Unconventional Monetary Policy and Household Credit Inequality

Ying Xu*

October 20, 2021

The latest version: here

Abstract

Does unconventional monetary policy have a distributional effect on household credit? To answer this question, I use granular data from the European Central Bank's Household Finance and Consumption Survey covering 17 countries in the euro area and compare household credit in the pre–Asset Purchase Programme period with household credit in the post period. Analyses of credit changes among wealth quintiles show that the credit gap between the top and bottom of the distribution widens, and the largest increase in credit is among middle-wealth households after the policy implementation. The recentered influence function regression and decomposition results suggest two potential policy transmission channels for household credit inequality: (1) the credit bias channel, which is expected to increase inequality through the assets valuation effect, and (2) the credit constraint channel, which is expected to reduce inequality by facilitating access to credit for low- and middle-wealth households. Finally, an investigation of household asset portfolios finds that property ownership and rising housing prices were the key drivers of household financing decisions after the Asset Purchase Programme went into effect.

Keywords: unconventional monetary policy, household credit, distributional effect, Asset Purchase Programmes, inequality

JEL-Classification: E5, D63, D14

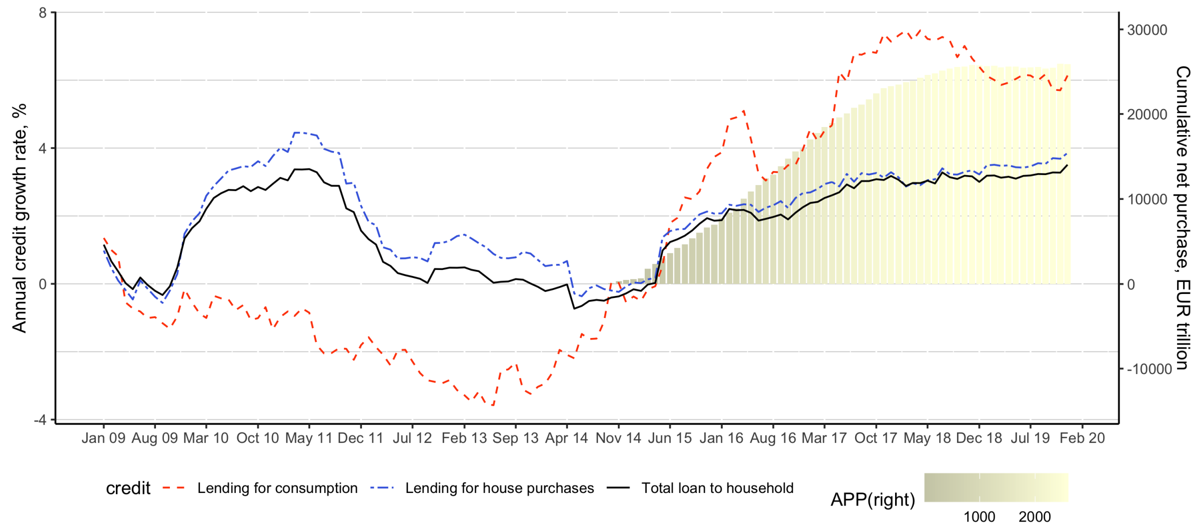
1 Introduction

In the aftermath of the global financial crisis, most central banks in advanced economies started experimenting with different types of unconventional monetary policies, and the COVID-19 crisis is likely to extend the use of these policies. In this paper, I focus on the experience of the European Central Bank (ECB) and

*Ph.D. candidate at Graduate Institute Geneva (IHEID) under the supervision of Ugo Panizza, whom I am extremely indebted for his guidance, ideas and support. I am also grateful for valuable comments and suggestions from Cédric Tille, Nathan Sussman, Beatrice Weder di Mauro, Diana Bonfim, Pau Rabanal, and seminar participants at the 52nd Money Macro and Finance Annual Conference, 20th journées Louis-André Gérard-Varet, Day-Ahead Workshop on Financial Regulation, Swiss Finance Institute Research Days 2021, 3rd International Conference on European Studies, and the IHEID Brown Bag Lunch. All remaining errors are my own. Email: ying.xu@graduateinstitute.ch

specifically how the ECB's net purchases of securities under the Asset Purchase Programme (APP) affected the distribution of household credit. Although there is evidence that household credit increased markedly after the ECB started implementing the APP (Figure 1), less is known about the distributional consequences of this policy. Specifically, while there is research on the distributional effects of unconventional monetary policy on income and wealth inequality (Colciago et al., 2019), to the best of my knowledge, there is no evidence on how it affects inequality in access to credit. This is an important question because in the euro area the distribution of household credit is more unequal than the distribution of household income (Denk and Cazenave-Lacroutz, 2015; Zabai, 2017). In addition, the distribution of household credit matters because an uneven credit expansion, especially one that is concentrated in the bottom of the distribution, can trigger financial instability, as happened before the outbreak of the global financial crisis (Moore and Palumbo, 2010; Philippon, 2015). With the lesson learned from the global financial crisis and the joint implementation of macro-prudential policies, how has the credit distribution changed in this round of credit expansion? This paper fills this gap and contributes to the literature on the distributional effects of unconventional monetary policy, with a specific focus on household credit.

Figure 1: Annual Household Credit Growth Rates and APP Cumulative Net Purchases, Euro Area



Notes: This figure presents the growth rates of total lending to households, lending for consumption, and lending for house purchase in the euro area(left axis). The black line is total loan to household, the blue line is lending for house purchase, and the red line is lending for consumption. The yellow bar (right axis) is the cumulative net purchases from the ECB Asset Purchase Programmes. The figure shows that right after the implementation of APP, all types of household credit growth rates become positive.

The ECB reacted to the global financial crisis by injecting liquidity into the banking system to facilitate policy transmission and stabilize markets in the euro area. The Securities Market Programme, which was effective between 2010 and 2012, allowed the ECB to purchase bonds issued by Greece, Portugal, Ireland, Spain, and Italy. In 2009 and 2011, the ECB initiated the first and second covered bond purchase programs.

After the termination of these programs, at the end of 2014, the ECB initiated the expanded APP, which is the focus of this paper. The (expanded) APP consists of the corporate sector purchase program, the public sector purchase program, the asset-backed securities purchase program, and the third covered bond purchase program. Compared with previous rounds of quantitative easing, the expanded APP conducts purchases of several types of assets, and the amount of assets purchased is on a much larger scale. Moreover, the program includes bonds issued by all euro area countries.

To measure the effect of the APP, I use data from the second and third waves of the ECB Household Finance and Consumption Survey (HFCS). These two waves include data for 2014, right before or at the beginning of the APP policy ("pre-APP" period), and 2017, during the period of policy implementation ("post-APP" period). With a sample of more than 138,000 observations from 17 countries in the euro area, I use this household-level granular data set to answer three critical questions on household credit inequality. First, does the APP policy increase credit inequality, or does it grant poorer households more access to credit? Second, how to explain the mixed effects of the policy on the distribution of credit, and what are the policy transmission channels? Third, what is the role of household asset portfolios in credit expansion and credit distribution?

To answer the first question on how APP affects credit inequality, I divide the households into wealth quintiles. By interacting the quintile dummies with the policy dummies (pre-APP and post-APP dummies) and using the top quintile as the base, I analyze how different wealth quintiles, relative to the top quintile, adjust their financing behaviors after the APP compared with the pre-APP period. To control for other unconventional monetary policies, such as negative interest rates implemented by the ECB and macroprudential policies implemented by national central banks during the sample period, I add country-year fixed effects to exclude all time- and country-varying macroeconomic factors. I also control for household characteristics, such as the household reference person's education, employment, household type, income, homeownership, and access to credit. The main findings are that the bottom wealth quintile has the smallest increase in credit, and the middle wealth quintile has the largest increase in credit compared with the top wealth quintile after the APP implementation. Based on these results, I propose that there is a *credit bias channel*, which takes root in traditional bank lending behavior and is amplified due to the increases in asset prices and market liquidity following the APP. The credit bias channel can further increase credit inequality, especially between households in the bottom and top quintiles, as the bottom usually has no assets while the top has plenty of assets. However, the credit bias channel can also boost credit for households in the middle wealth quintiles, which typically have some assets that appreciate after the policy and thus banks are more likely to extend credit to those households.

The second channel is the *credit constraint channel*. Bernanke (2015) and Montecino et al. (2015) emphasize the mortgage refinancing channel of quantitative easing for reducing inequality. They argue that homeowners with mortgages can benefit from easing policy by refinancing at a lower interest rate. In Europe, the conditions for refinancing are more demanding than those in the United States, but my paper provides supporting evidence for this channel in Europe. I find that households in the middle wealth quintiles, especially those with higher education, are the most likely to refinance after the APP. Moreover, on average, 60% of residence purchases contribute to new housing mortgages. After the APP, an additional 7.4% of household residence purchases led to new household mortgages. These are the households at the margin that were credit constrained before the APP, and now they can purchase houses with extended access to credit. Although the residence purchases are mainly from the higher wealth quintiles, compared with the existing owners, the new homeowners are mostly in the second wealth quintile (the bottom 20%-40% wealth group) in the post-APP period. This finding implies the existence of a credit constraint channel; that is, previously credit-constrained households now have access to credit due to the easing of credit conditions. The credit constraint channel can partially compensate for the existing credit inequality.

To quantify how much each channel contributes to the equalizing or dis-equalizing effect of household credit after the APP, I apply a recentered influence function (RIF) regression jointly with the Oaxaca-Blinder decomposition method proposed by Firpo et al. (2018). I use household access to credit to represent the credit constraint channel and household income and wealth to represent the credit bias channel. I estimate their contributions to the inequality of household debt in the pre-APP and post-APP periods, as well as their contributions to the change in credit inequality between the two periods. Overall, there is a minor increase in household credit inequality after the APP, measured by statistics such as the share of liability held by the top indebted households and Gini-type coefficients. But looking at the decomposition results of each component, it shows that the credit constraint channel in total contributes to a decrease in credit inequality. In contrast, the credit bias channel in total contributes to an increase in credit inequality.

Finally, an investigation of household portfolios suggests that household investment in property and rising property prices are the main drivers of the credit expansion after the APP policy. The APP raises asset prices, especially housing prices in Europe, which leads to the most benefits for the households that own the most property. Therefore, the greatest increase in mortgages is among households in the third and fourth wealth quintiles, with property as the primary component of their total portfolio. Meanwhile, the gap between the top quintile, which has the highest average property ownership rate, and the bottom, which has the lowest average property ownership rate, widens after the APP.

This paper contributes to three strands of literature. The first is the empirical research on the distributional effects of central bank policies. A survey by Colciago et al. (2019) summarizes the burgeoning literature on the relationship between central bank policies and inequality: the findings on the impact of conventional monetary policy, in general, conclude that higher inflation increases inequality, while the findings on the impact of unconventional monetary policy are mixed. Studies show that unconventional monetary policy stimulates economic activity, improves employment, and thus increases household income, which reduces inequality (Bivens, 2015; Hohberger et al., 2020; Guerello, 2018). However, unconventional monetary policy also favors richer people by boosting asset prices, which increases inequality (Montecino et al., 2015; Domanski et al., 2016; Saiki and Frost, 2014). Others insist that monetary policy is "neutral," without a long-term effect on inequality (Bernanke, 2015).

Household credit, or household debt, is another topic that has been widely discussed over the past decade. Some researchers find that household credit has been an early and powerful predictor of the recessions in the past (Mian et al., 2011). As many studies show, excessive leverage contributes to weakness in consumption during recessions (Mian et al., 2013; Mian and Sufi, 2018; Dynan et al., 2012; Bunn and Rostom, 2014). And this effect is more likely to be amplified if the debt is concentrated among households that are credit constrained and less likely to self-insure (Zabai, 2017), which are usually those in the bottom quintiles of the income and wealth distributions. Therefore, both the aggregate increase in household debt and its distribution among different household groups are important concerns of central banks. This paper focuses on household credit distribution following an unconventional central bank monetary policy.

This paper is also based on the broad literature on the impact of unconventional monetary policy and household credit as a transmission channel of unconventional monetary policy. Studies show that unconventional monetary policy contributes to declines in long-, medium-, and short-term interest rates (d'Amico et al., 2012; Glick et al., 2013; Joyce et al., 2011; Eser and Schwaab, 2016; Andrade et al., 2016), and has an upward effect on real gross domestic product and inflation (Gambetti and Musso, 2017), lowers volatilities and default-risk premiums (Gilchrist and Zakrajšek, 2013; Eser and Schwaab, 2016), eases funding conditions and market liquidity (Szczerbowicz, 2018; Chakraborty et al., 2020), increases bank credit supply (Garcia-Posada and Marchetti, 2016; Carpinelli and Crosignani, 2017; Chakraborty et al., 2020), leads to depreciation of the currency, and increases international capital flows (Georgiadis and Gräb, 2016). There are several channels for the transmission of unconventional monetary policy, including the signaling channel, the portfolio rebalancing channel, the exchange rate channel, the inflation channel, the duration and the credit channel (Gambetti and Musso, 2017; Sahuc, 2016; Altavilla et al., 2015). Studies on the credit channel mostly focus on increased credit to firms, and not so much on the household sector. The studies by Di Maggio et al. (2020) and Di Maggio et al. (2017) are closest to this paper. They investigate the effects of policy on household credit and consumption. They find that quantitative easing in the United States has led to mortgage rate reductions, increased originations of new mortgages by banks, increased refinancing activities, reduced interest payments for refinancing households, and a positive consumption response.

The rest of the paper proceeds as follows. Section 2 presents the data I use for the analyses. Section 3 focuses on cross-quintile analyses of changes in household credit after the APP. Section 4 measures the transmission channels of the APP. Section 5 examines the role of household asset portfolios in APP transmission. Sections 6 and 7 document several extensions and robustness tests, respectively. The last section concludes.

2 Data

My main data source is the ECB HFCS, a granular household-level data set. Countries that participated in the second wave of the HFCS survey mainly collected data in 2013 and 2014. This was the period right before or at the beginning of the implementation of the APP policy, so I call it the "pre-APP" period ($APP = 0$).The countries that participated in the third wave of the HFCS survey mainly conducted their fieldwork in 2016, 2017, and 2018. This is the period during the APP implementation, and I call it the "post-APP" period ($APP = 1$). To make the data comparable between the pre-APP and post-APP periods, I selected countries that participated in both the second and third waves of the survey. In total, there are 17 euro area countries in the sample. These countries do not always have panel data available for the analyses: only 10 countries have a panel component in their surveys. Even for the countries with a panel component, some of the households that do not have data for both periods. The other seven countries have entirely different households surveyed in each round. To have the maximum available observations in the sample, I pool all the countries from the two rounds and use these pooled data for the regression analyses. Table A.1 summarizes the reference years and number of observations for each country in the sample. The number of observations for each country is comparable between the two rounds but not comparable across different countries. Countries such as France and Finland have a much bigger sample than other countries relative to their population size. As discussed in section 3, I use weights to solve the unbalanced sample problem.

Table 1 lists the dependent and independent variables used in the analyses and the definitions of the variables. To simplify the economic interpretation of the regression results, most of the dependent variables are dummy variables. There are two groups of dependent variables. The first group is credit-related variables, which I employ to examine the distributional effect of the APP. This group includes variables on whether households have applied for the credit, have household main residence mortgages, have consumer credit, have refinanced, have purchased their main residence, have new mortgages for residence purchases, and the outstanding balance of household debt. Specifically, I use the outstanding balance of household liabilities as the dependent variable for the RIF regressions and decomposition analysis. The second group of dependent variables is households' ability to repay debt, including the debt-to-income (DTI) and loan-to-value (LTV) ratios, which are analyzed in the section on extensions.

For the explanatory variables, I mainly use household-level variables. Studies find that education, wealth, income (Andersen et al., 2015), household head's employment status (Zhu and Meeks, 1994), and homeownership (Parker et al., 2013) are the determinants of households' credit behavior. Hence, in my analyses, the household-level variables include the household reference person's education level, employment status, homeownership, total household gross income, household wealth, access to a credit card, access to overdraft facilities, rent payment, and household debt other than the household's main residence mortgages. On household wealth, I further decompose household portfolios. I calculate the share of each asset category among household total assets, including shares of property, non-publicly traded business, deposits, risky financial assets, stocks, and

Table 1: Definitions of Variables

Variable	Definitions
Dependent variables	
CreditApplication	= 1 if household has applied for credit in past 3 years; = 0 otherwise.
NewMortgage	For wave2, if $YearMortgage = 2013/2014$, $NewMortgage = 1$; = 0 otherwise; For wave3, if $YearMortgage > 2014$, $NewMortgage = 1$; = 0 otherwise, where $YearMortgage$ is the year when the last loan taken/refinanced using household main residence (HMR) as collateral.
BalanceMortgage	Outstanding balance of HMR mortgages. (Unit: Euro)
BalanceConsumption	Outstanding balance of consumer credit. (Unit: Euro)
ConsumerCredit	= 1 if $BalanceConsumption > 0$; = 0 otherwise.
Purchase	For wave2, if $YearAcq = 2013/2014$, $Purchase = 1$; = 0 otherwise; For wave3, if $YearAcq > 2014$, $Purchase = 1$; = 0 otherwise, where $YearAcq$ is the year of HMR acquisition.
Refinance	= 1 if the HMR mortgage is a refinancing mortgage; = 0 otherwise.
MortgagePurchase	= 1 if $NewMortgage \times Purchase = 1$, i.e., household has new mortgages for new residence purchases; = 0 otherwise.
DTI	Debt-to-income ratio.
LTV	Loan-to-value ratio of the main residence.
BalanceLiability	Outstanding balance of household total liabilities. (Unit: Euro)
Independent variables	
APP	= 1 if survey conducted after 2014 (wave3); = 0 otherwise.
OthMortgage	= 1 if household has other property debt other than HMR mortgages; = 0 otherwise.
BalanceOthMortgage	Outstanding balance of mortgages on other properties. (Unit: Euro)
Ownership	= 1 if household has the ownership of the main residence; = 0 otherwise.
Owned	For wave2, if $YearAcq < 2013$, $Owned = 1$; = 0 otherwise; For wave3, if $YearAcq < 2015$, $Owned = 1$; = 0 otherwise.
Age	Age of the household reference person.
Edu	Education level of the household reference person, the higher value the more advanced education level.
Employ	= 1 if the household reference person is employed; = 0 otherwise.
Income	Total household gross income. (Unit: hundred thousands Euro)
q.Income	Quintile of gross income, per country, weighted, $q \in [1, 5]$.
Wealth	Household gross wealth. (Unit: million Euro)
q.Wealth	Quintile of gross wealth, per country, weighted, $q \in [1, 5]$.
CreditCard	= 1 if household has credit card; = 0 otherwise.
Overdraft	= 1 if household has credit line or overdraft facility; = 0 otherwise.
Rent	Monthly amount paid as rent. (Unit: Euro)
HouseholdType	Dummies, 10 types based on characteristics of household composition. Details in Appendix B.
SshareProperty	market value of properties household owns divided by household total assets, %
ShareBusiness	market value of household investments in not publicly traded business divided by household total assets, %
ShareRiskyAsset	market value of household investments in risky assets divided by household total assets, %; risky assets include shares, bonds, mutual funds, managed accounts, or other financial assets.
ShareDeposits	value of household sight accounts and saving accounts divided by household total assets, %
ShareBonds	market value of household investments in bonds divided by household total assets, %
SharStocks	market value of household investments in stocks divided by household total assets, %
DepositsReturn	annualized interest rates on deposits with a maturity of up to one year, %
StocksReturn	annual return on national stock market index, %
BondsReturn	annualized secondary market yields of government bonds with maturities of close to ten years, %
PropertyReturn	annual growth rates of housing price index, %

bonds. Among all the explanatory variables, if there is direct corresponding data available from the HFCS survey, I apply the definitions from the survey. If the definitions are not directly available, I construct them based on the available data. For example, I define the variable *BalanceConsumption* as the total outstanding balance of private loans (for purposes 4 and 8[1]), non-collateral loans (for purposes 4 and 8), and credit card debt. I construct variables such as *NewMortgage* and *Purchase* using the directly available variables *YearMortgage* and *YearAcq*. I also include the household type (*HouseholdType*) as the control variable, following the classification proposed by the HFCS survey. Table B.1 shows the definitions and distributions of 10 household types. The sample has good and complete coverage of all types of households.

