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Consumer participation in the credit market during the COVID-19 pandemic and beyond

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Abstract

This paper analyses the consumer's decision to apply for credit and the probability of the credit being accepted in the euro area during a period characterized by the unprecedented concomitance of events and changing borrowing conditions linked to the global COVID-19 pandemic and the Russian invasion of Ukraine. We use data between 2020Q1 and 2023Q2 from the ECB's Consumer Expectations Survey. We find that credit demand is highest when the first lockdown ends and it drops when supportive monetary compensation schemes are implemented. There is evidence that constrained households are significantly less likely to apply for credit. Credit is more likely to be accepted under favourable borrowing conditions and after the approval of national recovery plans. We also find that demographic, economic factors, perceptions and expectations are associated with the demand for credit and the credit grant.

JEL classification: C23; D12; D14; G51

Keywords: Consumer finance; Liquidity constraints; Credit applications; Consumer Expectations Survey

Non-technical summary

The participation of households in the credit market receives wide attention in the consumer finance literature because consumer credit enters the monetary policy transmission mechanism through the so-called "credit channel": changes in credit demand and supply have an effect on consumers' spending and investment, which in turn affect economic growth. This paper analyses the consumer's decision to apply for credit and the probability of the credit being accepted in the euro area during a period characterized by the unprecedented concomitance of events and changing borrowing conditions linked to the global COVID-19 pandemic and the Russian invasion of Ukraine.

Our paper makes two main contributions to the literature. First, it adds to a rapidly growing literature on household borrowing behaviour during the COVID-19 pandemic; see, for example, Ho et al. (2022), Horvath et al. (2023), among others. Our paper goes beyond the pandemic period as it extends the analysis of consumers' demand for loans to the most recent months characterized by the outbreak of the war in Ukraine. The second contribution consists of the identification of any distributional effects during the pandemic and the monetary policy tightening period as we shed light on the borrowing behaviour of liquidity-constrained *vis-à-vis* liquidity-unconstrained households and of households having an opposite perception of their financial situation.

We use microdata from the ECB's Consumer Expectations Survey (hereinafter CES), focusing on an unbalanced panel based of quarterly data from Germany, France, Italy, Spain, Belgium and the Netherlands from January 2020 to July 2023. We provide evidence that credit applications and credit acceptances display a different pattern over time. We find that the credit demand is highest when the first lockdown ends and drops when supportive monetary compensation schemes are implemented There is evidence that constrained households are significantly less likely to apply for credit. Credit is more likely to be accepted under favourable borrowing conditions and after the approval of national recovery plans. We also document significant country fixed effects. In almost all countries households are significantly less likely to apply and to get their credit approved than in Germany. Only in Italy is the probability of applying for credit significantly higher than in Germany. We show that liquidity-constrained suffer more during the pandemic and monetary policy tightening period. In line with literature, we show that demographic and economic factors affect the probability for credit applications and credit approval. In addition, the paper shows that consumer perceptions and expectations matter when they decide to apply for credit.

1. Introduction

The participation of households in the credit market receives wide attention in the consumer finance literature because consumer credit enters the monetary policy transmission mechanism through the so-called "credit channel": changes in credit demand and supply have an effect on consumers' spending and investment, which in turn affect economic growth. This paper analyses the consumer's decision to apply for credit and the probability of the credit being accepted in the euro area during a period characterized by the unprecedented concomitance of events and changing borrowing conditions linked to the global COVID-19 pandemic and the Russian invasion of Ukraine. We use microdata from the ECB's Consumer Expectations Survey (hereinafter CES), a survey that measures consumer expectations and behaviour in the euro area. Its panel dimension 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 from Germany, France, Italy, Spain, Belgium and the Netherlands and covering the period between January 2020 and July 2023. This time span coincides with the outbreak of the COVID-19 pandemic in Europe and includes a post-pandemic period with an initial phase of low interest rates (and extensive public economic support measures) and a second phase of high interest rates as a consequence of the tightening of monetary policy in the face of rising inflation following the Russian invasion of Ukraine. This way we can gauge how credit applications and credit acceptances change under different, almost opposite, borrowing conditions.

Our paper makes two main contributions to the literature. First, it adds to a rapidly growing literature on household borrowing behaviour during the COVID-19 pandemic. Our paper goes beyond the pandemic period as it extends the analysis of consumers' demand for loans to the most recent months characterized by the outbreak of the war in Ukraine. The second contribution consists of the identification of any distributional effects during the pandemic and the monetary policy tightening period as we shed light on the borrowing behaviour of liquidity-constrained *vis-à-vis* liquidity-unconstrained households and of households having an opposite perception of their financial situation. We also distinguish between the demand for long-term secured loans (mortgages) and for short-term uncollateralized loans (consumer loans).

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

We use probit models to estimate the probability of the consumer to apply for credit and the credit being granted. Our findings can be summarized as follows. First, credit applications and credit acceptances display a different pattern over time. During the period studied (i.e., 2020Q1 – 2023Q2), the average application rate is 14.5 percent. The rate peaks in 2020Q3 which reflects the rebound in the demand for loans when the first lockdown ended. Credit acceptance is significantly more likely to occur at the beginning of the period and for most of 2022, reflecting the more favourable borrowing conditions in those quarters. These findings can be rationalized by the drop in household spending observed in the period due to the introduction of severe lockdown measures to contain the spread of the virus, and to the increased unemployment risk and reduction of hours worked. In addition, national governments supported households' income with specific policy measures, mostly monetary schemes aimed at compensating workers for the reduction in their economic activity and at enabling a smoother return to economic activity for workers and firms.

Second, we find significant country fixed effects. In almost all countries households are significantly less likely to apply and to get their credit approved than in Germany. Only in Italy is the probability of applying for credit significantly higher than in Germany. We interpret our results in the light of the microsimulation model by Christl *et al.* (2022) for the EU which highlights the cushioning effect of taxes and social transfers on both household income and household demand in the context of the COVID-19 pandemic.

Third, liquidity constrained households are significantly less likely to apply for credit in almost all quarters relative to 2020Q3, whereas for unconstrained households the credit applications do not significantly differ for most quarters. The magnitude of the estimated marginal effects is also always larger for the former group. However, when it comes to credit acceptance, we observe that the two groups of households are more similar. Our finding is consistent with Christl *et al.* (2022) who highlight the relevance of the tax-benefit systems in absorbing a significant share of the COVID-19 shock during 2020 and in offsetting the regressive nature of this shock on household incomes. We also find that being financially concerned due to the pandemic has an opposite association with the probability of applying for credit in the case of unconstrained households (positive) *vis-à-vis* constrained households (negative).

Fourth, the households whose financial situation is perceived to be more difficult at the time of the interview than 12 months earlier significantly decrease their credit applications in almost all quarters. By contrast, for the households whose financial situation is perceived to be easier at the time of interview we observe a significant decrease in the likelihood of credit applications until 2022Q2. Thereafter, the estimated marginal effects become positive, albeit insignificant, until our last observed period (2023Q2) when the likelihood becomes significantly higher than in 2020Q3.

Finally, we find some heterogeneity with respect to the type of credit, particularly between secured and unsecured debt. Unconstrained households significantly increased their demand for mortgage debt in 2021Q2 and 2021Q3, a period during which they still faced very favourable borrowing conditions and the pandemic was sensed to be under control due to the massive vaccination campaigns. Afterwards, the demand for mortgages becomes insignificant for unconstrained households and falls significantly for constrained households. The demand for consumer credit is insignificant for liquid households and decreases significantly for constrained households in the last two quarters of our timespan.

The rest of the paper is organized as follows. Section 2 provides a review of the literature closely related to our paper. Section 3 reports the main economic and non-economic events that characterise the time span covered in the analysis and make it so unique. Section 4 describes the sample and the data used for the empirical analysis. Section 5 explains the methodology and presents the regression results. Section 6 discusses the results and concludes the paper.

2. Literature review

This paper relates to two distinct strands of the literature. The first consists of a recently growing literature which explores consumer behaviour in the credit market during the COVID-19 pandemic, mostly in the United States. Sandler and Ricks (2020) show that consumers did not use credit card debt for financial liquidity in the early stage of the COVID-19 pandemic. Nagypál *et al.* (2020) report that credit card applications and new mortgage loans declined during the first months of the pandemic in regions with more unemployment insurance claims. Lu and Van der Klaauw (2021) show that there was a sharp drop in consumer credit demand, especially for credit cards. Ho *et al.* (2022) document that there was a substantial decrease in the usage of credit cards and home equity lines of credit by Canadian consumers. Crossley *et al.* (2023) analyse the extent to which pre-existing labour market and financial inequalities were exacerbated by the pandemic between April 2020 and September 2021 in the United Kingdom. Our study extends this body of literature as it includes a post-pandemic period and a cross-country dimension.

