level) higher for the unemployed, whereas being unemployed is not significant for the secured credit application.

We also find that being financially concerned due to the pandemic as well as being liquidity constrained are significant (at the 1-percent level) factors of unsecured credit applications, but not at all of secured credit applications. 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 (11 percentage points versus 8 percentage points). In the literature there is some evidence that education levels affect secured debt applications 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 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 (see columns 3-7 of Table 8), we notice that being highly educated is a significant (at the 1-percent level) determinant of applying for 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. We also observe that unemployed consumers are less likely to apply for a mortgage loan. This suggests that consumers who fail to find a job or experience a job loss are discouraged from applying for a mortgage loan possibly due to the uncertainty of labour income. 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 1-percent level) less likely to apply 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 significantly (at the 5-percent level) more likely to apply for consumer credit.

Table 8 about here

5. Concluding remarks

This paper analyses the household participation in the credit market in the euro area at the onset of the COVID-19 pandemic focusing on the determinants of credit applications and credit approvals. To do so we make use of novel data collected in the Consumer Expectations Survey between April 2020 and January 2022 in the six largest euro area countries.

We develop four hypotheses on how age, unemployment, financial literacy and the degree of urbanization can affect both the probability to apply for a loan, and to obtain credit albeit in opposite directions. We provide evidence in favour of these hypotheses. In particular, we show that the probability to apply for a loan decreases with age and financial literacy and increases with unemployment and for people who live in urban areas. The negative association between financial literacy and the probability to apply for a loan is entirely driven by those who are not subject to liquidity constraints. On the other hand, the probability of credit approval is negatively associated with age and unemployment and positively associated with financial literacy and with households who live in rural areas.

We also show how the COVID-19 pandemic affects the borrowing behaviour of consumers in the euro area. Financial concerns due to COVID-19 are positively associated with the probability to apply for a loan. Our results suggest 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 so that obtaining credit becomes significantly less likely after the onset of COVID-19 pandemic.

Finally, focusing on the broader definition of the type of credit, we show that there are heterogeneous effects for secured and unsecured credit. In particular, the probability of applying for unsecured credit is significantly higher for the unemployed, whereas being unemployed is not a significant driver for the secured credit application. We also find that being financially concerned due to the pandemic as well as being liquidity constrained are significant determinants of unsecured credit applications, but not at all of secured credit applications. Looking at specific credit applications, we provide unique evidence that unemployed consumers are discouraged from applying for mortgage loans whereas middle-income consumers are more likely to apply for consumer credit.

This paper has potentially important implications for monetary and fiscal policy and more broadly for welfare and economic growth. Our findings highlight which specific population groups have a higher demand for credit and which groups of consumers are more likely to be dropped out of the credit market, such as young, unemployed, financially illiterate and low-income consumers and consumers that have delinquencies on their payments and no home ownership. These subgroups of the population may become potentially vulnerable. Therefore, economic measures that could minimize the share of consumers being credit constrained, for example a tax cut, may target these groups of consumers.

We plan to extend our analysis in a number of directions. We intend to adopt the decomposition methodology à la Oaxaca (1973) and Blinder (1973) to identify and estimate the separate contributions of differences in parameters of individual demographic characteristics when accounting for mean differences in access to credit markets and credit approval between the employed and the unemployed, as well as between the high educated and the low educated. We are also interested in extending the analysis to the post-pandemic period, as well in studying changes in individual spending patterns, or the effect of (high) inflation and of monetary tightening on credit access.

Bibliographic references

Agarwal S, Chomsisengphet S, Liu C, Souleles N (2006) Do consumers choose the right credit contracts? Federal Reserve Bank of Chicago Working Paper 2006-11

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

Bianco M, Giacomelli S, Giorgiantonio C, Palumbo G, 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, Lusardi A (1996) Household saving: micro theories and micro facts. *Journal of Economic Literature* 4:1797–1855

Campbell J (2006) Household finance. *Journal of Finance* 61:1553–1604

Clark R, Lusardi A, Mitchell O (2021) Financial fragility during the COVID-19 pandemic. *AEA Papers and Proceedings* 111: 292-296