Table 2: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Country no data
CreditApplication	138,775	0.219	0.414	0	1	
NewMortgage	117,571	0.0390	0.194	0	1	FI
BalanceMortgage	138,811	27,158	77,837.36	0	5,500,000	
BalanceConsumption	138,811	1,703.382	12,431.7	0	2,600,000	
ConsumerCredit	138,811	0.192	0.394	0	1	
Purchase	117,571	0.0260	0.159	0	1	FI
Refinance	117,571	0.0462	0.210	0	1	FI
MortgagePurchase	117,571	0.0149	0.121	0	1	FI
DTI	138,811	70.952	4,004.911	0	812,035	
LTV	34,261	0.492	0.508	0	25.133	
BalanceLiability	138,811	43,419.61	163,452.2	0	3.05E+07	
APP	138,811	0.504	0.500	0	1	
OthMortgage	138,749	0.0645	0.246	0	1	
BalanceOthMortgage	138,811	9,884.762	125881.3	0	3.05E+07	
Ownership	138,811	0.722	0.448	0	1	
Owned	138,811	0.572	0.495	0	1	
Age	126,592	55.254	16.0379	16	85	IE, MT
Edu	138,452	3.267	1.407	1	5	
Employ	138,811	0.583	0.493	0	1	
Income	138,810	0.527	0.808	-1.620	55.195	
Wealth	138,729	0.436	2.0848	-0.000592	369.452	
CreditCard	138,811	0.318	0.466	0	1	
Overdraft	138,811	0.282	0.450	0	1	
Rent	138,811	116.680	275.899	0	7,770	
ShareProperty	138,811	0.594	0.394	0	1	
ShareBusiness	137,334	0.0301	0.118	-1.197	1	
ShareRiskasset	137,334	0.0239	0.0867	0	1	
ShareDeposits	137,334	0.162	0.260	-0.984	1	
ShareBonds	137,334	0.00404	0.0345	0	0.994	
ShareStocks	137,334	.00916	0.0502	0	1	
DepositsReturn	133,392	0.856	0.577	0.03	2.63	
StocksReturn	138,811	-19.180	271.108	-2,815	35.755	
BondsReturn	138,811	1.738	1.724	0.3	8.42	
PropertyReturn	138,811	2.321	4.625	-8.0292	15.561	

Because of the HFCS questionnaire's initial setup, there are limitations in the data and variables I can use. The survey defines the variable *CreditApplication* as whether households had applied for credit in the past

[1] In the survey, households provided their purposes for each type of the credit. Purpose 4 is "buy a vehicle or other means of transport," and purpose 8 is "cover living expenses or other purchases."

three years. Three years is a relatively long period for the policy event I study in this paper. Luckily, most countries have third-wave surveys that were conducted in 2017, so the past three years (2015-2017) would still be within the post-APP period. For the second wave, the past three years are mostly 2012-2014, which is during the pre-APP period. Therefore, this variable is valid for my analyses. Data on net income are not available, so I replace it with household gross income for my analyses. Lastly, for some variables, data are not available for some countries. In each regression, I make use of as many observations as possible. For Finland, data are not available for the variables $NewMortgage$, $Refinance$, $Purchase$ and $MortgagePurchase$. So for the regressions on mortgages, refinancing, and residence purchases, I cannot include Finland. For Ireland and Malta, the data for Age is not available. Therefore, in the baseline regressions, I do not include Age. But in the robustness tests, I add Age to the baseline, and results are consistent.

In addition, I have national-level data on asset returns as explanatory variables for the analyses on the asset valuation effects of the APP. I use growth rates of the national housing price index as returns on property and secondary market yields of government bonds with maturities of close to 10 years as returns on bonds. And I use bank interest rates on deposits with a maturity of up to one year as returns on deposits. The data source for the property price index, bond yields, and deposit interest rates is the ECB database. Additionally, I use returns from the national stock market index for stocks, and the data source is Datastream. Table 2 presents the summary statistics and the availability of the data for each variable.

3 Distributional Effects among the Quintiles

3.1 Empirical Strategy for Cross-Quintile Analyses

I start my empirical analyses by comparing changes in household credit among the wealth quintiles after the implementation of the APP. I use weighted least squares regressions to correct unbalanced sample sizes in different countries. Countries such as France and Finland have relatively more observations in the sample than other countries, considering each country's population size. Adding weights in the regression can correct this sample selection bias. The weights are directly available from the HFCS data set and are the inverse of the probability that a household is in the sample. The sum of the weights over all households in the sample is an estimation of the total number of households in the population of each respective country[2]. When creating the quintile dummy variables, I also consider the weights. After adjusting by weights, the sample matches the actual population size in each country.

By interacting the policy variable with different wealth or income quintiles in the regressions, I can examine the distributional effect of the APP policy, that is, the impact of the policy on each quintile. Model (1) measures

[2]accroding to the HFCS user guide

the changes in credit among different quintiles after the APP compared with the pre-APP period.

$$credit_{ijt} = \sum_{q=1}^{4} \beta_{1,q} APP_t \times q.Quintile_{ijt} + \sum_{q=1}^{4} \beta_{2,q} q.Quintile_{ijt} + \beta_3 HC_{ijt} + \gamma_{jt} + \epsilon_{ijt}, \qquad (1)$$

In the model, $credit_{ijt}$ is a set of credit-related dependent variables for household i in country j in year t, including $CreditApplication_{ijt}$, $NewMortgage_{ijt}$, $ConsumerCredit_{ijt}$, $BalanceMortgage_{ijt}$, $BalanceConsumption_{ijt}$, $Purchase_{ijt}$, and $Refinance_{ijt}$. APP_t is the pre-APP and post-APP policy dummy. $q.Quintile_{ijt}$ are dummy variables that identify which quintile q household i belongs to. In the baseline model, I present regression results using different wealth quintiles. Therefore, $q.Wealth_{ijt}$ will replace $q.Quintile_{ijt}$ in Model (1). $q.Wealth_{ijt}$ are dummy variables that define which wealth quintile q household i belongs to. For example, $1.Wealth_{ijt} = 1$ means the household's wealth is in the bottom 20%. In addition, I test the results based on different income quintiles, $q.Income_{ijt}$. Since there are five groups of households, I use the top quintile as the base for the regressions to present the inequalities between the top quintile and other quintiles. $\beta_{1,q}$ are thus the key coefficients for my analyses, representing the relative change in credit in each quintile q after the APP policy, compared with the top quintile. HC_{ijt} contains variables describing different household characteristics, such as the reference person's education level, age, employed or not, gross income, wealth, access to a credit card, access to overdraft facilities, house ownership, and household type. When I compare policy effects across the wealth quintiles, I drop wealth from HC_{ijt}. Similarly, when I compare policy effects across the income quintiles, I drop income from HC_{ijt}.

A potential concern with this strategy is that the effects I estimate could result from several ECB policies in the same period. On the one hand, there were other unconventional monetary policies, such as negative interest rates, and the targeted longer-term refinancing operations (TLTROs), implemented by the ECB at the same time, which also injected liquidity into financial institutions and encouraged them to provide credit to the private sector. The first and second series of TLTROs initiated in 2014 and 2016, overlapping the APP implementation period. The TLTROs targeted banks' lending to nonfinancial corporations and households, but they excluded loans to households for house purchases. In the euro area, household credit for house purchases accounts for 76% of total household credit (based on ECB data, December 2019). Figure 1 reassures that the total household credit growth rate closely follows the credit growth rate for house purchases. In this paper, because I only focus on the household sector and mainly mortgages, so the results should be mostly driven by the APP policy rather than the TLTROs.

On the other hand, during the post-crisis period, there were macroprudential policies that may have negatively affected household credit expansion. Based on the macroprudential policy database collected by Budnik and Kleibl (2018), six countries among the 16 countries in my sample[3] have a history of using macroprudential

[3]The six countries are Cyprus, Greece, Latvia, the Netherlands, Slovenia, and Slovakia, excluding Finland, for which household-level mortgage data were not available. Finland implemented a loosening policy in 2014 and then a tightening policy in 2016 on LTV limits.

policies on banking lending standards restrictions, such as LTV limits and/or debt service-to-income (DSTI) limits. After the global financial crisis, only four countries introduced new, related tools or revised the level of existing tools[4]. Cyprus had both loosening and tightening policies from 2007 to 2013. The total effect was ambiguous as the direction of the policy changed frequently. Latvia tightened from 2007 to 2009 but loosened in 2014. Slovakia and the Netherlands are the only two countries that gradually tightened their LTV and DSTI limits from 2013 to 2018, which could conflict with the APP policy I discuss in this paper. However, the change was not large. Taking the Netherlands as an example, the LTV limits decreased by 1% every year, from 106% in 2013 to 100% in 2018. Therefore, for the pre-APP and post-APP periods, most of the countries should face the same policy on LTV and DSTI limits, or they did not have a related macroprudential policy on household credit.

To control for, or at least partially mitigate, the enhancing or offsetting effects of these unconventional and macroprudential policies, I add year-country fixed effects, γ_{jt}, to the baseline model. The year-country fixed effects control for all euro area–level time- and country-varying factors, such as the ECB interest rates, national homeownership rate, national housing market, average household LTV and DSTI ratios, level of financial market development, and household consumption preference. But as a cost, the variable APP_t itself is dropped from the model due to collinearity. Thus, I cannot directly estimate the effects of the APP on each quintile, but I can present the relative policy effects between the top and other quintiles of the distribution.

3.2 Cross-Quintile Analysis Results

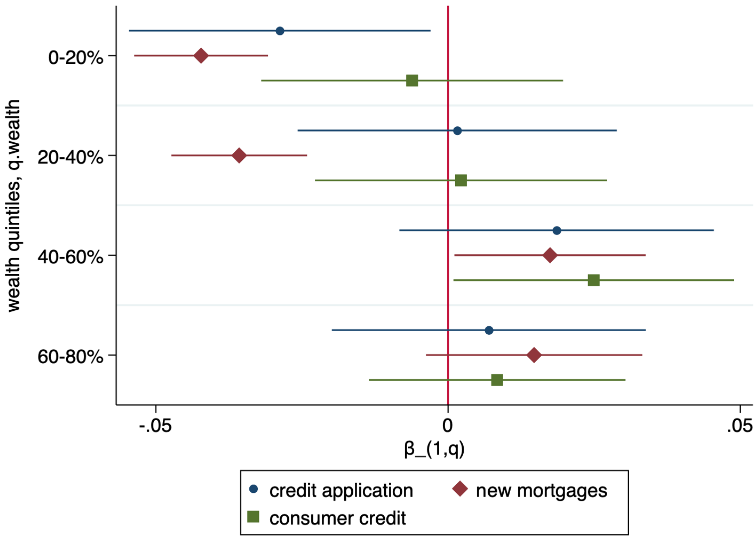
Following the strategy discussed, I find that the increase in household sector credit after the APP is unequal among the different wealth quintiles. First, compared with the top quintile, the bottom wealth quintile increased its credit the least, while the middle wealth quintile increased its credit the most after the APP. Second, households in the middle wealth quintile, especially those with higher education, increased refinancing the most after the APP. Third, on average, 60% of residence purchases lead to new mortgages. However, the ratio is 7.4% higher in the post-APP period than in the pre-APP period. Meanwhile, households in the second quintile contributed the most to residence purchases among all homeowners after the APP.

I first show the distributional effect of the APP policy at the extensive margin, which is the relative increase in household participation in the credit market. Figure 2 analyzes three credit-related dependent variables: $CreditApplication$, $NewMortgage$, and $ConsumerCredit$. All three variables are dummy variables, representing whether households applied for credit or not, have new household main residence mortgages or not, and have consumer credit or not, respectively. Figure 2 plots the estimated key coefficients $\beta_{1,q}$ for each quintile q in Model (1) and the 95% confidence intervals for these chosen dependent variables. The y-axis shows the household wealth quintiles. The bottom quintile is 0-20%, that is, $q = 1$. A negative value of β for a quintile, such as -0.05, indicates that households in that quintile are 5% less likely to have that specific

[4] Greece has not had a new LTV or DSTI policy after 2005. Slovenia has not had a new LTV policy after the first introduction of the tool in 1991.

type of credit than the top quintile after the APP. A positive value of β, such as 0.02, by contrast, indicates that households in that quintile are 2% more likely to have that specific type of credit than the top quintile after the APP. The trends are similar for all three credit variables. The estimated coefficients for the bottom quintile are all negative, while the estimated coefficients for the middle quintile are all positive. Especially for household new mortgage holdings and credit applications, the inequality is large between the top and bottom of the distribution because the blue and red dots for the bottom quintile are far to the left of the zero vertical line. The middle quintile has the largest increases in both holdings of new mortgages and consumer credit, compared with other households, after the APP, as the green and red dots for this quintile are to the right of the zero vertical line.

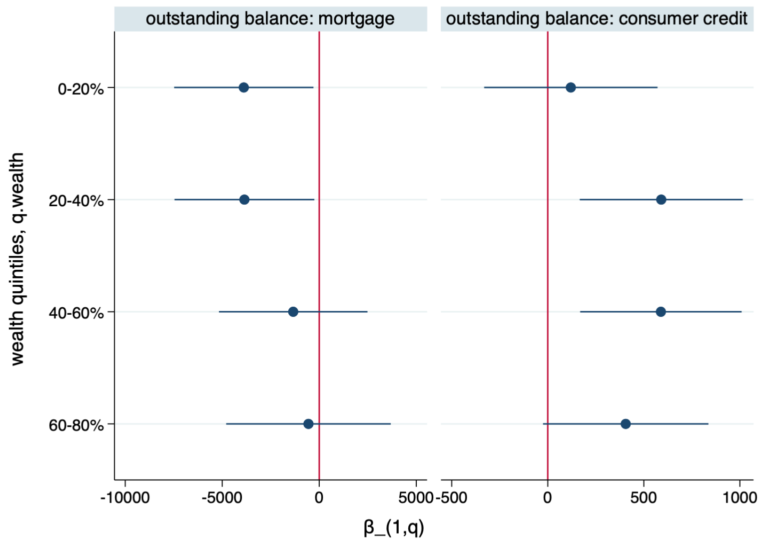
Figure 2: Household Credit among Different Quintiles at the Extensive Margin



Notes: This figure presents APP effects on household credit changes at the extensive margin for each wealth quintile. On the x-axis, it is the value of estimated coefficients $\beta_{1,q}$ of interaction terms and the 95% confidence intervals from regressions. On the y-axis, 0-20% represents the bottom 20% of the wealth distribution. I examine three dependent household credit variables (dummies): credit application, holding new household main residence mortgages, and holding consumer credit.

Figure 3 looks at the policy's distributional effects at the intensive margin, which is how much each household increases its borrowing. I analyze the relative increases in the outstanding balances of household main residence mortgages and consumer credit among the wealth quintiles. Again, I plot the estimated coefficients $\beta_{1,q}$ for each quintile q in Model (1) and the 95% confidence intervals for these two dependent variables. The y-axis shows the household wealth quintiles. A negative value of β for a quintile, such as -5000, indicates that households in that quintile are likely to have 5,000 euros less in outstanding household main residence mortgages (or consumer credit) compared with the top quintile after the APP. A positive value of β, such as 500, by contrast, indicates that households in that quintile are likely to have 500 euros more in outstanding consumer credit (or household main residence mortgages) compared with the top quintile after the APP. On the left-hand side of Figure 3, the dots for the bottom two quintiles are to the left of the zero vertical line, which implies that for households in the bottom 40% wealth group, their outstanding mortgage balances increased by much less than those of the top quintile after the APP. So the bottom two wealth quintiles increased the least not only in their chance of holding a mortgage, but also in the outstanding amount of their mortgages. The right-hand side of Figure 3 implies that the middle wealth groups (20%-60%), their consumer credit balance increased much more than that of the top quintile after the APP. So the middle wealth quintile had the greatest increase not only in their chance of holding consumer credit, but also the amount they borrow for consumption.

Figure 3: Household Credit among Different Quintiles at the Intensive Margin

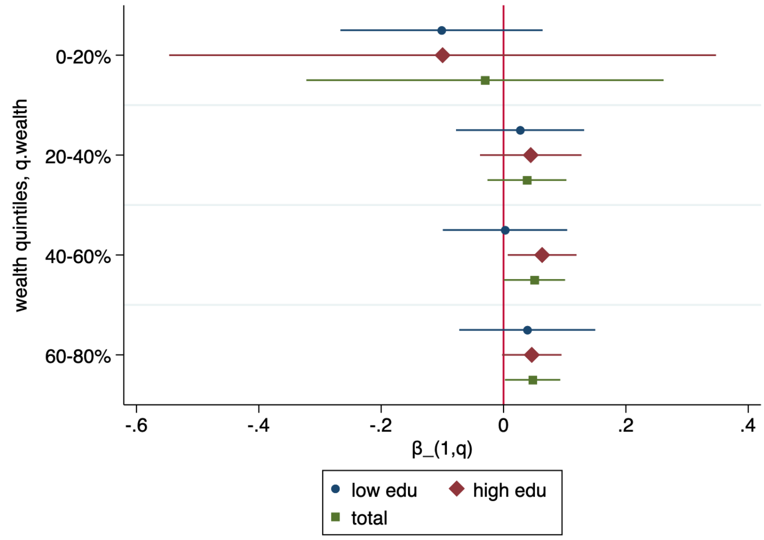


Notes: This figure presents APP effects on household credit changes at the intensive margin for each wealth quintile. On the x-axis, it is the value of estimated coefficients $\beta_{1,q}$ of interaction terms and the 95% confidence intervals from regressions. On the y-axis, 0-20% represents the bottom 20% of the wealth distribution. I examine two dependent household credit variables: outstanding balance of household main residence mortgages, and outstanding balance of consumer credit (unit: Euro).

Next, I study what drives the change in household mortgages. Several authors have emphasized the central role of mortgages as the transmission channel for consumption, primarily through refinancing existing mortgages or origination of new mortgages (Beraja et al., 2019; Eichenbaum et al., 2018; Cloyne et al., 2020; Hedlund et al., 2017; Agarwal et al., 2015). Mortgages that were carried out after the APP were mainly for refinancing and new residence purchases. Refinancing mortgages replace old mortgages, usually with better terms. Mortgages for new residence purchases are instead defined as mortgages contracted in the same year as residence purchases. I estimate that refinancing accounts for 15.8% of new mortgages before the APP and 44.4 % of new mortgages after the APP. Mortgages for new residence purchases increased from 38.2% of new mortgages before the APP to 40.1% of new mortgages after the APP.

Figure 4 illustrates the relative increase in refinancing decisions after the APP among different household groups. Specifically, I differentiate households by their reference person's education level. I group households whose reference person's education level is below upper secondary in "low edu" and for those with higher

Figure 4: Household Credit among Different Quintiles: Refinancing



Notes: This figure presents how APP affects the probability of mortgage refinancing across wealth quintiles and education groups. On the x-axis, it is the value of estimated coefficients $\beta_{1,q}$ of interaction terms and the 95% confidence intervals from regressions. On the y-axis, 0-20% represents the bottom 20% of the income or wealth distribution. I further differentiate high-education (in red) and low-education (in blue) households from the total sample (in green).

education levels in "high edu." The results in Figure 4 show that for the low edu group, there is no difference in refinancing among the different wealth quintiles. But for the high edu group, the middle wealth quintile had the greatest increase in refinancing after the APP. The high education households drive the increase in refinancing among the wealth quintiles. This is not surprising because the refinancing decision involves calculations of the relative loss in paying the penalty and benefit from the better loan terms. These calculations require a certain degree of financial literacy, which can be explained by the reference person's education level.