Our paper is also consonant with studies on the association between financial and demographic factors and consumers' participation in the credit market as well as on the demand for specific types of credit. The life cycle theory (Modigliani and Brumberg, 1954) and the permanent income hypothesis (Friedman, 1957) provide the workhorse theoretical economic framework for most empirical specifications. The underlying assumption of these models is that individual consumption depends on the resources available to the consumer over her entire lifetime, provided that capital markets are complete. While testing the predictions of the life cycle theory, a vast empirical literature highlights that consumer credit demand may be associated with factors other than total financial resources, mostly demographics, because consumers may face borrowing constraints due to capital market incompleteness (Ando and Modigliani, 1963; Modigliani, 1988; Deaton, 1992; Attanasio, 1999 among others). Hayashi (1985) and Zeldes (1989) infer that liquidity constraints are more pronounced in younger families with low levels of wealth and savings. Jappelli (1990) documents that the probability of a household being credit constrained decreases with age (see also Fabbri and Padula, 2004 and Crook, 2006), current income (see also Del Rio and Young, 2005) and wealth (see also Ruiz-Taggle and Vella, 2015). Cox and Jappelli (1993) find that the probability of holding debt is positively related to permanent earnings, current income, household size and households headed by women. Magri (2007) shows that education is positively associated with debt levels. Crook (2006) documents that married individuals are more likely to have unsecured debt than non-married individuals. Grant (2007) provides evidence on whether the low borrowing in some groups of the population is due to lower demand for loans or denial of credit. Focusing on unsecured borrowing, he finds that 31 percent of households in the United States are credit constrained with young college educated households being most constrained. Several studies explore household mortgage decisions (Campbell and Cocco, 2003; Campbell, 2006; Vickery, 2007; Coulibaly and Li, 2009 among others). We contribute to this body of literature by studying the borrowing behaviour of liquidity-constrained and unconstrained households with respect to long-term secured debt and short-term unsecured debt. We also highlight the role of expectations and perceptions in household borrowing behaviour.

3. Insights into the pandemic and post-pandemic time span

The time span analysed in this paper is characterized by the unprecedented concomitance of non-economic and economic events mostly linked to the global COVID-19 pandemic and the Russian invasion of Ukraine. Figure 1 provides a snapshot of the main events and economic indicators during our period of coverage. Three subperiods are considered.

January 2020 – October 2020 - The two main events are the outbreak of the COVID-19 pandemic and the consequential lockdowns in the euro area. The first confirmed case was in France (in January 2020) and the outbreak subsequently spread widely across the continent. By March 2020, every country in Europe had confirmed cases, and all reported at least one death, with the exception of Vatican City. Italy was the first European country to experience a major outbreak in early 2020, becoming the first country worldwide to introduce a national lockdown. By March 2020, the World Health Organization declared Europe the epicentre of the pandemic and lockdowns introduced in Europe affected more than 250 million people.

In April 2020 the European Commission launched two packages of support measures: the Coronavirus Response Investment Initiative (CRII) and the Coronavirus Response Investment Initiative Plus (CRII+), which were swiftly endorsed by the European Parliament and the European Council. This was supplemented in May 2020 with the presentation of the REACT-EU package. In October 2020 the EU ministers reached a political agreement on the Recovery and Resilience Facility (hereinafter RRF), the main instrument of the €750 billion recovery package negotiated by EU leaders at their July meeting.

The HICP inflation rate in the EU was very low (the highest value being 1.4 percent in January 2020) and entered negative territory in August 2020 (-0.2 percent). The key interest rates for the euro area (interest rate on the main refinancing operations (MRO), deposit facility rate (DFR), marginal lending facility rate (MLFR)) were also very low, close to or even below zero[3].

November 2020 – June 2022 – Whereas 2020 was dominated by the news of how COVID-19 spread across the globe, 2021 focused on ending the pandemic through vaccine distribution. In February 2021 EU leaders agreed

[3] Throughout this period the MRO was 0 percent, the DFR was -0.5 percent and the MLFR was 0.25 percent.

on the need to urgently combine their efforts to accelerate the provision of vaccines. Massive vaccination campaigns were put in place globally. In the EU daily doses peaked at 4.21 million people on 16 December 2021.

In February 2021 the EU Council adopted the regulation establishing the RRF. This facility – the heart of the Next Generation EU recovery instrument – would help member states address the economic and social impact of the COVID-19 pandemic. Most national recovery plans were approved by the EU Council.

On 24 February 2022, Russia launched a military invasion of Ukraine. The main economic consequence was the rise in energy prices, one of the main reasons that led to a surge in inflation worldwide. The HICP in the euro area rapidly increased from -0.3 percent to 8.6 percent throughout this period. To tackle rising prices, in the United States the Federal Reserve Bank started to raise policy rates in March 2022. In spring 2022, the European Central Bank announced its plans to adopt a less accommodative monetary policy as of July 2022. Nevertheless, the key ECB interest rates in the euro area still remained at low levels over these months and unchanged with respect to the previous subperiod.

July 2022 – April 2023 – During this subperiod COVID-19 concerns had mostly subsided. Inflation was on a rising path until October 2022 when it peaked at 10.6 percent. Thereafter the HICP started to fall gradually, albeit remaining at high levels (7 percent in April 2023). The ECB started tightening its monetary policy rapidly by implementing six interest rate increases which raised the MRO to 3.5 percent, the DFR to 3 percent and the MLFR to 3.75 percent in April 2023.

Figure 1 about here

4. Sample and data

This section describes the features of the data used in the empirical analysis. Table 1 reports the summary statistics of the outcome variables along with the explanatory variables used in the models described in Section 5. Our dataset consists of an unbalanced panel of 42,706 households and 177,251 total observations. For some variables, the number of available observations is lower due to (i) item non-response (e.g., the credit application rate and the risk aversion indicators) (ii) selection processes (e.g., the acceptance rate is conditional on having applied for credit) and (iii) the different frequency with which some variables have been collected. In particular, some variables were collected only after some survey waves in the monthly core questionnaire (expectations for interest rates on mortgages were collected only from September 2020 onwards) or up to a certain month (financial concerns due to COVID-19 were collected until June 2022). In addition, the core and quarterly modules in which most expectation and perception questions are fielded can be left uncompleted in some waves, whereas the one-off background module must be completed in order to become a panel member.

Table 1 about here

4.1. Credit applications and credit acceptances

The CES asks one question about credit applications in eight categories every quarter with respect to the three months prior to 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 an existing mortgage. From this question, the total **credit application rate in the past three months**, defined as the percentage of respondents who applied for at least one type of credit, is computed as 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. The **acceptance credit rate** is defined as the percentage of respondents who applied for credit **in the past three months** and had their amount granted in full.[4] If the respondent has applied for more than one type of credit, she is asked to refer to the most recent credit application. Figure 2 reports the time series of these variables.

Between January 2020 and July 2023, the average application rate in the euro area[5] is 14.5 percent[6] (see Table 1). The rate peaks in 2020Q3 (16.3 percent) and reflects the rebound in demand for loans when the first lockdown

[4] The applications that were only partially accepted are treated as zeros. They represent 22 percent of the applicants whose application's outcome is known. The observations with unknown outcomes are treated as missing. We experimented with an alternative definition of the acceptance rate where partially accepted applications were coded as ones. The findings remain robust.

[5] We follow ECB (2021) in defining "euro area" numbers as the results pooled across the largest six euro area countries included in the CES.

[6] In the 2017 and 2021 HFCS data the average application rate was about 21.4 percent and 22.3 percent, respectively.

ended. According to the Bank Lending Survey (hereinafter BLS), the net demand for housing loans and consumer credit increased in 2020Q3 compared to the previous quarter reflecting the improvement in consumer confidence after the lifting of the severe lockdown measures implemented in 2020Q1 and 2020Q2. In 2020Q4, however, the rate experiences the strongest decline (to 12.8 percent) in conjunction with the surge of COVID cases in late 2020 that led to a second lockdown. As of 2021Q1 most of the large public support measures start to be implemented to make sure that access to credit is not restrained and households are not credit-rationed. The lowest value for credit applications is recorded in 2022Q2 (12.2 percent), soon after the Russian invasion of Ukraine and the announcement of monetary policy tightening measures.

Over our full period the average acceptance rate is 71.2 (see Table 1). The highest value is observed at the beginning of the period (82.8 percent) and declines thereafter until 2021Q3 (63.7 percent), reflecting the tightening of credit standards for housing loans and consumer credit in response to the deterioration of the economic outlook and worsened credit worthiness of consumers hit by the pandemic. Between 2021Q3 and 2022Q3 the acceptance rate stays above the average values, mirroring the easing of credit standards for consumer credit and other lending to households during this period.[7] This value is restored in 2023Q2.