Cox D, 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, Grant C (eds) The Economics of Consumer Credit, Cambridge MA: MIT Press, pp 63-92

Crossley TF, Low HW (2014) Job loss, credit constraints, and consumption growth. *The Review of Economics and Statistics* 96(5):876–884

Del-Rio A, Young G (2005) The determinants of unsecured borrowing: Evidence from the British Household Panel Survey. Bank of England Working Paper 263
SSRN: https://ssrn.com/abstract=824164 or http://dx.doi.org/10.2139/ssrn.824164

Disney R, Gatherwood J (2013) Financial literacy and credit market portfolios. *Journal of Banking and Finance* 37:2246-2254

ECB (2021) The ECB's Consumer Expectations Survey: An overview and first evaluation. ECB Occasional Paper 287

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

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

Gabaix X, Laibson D (2006) Shrouded attributes, consumer myopia and information suppression in competitive markets. *Quarterly Journal of Economics* 121:505–540

Georgarakos D, Kenny G (2022) Household spending and fiscal support during the COVID-19 pandemic: Insights from a new consumer survey. *Journal of Monetary Economics* https://doi.org/10.1016/j.jmoneco.2022.02.007

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

Gross D, 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 RE, Mishkin FS (1982) The sensitivity of consumption to transitory income: Estimates from panel data on households. *Econometrica* 50(2):461-481

Jappelli T, Piske JS, 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

Lusardi A, Mitchell O (2007a) Baby boomer retirement security: The roles of planning, financial literacy and housing wealth. *Journal of Monetary Economics* 54 (1): 205-224

Lusardi A, Mitchell O (2007b) Financial literacy and retirement preparedness: Evidence and implications for financial education. *Business Economics* 42 (1): 35-44

Lusardi A, Mitchell O (2011a) Financial literacy and planning: Implications for retirement well-being. In Financial literacy: Implications for retirement security and the financial market place, edited by O.S. Mitchell and A. Lusardi, 17-39: Oxford and New York, Oxford University Press.

Lusardi A, Mitchell O (2011b) The outlook for financial literacy. In Financial literacy: Implications for retirement security and the financial market place, edited by O.S. Mitchell and A. Lusardi, 17-39: Oxford and New York, Oxford University Press.

Lusardi A, Tufano P (2009a) Debt literacy, financial experience and overindebtedness. NBER Working Paper 1480

Lusardi A, Tufano P (2009b) Teach workers about the perils of debt. *Harvard Business Review* 22-24

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

Meier S, Sprenger C (2010) Present-based preferences and credit card borrowing. *American Economic Journal: Applied Economics* 2:193–210

Stango V, Zinman J (2009) Exponential growth bias and household finance. *Journal of Finance* 44:2807–2849

Stango V, Zinman J (2011) Fuzzy math, disclosure regulation and credit market outcomes: evidence from truth-in-lending reform. *Review of Financial Studies* 24:506–553

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

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

Charts and Tables

Table 1: Summary Statistics

VARIABLE	Mean	Min	Max	Std.Dev.	N. Obs.	N. HHs
Credit application rate	0.150	0	1	0.357	84394	22462
Credit acceptance rate	0.703	0	1	0.457	8628	5431
Age 18-34 years	0.240	0	1	0.427	90900	26634
Age 35-50 years	0.339	0	1	0.474	90900	26634
Age 50-55 years	0.136	0	1	0.343	90900	26634
Age 56-60 years	0.100	0	1	0.300	90900	26634
Age 61-65 years	0.089	0	1	0.284	90900	26634
Age over 65 years	0.096	0	1	0.294	90900	26634
Female	0.507	0	1	0.500	90850	26614
Higher education	0.546	0	1	0.498	90900	26634
HH size (truncated)	2.678	1	5	1.191	90900	26634
Presence of a partner	0.644	0	1	0.479	90900	26634
Number of children	0.706	0	3	0.928	90900	26634
Net income quintiles	2.972	1	5	1.408	90403	25943
Unemployed	0.091	0	1	0.288	90900	26634
Low risk	0.486	0	1	0.500	89279	26161
Medium risk	0.227	0	1	0.419	89279	26161
High risk	0.287	0	1	0.452	89279	26161
Mortgage holders	0.299	0	1	0.458	90900	26634
Financial concerns	6.010	0	10	2.736	89729	23633
Credit access harder than 12 months earlier	0.291	0	1	0.454	88676	23407
Insufficient liquidity	0.292	0	1	0.455	90895	23779
Financial literacy	2.421	0	4	1.130	90900	26634
Degree of urbanization (categorical)	3.186	1	5	1.435	69035	12324
Expected net total household income growth	0.510	-30	30	8.761	90895	23939
Home ownership	0.650	0	1	0.477	90900	26634
At least 1 past late payment	0.109	0	1	0.312	85243	22484