Next, I present the effect of the APP on residence purchases and the related effect on mortgages following new residence purchases. Fuster and Zafar (2015) suggest that monetary policies can affect the housing market by the sensitivity of housing demand to mortgage rates and available leverage. A relaxation of down payment constraints has a large effect on households' willingness to pay, especially for relatively poorer and more credit-constrained borrowers. Table 3 shows the regression results on the relationship between residence purchases and new household main residence mortgages. The dependent variable is new household main residence mortgages. The first column in Table 3 considers all samples in both periods. On average, controlling for all other household characteristics, together with the year-country fixed effects, approximately 60% of residence purchases contribute to new mortgages. Column 2 in Table 3 distinguishes the contributions of residence purchases to mortgages before and after the APP. The coefficient of the interaction term ($Purchase \times APP$) is 0.074, which means that after the APP, an additional 7.4% of the residence purchases contribute to new mortgages. This 7.4% is precisely from households at the margin who wanted to buy new houses but were previously credit-constrained. Therefore, more households buy new houses with available mortgages after the

APP.

Table 3: Residence Purchases and New Household Main Residence Mortgages

Dependent Variable: New Mortgages		
	(1)	(2)
Purchase	0.601***	0.551***
	(0.0187)	(0.0310)
Purchase×APP		0.0740*
		(0.0376)
Owned	0.0498***	0.0498***
	(0.00257)	(0.00256)
Household characteristics	Y	Y
Household types FE	Y	Y
Year×Country FE	Y	Y
N	117149	117149

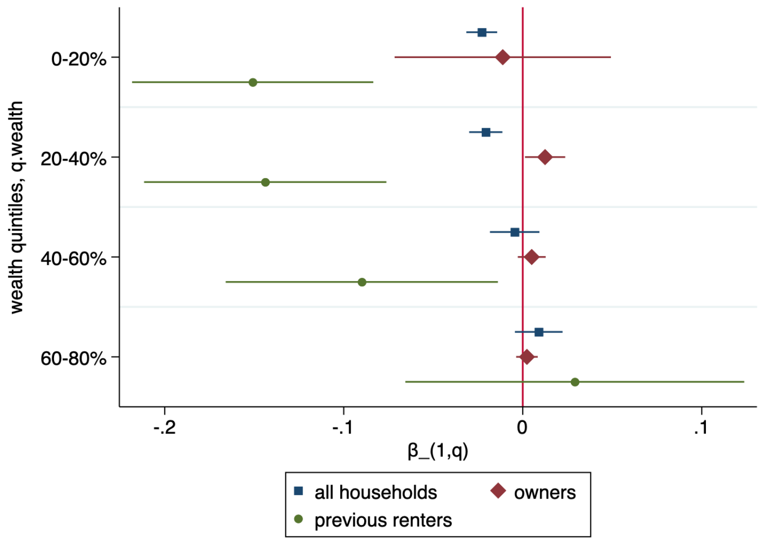
Notes: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table presents the relationship between residence purchases and new household main residence mortgages, and the APP effects on this relationship.

As there is a rising chance of carrying new mortgages following residence purchases after the APP, it is worth analyzing the change in residence purchases across the household wealth distribution. Figure 5 provides details on who is buying new residences. I run the same regressions as Model (1) and plot the coefficients of the interaction terms for each quintile in Figure 5. The dependent variable is *purchase*, and I exploit three groups of observations to run the same regression: the full sample, the subsample of households that are homeowners, and the subsample of households that previously were renters. For all households and previous renters, the lower the quintile of households is, the less likely it is that they make new purchases of the main residence after the APP. But the regression results for the owners' group are different. The red dot for the bottom 20%-40% quintile is to the right, rather than to the left, of the zero vertical line. Therefore, the lower wealth quintiles are generally less likely to buy new residences, but compared with existing homeowners, the new homeowners are mostly from the bottom 20%-40% wealth quintile after the APP.

In addition to the analyses across wealth quintiles, I also examine the changes in credit after the APP policy across income quintiles. Similar to the results for wealth quintiles, the credit gap between the top and bottom of the income distribution increases after the policy implementation. But different from the results on the wealth distribution, the middle-income households do not increase their credit the most after the policy. Instead, on average, the lower their income quintile is, the less likely the households were to increase their credit. This conclusion holds both at the extensive and intensive margins. For household refinancing and residence purchases, no matter the education level or previous home ownership status, the lower their income quintile is, the less likely the households were to increase refinancing and residence purchases. These results from the income quintiles suggest a potential key role of household wealth in APP transmission, which I will discuss further in the following sections.

The empirical findings I have discussed so far signal two main conclusions. First, the APP policy widens

Figure 5: Household Credit among Different Quintiles: Residence Purchases



Notes: This figure presents residence purchases after the APP across wealth quintiles. On the x-axis, it is the value of estimated coefficients $\beta_{1,q}$ of interaction terms and the 95% confidence intervals from regressions. On the y-axis, 0-20% represents the bottom 20% of the wealth distribution. I further differentiate households with different home ownership, i.e., previous renters (in green), and owners (in red) from the total sample (in blue).

the credit gap between households in the top and bottom quintiles of the income and wealth distributions. Second, households in the second and middle wealth quintiles are the most active participants in this round of credit expansion following the policy implementation. They have relatively greater increases in refinancing, residence purchases with new mortgages, and consumer credit compared with the other groups.

How to explain these distributional effects, and what is the policy transmission mechanism? I propose two potential channels that can rationalize the above results. The first channel is the credit bias channel. Banks naturally prefer to have richer clients, who are usually less risky and have proper collateral for credit, holding other factors the same. The APP policy boosts asset prices, which makes the rich richer. As a result of this wealth effect, banks lend relatively more to the richer and relatively less to the poorer. This preference can also explain why the middle wealth quintile has the greatest increase in credit after the policy implementation. From the supply side, some assets of the middle-wealth households appreciated after the policy, such as properties, which make banks more willing to lend. And from the demand side, the middle-wealth households need credit more compared with the higher end of the wealth distribution. The second channel is the credit constraint channel. With the liquidity injection and credit condition loosening thanks to the APP policy, banks can lend to previously credit-constrained households. Households in the lower and middle quintiles of the wealth distribution now have access to credit, especially new mortgages. On the one hand, the greater increase in refinancing by the middle wealth quintile signals that now they have access to cheaper credit or a larger amount of credit by refinancing their previous more expensive or limited-amount mortgages. On the other hand, compared with the pre-APP period, there is an additional 7.4% of residence purchases associated with new mortgages, while previously only 55% of households carried out a mortgage following the residence purchase. This 7.4% of households is exactly those who were at the margin, that is, those who wanted to buy new residences but were credit constrained. The loosening of credit constraints contributes to the relatively higher increase in homeownership for the bottom 20%-40% wealth quintile.

4 Credit Bias and Credit Constraint Channels

The empirical evidence presented in section 3 indicates that the APP policy raised the existing credit gap between the top and bottom of the wealth distribution, but the middle-wealth households increased their credit the most after the policy was implemented. To explain these distributional effects of the policy, I propose two potential channels of policy transmission, the credit bias channel and the credit constraint channel, which have divergent outcomes on the household credit distribution. In this section, I estimate the contribution of each channel using RIF regression and decomposition.

4.1 RIF Regression and Decomposition

I run the RIF regression jointly with the Oaxaca-Blinder decomposition method to analyze the policy transmission channels and their contributions to changes in credit inequality. Firpo et al. (2009) propose the RIF regression to compensate for the limitation of the widely used quantile regression method in the empirical literature. The conventional quantile regressions are actually conditional quantile regressions, so the impact of a covariate it measures is conditional on the specific values of other covariates. Results from conventional quantile regressions cannot be generalized to the unconditional population counterparts. Thus, we cannot use them to measure the more general policy or economic impact of a change in X on on certain distributional statistics of the overall distribution of Y. To understand and interpret a policy effect, such as how the APP policy affects household credit inequality, I need to use the (unconditional) RIF regression method. The coefficients estimated from the RIF regression can be interpreted as the usual ordinary least squares coefficients. In addition, the RIF method is not limited to quantiles but applies to many other distributional statistics. Furthermore, the RIF decomposition method proposed by Firpo et al. (2018) extends the traditional Oaxaca-Blinder decomposition method, which allows estimating the effects of covariates on inequality measures, such as the Gini coefficient, variance, quantiles, ratios, and other distributional statistics. The Oaxaca-Blinder decomposition method, however, is limited to the mean.

The influence function (IF) is a tool to quantify the effect of a perturbation on some given distribution, and it can check the robustness of distributional statistics (Cowell and Flachaire, 2015). Firpo et al. (2009) propose using an IF, especially an RIF, to analyze the impact of changes in the distribution of the explanatory variables on the unconditional distribution of an outcome variable. Given distribution F_Y, the influence function of statistic ν is defined as

$$IF(y_c; \nu(F_Y)) = \lim_{\varepsilon \to 0} \frac{\nu((1-\varepsilon)F_Y + \varepsilon H_{y_c}) - \nu(F_Y)}{\varepsilon} \tag{2}$$

where H_{y_c} is a probability distribution with all its mass at point y_c. The IF quantifies how statistics ν changes if distribution F_Y is contaminated by a small amount of data mass at point y_c. That is, the IF quantifies the influence of data point y_c on ν. The recentered version of the IF, that is, the RIF, proposed by Firpo et al. (2009), has the same properties as the IF, but it is crucial for implementing RIF decomposition. The RIF is equivalent to the first two terms of the Mises (1947) linear approximation of the corresponding distributional statistic ν:

$$RIF(y_i; \nu(F_Y)) = \nu(F_Y) + IF(y_i; \nu(F_Y)) \tag{3}$$

I adopt the following three steps. The first step of the procedure is to estimate the RIF statistics ($RIF(Y;\nu)$) of dependent variable Y for each observation for a chosen distributional statistic ν. In the second step, I estimate a set of regressions in which the dependent variable Y is the estimated RIF statistics, $RIF(Y;\nu)$, computed in the first step. The coefficients of these regressions show how changes in each explanatory variable X contribute to credit inequality, measured by the above-mentioned distributional statistics ν. In the last step, I apply the RIF decomposition by extending the classic Oaxaca-Blinder decomposition method to decompose the chosen distributional statistics ν. From this step, I analyze the differences between the pre-APP and post-APP periods for the distributional statistics of my interests, that is, $\Delta\nu_{post-pre}$, and measure the contribution of each explanatory variable to the effect of the APP on the evolution of household credit inequality. Here, the dependent variable Y is the outstanding balance of the household's liability. The distributional statistics ν(s) are the shares of liabilities held by the top 30%, 20%, 10%, 5%, and 1% of indebted households and the Gini-type coefficient. I do not work with quantiles, interquartile ranges, or top-bottom ratios because household debt is highly unevenly distributed. In my sample, the bottom 50% of the distribution is all zeros, so more than 50% of the households do not have any liability. There is not enough variation for RIF statistics created based on these distributional statistics.

I consider three main groups of explanatory variables X. The first group focuses on household characteristics, such as education level and employment status. The second group focuses on access to credit, aiming to measure the credit constraint channel. The last group focuses on household income and wealth, aiming to measure the credit bias channel. For each group, I examine whether the explanatory variables contribute to the equalizing or dis-equalizing effect of the APP policy on household credit.

4.2 RIF Regression and Decomposition Results

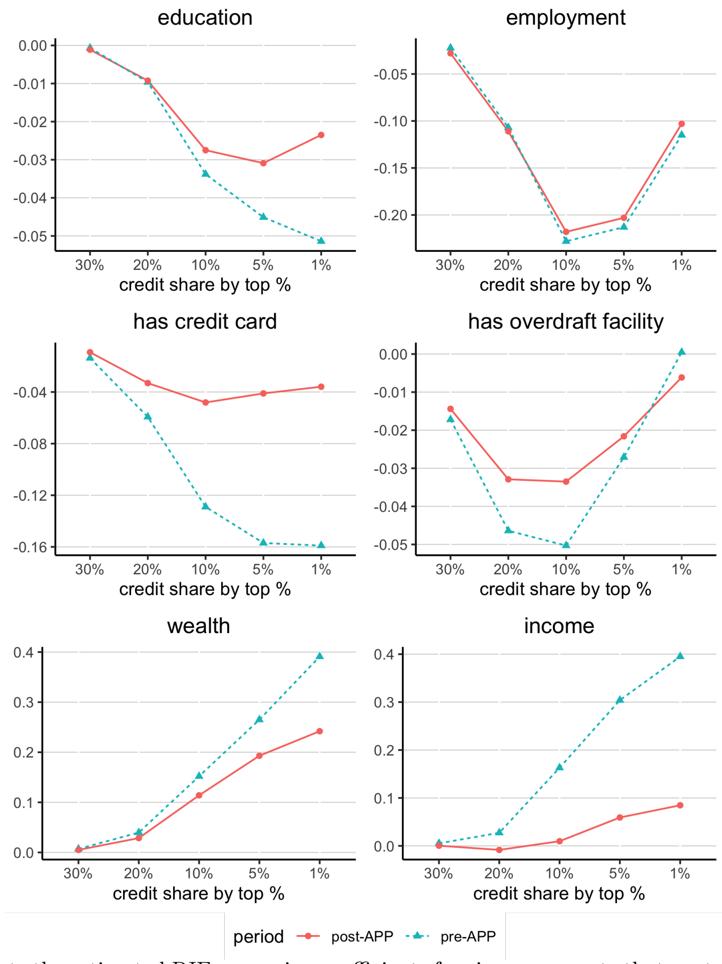
As expected, the recentered influence regression and decomposition results suggest that the credit bias channel contributes to the dis-equalizing effect, while the credit constraint channel contributes to the equalizing effect.

The countervailing effects of the APP through different channels overall lead to no significant increase in household credit inequality (measured by Gini-type coefficients and liability shares of the top percentiles of the distribution) after the policy implementation.

Figure 6 presents the estimated RIF coefficients for six components that contribute to uneven credit distribution in the pre-APP and post-APP periods. The dependent variable is the outstanding balance of household liability. And I analyze five distributional statistics based on the dependent variable, that is, the shares of liabilities held by the top 30%, 20%, 10%, 5%, and 1% of indebted households. The higher these statistics are, the more unequal the household debt distribution is. Meanwhile, I group six explanatory variables into three categories. The top panel in Figure 6 focuses on household characteristics, including employment status and education level. The middle panel focuses on household access to credit, including access to a credit card and overdraft facilities. I use access to credit as a proxy for measuring the degree of credit constraint the household faces. If households have access to these two types of credit, they are less credit-constrained. Therefore, it represents the credit constraint channel. And the bottom panel presents household income and wealth, which represent the credit bias channel. The higher the household's income and wealth are, the more banks are biased toward the household. I run regressions for each of the distributional statistics with all six components and plot the estimated coefficients of each component from the five regressions in Figure 6. For all the RIF regressions, I add household type, year-country fixed effects, and the weight of each observation. The dotted blue lines are the estimations for the pre-APP period, and the solid red lines are the estimations for the post-APP period.

There are two main results from Figure 6. First, for both periods, the coefficients for the components in the top two panels are all mainly negative. This implies that, in both periods, being employed and having a higher education level have an equalizing effect on household debt because they lower the debt shares of the top percentiles. Similarly, in both periods, having access to a credit card and overdraft facilities also lowers the debt shares of the top percentiles, which has an equalizing effect on household debt. The contributions of these four components are approximately U-shaped. This U shape means that these variables have a relatively small equalizing effect on the concentration of credit in the top 1% of indebted households. Especially for access to overdraft facilities, it does not affect or even increases the debt share held by the top 1%. By contrast, the coefficients of the components in the bottom panel are mostly positive. These imply that household income and wealth contribute to a dis-equalizing effect on household debt in both periods because they lead to increases in the credit share of the top percentiles. The positive slopes of wealth and income in the figure imply that the credit bias channel contributes to a further concentration of credit among the top credit holders. The increase in wealth and income can lead to a greater increase in credit among the top 1% of indebted households than the top 10% of indebted households. Second, for all the components, the red lines are flatter than the blue lines. Therefore, for each component, its effect on household debt inequality, either enhancing or decreasing inequality, is milder after the APP policy.

Figure 6: RIF Regression Coefficients: Pre- and Post-APP



Notes: This figure plots the estimated RIF regression coefficients for six components that contribute to uneven credit distribution in both "pre-APP" (blue) and "post-APP" (red) periods. On the y-axis, it is the value of the estimated coefficients of each components from regressions. On the x-axis, it is the five distributional statistics I examined for each regression, i.e., the shares of liabilities held by the top 30%, 20%, 10%, 5%, and 1% of indebted households.

Next, I study the overall change in household credit inequality after the APP policy and how each component contributes to this change. From the RIF regression results discussed above, I can only measure the contribution of each variable period by period. To examine the contributions to the changes between the two periods, I apply the RIF decomposition method. Table 4 reports the RIF decomposition results for the change in credit inequality between the pre-APP and post-APP periods. I use three distributional statistics to measure inequality: column (1) is the Gini-typed coefficient, column (2) is the liability share of the top 10% of indebted households, and column (3) is the liability share of the top 5% of indebted households. The dependent variable is the same as in the RIF regressions, that is, the outstanding balance of household liability. For the decomposition regressions, I add control variables such as household homeownership, household type, and country fixed effects. I also take weights into consideration. Panel (a) indicates that there is a minor increase in household credit inequality after the APP; however, it is not statistically significant. The overall composition and structural effects are not statistically significant.

Panel (b) in Table 4 shows the composition effects and, central to this study, the "policy effect" mentioned in Firpo et al. (2009). In their paper, In their paper, the policy consists of changing the distribution of X from its value at $T = 0$ to $T = 1$, and the effect is how this change in the distribution affects statistic ν. For my study, I analyze how the APP policy changes the distributions of households' access to credit, wealth, and income from the pre-APP period to the post-APP period, which in the end contributes to the change in credit inequality statistics. Thus, the composition effects estimated here exactly measure how much the credit bias and credit constraint channels transmit the policy shock to credit inequality.