Figure 2 about here

4.2. Demographic and economic variables

In the baseline regressions, we follow the literature and we control for age (in dummies), gender (female indicator), education (high-education indicator)[8], household size[9], the presence of a partner, the number of children[10], net income quintiles (values are imputed), being unemployed, risk attitude, having an outstanding mortgage or home ownership, being concerned about the financial situation of the respondent's household due to

[7] See for BLS results: https://www.ecb.europa.eu/stats/ecb_surveys/bank_lending_survey/html/index.en.html

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

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

[10] 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.

COVID-19 (ordered scale from 0, not concerned, to 10, extremely concerned), credit access being harder than 12 months earlier (indicator for respondents reporting it to be much harder or somewhat harder[11]), having insufficient liquidity and financial literacy.

In the augmented regressions for credit applications, we also control for whether the household situation is worse than 12 months before the interview as well as for expectations about interest rates on mortgages in the 12 months after the interview in the country the respondent lives in. These are two variables collected in the CES that relate to perceptions and expectations, dimensions that are hardly incorporated in the empirical literature on household borrowing behaviour despite the fact that it is reasonable to assume an association between credit applications and each of them.

Finally, in the augmented regressions for credit acceptance, we control for past delinquencies. The CES collects quarterly data on late payments on debt and non-debt obligations. At least one late payment in the past 12 months is an indicator taking value 1 if the respondent reports having had difficulty making payments on time for at least one of the following: rent, mortgage, other loans, utility bills.

5. Regression analysis

In this section we empirically investigate how credit applications and acceptances vary over time and across households. We adopt a regression approach that has two main advantages. First, we can check whether inferences are robust to multiple sources of household heterogeneity. Second, we can investigate the presence of non-linearities in how liquidity and the credit type interact in explaining credit applications.

5.1. Base models of credit applications and credit acceptances

We estimate the probability that a household will apply for a loan through a binary probit model of the following form:

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

$$P(Apply_{h,t}=1|\ X_{h,t})=\Phi(\gamma' X_{h,t})\ , \qquad (1)$$

where $Apply_{h,t}$ is a dummy variable that denotes whether the household *h* has applied for a loan in the three months prior to the interview date t, Φ is the cumulative distribution function of a standard normal distribution and γ is the slope for explanatory demographic and economic variables $X_{h,t}$ that include a full set of time and country fixed effects.

Likewise, we use a probit model to estimate the probability of a household's credit application being accepted as follows:

$$P(Accepted_{h,t}=1|\ X_{h,t})=\Phi(\gamma' X_{h,t}), \qquad (2)$$

where $Accepted_{h,t}$ is a dummy variable that denotes whether the household's credit application has been fully accepted. In our analysis, survey weights are employed to ensure population representativity and standard errors are clustered at the respondent's level. For both applications and acceptances, we run a baseline as well as an augmented version of the models, with the variables reported in Section 4.2 for which economic theory suggests they are related to credit applications and acceptances or where previous empirical studies have proven them to be important determinants. Throughout this section, all figures show the marginal effects and the 95% confidence intervals for the estimated quarterly time dummies. 2020Q3 serves as a reference category.

Figure 3 reports the estimated marginal effects for the time dummies in model (1) and model (2) in their baseline and in their augmented specification. Credit applications and credit acceptances display a different pattern over time. In the baseline specification, compared to 2020Q3 households are less likely to apply for credit in all quarters, except the last one. The marginal effects for the significant estimates range from -3.7 to -1.3 percentage points. Adding the household financial situation and interest rate expectations improves the precision of the estimated marginal effects for the most recent quarters and it amplifies the magnitude of the association as of 2022Q1. The marginal effects for the significant estimates range from -4.3 to -1.3 percentage points. It reverses the sign of the coefficient only in 2023Q1, even if it remains insignificant. The lowest estimated marginal effect (-0.037 and -0.043 for the baseline and the augmented specification, respectively) is found in 2022Q2, after the first interest rate hike by the FED and right before the start of the tightening of the monetary policy in the euro area. This finding is also similar to the BLS report for the same quarter, which states that the decrease in the net demand for housing loans is mainly due to the recent considerable increases in interest rates on loans for house purchases and to the significant decline of the consumer confidence indicator, reaching its lowest level in June 2022 since the early stages of the pandemic. The probability of applying for a loan continues to decline until 2023Q1, albeit that the estimated coefficients are higher in magnitude. The estimated marginal effect in 2021Q4 (-0.02) is similar to the drop in the European Commission's consumer sentiment indicator for the same quarter, reflecting the reintroduction of the containment measures in some euro area countries and the uncertainties triggered by the virus' Omicron variant.

By contrast, compared to 2020Q3 credit acceptance is significantly more likely to occur in 2020Q1 and 2020Q2 in both model specifications. From the start of the COVID-19 pandemic the ECB adopted a set of monetary measures (e.g., the increase of asset purchases, a revision of the structure and pricing in the TLTRO programme and the easing of the collateral framework) to ensure credit supply and stabilise the euro area economy. Credit acceptance is also significantly higher in 2022Q4 (the estimated marginal effect equals 0.064 and 0.070 for the baseline and the augmented specification, respectively), reflecting the decline in the share of rejected applications as reported in the BLS report for that quarter. The probability of credit acceptance further increases significantly in the first three quarters of 2022 and, controlling for late payments, in 2023Q2 (the estimated marginal effect is 0.070).

Overall, our findings mirror the increasing propensity of households to save in the second quarter of 2020 (as measured by the DG-ECFIN and Eurostat euro area data from the sectoral accounts as well as the European Commission's consumer survey indicator), which reached unprecedented levels in response to COVID-19 (Dossche and Zlatanos, 2020). Our findings are also in line with Ho *et al.* (2022) – who show that Canadian consumers were able to meet their financial needs during the pandemic without increasing their debt burdens – and with Horvath *et al.* (2023) – who show that in the United States the local pandemic severity had a strong negative effect on credit card spending early in the pandemic, which diminished over time. The drop in household demand for credit can be related to two main factors: the severe restrictions imposed by the lockdown measures to contain the virus as well as the uncertainty generated by the sudden outbreak of the pandemic in terms of unemployment and expected income risk.

Figure 3 about here

We now turn our attention to the estimated results for the other explanatory variables in model (1) and model (2) for the probability of credit application and for credit acceptance in their baseline and in their augmented specifications. Table 2 reports our findings. The sample size is much larger for the application regressions (34,377 and 32,377 households, implying 160,296 and 145,381 total observations) than for the acceptance regressions (8,615 and 8,371 households, implying 15,424 and 14,940 total observations). This is due to the fact that we look at the subsample of respondents who applied for credit and that 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.

We find significant country effects in all regressions with very comparable signs and magnitudes. In almost all countries households are significantly less likely to apply and significantly more likely to get their credit approved than in Germany. Only in Italy is the probability of applying for credit significantly higher than in Germany. Christl *et al.* (2022) use the microsimulation model for the EU, with the underlying EU-SILC 2019 data, to estimate the cushioning effect of taxes and social transfers on both household income and household demand in the context of the COVID-19 pandemic. They document a general high demand-stabilising effect in all EU member states, albeit with some heterogeneity. Many tax-benefit systems can stabilise demand at a very high level. For the Netherlands, Belgium and France demand stabilisation coefficients are very close to 100, meaning that household demand was almost completely stabilized during the pandemic. For those countries we indeed find the highest marginal effects (-3.1, -2.6 and -1.7 percentage points, respectively in the augmented specification). In Italy the stabilisation coefficient is the lowest amongst the countries analysed in our paper, implying that household demand was not fully stabilized and therefore in need to rely on formal credit market participation. For Germany, the coefficient is higher than for Italy but lower than all other countries, and our estimated marginal effect for Italy is 1.2 percentage points in the augmented specification.

As for the demographic and economic controls our findings are very much relatable to the existing literature and can be summarized as follows. Credit applications are significantly associated with age (credit demand is monotonically decreasing with age), gender (women apply less than men), education level (the highly educated are more likely to apply than the low-educated), having a partner (positive association), household income (people in the two lowest quintiles are less likely to apply than those in the top quintile), being unemployed and financial literacy (negative association), risk aversion (risk-averse or risk-neutral respondents are less likely to apply than risk-loving respondents), mortgage holding, being financially concerned, or liquidity-constrained and credit condition (positive association). Interestingly, we find also a significant and positive association for household financial situation perceptions and for mortgage interest rate expectations in the augmented specification, whereas the findings for the other variables remain robust in the augmented specification.