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

Table 2: Application and Acceptance Rates across time and countries

Application Rate							
Time Period	EA	BE	DE	ES	FR	IT	NL
Apr-20	15.0	13.2	14.0	19.3	15.1	14.0	11.5
Jul-20	14.7	11.0	14.9	15.9	13.7	15.6	13.3
Oct-20	16.3	16.4	16.2	16.7	16.7	17.7	9.3
Jan-21	12.8	12.6	13.0	13.4	11.1	13.7	12.9
Apr-21	14.0	12.4	16.0	16.1	11.8	13.3	10.4
Jul-21	13.9	10.8	13.6	16.1	11.5	16.2	12.6
Oct-21	14.4	12.8	14.9	16.0	11.6	17.1	8.9
Jan-22	13.7	11.6	13.7	13.4	13.5	14.9	11.4
Credit Acceptance Rate							
Time Period	EA	BE	DE	ES	FR	IT	NL
Apr-20	82.8	78.3	83.0	75.9	88.7	85.3	78.2
Jul-20	73.9	77.6	66.8	68.3	83.9	79.5	71.9
Oct-20	65.2	62.0	57.0	68.2	66.4	77.1	63.3
Jan-21	65.7	70.2	58.6	70.5	68.9	75.5	46.4
Apr-21	65.4	70.2	52.8	74.2	67.9	80.9	60.1
Jul-21	63.7	63.2	53.8	66.9	62.1	72.9	71.2
Oct-21	68.9	70.1	63.9	64.7	73.8	76.6	64.7
Jan-22	72.7	73.8	68.2	77.2	69.2	79.9	67.3

Notes: This table reports the credit application and acceptance rates across time and countries. Weighted estimates. Data are obtained from April 2020 to January 2022 quarterly waves of the CES.

Table 3: Probit model of Credit Applications

	(1)	(2)	(3)	(4)
VARIABLES	Marg. Effects	Marg. Effects II	Sufficient liquidity	Liquidity constrained
Age 18-34	0.107***	0.089***	0.081***	0.101***
	(0.009)	(0.010)	(0.010)	(0.024)
Age 35-49	0.049***	0.048***	0.048***	0.044**
	(0.008)	(0.009)	(0.009)	(0.022)
Age 50-55	0.028***	0.026**	0.024**	0.030
	(0.009)	(0.010)	(0.010)	(0.026)
Age 56-60	0.022**	0.015	0.008	0.028
	(0.009)	(0.010)	(0.010)	(0.027)
Age 61-65	0.018*	0.018*	0.017*	0.019
	(0.009)	(0.010)	(0.010)	(0.029)
Age over 65 = o	-	-	-	-
Female	-0.036***	-0.029***	-0.023***	-0.049***
	(0.005)	(0.005)	(0.006)	(0.012)
High education	0.019***	0.018***	0.012**	0.037***
	(0.005)	(0.005)	(0.006)	(0.012)
Household size (censored)	0.002	0.003	0.002	0.001
	(0.003)	(0.004)	(0.004)	(0.007)
Partner	0.003	0.004	0.012*	-0.017
	(0.006)	(0.006)	(0.006)	(0.014)
Number of children (censored)	0.015***	0.013***	0.012**	0.021**
	(0.004)	(0.005)	(0.005)	(0.009)
1st income quintile	-0.042***	-0.047***	-0.027***	-0.114***
	(0.008)	(0.009)	(0.009)	(0.026)
2nd income quintile	-0.025***	-0.029***	-0.024***	-0.078***
	(0.008)	(0.009)	(0.009)	(0.026)
3rd income quintile	-0.007	-0.006	-0.006	-0.044
	(0.008)	(0.009)	(0.009)	(0.027)
4th income quintile	-0.005	-0.008	-0.008	-0.031
	(0.007)	(0.008)	(0.008)	(0.027)
Unemployed	0.047***	0.046***	0.070***	0.022
	(0.008)	(0.010)	(0.013)	(0.014)
Risk averse	-0.013**	-0.007	-0.013**	0.010
	(0.006)	(0.006)	(0.007)	(0.013)
Risk neutral	-0.018***	-0.016**	-0.019***	-0.004
	(0.006)	(0.007)	(0.007)	(0.016)
Outstanding mortgage	0.041***	0.040***	0.037***	0.042***
	(0.005)	(0.006)	(0.007)	(0.013)
Financial concerns	0.005***	0.004***	0.007***	-0.008***