Panel (b) in Table 4 decomposes the effect into six components and measures the actual quantitative contribution of each component to the change in credit inequality. The same as for the RIF regressions, I again divide the explanatory variables into three groups. The contrary effects of the different groups on credit inequality offset each other and lead to minor overall composition effects. First, for both components of the household characteristics, the coefficients are significantly less than zero. These imply that when the APP policy increases employment rates, and the panel components of the sample contribute to higher education levels in the post-APP period, both changes have a negative effect on credit concentration. Therefore, the composition effects of education and employment both decrease credit inequality after the APP. Similarly, the sum of the coefficients of the two components of the credit constraint channel is also negative. This implies that when the APP policy loosens the credit constraints, credit inequality would also decrease due to this change. A potential explanation for the positive coefficient of the overdraft facility is that here I only measure the policy effect at the extensive margin, not the intensive margin. It could be that banks loosen the credit constraints by raising the overdraft limits for existing clients after the policy. This policy response can lead to further credit concentration among previously indebted households. By contrast, the coefficients of the components of the credit bias channel are positive. The changes in the household wealth and income distributions triggered by the APP policy, mainly the increases in wealth and income, contribute to credit inequality. For all the

Table 4: Decomposition Results: Inequality Measures on Outstanding Balance of Household Liability

	Gini (1)	Share by Top 10% (2)	Share by Top 5% (3)
a. Overall			
Difference (*post* − *pre*)	0.174	0.715	0.219
	(0.281)	(0.718)	(0.869)
Composition Effects	0.104	0.188	0.444
	(0.121)	(0.317)	(0.320)
Structure Effects	0.0696	0.527	-0.224
	(0.257)	(0.653)	(0.819)
b. Composition Effects			
Household characteristics			
Edu	-0.0315**	-0.0852***	-0.0959**
	(0.0123)	(0.0329)	(0.0378)
Employ	-0.112***	-0.287***	-0.267***
	(0.0384)	(0.0986)	(0.0927)
Credit constraint channel			
Credit Card	-0.0580***	-0.130***	-0.111**
	(0.0186)	(0.0470)	(0.0514)
Overdraft	0.0282**	0.0551*	0.0356
	(0.0130)	(0.0310)	(0.0321)
Credit bias channel			
Wealth	0.0579*	0.125*	0.211*
	(0.0307)	(0.0639)	(0.112)
Income	0.0304	0.0325	0.199
	(0.0383)	(0.0840)	(0.144)
c. Structure Effects			
Household characteristics			
Edu	1.14	1.97	4.43
	(0.987)	(2.24)	(3.37)
Employ	0.130	0.599	0.570
	(0.413)	(1.01)	(1.35)
Credit constraint channel			
Credit Card	1.09***	2.46***	3.51***
	(0.303)	(0.719)	(0.993)
Overdraft	0.284	0.731	0.239
	(0.399)	(0.989)	(1.29)
Credit bias channel			
Wealth	-0.562	-0.935	-1.75
	(0.764)	(1.53)	(2.74)
Income	-2.79*	-6.20*	-9.89*
	(1.57)	(3.19)	(5.69)
_cons	0.193	0.779	0.171
	(0.946)	(2.27)	(3.13)

Notes: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Coefficients are normalized to solve the problem of the base level choice associated with categorical variables, such as countries and household types.

effects of the distributional measures on credit inequality, the absolute values of the estimations are different, but the signs are the same for the coefficients of the same component, so the conclusion is robust.

5 Property as the Key Driver

So far, I have based all my analyses on household total assets. Further investigation of household asset portfolios provides a better understanding of how the APP policy transmits to household credit. I find that property ownership is the key driver of expanded credit market participation by households. In particular, higher property prices following the APP lead to more new mortgages by households with a higher share of property in their portfolios.

5.1 Household Portfolio Composition

I start with a summary of household portfolio composition in my sample, as presented in Table 5. I calculate the share of each asset category in each household's total portfolio by taking the market value of each asset category divided by the household's total assets. The data I present are the simple averages of the shares for all the households in the sample. The information in Table 5 yields several messages. First, properties account for most of the total household assets, especially for the fourth and third quintiles, but not the bottom quintile. Second, among households in the bottom quintile, deposits are the largest component of their portfolios. And the share of deposits among the total portfolio decreases as the quintile increases. Third, both risky financial assets and private business make up a minor portion of the households' portfolios. The top quintile has the highest shares for both assets, which lowers the portion of properties in their portfolio. Last, the second quintile has a higher share of risky assets (such as bonds, mutual funds, and stocks) in their portfolios than the third and fourth quintiles.

Table 5: Market Value of Asset Category Divided by the Household's Total Assets, Sample Average, %

Wealth quintile	Asset types				Risky asset				
	Property	Risky Assets	Deposits	Business	Bonds	Mutual Funds	Managed Accounts	Stocks	Other Financial Assets
1	6.38	0.93	45.03	0.89	0.11	0.35	0.0030	0.26	0.20
2	49.74	2.26	24.14	1.98	0.43	0.87	0.030	0.65	0.28
3	76.14	1.46	10.11	1.40	0.32	0.53	0.027	0.38	0.20
4	79.92	1.79	7.97	1.76	0.39	0.62	0.042	0.55	0.20
5	73.38	4.14	7.47	6.47	0.59	1.15	0.11	1.96	0.32

Notes: This table presents shares of different asset categories within the household's total portfolio across wealth quintiles. The share of each asset type is the market value of each asset category divided by the household's total assets. Risky assets include bonds, stocks, mutual funds, managed accounts, and other financial assets. Shares do not add up to 100% for each quintile because other assets such as vehicles, other valuables, pensions, life insurance, and money lent to others are not considered part of the household portfolio but are included in the total assets.

Does household portfolio composition matter for APP policy transmission and lead to household-level heterogeneous credit responses? To answer this question, I regress household credit on the share of each asset type within the portfolio and the interaction of the policy dummy with the share of each asset type.

$$credit_{ijt} = \beta_1 asset_{ijt} + \beta_2 asset_{ijt} \times APP_t + \beta_3 HC_{ijt} + \gamma_{jt} + \epsilon_{ijt}, \tag{4}$$

In model (4), $credit_{ijt}$ contains four credit-related variables for household i, in country j, in year t: new household main residence mortgages, mortgage refinancing, mortgages for new residence purchases, and consumer credit. These are all dummy variables. $asset_{ijt}$ are shares of different asset categories within the household's total portfolio, including the share of properties, deposits, risky financial assets, and privately owned business. I control for household characteristics and country-year fixed effects in the model. Table 6 shows the estimated coefficients for each asset type and the interactions. The estimated coefficients for $share\ of\ deposits \times APP$ are always negative (column (2)). The greater is the share of deposits in the total household portfolio, the less likely it is that the households increase their credit after the APP policy. For new mortgages, no matter whether refinancing or mortgages for new residence purchases, the coefficients of $share\ of\ property \times APP$ are positive (column (1)), so households with a higher share of property within their portfolio will be more likely to have new mortgages and refinance after the APP policy. The coefficients of $share\ of\ risky\ assets \times APP$ are negative (column (3)). This implies that households with lower shares of risky financial assets within their portfolio will more likely increase their mortgages and refinancing.

These results are consistent with my previous findings from the cross-quintile comparisons. As shown in Table 5, the lower end of the distribution has higher shares of deposits within their portfolios, while the higher end of the distribution has lower shares of deposits within their portfolios. A negative relationship between deposit shares and household credit after the APP is consistent with the increasing gap between the top and the bottom of the distribution. Additionally, the middle and fourth quintiles have relatively higher shares of property and relatively lower shares of risky financial assets in their portfolio composition. A positive relationship between the share of property and mortgages and a negative relationship between the share of risky financial assets and mortgages both recall my previous findings that the greatest increase in mortgages after the APP occurs in the middle wealth quintile.

5.2 Divergent Valuation Effects

There are contrasting APP effects on household credit for different portfolio compositions. A potential explanation is the divergent valuation effects on different asset categories from the APP. Among all the asset categories, the APP policy boosts the wealth of households with properties the most. Figure 7 presents annualized returns for different asset categories in the pre-APP and post-APP periods. Returns on deposits and government bonds decrease to almost zero after the APP. The price of stocks is more volatile compared with other assets, but on average, the return is close to zero and slightly negative during the APP period. Housing

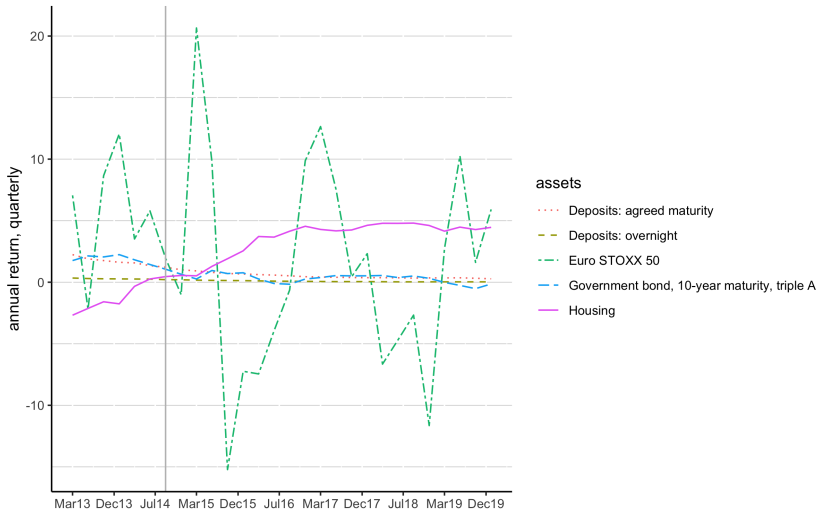
Table 6: Household Portfolio and APP Effects on Household Credit

Asset type	Property (1)	Deposits (2)	Risky Assets (3)	Business (4)
Dependent variable	a. New Mortgages			
share of asset type	0.0778***	-0.0385***	-0.0557***	-0.0359***
	(0.00406)	(0.00402)	(0.00844)	(0.00931)
share of asset type × APP	0.0365***	-0.0597***	-0.0361***	0.0164
	(0.00510)	(0.00652)	(0.0124)	(0.0154)
Dependent variable	b. Refinance			
share of asset type	0.0743***	-0.0415***	-0.0381***	-0.0350***
	(0.00357)	(0.00391)	(0.0110)	(0.00926)
share of asset type × APP	0.0145***	-0.0297***	-0.0353**	0.00483
	(0.00373)	(0.00516)	(0.0141)	(0.0128)
Dependent variable	c. Mortgages for New Residence Purchases			
share of asset type	0.0353***	-0.0151***	-0.0183***	-0.0225***
	(0.00257)	(0.00204)	(0.00428)	(0.00438)
share of asset type × APP	0.0180***	-0.0313***	-0.0247***	-0.000476
	(0.00328)	(0.00426)	(0.00738)	(0.00788)
N	115819	115819	115819	115819
Dependent variable	d. Consumer Credit			
share of asset type	-0.0347***	-0.0504***	-0.129***	-0.0785***
	(0.00723)	(0.0138)	(0.0335)	(0.0301)
share of asset type × APP	0.00740	-0.0403**	-0.0276	0.0209
	(0.00759)	(0.0162)	(0.0403)	(0.0382)
N	136973	136973	136973	136973
Year × Country fixed effects	Y	Y	Y	Y
Household characteristics	Y	Y	Y	Y
Household type fixed effects	Y	Y	Y	Y

Notes: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

property is the only type of asset that has an increased price and both large and increasing returns, with a 5% annual return at the end of the APP.

Figure 7: Asset Returns, Euro Area



Notes: This figure presents quarterly data on the annual return of different household assets within the Euro area. For deposits with agreed maturity and overnight deposits, it is the annual interest rates. For properties, it is the return on the housing price index in the Euro area. On stocks, it is the return from the Euro STOXX 50 index. And on bonds, it is the yield of European triple-A government bonds, with a 10-year maturity. Source: ECB and OECD.

To examine the role of divergent valuation effects on household credit responses and taking into account country heterogeneity in asset markets, I add country-level asset returns to my analyses.

$$credit_{ijt} = \beta_1 asset_{ijt} + \beta_2 asset_{ijt} \times APP_t + \beta_3 asset_{ijt} \times return_{jt} + \beta_4 HC_{ijt} + \gamma_{jt} + \epsilon_{ijt}, \tag{5}$$

$return_{jt}$ is the asset return for each asset category in country j in year t, and I interact it with the share of that specific asset category within the household portfolio. Due to data availability, I examine asset returns for four groups of assets: deposits, stocks, bonds, and housing. If the estimated coefficient β_2 becomes not statistically significant, while the estimated coefficient β_3 is statistically significant, , then the APP effects are transmitted through appreciation or depreciation of that specific asset within the household portfolio to influence household financing decisions.

Table 7 presents the results of Model (5) for all four groups of assets. Panel (a) focuses on new mortgages, and column (1) shows that the APP effect is mainly through the price of housing, which encourages households to get new mortgages. Column (3) shows that the decrease in the returns on government bonds due to the APP lowers the chance of new mortgages by households with high investments in bonds within their portfolios. Although the estimated coefficients for bonds are larger compared with the estimated coefficients for property, on average, bonds account for less than 1% of household total assets, while property accounts for most of the household assets (except for the bottom quintile). Thus, appreciation of the value of property is the main driver of the increase in mortgages after the APP. Changes in the returns on stocks and deposit interest rates

Table 7: Household Portfolio and Asset Returns on Household Credit

Asset type	Property (1)	Deposits (2)	Bonds (3)	Stocks (4)
Dependent variable		a. New Mortgages		
share of asset type	0.0768***	-0.0408***	-0.165***	-0.0829***
	(0.00375)	(0.00759)	(0.0242)	(0.0183)
share of asset type × APP	0.00596	-0.0586***	-0.0223	-0.0374
	(0.00476)	(0.00670)	(0.0151)	(0.0276)
share of asset type × asset return	0.00973***	0.00247	0.0788***	0.000803*
	(0.000774)	(0.00556)	(0.0129)	(0.000452)
N	115819	110476	115819	115819
Dependent variable		b. Consumer Credit		
share of asset type	-0.0335***	-0.0316	-0.347***	-0.313***
	(0.00718)	(0.0240)	(0.116)	(0.0474)
share of asset type × APP	0.0321***	-0.0477***	-0.0101	0.0470
	(0.00930)	(0.0176)	(0.0584)	(0.0612)
share of asset type × asset return	-0.00821***	-0.0207	0.121**	-0.000819
	(0.00147)	(0.0153)	(0.0603)	(0.00154)
N	136973	131630	136973	136973
Year × Country fixed effects	Y	Y	Y	Y
Household characteristics	Y	Y	Y	Y
Household type fixed effects	Y	Y	Y	Y

Notes: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

do not have much power to explain changes in household mortgages. Panel (b) focuses on consumer credit. Similar to panel (a), lower returns from government bonds lower the chance of households holding consumer credit, and lower deposit interest rates do not affect household consumer credit. However, different from the results in panel (a), the positive coefficients of *share of property* × *APP* and the negative coefficients of *share of property* × *return on property* suggest mixed effects. On the one hand, there is a general credit easing after the APP for homeowners, therefore increasing homeowners' consumer credit. On the one hand, there is a general easing of credit after the APP for homeowners, therefore increasing homeowners' consumer credit. On the other hand, increased housing prices lead to a lower chance of consumer credit after the APP among homeowners as households are now able to substitute expensive non-collateral debt (consumer credit) for property-based debt (mortgages) (Brown et al., 2015).

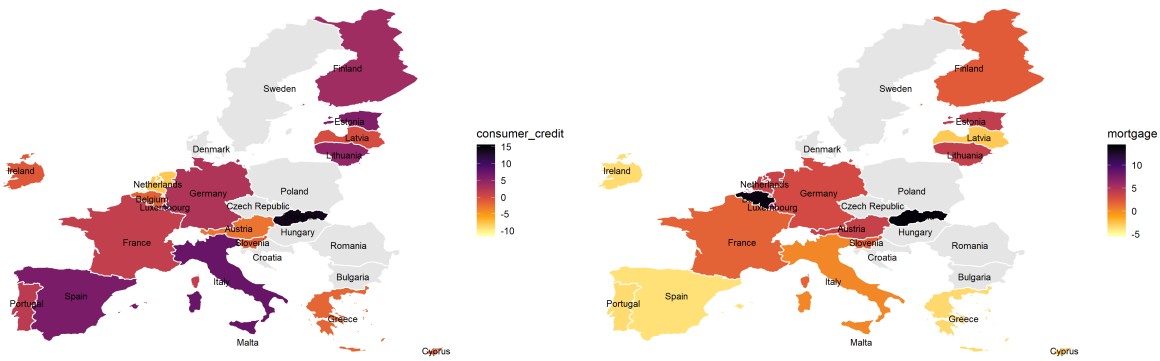
6 Extensions

6.1 Country Heterogeneity

In addition to household-level heterogeneity, there is also country-level heterogeneity in APP transmission. I investigate the divergent effects of the APP on the distribution of household credit in core and peripheral countries within the euro area. In peripheral countries, households in the relatively lower ends of the income and wealth distributions have a greater increase in credit. In comparison, in core countries, mainly the middle and higher wealth quintiles have a greater increase in credit after the APP policy. Thus, the credit constraint channel seems to be stronger in peripheral countries than in core countries.

The macro-level data suggest that there are divergent responses in different euro area countries. Figure 8 depicts the average annual growth rate for each euro area country from October 2014 to December 2016. The left panel shows consumer credit growth rates, and the right panel shows mortgage growth rates. Darker color indicates a higher growth rate. On average, in the core countries there is mainly an increase in household mortgages after the APP, while in the peripheral countries there is a significant increase in consumer credit and less of an increase in mortgages. The reasons behind the regional differences may be the different financial structures and banking regulations, economic situations before the policy implementation, housing markets, and household preferences in different countries.

Figure 8: Country Heterogeneity: Household Credit Annual Growth Rates (%, 2014 Oct - 2016 Dec Average)



(a) (b)

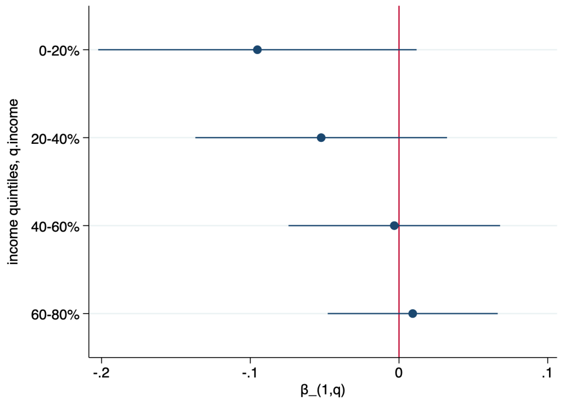
Notes: Panel (a) is the average annual growth rate for consumer credit, and Panel (b) is for housing mortgages. Darker color indicates a higher growth rate. Source: ECB, calculated by author.

Following the divergence at the macro level, I divide the micro-sample into two groups of countries, the core and peripheral countries, and examine whether there are dissimilar APP effects on credit distribution between these two groups. The peripheral countries are Ireland, Portugal, Italy, Greece, and Cyprus. The typical peripheral country, Spain, is missing because no post-APP survey data are available. The core countries are Austria, Belgium, Germany, France, Finland, Luxembourg, and the Netherlands. I run the same regressions using the baseline model for each of the two groups. I report detailed results in Appendix E.To summarize, the results for the core countries are mostly consistent with the baseline results. However, the effects of the APP on the household credit distribution are very different in the peripheral countries. The estimated coefficients are not always statistically significant, but the patterns are not identical to those of the core countries.