Credit acceptance is significantly associated with age (the age function is concave with 50-55-year-old respondents having the highest probability of getting their credit application approved compared to those of retirement age), household size (negative association), household income (compared to the highest quintile the households in any of the lower quintiles are less likely to get approval), being unemployed (negative association), risk aversion, home ownership and financial literacy (positive association for all), as well as past payment delinquencies (negative association).

Table 2 about here

In order to better investigate the heterogeneity in credit demand, we focus on the augmented specifications of model (1) and model (2) and estimate them for two sample splits. The first split is between liquid and illiquid households. There are two main motivations behind this split. Consumers typically have two main sources of finance: savings and bank credit. In the presence of a credit shortage, households may become constrained. When households do not face any borrowing constraints, the standard life cycle theory (Ando and Modigliani, 1963) finds that household consumption is only driven by the level of a household's net wealth and lifetime income. Economic theory postulates that only unconstrained households can borrow in order to smooth consumption after an unexpected temporary adverse shock, such as a drop in income due to illness or short-term unemployment (Galí *et al.*, 2007; Clinton *et al.*, 2011). In addition, the empirical literature shows that households borrow to finance investment in illiquid assets with high long-term returns such as housing (Kaplan *et al.*, 2014), and that unconstrained households voluntarily take on more debt and in increasing amounts (La Cava and Simon, 2005).

Figure 4 shows that constrained households are significantly less likely to apply for credit in almost all quarters *vis-à-vis* 2020Q3, whereas for unconstrained households the credit applications do not significantly differ for most quarters.[12] The magnitude of the estimated marginal effects is also always larger for the constrained respondents, and it ranges between -0.075 in 2023Q1 and -0.032 in 2021Q4. By contrast, the probability of getting credit is significantly higher for the liquid households in almost all quarters compared to 2020Q3. The estimated marginal effect ranges between 0.064 in 2021Q2 and 0.151 in 2020Q1. For the illiquid households, the time marginal effect is estimated much more imprecisely due to the lower number of observations (40,634 vs 104,747), but it is significant in 2020Q1 and 2021Q1 with estimated marginal effects of 0.10 and -0.166, respectively.

Christl *et al.* (2022) demonstrate that monetary compensation schemes substantially limited the increase in liquidity-constrained households caused by the pandemic by diminishing their income loss. For example, in the Netherlands they expected an increase in liquidity-constrained people of 0.1 percentage points that would have been 1.5 percentage points in the absence of those schemes. Our findings can also be related to Li *et al.* (2020), who document that in China the households' likelihood of liquidity constraints increases with the severity of the pandemic, mainly due to the pandemic's adverse effect on employment and household income. When splitting our sample by liquidity constraints, we find that reporting having financial concerns due to the pandemic has an opposite association with the probability of applying for credit for unconstrained households (0.50) *vis-à-vis* constrained households (-0.50).

Figure 4 about here

The second split involves the household's perception of its own financial situation at the time of interview compared to one year earlier. The reason for this is that credit demand might rise because households are optimistic about income prospects, or because borrowing costs (interest rates) are low. The years covered in this paper include an initial period of extraordinary monetary accommodation (inherited from the end of the Great Moderation years) with very low borrowing rates and low returns on safe assets, followed by a period of monetary tightening due to increasing inflation pressure. This feature of our data, along with the collection of household

[12] The full estimation results are reported in Table 3.

perceptions, allows us to study how the household's perception of its own finances is associated with its borrowing behaviour. For the households whose financial situation is perceived to be easier at the time of interview than 12 months earlier we observe a significant decrease in the likelihood of credit applications until 2022Q2 (Figure 5).[13] The estimated marginal effects range between -0.044 in 2022Q2 and -0.014 in 2021Q3. Thereafter, the estimated marginal effects become positive, albeit insignificant, until 2023Q2 when it becomes significantly higher than in 2020Q3 (the marginal effect equals 0.02). By contrast, the households whose financial situation is perceived to be harder at the time of interview than 12 months earlier significantly reduce their demand for credit in all quarters. The magnitude of the estimated marginal effects is also larger, in the range between -0.087 in 2023Q1 and -0.024 in 2021Q1, and particularly in the most recent quarters when the ECB repeatedly increased interest rates. However, when it comes to credit acceptances the differences between the two subgroups are less strong. The probability of obtaining credit is significantly higher for both subgroups in the first half of 2020, whereas the respondents whose financial situation is easier than in the previous year have their credit accepted also in the first half of 2021. These findings can be rationalized if we think that credit acceptance should be mostly associated with supply factors rather than with household perceptions.

Figure 5 about here

5.2. Interactive models of credit applications

A vast body of the microeconomic literature shows that households may not be able to purchase a home, own a business or reach their potential to accumulate wealth due to liquidity constraints (Hall and Mishkin, 1982; Calem and Mester, 1995 among others). For this reason, we want to dive into the interaction between household liquidity and credit types. A common distinction made in the literature and by practitioners is between secured and unsecured debt. Secured debt is backed by collateral so that if a borrower defaults on a secured loan, the lender could repossess the collateral. Moreover, secured debt typically involves (much) larger amounts of money. The analysis by credit type is conducted separately for liquid and illiquid households. We restrict our analysis in two ways. First, we select mortgages and consumer credit as the two mostly reported categories for secured and

[13] The full estimation results are reported in Table 3.

unsecured credit, respectively. Second, we run the analysis for credit applications only, because for credit acceptances the sample size is too small. This implies that we estimate a slightly different version of model (1) as follows:

$$P(Apply\_Mortgage_{h,t}=1|Liquid=0, , X_{h,t})=\Phi(\gamma' X_{h,t}) \quad (3a)$$

$$P(Apply\_Mortgage_{h,t}=1|Liquid=1, X_{h,t})=\Phi(\gamma' X_{h,t}) \quad (3b)$$

And

$$P(Apply\_ConsumerCredit_{h,t}=1|Liquid=0, X_{h,t})=\Phi(\gamma' X_{h,t}) \quad (3c)$$

$$P(Apply\_ConsumerCredit_{h,t}=1|Liquid=1, X_{h,t})=\Phi(\gamma' X_{h,t}) \quad (3d)$$

Figure 6 reports the estimated marginal effects of the time dummies for models (3a) to (3d).[14] We observe that liquid households significantly increase their demand for mortgage debt in 2021Q2 and 2021Q3, during which they still have very favourable borrowing conditions and the pandemic is sensed to be under control due to the massive vaccination campaigns. By the end of 2021, however, a second lockdown was introduced and at the start of 2022 the Russian invasion of Ukraine materialized. Shortly afterwards the monetary policy started to be less accommodative. The demand for mortgages became insignificant for unconstrained households and fell significantly in the case of constrained households, especially from 2022Q3, when the ECB tightened its monetary policy stance in response to high inflation.

The right-hand side panel of Figure 6 shows that the demand for consumer credit is insignificant for both liquid and illiquid households. We can think of several explanations for this finding. The two 2020 lockdowns severely reduced household spending needs, especially for some items like transportation and recreation activities. During the pandemic some government interventions were implemented to alleviate short-term financial needs for a large

[14] The full estimation results are reported in Table 4.

share of the working population (mostly the self-employed). After the pandemic, borrowing conditions worsened rapidly.

We also find (see Table 4) that perceptions about access to credit and financial situation vary among constrained and unconstrained households for both credit types. Perceptions about harder credit access are positively associated with the probability of applying for a mortgage and higher for unconstrained households. Perceptions of a harder financial situation with regard to the probability of applying for a mortgage are entirely driven by unconstrained households. Unlike in the case of mortgage loans, consumer loan applications are positively associated with households perceiving their financial situation to be harder and with constrained households.

Figure 6 about here

6. Discussion and concluding remarks

We use quarterly data from the CES between January 2020 and July 2023 in the six largest euro area countries to study household participation in the credit market. The time span covered in this paper is unique in many respects. In the years just prior to the outbreak of the COVID-19 pandemic, advanced economies were locked in a persistent liquidity trap with sluggish demand, weak inflation and low interest rates. At the lower bound, falling inflation expectations pushed up real rates, compounding economic stagnation and low inflation. Expectations of weak demand discouraged households from borrowing from future income, making those initial pessimistic expectations self-fulfilling. It was in this context that the COVID-19 pandemic broke out at the start of 2020. All EU countries experienced large reductions in their gross domestic product and households faced an increased risk of unemployment due to lockdown measures and the general reduction in economic activity. National governments tried to withstand the crisis with targeted policy measures, mostly monetary compensation schemes, to help workers stabilise household income and demand. After a massive vaccination campaign starting in 2021 the virus was gradually brought under control and the economy rebounded in all countries. At the beginning of 2022 the Russia’s invasion of Ukraine introduced a new shock related to energy prices. Inflation pressures induced a prolonged phase of monetary tightening that increased the financial burden on households.