	(0.001)	(0.001)	(0.001)	(0.002)
Credit harder than 12 months earlier	0.054***	0.054***	0.065***	0.041***
	(0.005)	(0.006)	(0.008)	(0.010)
Insufficient liquidity	0.032***	0.034***	-	-
	(0.006)	(0.007)		
Financial literacy	-0.015***	-0.013***	-0.014***	-0.002
	(0.002)	(0.003)	(0.003)	(0.005)
Big city (residence)		0.022***	0.012	0.046***
		(0.008)	(0.008)	(0.018)
Suburb of big city (residence)		0.044***	0.035***	0.065***
		(0.009)	(0.009)	(0.017)
Mid-size city (residence)		0.039***	0.035***	0.047***
		(0.009)	(0.009)	(0.017)
Small city (residence)		0.002	-0.003	0.015
		(0.007)	(0.007)	(0.015)
Rural area (residence) = o				
Expected net total HH income growth		0.000	0.000	-0.001
		(0.000)	(0.000)	(0.000)
Constant				
Observations	79,616	60,313	44,075	16,238
HHs (Cluster)	21192	11046	9238	4623
Pseudo R-squared	0.055	0.056	0.0622	0.0554
Joint Country (p-value)	0.000	0.000	0.00	0.00
Joint Wave (p-value)	0.000	0.000	0.00	0.00
Joint Age (p-value)	0.000	0.000	0.00	0.00
Joint Income (p-value)	0.000	0.000	0.01	0.00

Note: This table reports the probit marginal effects of credit applications. Data are obtained from April 2020 to January 2022 quarterly waves of the CES. Time and country dummies are also included, ***, ** and * denote significance at 1%, 5% and 10% level. Standard errors clustered at the household level are reported in parentheses. Reported numbers are the estimated marginal effects at means. Estimated coefficients are available upon request.