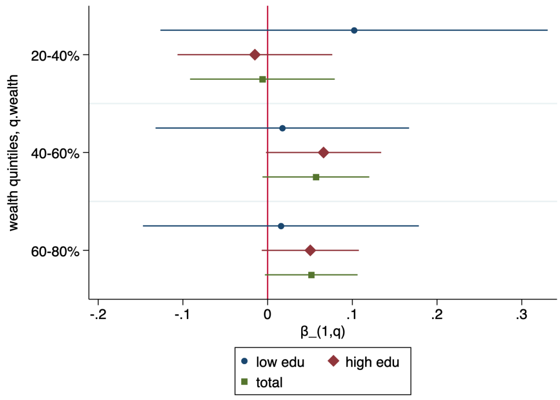
Figure 9 provides an example of divergent APP effects and shows the findings from household refinancing in the core and peripheral countries across income and wealth quintiles. Panels (a) and (b) present the estimated coefficients for the core countries, which suggest that the middle and fourth wealth quintiles increased their refinancing more after the APP (statistically significant at the 10% level), but there is no difference across income quintiles in the core countries. Panels (c) and (d) present the estimated coefficients for the peripheral

Figure 9: Country Heterogeneity: Refinancing

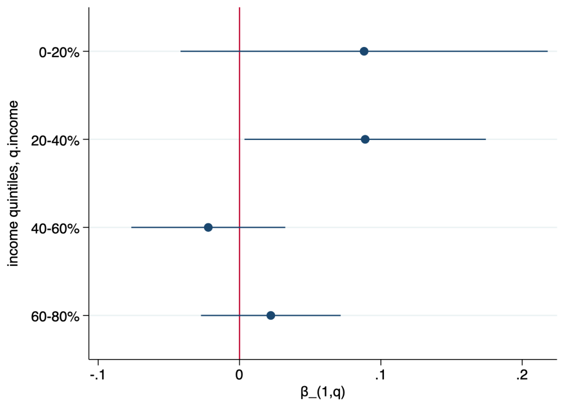
(a) core countries, income quintile



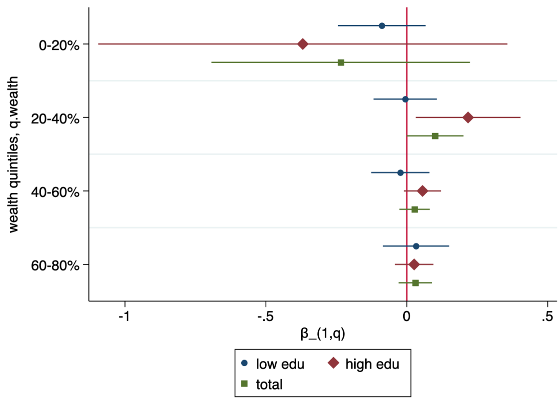
(b) core countries, wealth quintile



(c) peripheral countries, income quintile



(d) peripheral countries, wealth quintile



Notes: This figure presents different APP effects on the probability of mortgage refinancing in core and peripheral countries. It plots the estimated coefficients $\beta_{1,q}$ of interaction terms and the 95% confidence intervals from regressions. Panel (b) is missing the bottom 20% because in core countries, for households with mortgages, nobody is in the bottom wealth quintile.

countries, suggesting that both the second income quintile and the second wealth quintile in the peripheral countries have the greatest increase in the chance of refinancing after the APP compared with the other quintiles. I draw similar conclusions from analyses on other credit-related dependent variables.

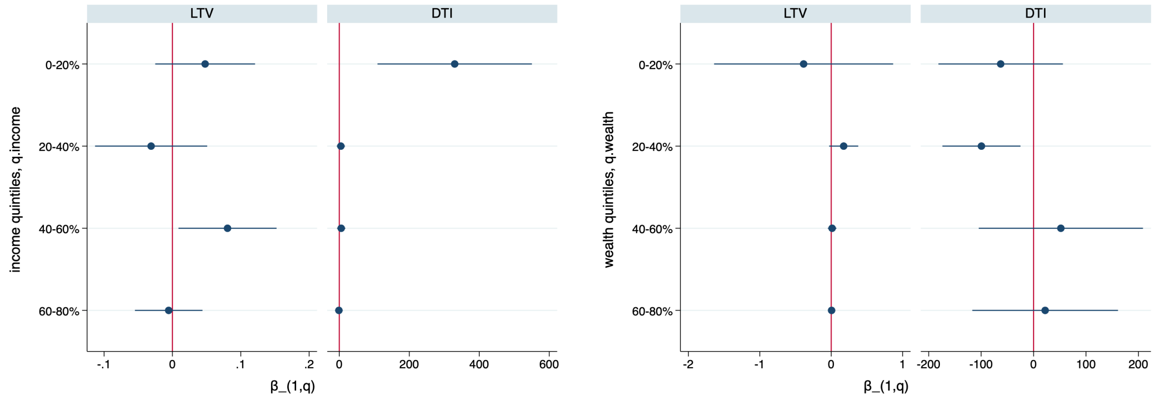
In conclusion, compared with the core countries, households in the relatively lower ends of the income and wealth distributions increase their credit more after the APP in the peripheral countries. This difference implies that the credit equalizing effect of the APP policy through the credit constraint channel is stronger in the peripheral countries than in the core countries.

6.2 Debt Repayment Ability of Different Groups

The last question I explore in this paper is how different households' ability to repay debt changes after the APP policy. Kumhof et al. (2015) show that the Great Depression and the global financial crisis were preceded by a sharp increase in income inequality and a similarly sharp increase in DTI ratios among low- and middle-income households. The result marked by my analyses is that the DTI ratios had much greater increases in the bottom income quintile than in the other income quintiles after the APP policy. The middle income quintile had the greatest increases in LTV ratios compared with the other quintiles. The increase in DTI ratios in the bottom income quintile is not a good signal for financial stability, especially if there is an unexpected negative shock on income (such as the lockdown due to COVID-19) or housing prices.

Figure 10 depicts the changes in the LTV and DTI ratios across quintiles after the APP implementation. I again run regressions of Model (1), but the dependent variables are the LTV and DTI ratios, and plot the estimated coefficients $\beta_{1,q}$ for the interaction terms. Panel (a) of Figure 10 the distribution across the income quintiles. For the LTV ratio, the middle quintile increases the most relative to the top quintile after the APP. The large increase in LTV ratios in the middle income quintile may be the result of refinancing. For collateral of the same value, now households can borrow a much higher amount of credit. For the DTI ratio, in the figure, the dot for the bottom quintile is far to the right of the zero vertical line. Thus, the bottom quintile's DTI ratios increased the most relative to the top quintile after the APP. A potential explanation for the relative increase in the DTI ratios in the bottom income quintile is that the bottom income households switched from paying rent to paying mortgages. The amount of total expenditure may not change much or become even lower, but households have higher debt after the APP. Thus, the DTI ratios surge. Panel (b) is the distribution across the wealth quintiles. There is no difference in LTV ratios for households across the different quintiles, but compared with the other quintiles, the DTI ratios increased the least in the bottom 20%-40% quintile.

Figure 10: Household Credit among Different Quintiles: Debt Repayment Ability



(a) (b)

Notes: This figure shows the APP effects on the relative changes of households' ability to repay debt, measured by the LTV and DTI ratios, across income and wealth quintiles. On the x-axis, it is the value of estimated coefficients $\beta_{1,q}$ of interaction terms and the 95% confidence intervals from regressions. On the y-axis, 0-20% represents the bottom 20% of the income or wealth distribution. Panel (a) is the results for different income quintiles, and Panel (b) is the results for different wealth quintiles.

My findings on the relative rise in LTV ratios for the middle income quintile and the relative surge in DTI ratios for the bottom income quintile are alarming. The LTV and DTI ratios are indicators of systemic risks in the financial sector. Households in the bottom quintile are vulnerable to unexpected shocks, such as the decrease in income caused by the lockdown during the COVID-19 period, or an asset price drop, especially a reduction in housing prices. These shocks can make already high LTV and DTI ratios even higher, and households may finally default, with no other choice. Thus, the high LTV and DTI ratios for households in the bottom quintile may be linked to macroeconomic fluctuations and systemic banking distress; thus, the ratios are of interest to central banks.

7 Robustness

I consider several tests for robustness checks. While the quantitative values vary a bit across the tests, the main conclusions are robust. The following discussion is intentionally brief, but more details are available in Appendix F.

I start by adding more household characteristics as control variables in the regressions. Household characteristics such as age (Andersen et al., 2015; Zhu and Meeks, 1994) are also determinants of household credit. I do not include age in the baseline models because I want to have as many observations as possible. If *Age* were included, observations from countries such as Ireland and Malta would be missing. The regression results with additional household characteristics are consistent with the baseline estimations.

There is controversy on whether weights should be included in regressions. Using weights can compensate for the unequal probability of the household participating in the survey and reduce sample selection biases. Therefore, I apply weights for both dividing the households into quintiles and performing regression analyses in the baseline models. As a robustness check, I use the raw data without weighting and run the regressions without weights. There are several differences in the results of the unweighted regressions compared with the baseline results. First, households in the fourth wealth quintile increase participation in the credit market the most and refinance their household main residence mortgages the most after the APP. In the baseline model, the middle quintile (40%-60%) increases the most. Second, on the amount households borrowed for consumption, there is no difference across the different wealth quintiles, while in the baseline results, the 20%-60% groups increased consumer credit by a much larger amount than the top quintile did. Third, for the LTV ratios in the unweighted regressions, in addition to the middle income quintile, the bottom income quintile also has LTV ratios that are higher than those of the top quintile, but in the baseline model, the coefficient is not statistically significant. As expected, the unweighted regression results are biased toward countries with more observations, such as France. Due to country heterogeneity, in the core countries, households in the middle and higher end of the distribution increased their credit the most, while in the peripheral countries, households in the lower end of the distribution increased their credit the most. Without weighting and with more observations from the core countries, the regression results are biased toward the higher end of the distribution. Overall, however, the main conclusions still hold.

Next, I use the middle quintile as the base group for a robustness check. In the baseline models, I use the top quintile as the base group, which facilitates the interpretation of changes in credit inequality. Using another quintile as the base group does not change the conclusions drawn as I am looking at the relative increase across different quintiles. As the figures in Appendix F show, most of the estimated coefficients are negative, which implies that compared with the other quintiles, credit increases the most in the middle quintile, which is now used as the base group. Specifically, for new house purchases across the different wealth quintiles, the estimated coefficients are positive for the top two quintiles for the full sample and the subsample of previous renters. For the subsample of owners, the coefficient is positive only for the bottom 20%-40% quintile, although it is not statistically significant. These results again confirm the baseline results.

All the above analyses make use of quintiles per country. For my last robustness test, I work with quintiles across all countries. Households are no longer divided into five groups within their home country but at the overall euro area level. The regression results using quintiles at the cross-country level are basically the same as the within-country-level grouping. Similar to the unweighted case, there are several differences compared with the baseline results. Within the euro area, households in the top 60%-80% wealth quintile have the largest increase in participation in the mortgage market and in refinancing after the APP. In the baseline, it is mainly the middle quintile that has the largest increases. This result, again, may be due to country heterogeneity. As shown previously, core countries have higher mortgage growth rates than peripheral countries. Meanwhile, the average level of household wealth in core countries is higher than that in peripheral countries. Thus, households that are in the middle wealth group in their home country may be in a higher group within the entire euro area. Furthermore, for the LTV ratios, there is no statistically significant difference across different income quintiles, which is different from the baseline results.

8 Conclusions

Does unconventional monetary policy have a distributional effect on household credit? This paper used data from the ECB HFCS, covering 17 euro area countries, to compare household credit in the pre-APP and post-APP periods. The findings show that the APP policy enlarged the credit gap between the top and bottom of the distribution, while credit increased the most among middle-wealth households.

I studied two potential policy transmission channels in the household credit distribution. The credit bias channel has dis-equalizing effects on household credit. It increases credit inequality between the top and bottom quintiles of the income and wealth distributions because the APP boosts the price of properties the most among all types of assets. And this wealth effect increases the chance of obtaining credit for property owners. Since the lower quintile households have a lower share of property investment in their household portfolios, in the end, compared with the top, the bottom has the smallest increase in credit. By contrast, the credit constraint channel contributes to the equalizing effects of the policy. It reduces credit inequality because previously credit-constrained households have more access to credit due to credit loosening and property appreciation after the APP. Empirical evidence from cross-quintile comparisons revealed that households in the second and middle wealth quintiles had relatively greater increases in refinancing and new mortgages for residence purchases after the APP. Moreover, household characteristics such as education and employment may also have contributed to the credit equalization after the APP.

There is also country heterogeneity within the euro area on policy transmission. The same ECB policy has different distributional effects in different countries. Compared with households in core countries, households in the relatively lower ends of the income and wealth distributions in the peripheral countries have greater increases in credit after the APP. Thus, the credit constraint channel is stronger in peripheral countries than in core countries.

Another conclusion from my study is that the bottom income quintile's DTI ratio increased the most, and the middle income quintile's LTV ratio increased the most after the APP. These uneven increases can add risks to overall stability if the economy faces a sudden negative income or asset price shock.

One of the limitations of this study is the low frequency of the available data. For both the pre-APP and post-APP periods, I only have one wave of survey data for each period. Survey data at a higher frequency with more waves or other high-frequency data from credit institutions could better identify policy effects on household credit inequality.

References

Viral V Acharya, Tim Eisert, Christian Eufinger, and Christian W Hirsch. Whatever it takes: The real effects of unconventional monetary policy. 2017.

Sumit Agarwal, Chunlin Liu, and Nicholas S Souleles. The reaction of consumer spending and debt to tax rebates—evidence from consumer credit data. *Journal of political Economy*, 115(6):986–1019, 2007.

Sumit Agarwal, Gene Amromin, Souphala Chomsisengphet, Tim Landvoigt, Tomasz Piskorski, Amit Seru, and Vincent Yao. Mortgage refinancing, consumer spending, and competition: Evidence from the home affordable refinancing program. Technical report, National Bureau of Economic Research, 2015.

Carlo Altavilla, Giacomo Carboni, and Roberto Motto. Asset purchase programmes and financial markets: lessons from the euro area. 2015.

Steffen Andersen, John Y Campbell, Kasper Meisner Nielsen, and Tarun Ramadorai. Sources of inaction in household finance: Evidence from the danish mortgage market. Technical report, National Bureau of Economic Research, 2015.

Philippe Andrade, Johannes Breckenfelder, Fiorella De Fiore, Peter Karadi, and Oreste Tristani. The ecb's asset purchase programme: an early assessment. 2016.

Martin Beraja, Andreas Fuster, Erik Hurst, and Joseph Vavra. Regional heterogeneity and the refinancing channel of monetary policy. *The Quarterly Journal of Economics*, 134(1):109–183, 2019.

Ben S. Bernanke. Monetary policy and inequality. *Brookings Institution blog*, 2015.

Josh Bivens. Gauging the impact of the fed on inequality during the great recession. *Hutchins Center Working Papers*, 2015.

Meta Brown, Sarah Stein, and Basit Zafar. The impact of housing markets on consumer debt: credit report evidence from 1999 to 2012. *Journal of money, credit and Banking*, 47(S1):175–213, 2015.

Katarzyna Barbara Budnik and Johannes Kleibl. Macroprudential regulation in the european union in 1995-2014: introducing a new data set on policy actions of a macroprudential nature. 2018.

Philip Bunn and May Rostom. Household debt and spending. *Bank of England Quarterly Bulletin*, page Q3, 2014.

Luisa Carpinelli and Matteo Crosignani. The effect of central bank liquidity injections on bank credit supply. 2017.

Indraneel Chakraborty, Itay Goldstein, and Andrew MacKinlay. Monetary stimulus and bank lending. *Journal of Financial Economics*, 136(1):189–218, 2020.

Satyajit Chatterjee, Dean Corbae, Makoto Nakajima, and José-Víctor Ríos-Rull. A quantitative theory of unsecured consumer credit with risk of default. *Econometrica*, 75(6):1525–1589, 2007.

James Cloyne, Clodomiro Ferreira, and Paolo Surico. Monetary policy when households have debt: new evidence on the transmission mechanism. *The Review of Economic Studies*, 87(1):102–129, 2020.

Olivier Coibion, Yuriy Gorodnichenko, Marianna Kudlyak, and John Mondragon. Does greater inequality lead to more household borrowing? new evidence from household data. Technical report, National Bureau of Economic Research, 2014.

Andrea Colciago, Anna Samarina, and Jakob de Haan. Central bank policies and income and wealth inequality: A survey. *Journal of Economic Surveys*, 33(4):1199–1231, 2019.

Frank A Cowell and Emmanuel Flachaire. Statistical methods for distributional analysis. In *Handbook of income distribution*, volume 2, pages 359–465. Elsevier, 2015.

Oliver Denk and Alexandre Cazenave-Lacroutz. Household finance and income inequality in the euro area. 2015.

Marco Di Maggio, Amir Kermani, Benjamin J Keys, Tomasz Piskorski, Rodney Ramcharan, Amit Seru, and Vincent Yao. Interest rate pass-through: Mortgage rates, household consumption, and voluntary deleveraging. *American Economic Review*, 107(11):3550–88, 2017.

Marco Di Maggio, Amir Kermani, and Christopher J Palmer. How quantitative easing works: Evidence on the refinancing channel. *The Review of Economic Studies*, 87(3):1498–1528, 2020.

Dietrich Domanski, Michela Scatigna, and Anna Zabai. Wealth inequality and monetary policy. *BIS Quarterly Review March*, 2016.

Karen Dynan, Atif Mian, and Karen M Pence. Is a household debt overhang holding back consumption?[with comments and discussion]. *Brookings Papers on Economic Activity*, pages 299–362, 2012.

Stefania d'Amico, William English, David López-Salido, and Edward Nelson. The federal reserve's large-scale asset purchase programmes: Rationale and effects. *The Economic Journal*, 122(564), 2012.

Martin Eichenbaum, Sergio Rebelo, and Arlene Wong. State dependent effects of monetary policy: The refinancing channel. Technical report, National Bureau of Economic Research, 2018.

Fabian Eser and Bernd Schwaab. Evaluating the impact of unconventional monetary policy measures: Empirical evidence from the ecb's securities markets programme. *Journal of Financial Economics*, 119(1):147–167, 2016.

Boniface Essama-Nssah and Peter J Lambert. Influence functions for policy impact analysis. In *Inequality, mobility and segregation: Essays in honor of Jacques Silber*. Emerald Group Publishing Limited, 2012.

Brett W Fawley, Christopher J Neely, et al. Four stories of quantitative easing. *Federal Reserve Bank of St. Louis Review*, 95(1):51–88, 2013.

Sergio Firpo, Nicole M Fortin, and Thomas Lemieux. Unconditional quantile regressions. *Econometrica*, 77 (3):953–973, 2009.

Sergio P Firpo, Nicole M Fortin, and Thomas Lemieux. Decomposing wage distributions using recentered influence function regressions. *Econometrics*, 6(2):28, 2018.

Marcel Fratzscher, Marco Lo Duca, and Roland Straub. On the international spillovers of us quantitative easing. *The Economic Journal*, 128(608):330–377, 2018.

Andreas Fuster and Basit Zafar. The sensitivity of housing demand to financing conditions: evidence from a survey. *FRB of New York Staff Report*, (702), 2015.

Luca Gambetti and Alberto Musso. The macroeconomic impact of the ecb's expanded asset purchase programme (app). 2017.

Miguel Garcia-Posada and Marcos Marchetti. The bank lending channel of unconventional monetary policy: The impact of the vltros on credit supply in spain. *Economic Modelling*, 58:427–441, 2016.

Georgios Georgiadis and Johannes Gräb. Global financial market impact of the announcement of the ecb's asset purchase programme. *Journal of Financial Stability*, 26:257–265, 2016.

Mark Gertler and Peter Karadi. A model of unconventional monetary policy. *Journal of monetary Economics*, 58(1):17–34, 2011.

Simon Gilchrist and Egon Zakrajšek. The impact of the federal reserve's large-scale asset purchase programs on corporate credit risk. *Journal of Money, Credit and Banking*, 45(s2):29–57, 2013.

Reuven Glick, Sylvain Leduc, et al. The effects of unconventional and conventional us monetary policy on the dollar. Citeseer, 2013.

Chiara Guerello. Conventional and unconventional monetary policy vs. households income distribution: An empirical analysis for the euro area. *Journal of International Money and Finance*, 85:187–214, 2018.

Aaron Hedlund, Fatih Karahan, Kurt Mitman, and Serdar Ozkan. Monetary policy, heterogeneity, and the housing channel. *Unpublished manuscript*, 2017.

Stefan Hohberger, Romanos Priftis, and Lukas Vogel. The distributional effects of conventional monetary policy and quantitative easing: Evidence from an estimated dsge model. *Journal of Banking & Finance*, 113:105483, 2020.