All our findings, in particular the overall fall in credit applications and the absence of demand for short-term consumer credit, point to the role of the severe lockdown measures and to the cushioning effect of taxes and social transfers in the context of the COVID-19 pandemic on the one hand, and to the less favourable borrowing conditions in the euro area at the aftermath of the outbreak of the war on the other hand.

Our results are robust to several checks. We run the models for credit applications and acceptances for each of the three subperiods described in Section 3, by country, and by income quintiles. All robustness checks aim to investigate whether the demographic and economic controls change across the subperiods, the countries and along the income gradient.

While able to capture the financial distress in the household sector reasonably well, our data suffers from several limitations. First, it does not allow to shed light on the intensive margin of the credit demand, as information on the amounts requested and granted is not available. Second, a more comprehensive analysis of credit acceptances, even if only for the extensive margin, is hampered by the low number of observations. Third, the data are unable to reveal the intrinsic nature of different debt types, in particular between collateralized and non-collateralized debt. Nevertheless, this paper has potentially important implications for monetary and fiscal policy and more broadly for individual wellbeing and economic growth. It highlights the countercyclical role of fiscal policies in times of severe distress for some groups of the population, such as constrained households. It also shows that subjective perceptions of credit access, financial concerns and expectations on interest rates matter for the demand for credit.

References

Ando, A. and Modigliani, F. (1963) The life-cycle hypothesis of saving: aggregate implications and tests. *American Economic Review*, 53, 55-84.

Attanasio, O. (1999) Consumption In: Taylor JB, Woodford M. (eds) Handbook of macroeconomics, Elsevier, Amsterdam.

Calem, S.P. and Mester, L. (1995) Consumer behavior and the stickiness of credit-card interest rates. *American Economic Review*, 85, 1327–1336.

Campbell, J.Y. and Cocco, F. (2003) Household risk management and optimal mortgage choice. *Quarterly Journal of Economics*, 119, 1449-1494.

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

Clinton, K., Kumhof, M., Laxton, D. and Mursula, S. (2011) Deficit reduction: Short-term pain for long-term gain. *European Economic Review* 55, 118–139.

Coulibaly, B. and Li, G. (2009) Choice of Mortgage contracts: evidence from the survey of consumer finances. *Real Estate Economics*, 37, 659-673.

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

Christl, M., De Poli, S., Figari, F., Hufkens, T., Leventi, C., Papini, A. and Tumino, A. (2022) Monetary ompensation schemes during the COVID-19 pandemic: Implications for household incomes, liquidity constraints and consumption across the EU. JRC Working Papers on Taxation and Structural Reforms 03/2022.

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

Crossley, T.F., Fisher, P., Low, H. and Levell, P. (2023) A year of COVID: The evolution of labour market and financial inequalities through the crisis. *Oxford Economic Papers*, 75, 589-612.

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

Del-Rio, A. and Young, G. (2005) The determinants of unsecured borrowing: Evidence from the British Household Panel Survey. Bank of England Working Paper 263.

Dossche, M. and Zlatanos, S. (2020) COVID-19 and the increase in household savings: precautionary or forced? ECB Economic Bulletin, June.

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

Fabbri, D. and Padula, M. (2004) Does poor judicial enforcement make households credit-constrained *Journal of*

Friedman, M. (1957) A theory of consumption function. Princeton University Press.

Galí, J., López-Salido, J.D. and Vallés, J. (2007) Understanding the effects of government spending on consumption. *Journal of the European Economic Association* 5, 227–270

Georgarakos, D. and Kenny, G. (2022) Household spending and fiscal support during the COVID-19 pandemic: Insights from a new consumer survey. *Journal of Monetary Economics*, 129, S1-S14.

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

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

Hayashi, F. (1985) The effect of liquidity constraints on consumption: a cross-sectional analysis. *The Quarterly Journal of Economics*, 100, 183-206.

Ho, A.T.Y., Morin, L., Paarsch, H.J. and Huynh, K.P. (2022) Consumer credit usage in Canada during the coronavirus pandemic. *Canadian Journal of Economics/Revue canadienne d'économique*, Special issues on Covid Economics.

Horvath, A., Kay, B. and Wix, C. (2023) The COVID-19 shock and consumer credit: Evidence from credit card data. *Journal of Banking & Finance*, 152.

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

Kaplan, G., Violante, G. and Wiedner, J. (2014) The wealthy hand-to-mouth. *Brookings Papers on Economic Activity*, 45, 77-153.

La Cava, G. and Simon, J. (2005) Household debt and financial constraints in Australia. *The Australian Economic Review*, 38, 40–60.

Li, J., Song, Q., Peng C. and Wu, Y. (2020) COVID-19 Pandemic and Household Liquidity Constraints: Evidence from Micro Data. Emerging Markets Finance and Trade, 56, Issue 15.

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. and Brumberg, R. (1954) Utility analysis and the consumption function: an interpretation of cross-section data. In Kurihara, K., (ed), *Post-Keynesian Economics*, Rutgers University Press, New Brunswick.

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

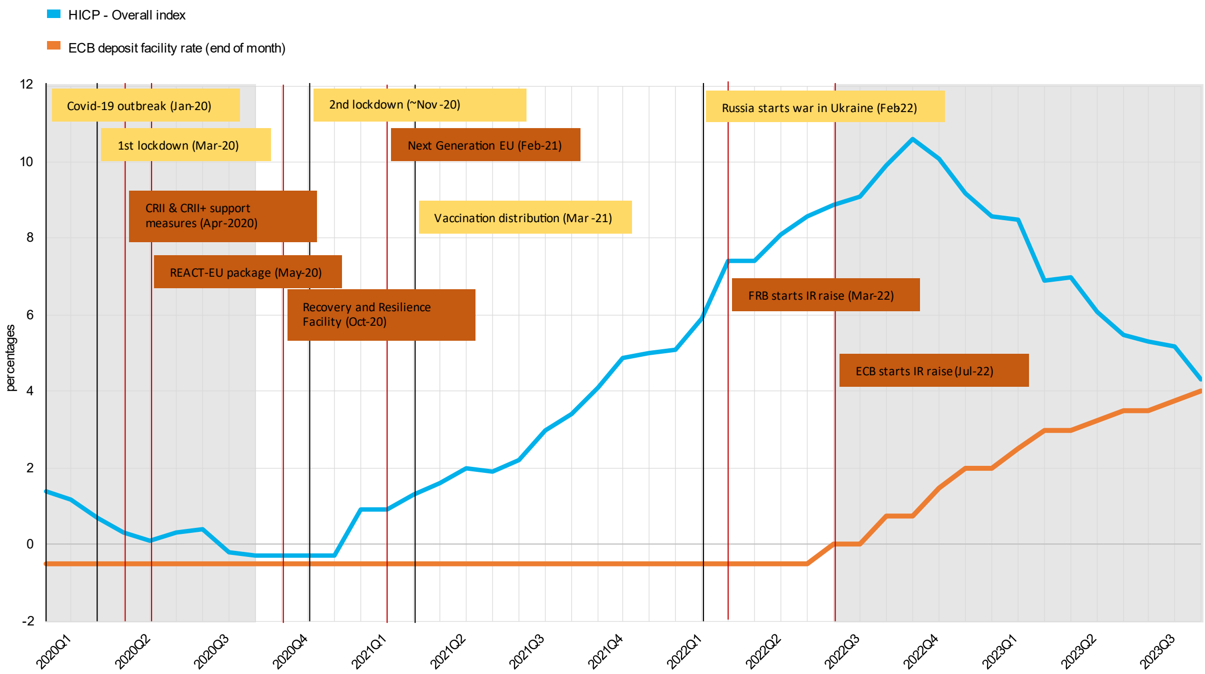
Ruiz-Taggle, J. and Vella, F. (2015) Borrowing constraints and credit demand in a developing economy. *Journal of Applied Econometrics*, 31, 865-891.

Vickery, J. (2007) Interest rates and consumer choice in the residential mortgage market. Working Paper, Federal Reserve Bank of New York.