Table 4: Probit model of Credit Acceptance

	(1)	(2)	(3)
VARIABLES	Marg. Effects	Marg. Effects	Marg. Effects
Age 18-34	-0.108***	-0.088**	-0.081**
	(0.035)	(0.035)	(0.041)
Age 35-49	-0.040	-0.036	-0.014
	(0.034)	(0.034)	(0.040)
Age 50-55	0.040	0.036	0.055
	(0.036)	(0.037)	(0.042)
Age 56-60	-0.034	-0.017	-0.005
	(0.041)	(0.040)	(0.048)
Age 61-65	-0.046	-0.034	-0.020
	(0.040)	(0.040)	(0.046)
Age over 65 = o,	-	-	-
Female	0.006	-0.002	-0.002
	(0.016)	(0.016)	(0.019)
High education	0.006	0.022	0.030
	(0.017)	(0.016)	(0.020)
Household size (censored)	-0.017	-0.014	-0.014
	(0.011)	(0.011)	(0.014)
Partner	0.012	0.002	-0.022
	(0.019)	(0.019)	(0.022)
Number of children (censored)	-0.013	-0.001	-0.009
	(0.014)	(0.014)	(0.017)
1st income quintile	-0.105***	-0.080***	-0.062*
	(0.028)	(0.028)	(0.034)
2nd income quintile	-0.080***	-0.060**	-0.043
	(0.026)	(0.025)	(0.031)
3rd income quintile	-0.023	-0.012	0.015
	(0.023)	(0.023)	(0.027)
4th income quintile	-0.052**	-0.051**	-0.031
	(0.024)	(0.024)	(0.028)
Unemployed	-0.262***	-0.213***	-0.210***
	(0.025)	(0.026)	(0.031)
Risk averse	0.035*	0.036**	0.037*
	(0.019)	(0.018)	(0.022)
Risk neutral	0.025	0.006	-0.004
	(0.021)	(0.021)	(0.025)
Home ownership	0.041**	0.032*	0.024
	(0.017)	(0.017)	(0.020)
Financial literacy	0.067***	0.047***	0.052***
	(0.007)	(0.008)	(0.009)
At least 1 late payment		-0.264***	-0.250***

		(0.020)	(0.025)
Big city (residence)			-0.051*
			(0.029)
Suburb of big city (residence)			-0.162***
			(0.031)
Mid-size city (residence)			-0.103***
			(0.027)
Small city (residence)			-0.037
			(0.025)
Rural area (residence) = o,			-
Constant			
Observations	8,381	8,097	5,946
HHs (Cluster)	5251	5089	3383
Pseudo R-squared	0.114	0.152	0.164
Joint Country (p-value)	0.000	0.000	0.000
Joint Wave (p-value)	0.000	0.000	0.000
Joint Age (p-value)	0.000	0.000	0.000
Joint Income (p-value)	0.000	0.010	0.100

Note: This table reports the probit marginal effects of credit acceptance. Data are obtained from April 2020 to January 2022 quarterly waves of the CES. Time and country dummies are also included, ***, ** and * denote significance at 1%, 5% and 10% level. Standard errors clustered at the household level are reported in parentheses. Reported numbers are the estimated marginal effects at means. Estimated coefficients are available upon request.

Table 5: Country and Time Marginal Effects of Credit Applications

	(1)	(2)
DUMMIES	Marg. Effects	Marg. Effects
Belgium	-0.041***	-0.041***
	(0.008)	(0.009)
Spain	-0.025***	-0.030***
	(0.007)	(0.008)
France	-0.035***	-0.034***
	(0.006)	(0.007)
Italy	-0.007	-0.005
	(0.007)	(0.008)
Netherlands	-0.048***	-0.052***
	(0.008)	(0.009)
July 2020	0.006	0.008
	(0.007)	(0.008)
October 2020	0.009	0.009
	(0.007)	(0.007)
January 2021	-0.025***	-0.027***
	(0.006)	(0.007)
April 2021	-0.012*	-0.015*
	(0.007)	(0.008)
July 2021	-0.012*	-0.019**
	(0.007)	(0.008)
October 2021	-0.004	-0.010
	(0.007)	(0.008)
January 2022	-0.016***	-0.021***
	(0.006)	(0.008)
Constant		
Observations	79,616	60,313
HHs (Cluster)	21192	11046
Pseudo R-squared	0.055	0.056
Joint Country (p-value)	0.000	0.000
Joint Wave (p-value)	0.000	0.000

Note: This table reports the probit marginal effects of country and time dummies of credit application. Data are drawn from April 2020 to January 2022 quarterly waves of the CES. Time and country dummies are also included, ***, ** and * denote significance at 1%, 5% and 10% level. Standard errors clustered at the household level are reported in parentheses. Reported numbers are the estimated marginal effects at means. Estimated coefficients are available upon request.