Michael Joyce, Ana Lasaosa, Ibrahim Stevens, Matthew Tong, et al. The financial market impact of quantitative easing in the united kingdom. *International Journal of Central Banking*, 7(3):113–161, 2011.

Michael Kumhof, Romain Rancière, and Pablo Winant. Inequality, leverage, and crises. *American Economic Review*, 105(3):1217–45, 2015.

Christopher J Mayer and Karen Pence. Subprime mortgages: what, where, and to whom? Technical report, National Bureau of Economic Research, 2008.

Atif Mian and Amir Sufi. Finance and business cycles: the credit-driven household demand channel. *Journal of Economic Perspectives*, 32(3):31–58, 2018.

Atif Mian, Amir Sufi, et al. Household leverage and the recession of 2007 to 2009. *SBP Research Bulletin*, 7: 125–173, 2011.

Atif Mian, Kamalesh Rao, and Amir Sufi. Household balance sheets, consumption, and the economic slump. *The Quarterly Journal of Economics*, 128(4):1687–1726, 2013.

R v Mises. On the asymptotic distribution of differentiable statistical functions. *The annals of mathematical statistics*, 18(3):309–348, 1947.

Juan Antonio Montecino, Gerald Epstein, et al. Did quantitative easing increase income inequality? *Institute for New Economic Thinking*, 2015.

Kevin B Moore and Michael G Palumbo. The finances of american households in the past three recessions: Evidence from the survey of consumer finances. 2010.

Jonathan A Parker, Nicholas S Souleles, David S Johnson, and Robert McClelland. Consumer spending and the economic stimulus payments of 2008. *American Economic Review*, 103(6):2530–53, 2013.

Cristiano Perugini, Jens Hölscher, and Simon Collie. Inequality, credit and financial crises. *Cambridge Journal of Economics*, 40(1):227–257, 2016.

Thomas Philippon. Has the us finance industry become less efficient? on the theory and measurement of financial intermediation. *American Economic Review*, 105(4):1408–38, 2015.

Fernando Rios Avila. Recentered influence functions in stata: Methods for analyzing the determinants of poverty and inequality. *Levy Economics Institute, Working Paper*, 927, 2019.

Jean-Guillaume Sahuc. The ecb's asset purchase programme: A model-based evaluation. *Economics letters*, 145:136–140, 2016.

Ayako Saiki and Jon Frost. Does unconventional monetary policy affect inequality? evidence from japan. *Applied Economics*, 46(36):4445–4454, 2014.

Urszula Szczerbowicz. The ecb unconventional monetary policies: have they lowered market borrowing costs for banks and governments? *42th issue (December 2015) of the International Journal of Central Banking*, 2018.

Anna Zabai. Household debt: recent developments and challenges. *BIS Quarterly Review, December*, 2017.

Lillian Y Zhu and Carol B Meeks. Effects of low income families' ability and willingness to use consumer credit on subsequent outstanding credit balances. *Journal of Consumer Affairs*, 28(2):403–422, 1994.

APPENDIX

A Sample Summary

Table A.1: Reference Years and Numbers of Observations

Country	Wave 2		Wave 3	
	Reference year	# obs	Reference year	# obs
Austria	2014	2997	2017	3072
Belgium	2014	2238	2017	2329
Cyprus	2014	1289	2017	1303
Germany	2014	4461	2017	4942
Estonia	2013	2220	2017	2679
Finland	2013	11030	2016	10210
France	2014	12035	2017	13685
Greece	2014	3003	2018	3007
Ireland	2013	5419	2018	4793
Italy	2014	8156	2016	7420
Luxembourg	2014	1601	2018	1616
Latvia	2014	1202	2017	1249
Malta	2013	999	2016	1004
Netherlands	2013	1284	2017	2556
Portugal	2013	6207	2017	5924
Slovenia	2014	2553	2017	2014
Slovakia	2014	2135	2017	2179
Total		68829		69982

B Household types

Table B.1: Definitions and Distribution of Household Types

Type	Definition	Freq.	Percent
6	2 adults, <65	21,448	15.45
7	2 adults, at least 1 >65 +	24,780	17.85
8	3 or 3 + adults	10,186	7.34
9	1 parent with children	6,049	4.36
10	2 adults with 1 child	12,620	9.09
11	2 adults with 2 children	15,069	10.86
12	2 adults with 3 or 3+ children	6,541	4.71
13	3 or 3+ adults with children	6,061	4.37
51	1 adult, <65	19,952	14.37
52	1 adult, >65	16,102	11.60
Total		138,808	100.00

C Functional Statistics and RIFs

This table presents definitions and formula to construct recentered influence function (RIF) statistics used in my analyses.

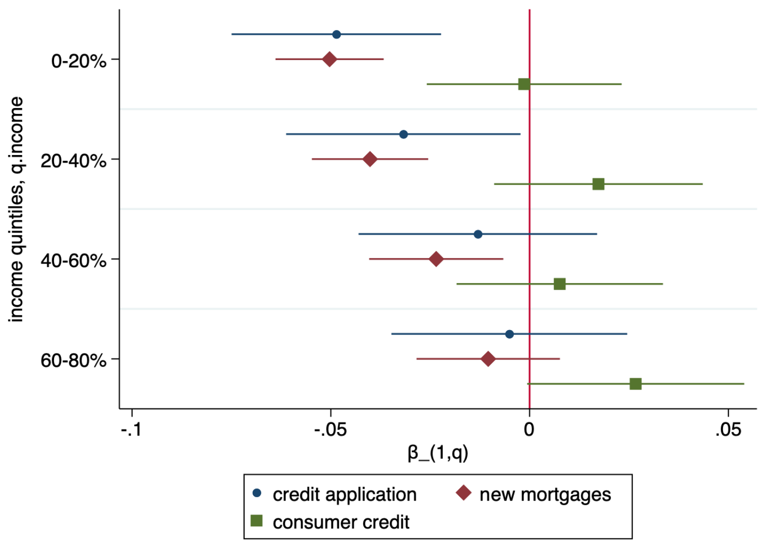
Table C.1: Functional Statistics and RIF

Statistics	Definition	RIF	Source
Gini	$Gini_Y = 1 - \frac{2}{\mu_Y} R_Y$	$RIF(y, Gini_Y) = 1 + \frac{2}{\mu_Y^2} R_Y - \frac{2}{\mu_Y}[y(1 - F_Y(y))]$	Firpo et al. (2018)
	$R_Y = \int_0^1 GL_y(p)dp$		
	$GL_y(p) = \int_{-\infty}^{q_Y(p)} ydF_Y(y)$		
Lorenz ordinate	$L_Y(p) = \frac{GL_y(p)}{\mu_Y}$	$RIF(y, L_Y(p)) = L_Y(p)(1 - \frac{y}{\mu_Y}) + \frac{pq_Y(p)}{\mu_Y} + (\frac{y - q_Y(p)}{\mu_Y})(y < q_Y(p))$	Essama-Nssah and Lambert (2012)
		$IF(y, L_Y(p)) = -\frac{y}{\mu_Y} L_Y(p) + \frac{pq_Y(p)}{\mu_Y} + (\frac{y - q_Y(p)}{\mu_Y})(y < q_Y(p))$	
Upper class share	$ucs_Y(p) = 1 - L_Y(p)$	$RIF(y, ucs_Y(p)) = ucs_Y(p) - IF(y, L_Y(p))$	Rios Avila (2019)

D Results across income quintiles

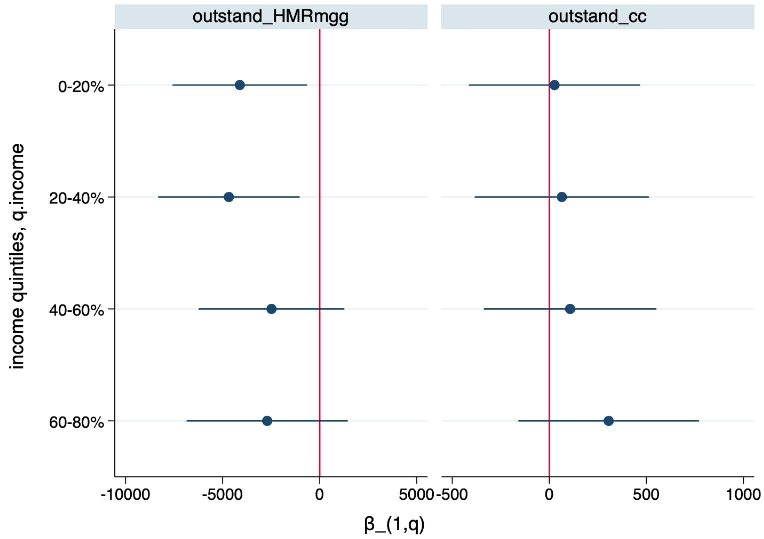
In this section, I examine the credit changes after the APP policy across different income quintiles. Similar to the results from different wealth quintiles, the credit gap between the top and bottom income distribution increases after the policy implementation. But different from the results on the wealth distribution, the middle income households do not increase their credit the most after the policy. On the contrary, on average, the lower income quintile households belonging to, the less likely they will increase their credit. The results from income quintiles suggest the key role of household wealth in transmitting APP policy effects on household credit.

Figure D.1: Household credit among different income quintiles at the extensive margin



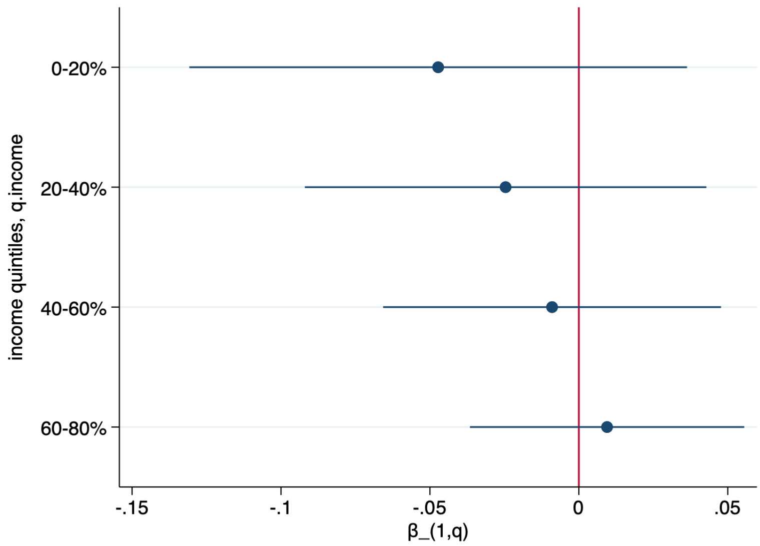
Notes: This figure presents APP effects on household credit changes at the extensive margin for each income quintile. On the x-axis, it is the value of estimated coefficients $\beta_{1,q}$ of interaction terms and the 95% confidence intervals from regressions. On the y-axis, 0-20% represents the bottom 20% of the wealth distribution. I examine three dependent household credit variables: credit application, holding new household main residence mortgages, and holding consumer credit.

Figure D.2: Household credit among different income quintiles at the intensive margin



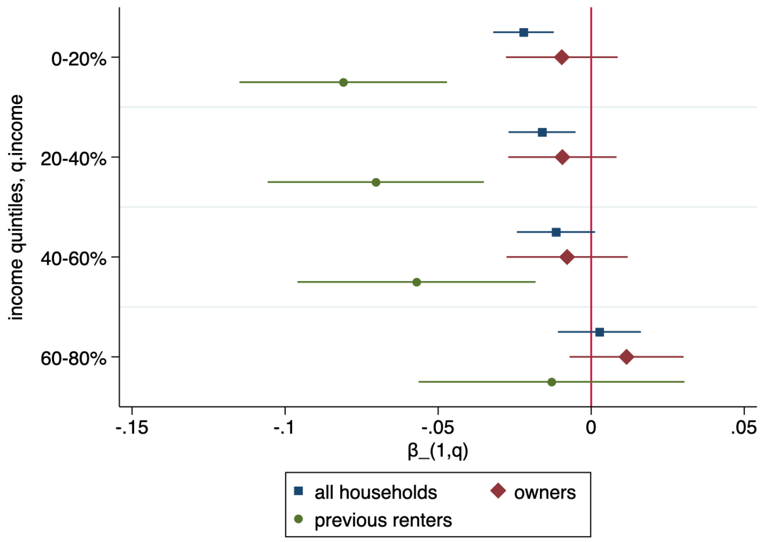
Notes: This figure presents APP effects on household credit changes at the intensive margin for each income quintile. On the x-axis, it is the value of estimated coefficients $\beta_{1,q}$ of interaction terms and the 95% confidence intervals from regressions. On the y-axis, 0-20% represents the bottom 20% of the wealth distribution. I examine two dependent household credit variables: outstanding balance of household main residence mortgages, and outstanding balance of consumer credit. The unit is Euro.

Figure D.3: Household credit among different quintiles: refinancing



Notes: This figure presents how APP affects the probability of mortgage refinancing across income quintiles and education groups. On the x-axis, it is the value of estimated coefficients $\beta_{1,q}$ of interaction terms and the 95% confidence intervals from regressions. On the y-axis, 0-20% represents the bottom 20% of the income or wealth distribution.

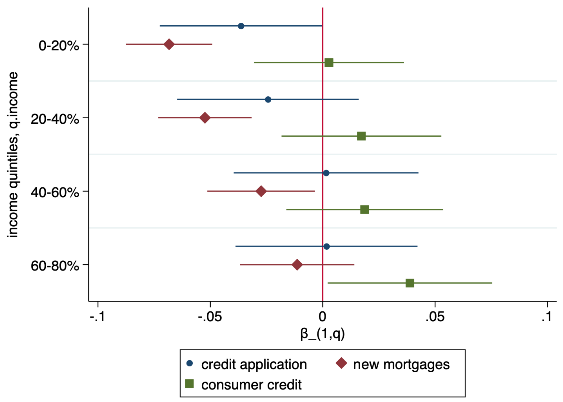
Figure D.4: Household credit among different quintiles: residence purchases



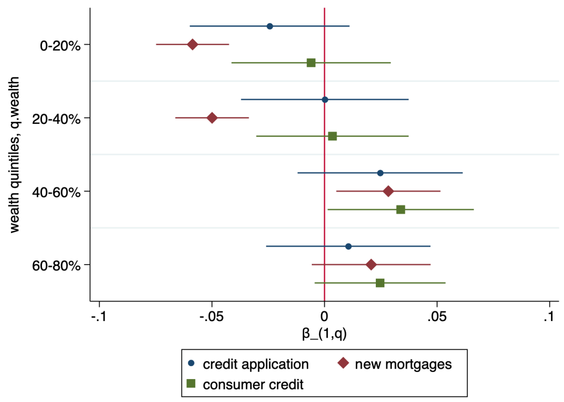
Notes: This figure presents residence purchases after the APP across income quintiles. On the x-axis, it is the value of estimated coefficients $\beta_{1,q}$ of interaction terms and the 95% confidence intervals from regressions. On the y-axis, 0-20% represents the bottom 20% of the wealth distribution. I further differentiate households with different home ownership, i.e., previous renters (in green), and owners (in red) from the total sample (in blue).

E Country Heterogeneity

E.1 Results for core countries

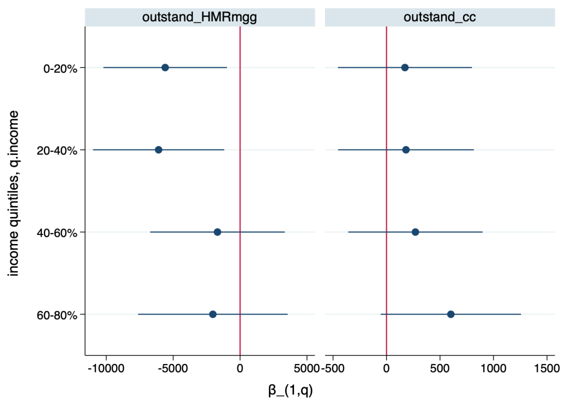


(a)

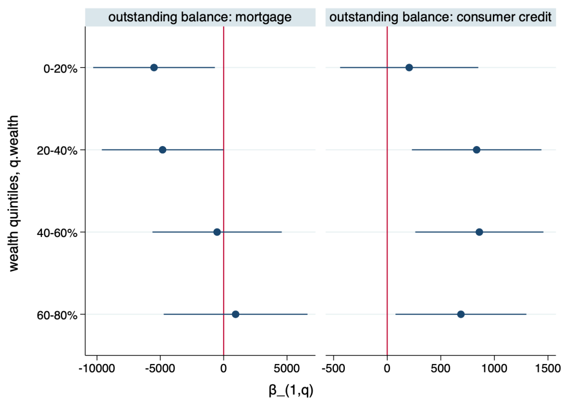


(b)

Figure E.1: Household credit across different quintiles at the extensive margin

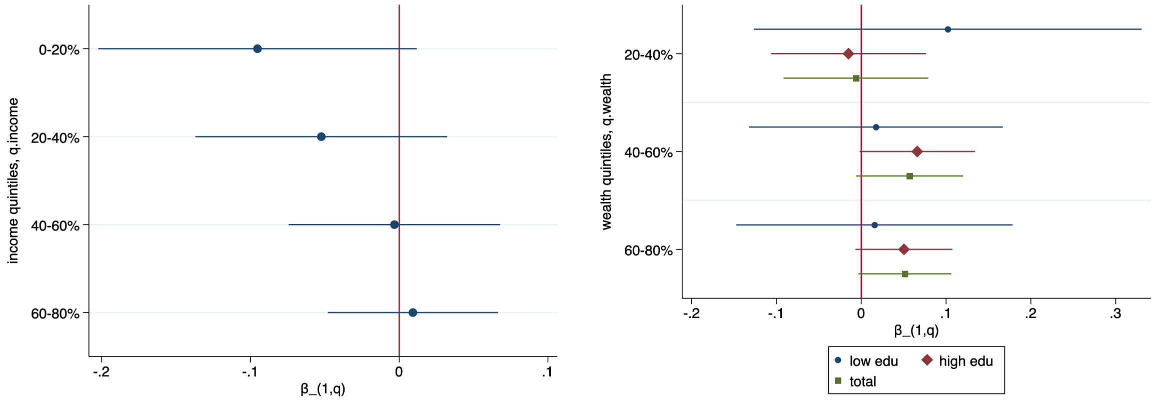


(a)



(b)

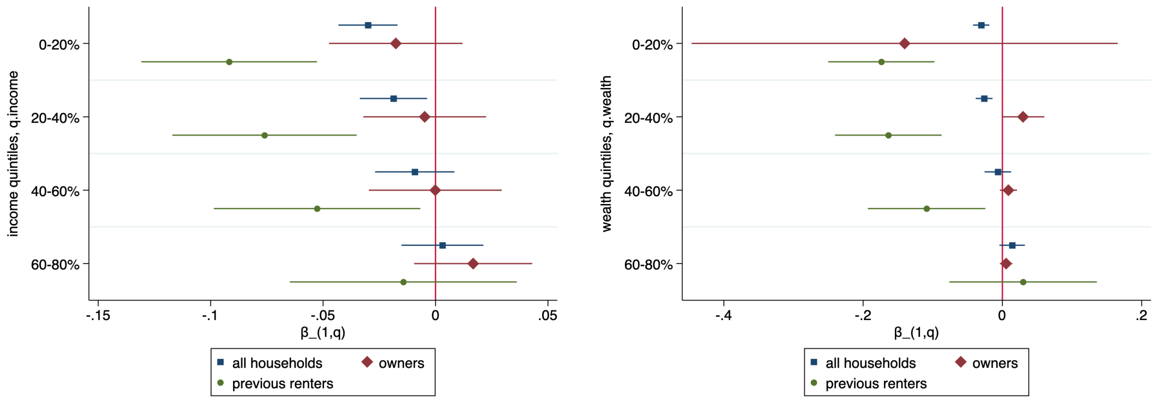
Figure E.2: Household credit across different quintiles at the intensive margin



(a) (b)

Figure E.3: Household credit among different quintiles: refinance

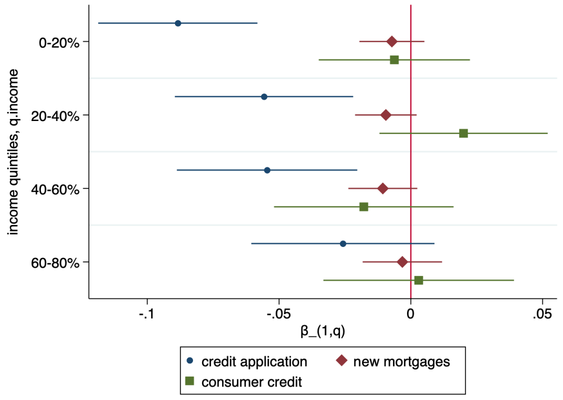
Notes: Panel (b) is missing the bottom 20%. It is because in core countries, for households with mortgages, nobody is in the bottom wealth quintile.