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

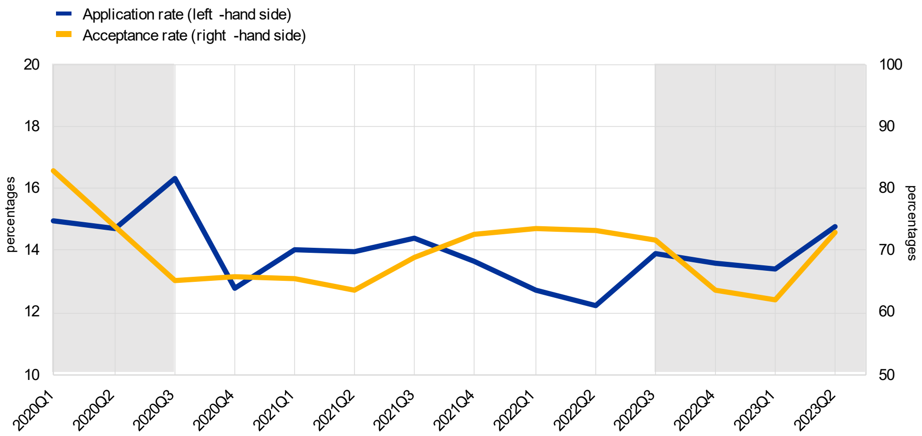
Figures and Tables

Figure 1: Snapshot of the timeline of the main economic and non-economic events



Notes: This figure visualises the content of Section 3. The non-economic events are in yellow boxes; the economic events are in red boxes. The shaded and unshaded areas refer to the three subperiods.

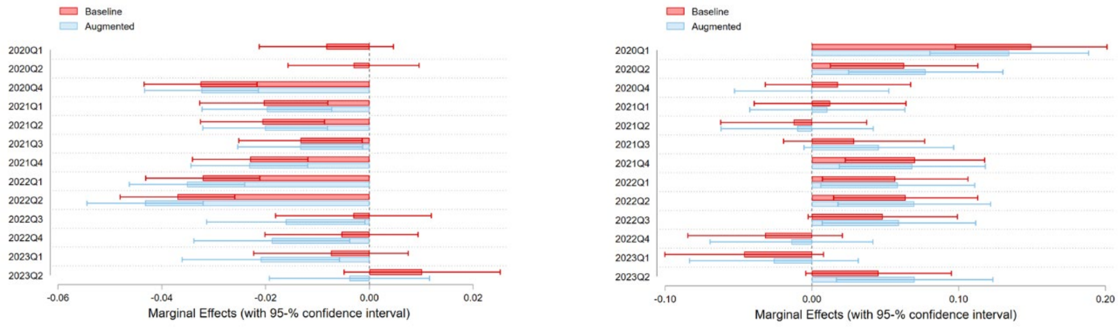
Figure 2: Credit applications and credit acceptances over time



Notes: This figure reports the two dependent variables as described in Section 4.1.

Figure 3: Time effects for credit applications and credit acceptances – baseline and augmented models

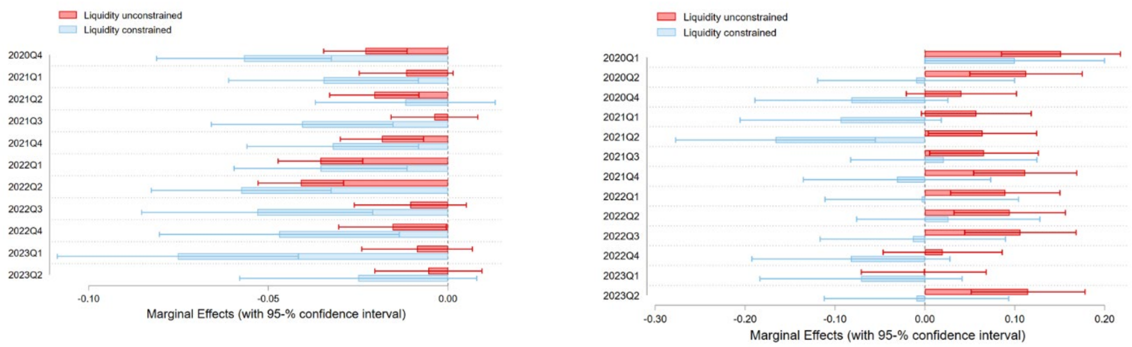
Credit applications | Credit acceptances



Notes: The figure reports the estimated marginal effects for the time dummies in model (1) and model (2) in their baseline (red) and augmented (blue) specification as explained in Section 4.1 and Section 4.2. 2020Q3 serves as a reference category. The estimated marginal effects of the other control variables are reported in Table 2.

Figure 4: Time effects for credit applications and credit acceptances - augmented models by liquidity constraints

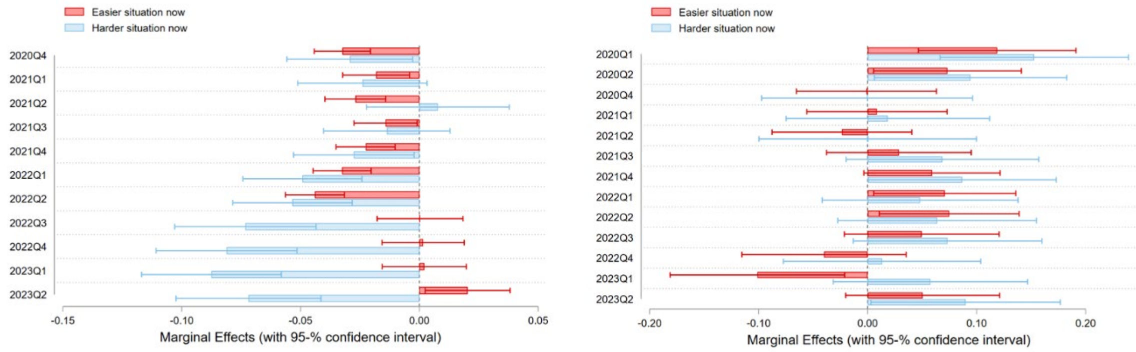
Credit applications | Credit acceptances



Notes: The figure reports the estimated marginal effects for the time dummies in model (1) and model (2) in their augmented specification as explained in Section 4.1 and Section 4.2 for liquidity-constrained (blue) and liquidity-unconstrained (red) households. 2020Q3 serves as a reference category. The estimated marginal effects of the other control variables are reported in Table 3, columns 1-2 and 5-6.

Figure 5: Time effects for credit applications and credit acceptances - augmented models by perceptions of own household financial situation

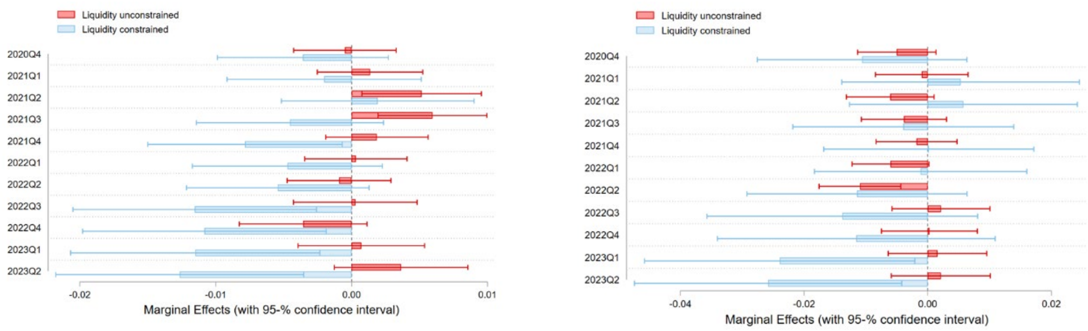
Credit applications | Credit acceptances



Notes: The figure reports the estimated marginal effects for the time dummies in model (1) and model (2) in their augmented specification as explained in Section 4.1 and Section 4.2 for housheholds that report their financial situation to be easier (red) and harder (blue) at the time of interview than 12 months before. 2020Q3 serves as a reference category. The estimated marginal effects of the other control variables are reported in Table 3, columns 3-4 and 7-8.

Figure 6: Time effects for credit applications – interactive models for mortgages and consumer credit by liquidity constraints

Mortgage credit applications | Consumer credit applications



Notes: The figure reports the estimated marginal effects for the time dummies in models (3)-(6) as explained in Section 5.2 for mortgages (left-hand panel) and consumer credit (right-hand panel) for liquidity-constrained (blue) and liquidity-unconstrained (red) households. 2020Q3 serves as a reference category. The estimated marginal effects of the other control variables are reported in Table 4.