Table 6: Country and Time Marginal Effects of Credit Acceptance

	(1)	(2)	(3)
DUMMIES	Marg. Effects	Marg. Effects	Marg. Effects
Belgium	0.060**	0.068**	0.086**
	(0.031)	(0.030)	(0.036)
Spain	0.079***	0.061**	0.076***
	(0.025)	(0.025)	(0.030)
France	0.095***	0.057**	0.064**
	(0.023)	(0.023)	(0.027)
Italy	0.133***	0.135***	0.141***
	(0.023)	(0.022)	(0.027)
Netherlands	0.006	0.021	0.045
	(0.035)	(0.035)	(0.047)
July 2020	-0.088***	-0.057**	-0.055*
	(0.025)	(0.026)	(0.029)
October 2020	-0.152***	-0.135***	-0.122***
	(0.026)	(0.028)	(0.030)
January 2021	-0.135***	-0.134***	-0.128***
	(0.025)	(0.025)	(0.028)
April 2021	-0.139***	-0.124***	-0.131***
	(0.026)	(0.026)	(0.029)
July 2021	-0.164***	-0.143***	-0.140***
	(0.026)	(0.026)	(0.031)
October 2021	-0.122***	-0.085***	-0.066**
	(0.025)	(0.025)	(0.031)
January 2022	-0.089***	-0.073***	-0.051*
	(0.024)	(0.024)	(0.029)
Constant			
Observations	8,381	8,097	5,946
HHs (Cluster)	5251	5089	3383
Pseudo R-squared	0.114	0.152	0.164
Joint Country (p-value)	0.000	0.000	0.000
Joint Wave (p-value)	0.000	0.000	0.000

Note: This table reports the probit marginal effects of country and time dummies of credit acceptance. Data are drawn from April 2020 to January 2022 quarterly waves of the CES. Time and country dummies are also included, ***, ** and * denote significance at 1%, 5% and 10% level. Standard errors clustered at the household level are reported in parentheses. Reported numbers are the estimated marginal effects at means. Estimated coefficients are available upon request.

Table 7: 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	3.44	3.43	3.24	0.93	2.67	1.02	1.00	2.23
Jul20	3.76	2.30	1.24	2.11	1.65	1.04	0.34	2.21
Oct20	4.15	5.23	3.35	2.08	3.72	1.59	1.17	1.64
Jan21	3.40	2.99	2.95	1.53	2.21	1.63	1.84	1.99
Apr21	3.76	2.99	2.43	1.90	2.65	1.06	1.10	1.52
Jul21	3.69	2.69	3.02	0.72	1.98	0.86	1.54	1.23
Oct21	3.11	3.30	3.66	2.39	2.95	1.64	1.14	0.88
Jan22	3.10	3.61	2.54	1.50	1.87	0.74	0.88	1.04
DE	Mortgage	Car loan	Consumer credit	Leasing contract	Credit card or overdraft	Student loan	Limit Increase in existing loan	Mortgage refinance
Apr20	1.82	2.46	3.58	2.44	3.51	0.87	1.27	1.70
Jul20	2.23	2.46	2.92	3.23	2.95	1.75	1.11	1.32
Oct20	1.26	5.88	4.29	2.15	2.04	0.69	0.83	1.16
Jan21	1.39	3.36	3.52	2.95	2.32	0.56	0.95	0.56
Apr21	1.20	4.22	6.01	3.61	2.13	0.43	0.86	0.66
Jul21	1.68	4.05	4.38	2.21	2.26	0.42	0.61	0.63
Oct21	2.50	5.12	4.15	2.76	2.66	0.97	1.34	0.88
Jan22	1.31	4.54	4.20	2.69	2.09	0.90	1.09	1.03
ES	Mortgage	Car loan	Consumer credit	Leasing contract	Credit card or overdraft	Student loan	Limit Increase in existing loan	Mortgage refinance
Apr20	2.38	4.17	7.69	1.15	4.16	1.65	2.79	1.21
Jul20	1.67	3.13	5.88	1.15	3.52	0.97	3.47	1.14
Oct20	2.01	3.79	6.36	1.37	2.86	1.10	2.06	0.72
Jan21	2.20	2.65	5.00	1.55	2.30	1.04	1.32	0.63
Apr21	2.96	3.92	6.59	0.87	3.05	0.88	1.67	0.82
Jul21	3.87	2.82	5.19	1.43	3.60	1.04	1.98	0.61
Oct21	2.88	3.82	4.63	1.90	3.58	1.08	2.56	0.71
Jan22	2.02	2.57	5.40	1.13	3.13	0.75	1.52	0.74
FR	Mortgage	Car loan	Consumer credit	Leasing contract	Credit card or overdraft	Student loan	Limit Increase in existing loan	Mortgage refinance
Apr20	3.12	3.27	5.04	0.71	3.14	0.77	0.88	1.51
Jul20	2.73	3.41	3.94	1.18	2.23	0.73	1.40	0.86
Oct20	3.22	5.00	4.15	2.46	2.45	0.87	0.91	0.79
Jan21	2.60	3.22	3.92	1.31	1.40	0.54	1.00	0.57
Apr21	2.86	3.77	3.56	1.79	1.94	0.68	0.84	0.66
Jul21	2.49	3.08	3.66	1.41	1.62	1.17	0.91	0.72
Oct21	2.96	2.76	3.77	1.27	1.65	1.13	0.79	0.38
Jan22	2.74	3.03	4.74	1.70	1.56	1.33	1.05	1.19
IT	Mortgage	Car loan	Consumer credit	Leasing contract	Credit card or overdraft	Student loan	Limit Increase in existing loan	Mortgage refinance
Apr20	1.57	3.06	6.06	0.36	3.58	0.41	0.75	1.67
Jul20	2.28	3.95	5.15	0.95	2.83	0.58	1.13	1.82
Oct20	3.25	3.74	5.65	1.22	3.99	0.61	1.19	1.95
Jan21	2.45	2.50	4.69	0.78	3.76	0.33	1.08	0.96