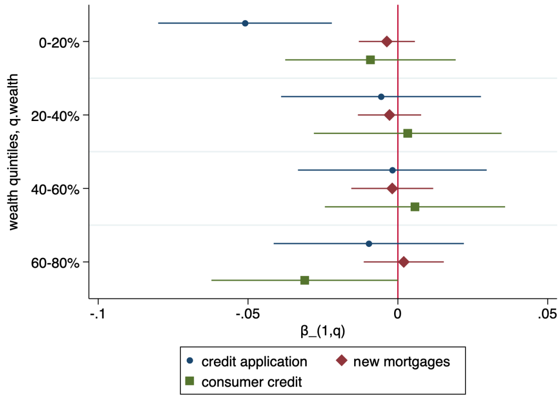
(a) (b)

Figure E.4: Household credit among different quintiles: residence purchase

E.2 Results for peripheral countries

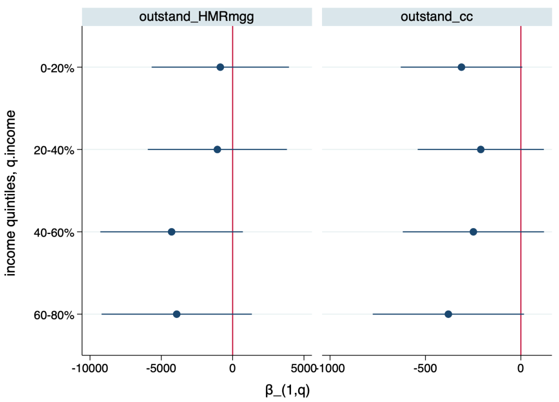


(a)

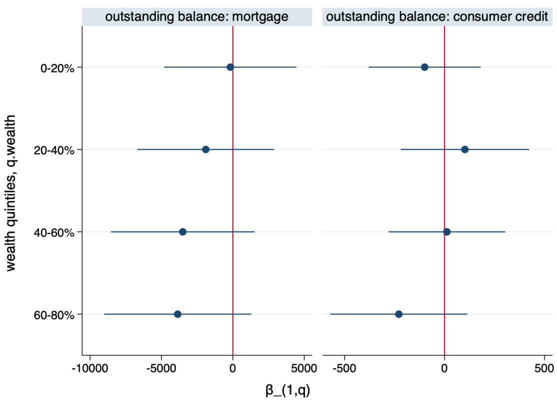


(b)

Figure E.5: Household credit among different quintiles at the extensive margin

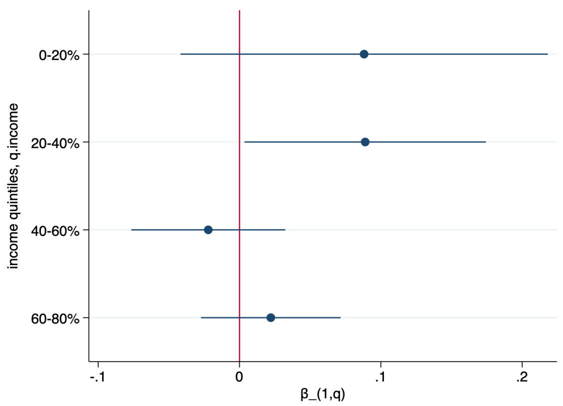


(a)

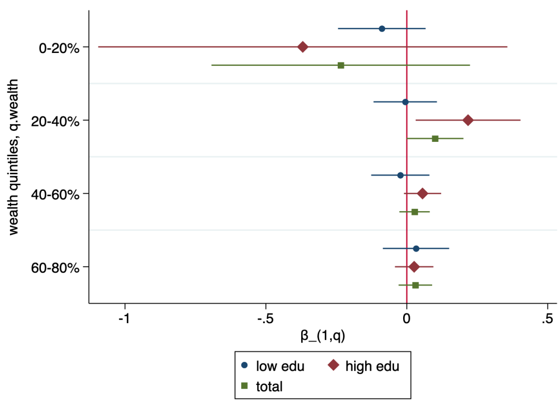


(b)

Figure E.6: Household credit among different quintiles at the intensive margin

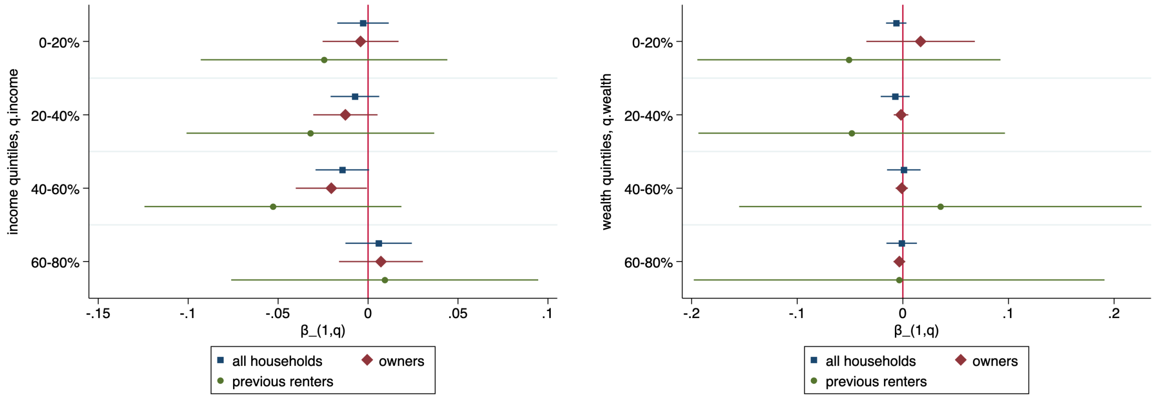


(a)



(b)

Figure E.7: Household credit among different quintiles: refinance



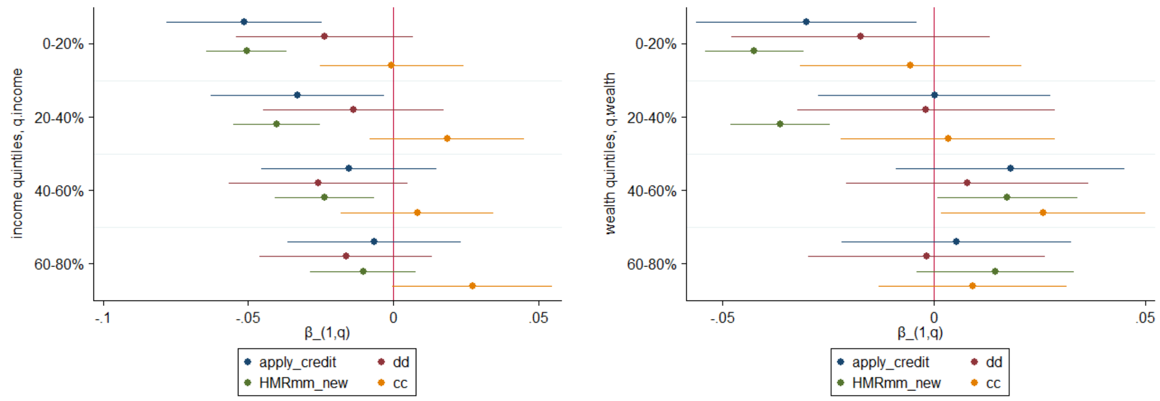
(a)

(b)

Figure E.8: Household credit among different quintiles: residence purchase

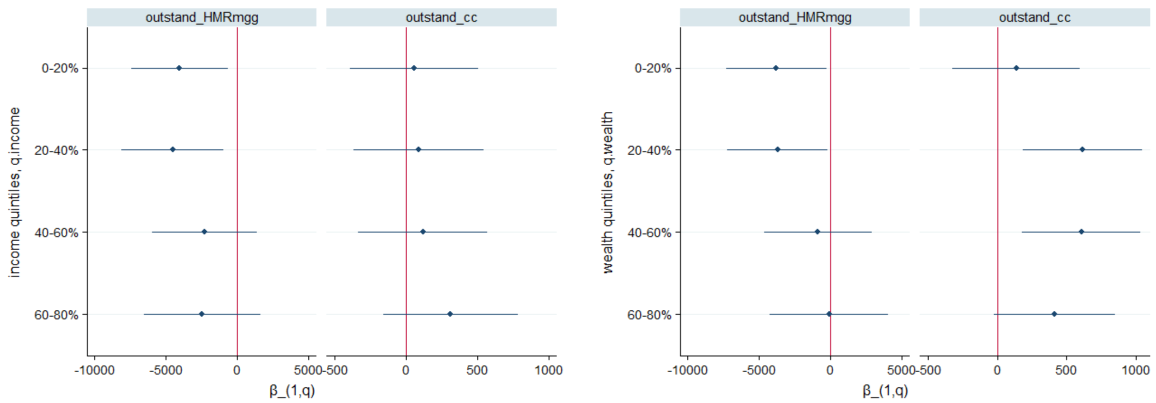
F Robustness Results

F.1 Add additional household characteristics



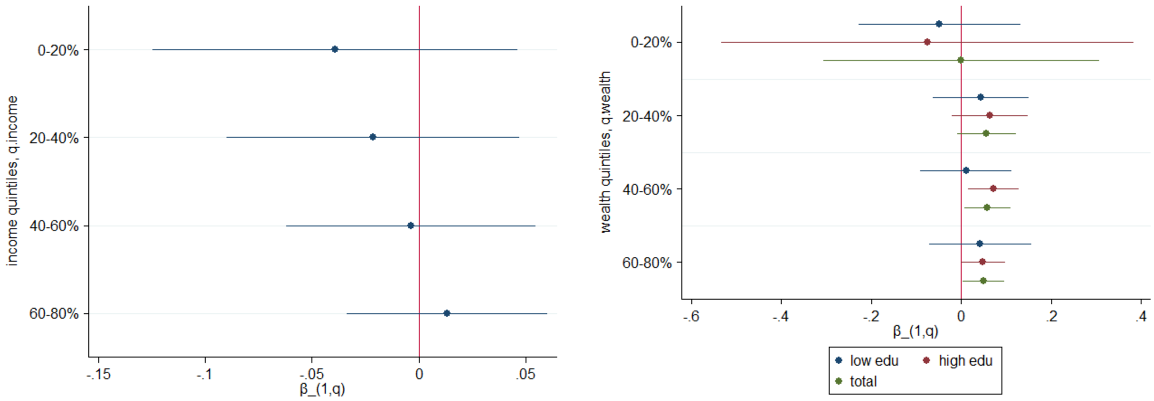
(a) (b)

Figure F.1: Household credit among different quintiles at the extensive margin



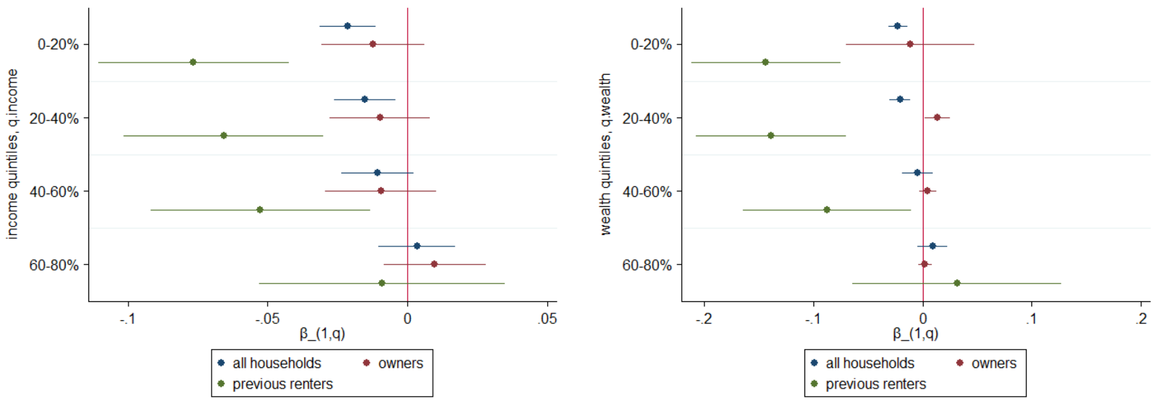
(a) (b)

Figure F.2: Household credit among different quintiles at the intensive margin



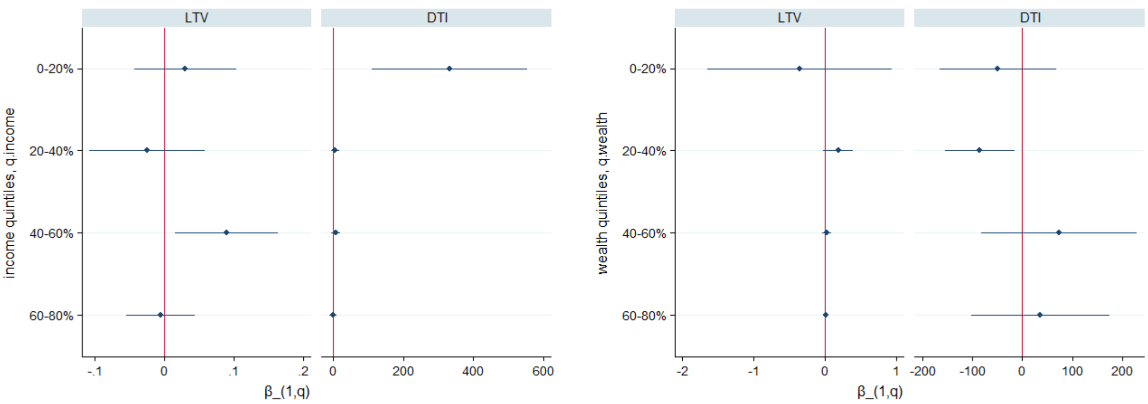
(a) (b)

Figure F.3: Household credit among different quintiles: refinance



(a) (b)

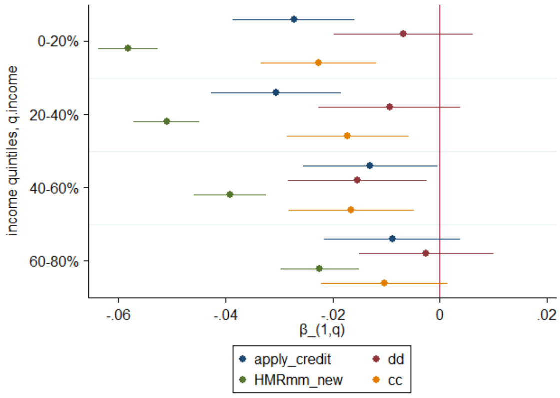
Figure F.4: Household credit among different quintiles: residence purchase



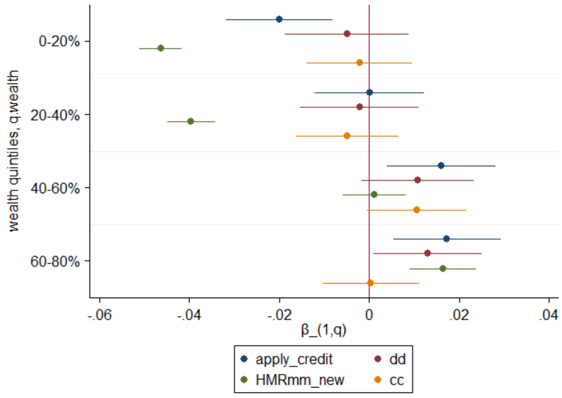
(a) (b)

Figure F.5: Household credit among different quintiles: Ability of debt repayment?

F.2 No weights

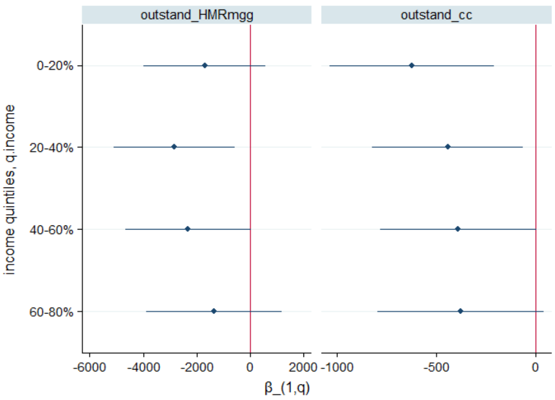


(a)

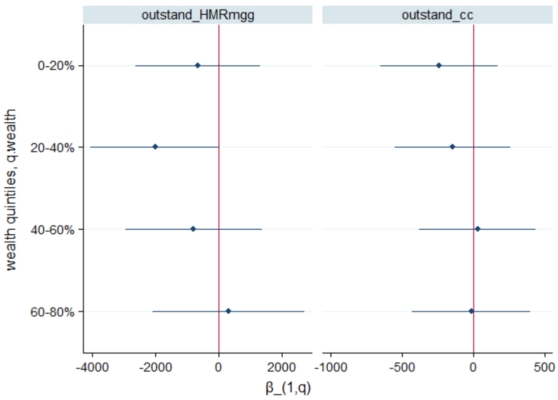


(b)

Figure F.6: Household credit among different quintiles at the extensive margin

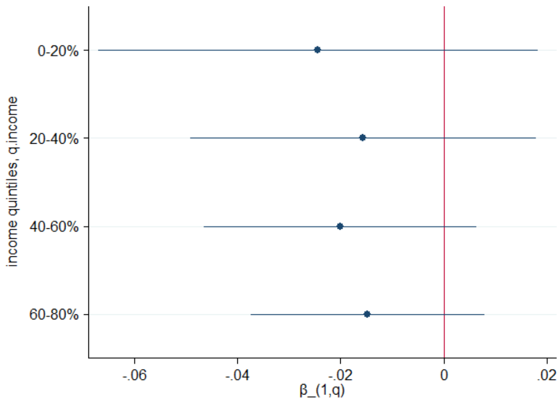


(a)

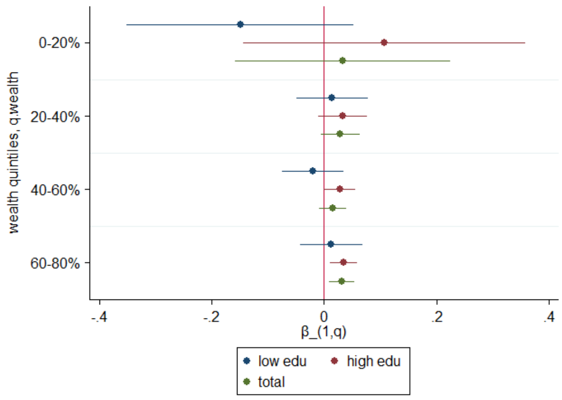


(b)