Table 1: Summary Statistics

Variable	Mean	Min	Max	Std.Dev.	N.Obs.	N.HHs
Applied for credit	0.145	0	1	0.352	166,270	35,357
Accepted credit application	0.712	0	1	0.453	15,750	8,790
Age 18-34	0.235	0	1	0.424	177,251	42,706
Age 35-50	0.333	0	1	0.471	177,251	42,706
Age 50-55	0.137	0	1	0.344	177,251	42,706
Age 56-60	0.102	0	1	0.302	177,251	42,706
Age 61-65	0.091	0	1	0.288	177,251	42,706
Age over 65	0.101	0	1	0.302	177,251	42,706
Female	0.505	0	1	0.500	177,151	42,666
Higher education	0.548	0	1	0.498	177,251	42,706
HH size (truncated)	2.655	1	5	1.188	177,251	42,706
Partner	0.643	0	1	0.479	177,251	42,706
Number of children	0.698	0	3	0.921	177,251	42,706
Income quintile	2.973	1	5	1.408	177,251	42,706
Unemployed	0.080	0	1	0.271	177,251	42,706
Risk averse	0.490	0	1	0.500	174,238	41,988
Risk neutral	0.230	0	1	0.421	174,238	41,988
Risk loving	0.280	0	1	0.449	174,238	41,988
Financial literacy	2.442	0	4	1.123	177,251	42,706
With mortgage	0.296	0	1	0.457	177,251	42,706
Financial concerns	4.000	0	10	3.583	175,646	39,386
Credit harder than 12 months earlier	0.324	0	1	0.468	175,027	36,923
Insufficient liquidity	0.292	0	1	0.455	177,246	37,287
Hh situation worse than 12 months earlier	0.364	0	1	0.481	177,246	37,639
Mortgage interest rate expectations	4.000	-2	25	3.150	158,076	34,559
Home owner	0.655	0	1	0.475	177,251	42,706
With late payment	0.108	0	1	0.311	165,795	35,232
Belgium	0.081	0	1	0.273	177,251	42,706
Germany	0.203	0	1	0.402	177,251	42,706
Spain	0.209	0	1	0.407	177,251	42,706
France	0.208	0	1	0.406	177,251	42,706
Italy	0.219	0	1	0.414	177,251	42,706
Netherlands	0.079	0	1	0.270	177,251	42,706

Table 2: Baseline regressions for credit applications and acceptances

	Applications		Acceptances	
	Model (1) base	Model (1) augmented	Model (2) base	Model (2) augmented
Age 18-34 years	0.105***	0.107***	-0.106***	-0.077***
	(0.007)	(0.007)	(0.027)	(0.029)
Age 35-49 years	0.043***	0.044***	-0.035	-0.024
	(0.006)	(0.006)	(0.027)	(0.028)
Age 50-55 years	0.019***	0.015**	0.047	0.049
	(0.007)	(0.007)	(0.029)	(0.030)
Age 56-60 years	0.012*	0.011	0.010	0.025
	(0.007)	(0.007)	(0.031)	(0.031)
Age 61-65 years	0.004	0.001	-0.010	0.003
	(0.007)	(0.007)	(0.031)	(0.031)
Female	-0.035***	-0.038***	0.006	-0.000
	(0.004)	(0.004)	(0.013)	(0.013)
High education	0.016***	0.016***	0.020	0.033**
	(0.004)	(0.004)	(0.013)	(0.013)
Household size (censored)	0.000	-0.001	-0.021**	-0.016*
	(0.002)	(0.002)	(0.008)	(0.009)
Partner present	0.008*	0.011**	0.019	0.010
	(0.004)	(0.004)	(0.016)	(0.016)
Number of children (censored)	0.015***	0.015***	-0.008	0.001
	(0.003)	(0.003)	(0.011)	(0.011)
Net hh income quintile 1	-0.041***	-0.044***	-0.116***	-0.086***
	(0.006)	(0.006)	(0.023)	(0.023)
Net hh income quintile 2	-0.024***	-0.025***	-0.090***	-0.064***
	(0.006)	(0.006)	(0.020)	(0.020)
Net hh income quintile 3	-0.004	-0.006	-0.052***	-0.044**
	(0.006)	(0.006)	(0.018)	(0.018)

Net hh income quintile 4	-0.008	-0.009*	-0.035**	-0.036**
	(0.006)	(0.006)	(0.018)	(0.018)
Unemployed	0.052***	0.064***	-0.269***	-0.223***
	(0.007)	(0.007)	(0.021)	(0.023)
Risk-averse	-0.011***	-0.011***	0.042***	0.036**
	(0.004)	(0.004)	(0.015)	(0.015)
Risk-neutral	-0.014***	-0.011**	0.029*	0.009
	(0.005)	(0.005)	(0.017)	(0.017)
Financial literacy	-0.017***	-0.018***	0.062***	0.041***
	(0.002)	(0.002)	(0.006)	(0.006)
With mortgage	0.038***	0.037***		
	(0.004)	(0.004)		
Financial concerns	0.004***	0.003***		
	(0.001)	(0.001)		
Credit harder than 12 months earlier	0.049***	0.041***		
	(0.004)	(0.004)		
Insufficient liquidity	0.047***	0.044***		
	(0.004)	(0.004)		
Hh situation worse than 12 months earlier		0.017***		
		(0.003)		
Mortgage interest rate expectations		0.005***		
		(0.001)		
Home owner			0.034**	0.028**
			(0.014)	(0.014)
With late payment				-0.243***
				(0.015)
Belgium	-0.028***	-0.026***	0.072***	0.071***
	(0.006)	(0.006)	(0.024)	(0.024)

Spain	-0.011**	-0.011**	0.098***	0.073***
	(0.006)	(0.005)	(0.020)	(0.020)
France	-0.020***	-0.017***	0.079***	0.043**
	(0.005)	(0.005)	(0.019)	(0.019)
Italy	0.011**	0.012**	0.140***	0.134***
	(0.006)	(0.006)	(0.019)	(0.019)
Netherlands	-0.032***	-0.031***	0.018	0.039
	(0.007)	(0.007)	(0.030)	(0.030)
Observations	160,296	145,381	15,424	14,940
HHs (Cluster)	34,377	32,377	8,615	8,371
Pseudo R-squared	0.0576	0.0647	0.113	0.147

The table reports marginal effects and robust standard errors (in parenthesis) estimated for model (1) and model (2) as specified in Section 4. These regressions include the quarterly dummies whose estimated marginal effects are displayed in Figure 3.

***, **, * denote significant at 1, 5, 10 percent level respectively.

Table 3: Regressions for credit applications and acceptances – by liquidity constraints and own household financial situation perceptions

	Applications - Model (1) augmented				Acceptances - Model (2) augmented			
	Liquidity		HH financial situation now vs past		Liquidity		HH fin. situation now vs past	
	Unconstrained	Constrained	Easier	Harder	Unconstrained	Constrained	Easier	Harder
Age 18-34 years	0.095***	0.095***	0.099***	0.126***	-0.043	-0.156***	-0.036	-0.133***
	(0.007)	(0.018)	(0.007)	(0.012)	(0.033)	(0.049)	(0.038)	(0.037)
Age 35-49 years	0.045***	0.040**	0.054***	0.029***	-0.000	-0.075	-0.004	-0.055
	(0.007)	(0.018)	(0.006)	(0.010)	(0.032)	(0.046)	(0.038)	(0.035)
Age 50-55 years	0.020**	0.004	0.024***	0.004	0.050	0.041	0.083**	0.004
	(0.008)	(0.020)	(0.007)	(0.011)	(0.034)	(0.051)	(0.040)	(0.038)
Age 56-60 years	0.014*	0.000	0.016**	0.004	0.075**	-0.064	0.070*	-0.022
	(0.008)	(0.021)	(0.007)	(0.011)	(0.034)	(0.055)	(0.041)	(0.041)
Age 61-65 years	0.006	-0.014	0.016**	-0.022**	0.031	-0.062	0.038	-0.035
	(0.008)	(0.021)	(0.007)	(0.011)	(0.036)	(0.057)	(0.043)	(0.041)
Female	-0.032***	-0.052***	-0.033***	-0.046***	-0.025*	0.061***	-0.013	0.017
	(0.004)	(0.008)	(0.004)	(0.006)	(0.015)	(0.023)	(0.016)	(0.018)
High education	0.009**	0.032***	0.014***	0.015**	0.034**	0.028	0.040**	0.027
	(0.004)	(0.008)	(0.004)	(0.006)	(0.015)	(0.022)	(0.016)	(0.018)
Household size (censored)	-0.001	-0.002	-0.002	0.003	-0.013	-0.014	-0.017	-0.010
	(0.003)	(0.005)	(0.002)	(0.004)	(0.010)	(0.015)	(0.011)	(0.013)
Partner present	0.016***	0.000	0.014***	0.002	0.015	-0.005	0.003	0.017
	(0.004)	(0.009)	(0.004)	(0.007)	(0.018)	(0.028)	(0.020)	(0.023)
Number of children (censored)	0.016***	0.012**	0.014***	0.016***	-0.002	0.003	0.003	-0.006
	(0.003)	(0.006)	(0.003)	(0.005)	(0.012)	(0.019)	(0.014)	(0.016)
Net hh income quintile 1	-0.012**	-0.138***	-0.033***	-0.064***	-0.091***	-0.014	-0.115***	-0.052
	(0.006)	(0.015)	(0.006)	(0.011)	(0.027)	(0.042)	(0.029)	(0.031)
Net hh income quintile 2	-0.016***	-0.086***	-0.019***	-0.039***	-0.079***	0.025	-0.082***	-0.022
	(0.006)	(0.015)	(0.006)	(0.010)	(0.023)	(0.038)	(0.024)	(0.029)