Apr21	2.88	3.47	3.73	0.60	3.51	0.99	0.78	0.94
Jul21	3.48	4.03	4.80	1.36	4.08	0.87	1.20	0.73
Oct21	3.06	4.29	5.74	1.24	4.25	0.82	0.72	0.83
Jan22	2.89	3.98	4.97	1.31	3.40	0.98	0.79	0.69

NL	Mortgage	Car loan	Consumer credit	Leasing contract	Credit card or overdraft	Student loan	Limit Increase in existing loan	Mortgage refinance
Apr20	4.51	0.97	2.23	1.32	2.21	1.87	0.73	1.52
Jul20	4.09	2.11	1.83	1.81	2.22	2.33	0.88	1.84
Oct20	2.40	1.60	1.66	1.83	2.68	1.43	0.75	1.31
Jan21	1.98	2.24	1.88	3.28	1.51	2.12	1.65	1.93
Apr21	3.32	1.47	2.15	1.50	2.22	1.17	0.98	1.94
Jul21	4.35	3.00	2.75	2.59	2.25	1.28	0.59	2.38
Oct21	3.20	1.36	1.27	1.03	2.00	0.89	1.00	2.01
Jan22	4.86	2.14	2.89	1.87	1.40	0.71	0.48	2.66

Note: This table reports the application rate (%) for each type of credit application across countries and over time. Weighted estimates.