Net hh income quintile 3	-0.005	-0.046***	-0.005	-0.010	-0.031	0.002	-0.057**	-0.008
	(0.005)	(0.015)	(0.006)	(0.011)	(0.019)	(0.038)	(0.022)	(0.026)
Net hh income quintile 4	-0.009*	-0.033**	-0.003	-0.023**	-0.047**	0.039	-0.054**	0.007
	(0.005)	(0.015)	(0.006)	(0.010)	(0.019)	(0.040)	(0.023)	(0.027)
Unemployed	0.074***	0.042***	0.105***	0.013	-0.231***	-0.195***	-0.261***	-0.177***
	(0.007)	(0.009)	(0.010)	(0.009)	(0.027)	(0.035)	(0.029)	(0.031)
Risk-averse	-0.019***	0.014	-0.007	-0.020***	0.051***	0.009	0.071***	-0.014
	(0.004)	(0.009)	(0.004)	(0.007)	(0.017)	(0.027)	(0.019)	(0.021)
Risk-neutral	-0.014***	0.007	-0.008*	-0.014*	0.020	-0.027	0.052**	-0.049**
	(0.005)	(0.010)	(0.005)	(0.008)	(0.018)	(0.031)	(0.020)	(0.025)
Financial literacy	-0.018***	-0.012***	-0.012***	-0.030***	0.044***	0.030**	0.059***	0.017*
	(0.002)	(0.003)	(0.002)	(0.003)	(0.007)	(0.012)	(0.008)	(0.009)
With mortgage	0.034***	0.031***	0.036***	0.040***				
	(0.004)	(0.008)	(0.005)	(0.007)				
Financial concerns	0.005***	-0.005***	0.005***	-0.004***				
	(0.001)	(0.001)	(0.001)	(0.001)				
Credit harder than 12 months earlier	0.052***	0.010	0.050***	0.035***				
	(0.004)	(0.007)	(0.005)	(0.005)				
Insufficient liquidity			0.049***	0.041***				
			(0.005)	(0.007)				
Hh situation worse than 12 months earlier	0.015***	0.020***						
	(0.004)	(0.007)						
Mortgage interest rate expectations	0.006***	0.003***	0.005***	0.004***				
	(0.001)	(0.001)	(0.001)	(0.001)				
Home owner					0.031*	0.012	0.030*	0.032
					(0.017)	(0.023)	(0.017)	(0.020)
With late payment					-0.248***	-0.224***	-0.244***	-0.240***
					(0.019)	(0.024)	(0.021)	(0.021)
Belgium	-0.027***	-0.026*	-0.022***	-0.029***	0.087***	0.025	0.072**	0.045
	(0.007)	(0.014)	(0.007)	(0.010)	(0.027)	(0.044)	(0.031)	(0.034)

Spain	-0.019***	0.015	-0.019***	0.009	0.088***	0.023	0.073***	0.055*
	(0.005)	(0.012)	(0.005)	(0.009)	(0.022)	(0.038)	(0.024)	(0.030)
France	-0.017***	-0.023**	-0.024***	-0.001	0.060***	0.001	0.017	0.059*
	(0.005)	(0.010)	(0.005)	(0.008)	(0.022)	(0.037)	(0.023)	(0.030)
Italy	0.012**	0.021*	0.008	0.020**	0.145***	0.085**	0.163***	0.083***
	(0.005)	(0.012)	(0.006)	(0.009)	(0.019)	(0.036)	(0.021)	(0.029)
Netherlands	-0.022***	-0.071***	-0.019**	-0.051***	0.075**	-0.154**	0.033	0.035
	(0.008)	(0.018)	(0.008)	(0.010)	(0.031)	(0.060)	(0.039)	(0.043)
Observations	104,747	40,634	91,799	53,582	10,174	4,766	8,426	6,514
HHs (Cluster)	25,555	13,248	24,178	19,136	6,030	3,131	5,489	4,146
Pseudo R-squared	0.0749	0.0462	0.0690	0.0657	0.184	0.103	0.180	0.126

The table reports marginal effects and robust standard errors (in parenthesis) estimated for model (1) and model (2) in their augmented specification as specified in Section 4. These regressions include the quarterly dummies whose estimated marginal effects are displayed in Figure 4 (liquidity constraints split) and Figure 5 (perception of own household financial situation split). ***, **, * denote significant at 1, 5, 10 percent level respectively.

Table 4: Regressions for credit applications – by liquidity constraints and credit type

	Applications - Model (1) interacted			
	Mortgage credit		Consumer credit	
	Unconstrained	Constrained	Unconstrained	Constrained
Age 18-34 years	0.032***	0.026***	0.017***	0.015
	(0.002)	(0.004)	(0.004)	(0.011)
Age 35-49 years	0.023***	0.018***	0.006	-0.003
	(0.002)	(0.004)	(0.004)	(0.011)
Age 50-55 years	0.011***	0.004	0.001	-0.006
	(0.003)	(0.005)	(0.004)	(0.012)
Age 56-60 years	0.009***	0.010*	-0.000	-0.005
	(0.003)	(0.005)	(0.004)	(0.013)
Age 61-65 years	0.008***	-0.001	0.000	-0.009
	(0.003)	(0.006)	(0.005)	(0.013)
Female	-0.004***	-0.003*	-0.009***	-0.020***
	(0.001)	(0.002)	(0.002)	(0.004)
High education	0.003**	0.007***	0.001	0.009*
	(0.001)	(0.002)	(0.002)	(0.005)
Household size (censored)	0.000	0.001	0.001	-0.004
	(0.001)	(0.001)	(0.001)	(0.003)
Partner present	0.003**	0.004*	0.006***	-0.006
	(0.001)	(0.002)	(0.002)	(0.006)
Number of children (censored)	0.001	0.001	0.002*	0.009**
	(0.001)	(0.001)	(0.001)	(0.004)
Net hh income quintile 1	-0.006***	-0.013***	-0.001	-0.046***
	(0.002)	(0.003)	(0.003)	(0.008)
Net hh income quintile 2	-0.009***	-0.008**	-0.002	-0.025***
	(0.002)	(0.003)	(0.003)	(0.008)
Net hh income quintile 3	-0.008***	-0.004	0.003	-0.009
	(0.002)	(0.003)	(0.003)	(0.008)
Net hh income quintile 4	-0.005***	-0.004	-0.001	-0.007

	(0.001)	(0.003)	(0.003)	(0.008)
Unemployed	-0.006***	-0.007**	0.023***	0.004
	(0.002)	(0.003)	(0.003)	(0.006)
Risk averse	-0.001	-0.003	-0.004*	0.019***
	(0.001)	(0.002)	(0.002)	(0.005)
Risk neutral	-0.001	-0.006**	-0.004*	0.004
	(0.001)	(0.002)	(0.002)	(0.006)
Financial literacy	-0.003***	-0.002**	-0.005***	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)
With mortgage	0.010***	0.012***	0.008***	0.004
	(0.001)	(0.002)	(0.002)	(0.005)
Financial concerns	0.000	-0.001***	0.002***	-0.002**
	(0.000)	(0.000)	(0.000)	(0.001)
Credit harder than 12 months earlier	0.011***	0.005***	0.013***	0.007
	(0.001)	(0.002)	(0.002)	(0.004)
Hh situation worse than 12 months earlier	0.004***	0.003	0.009***	0.024***
	(0.001)	(0.002)	(0.002)	(0.004)
Mortgage interest rate expectations	0.000	0.000	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Belgium	0.007***	0.014***	-0.013***	-0.023***
	(0.002)	(0.003)	(0.004)	(0.008)
Spain	0.002	0.009***	0.002	0.018**
	(0.002)	(0.003)	(0.003)	(0.007)
France	0.006***	0.008***	-0.000	-0.004
	(0.002)	(0.003)	(0.003)	(0.006)
Italy	0.008***	0.017***	0.007***	0.014*
	(0.002)	(0.003)	(0.003)	(0.007)
Netherlands	0.007***	0.014***	-0.019***	-0.055***
	(0.002)	(0.004)	(0.004)	(0.012)
Observations	104,747	40,634	104,747	40,634
HHs (Cluster)	25555	13248	25555	13248
Pseudo R-squared	0.100	0.0877	0.0489	0.0287

The table reports marginal effects and robust standard errors (in parenthesis) estimated for model (1) as specified in section 5.2. These regressions include the quarterly dummies whose estimated marginal effects are displayed in Figure 6. ***, **, * denote significant at 1, 5, 10 percent level respectively.

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