Table 8: 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	0.045***	0.037***	0.026***	0.033***	0.011*	0.017***
	(0.006)	(0.008)	(0.003)	(0.004)	(0.006)	(0.004)
Age 35-49	0.021***	0.017**	0.017***	0.019***	0.005	0.002
	(0.005)	(0.007)	(0.003)	(0.003)	(0.005)	(0.003)
Age 50-55	0.007	0.012	0.007***	0.011***	0.005	-0.002
	(0.005)	(0.008)	(0.002)	(0.004)	(0.006)	(0.004)
Age 56-60	0.002	0.008	0.005**	0.009**	0.003	-0.005
	(0.005)	(0.008)	(0.003)	(0.004)	(0.006)	(0.004)
Age 61-65	-0.001	0.012	0.003	0.010***	0.007	-0.005
	(0.005)	(0.009)	(0.003)	(0.004)	(0.007)	(0.004)
Female	-0.011***	-0.015***	-0.001	-0.007***	-0.008***	-0.009***
	(0.003)	(0.004)	(0.001)	(0.002)	(0.003)	(0.002)
High education	0.011***	0.008**	0.005***	0.003	0.004	0.007***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
Household size (censored)	0.000	0.003	0.001	0.003**	0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Partner	0.004	0.001	0.004*	0.002	0.001	-0.001
	(0.003)	(0.005)	(0.002)	(0.002)	(0.003)	(0.002)
Number of children (censored)	0.006**	0.008**	-0.001	0.003*	0.003	0.005***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
1st income quintile	-0.014***	-0.014**	-0.011***	-0.008**	-0.004	-0.001
	(0.005)	(0.006)	(0.003)	(0.003)	(0.005)	(0.003)
2nd income quintile	-0.014***	-0.009	-0.008***	-0.002	-0.001	-0.004
	(0.005)	(0.006)	(0.003)	(0.003)	(0.005)	(0.003)
3rd income quintile	-0.006	0.006	-0.007**	-0.002	0.012**	0.001
	(0.005)	(0.007)	(0.003)	(0.003)	(0.005)	(0.003)
4th income quintile	-0.004	-0.005	-0.004	0.003	0.002	0.001
	(0.005)	(0.006)	(0.003)	(0.003)	(0.004)	(0.003)
Unemployed	-0.002	0.022***	-0.005**	0.016***	0.010**	0.004
	(0.005)	(0.006)	(0.002)	(0.004)	(0.005)	(0.003)
Risk averse	-0.001	0.000	-0.001	-0.006***	0.003	0.001
	(0.003)	(0.005)	(0.002)	(0.002)	(0.003)	(0.002)
Risk neutral	-0.000	-0.009*	-0.002	-0.009***	-0.009***	0.003
	(0.004)	(0.005)	(0.002)	(0.003)	(0.003)	(0.002)
Outstanding mortgage	0.029***	0.013***	0.014***	0.006**	0.010***	-0.002
	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)
Financial concerns	0.001	0.003***	-0.000	0.001**	0.002***	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Credit harder than 12 months earlier	0.025***	0.022***	0.012***	0.019***	0.016***	0.009***

	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)
Insufficient liquidity = 1	0.003	0.038***	-0.003*	-0.004*	0.026***	0.003
	(0.003)	(0.005)	(0.002)	(0.002)	(0.004)	(0.002)
Financial literacy = 1	-0.003**	-0.006***	-0.002***	-0.005***	-0.001	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Big city (residence)	0.010**	0.012**	0.003	0.005*	0.005	0.008**
	(0.004)	(0.006)	(0.002)	(0.003)	(0.004)	(0.003)
Suburb of big city (residence)	0.015***	0.017***	0.003	0.019***	0.001	0.009***
	(0.005)	(0.006)	(0.002)	(0.004)	(0.004)	(0.003)
Mid-size city (residence)	0.016***	0.018***	0.005**	0.014***	0.009*	0.010***
	(0.005)	(0.006)	(0.002)	(0.003)	(0.005)	(0.003)
Small city (residence)	0.001	-0.002	0.001	0.003	-0.004	0.001
	(0.004)	(0.005)	(0.002)	(0.002)	(0.004)	(0.002)
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	60,313	60,313	60,313	60,313	60,313	60,313
HHs (Cluster)	11046	11046	11046	11046	11046	11046
Pseudo R-squared	0.0553	0.0507	0.0749	0.0658	0.0480	0.0440
Joint Country (p-value)	0.00	0.00	0.00	0.00	0.00	0.00
Joint Wave (p-value)	0.00	0.01	0.04	0.00	0.05	0.00

Note: This table reports the probit marginal effects of credit applications. Data are obtained from April 2020 to January 2022 quarterly waves of the CES. Time and country dummies are also included, ***, ** and * denote significance at 1%, 5% and 10% level. Standard errors clustered at the household level are reported in parentheses. Reported numbers are the estimated marginal effects at means. Estimated coefficients are available upon request.

DeNederlandscheBank

EUROSYSTEEM

De Nederlandsche Bank N.V.
Postbus 98, 1000 AB Amsterdam
020 524 91 11
dnb.nl