Figure F.7: Household credit among different quintiles at the intensive margin

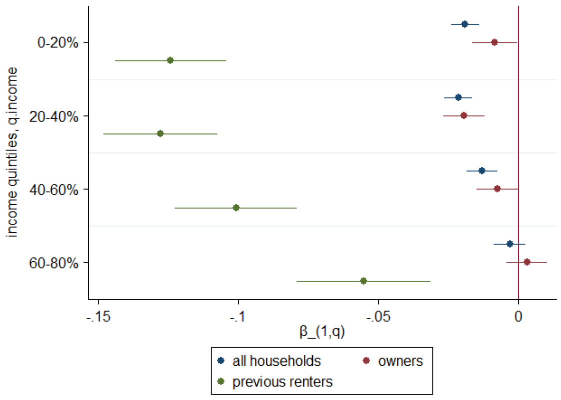


(a)

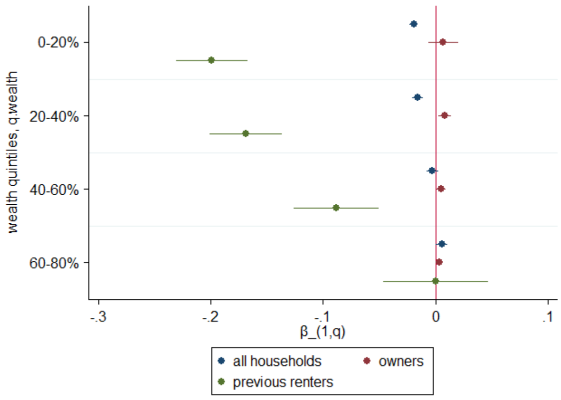


(b)

Figure F.8: Household credit among different quintiles: refinance

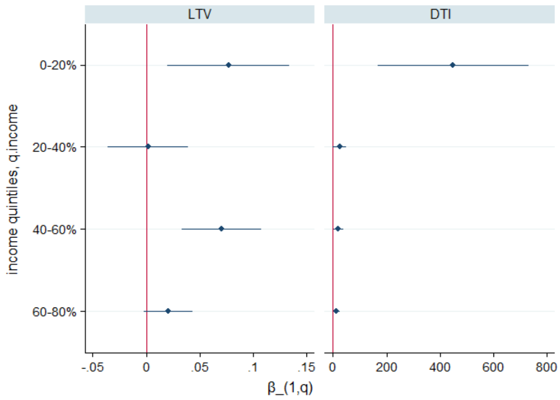


(a)

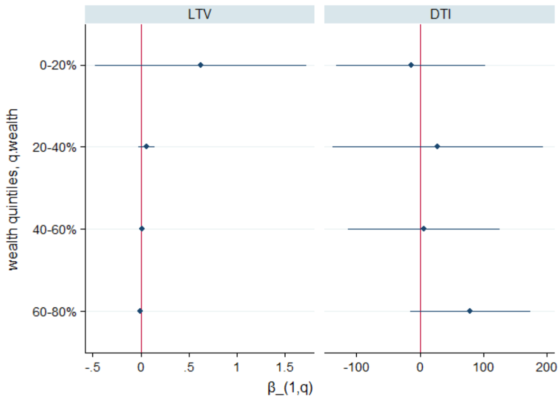


(b)

Figure F.9: Household credit among different quintiles: residence purchase



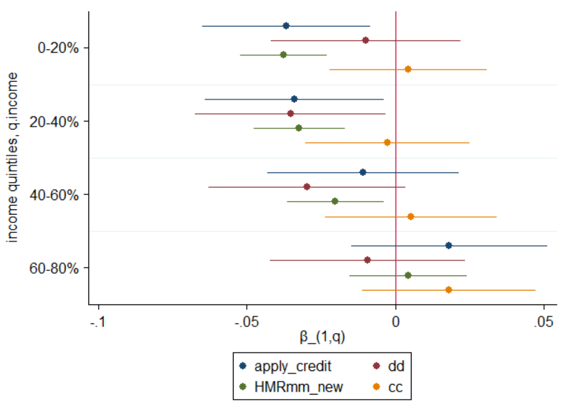
(a)



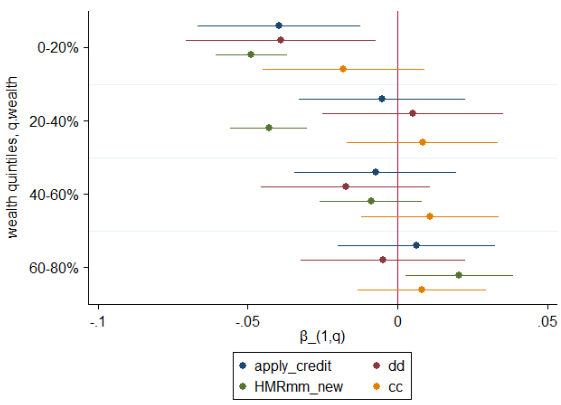
(b)

Figure F.10: Household credit among different quintiles: Ability of debt repayment?

F.3 Quintiles among all countries

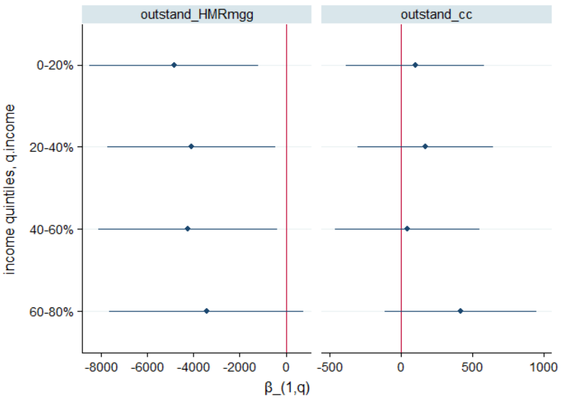


(a)

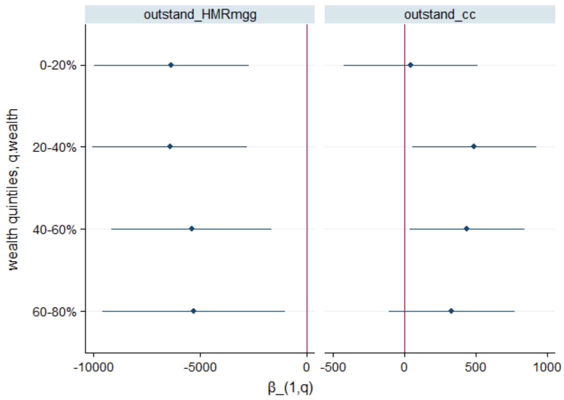


(b)

Figure F.11: Household credit among different quintiles at the extensive margin

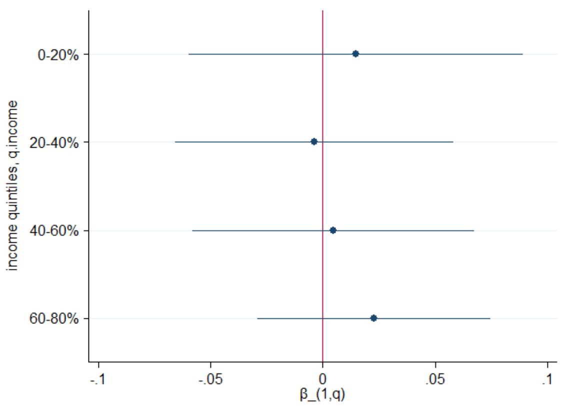


(a)

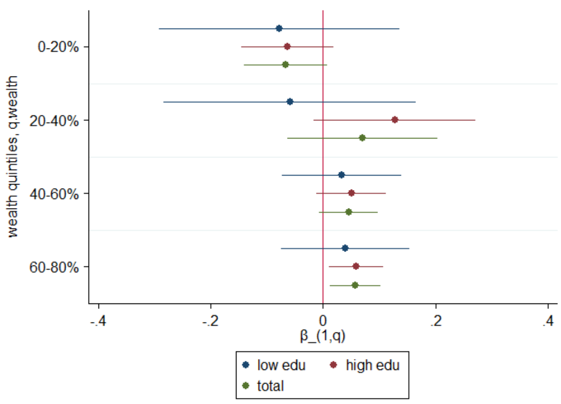


(b)

Figure F.12: Household credit among different quintiles at the intensive margin

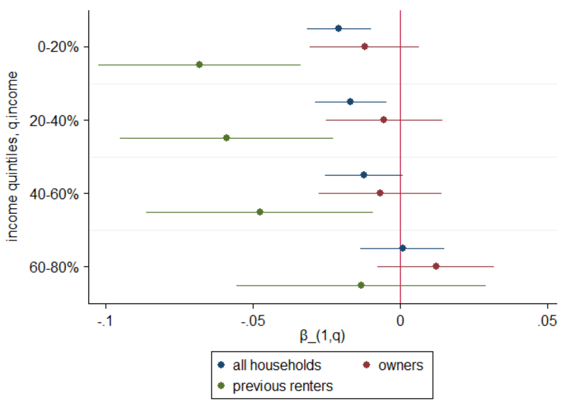


(a)

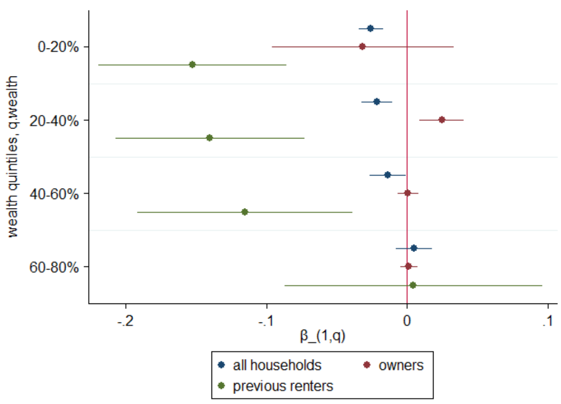


(b)

Figure F.13: Household credit among different quintiles: refinance

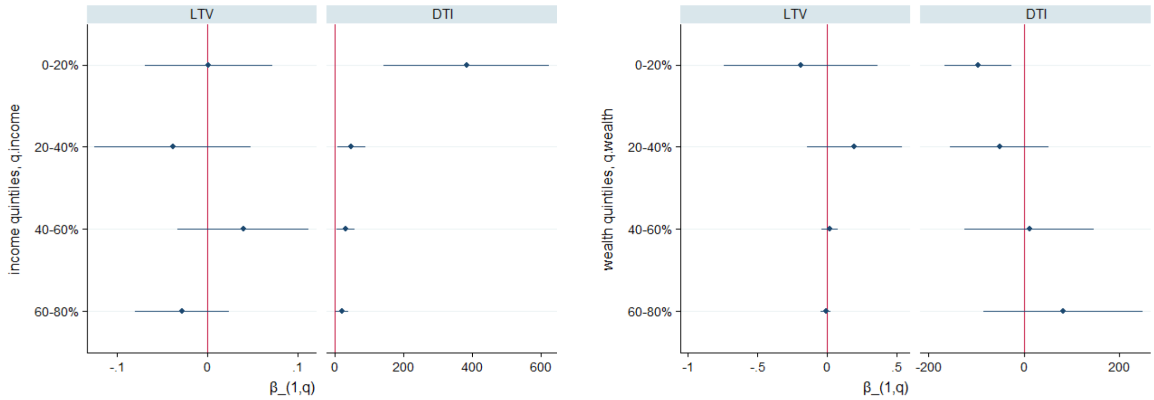


(a)



(b)

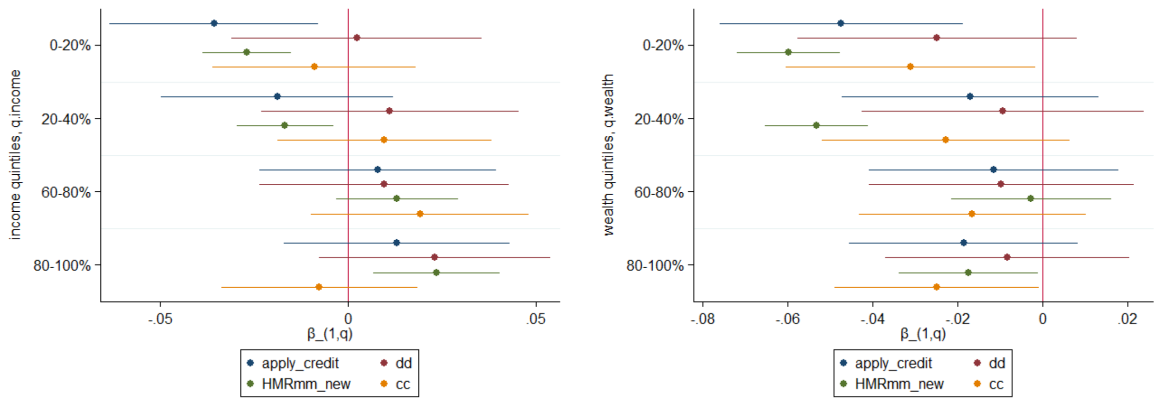
Figure F.14: Household credit among different quintiles: residence purchase



(a) (b)

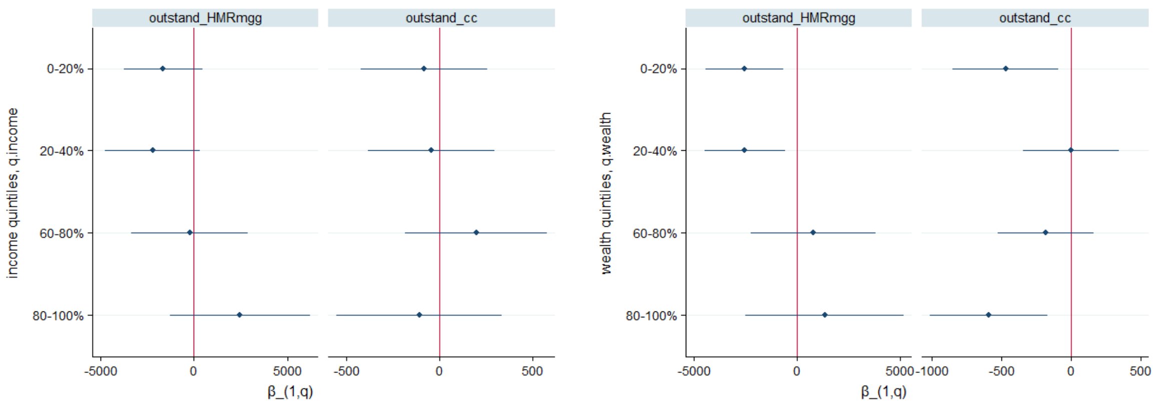
Figure F.15: Household credit among different quintiles: Ability of debt repayment?

F.4 Middle quintile as the base



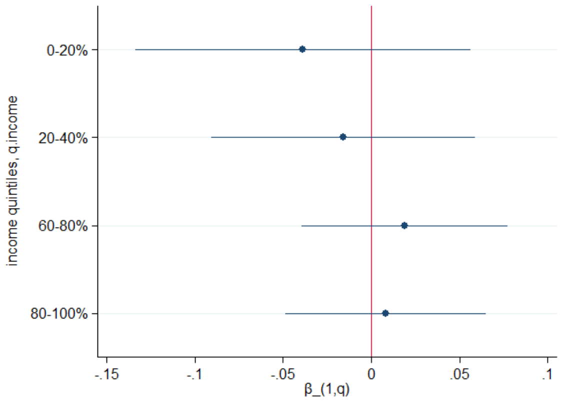
(a) (b)

Figure F.16: Household credit among different quintiles at the extensive margin

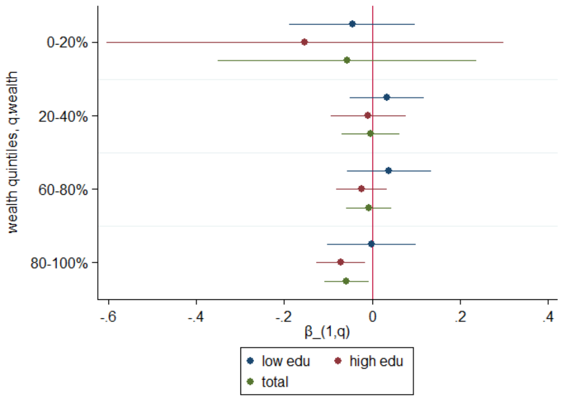


(a) (b)

Figure F.17: Household credit among different quintiles at the intensive margin

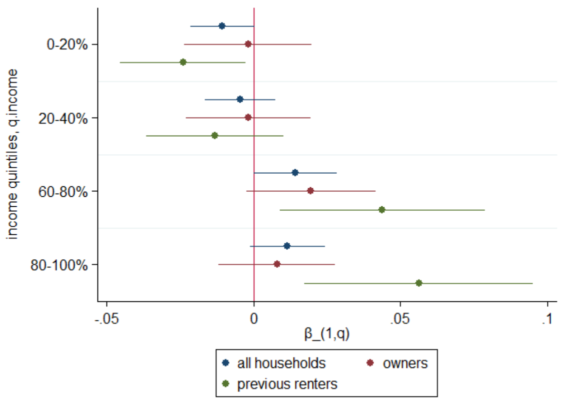


(a)

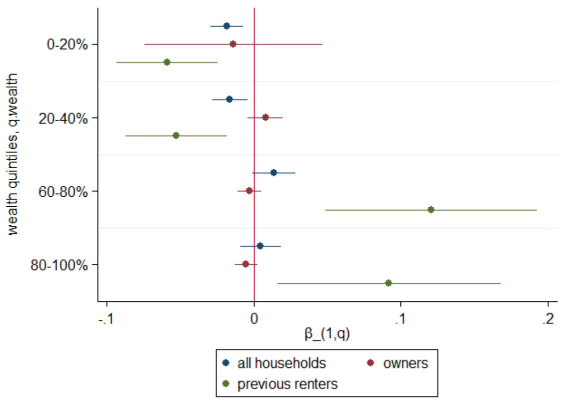


(b)

Figure F.18: Household credit among different quintiles: refinance

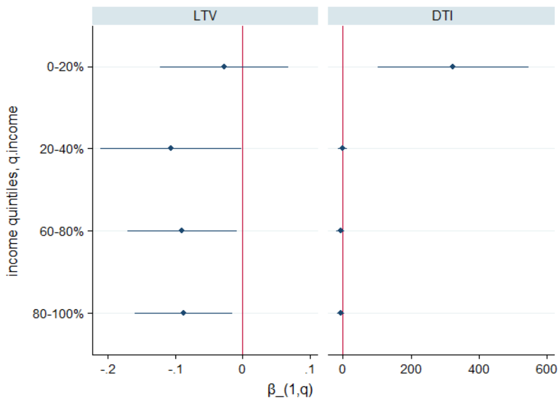


(a)

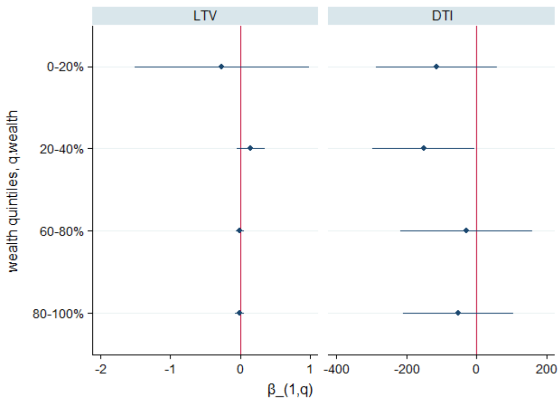


(b)

Figure F.19: Household credit among different quintiles: residence purchase



(a)



(b)

Figure F.20: Household credit among different quintiles: Ability of debt repayment?

G Additional Results

Table G.1: Percentage of households with different asset ownership, sample average

Wealth quintile	Asset types				Risky asset				
	Property	Deposit	Business	Risky asset	Stocks	Mutual funds	Managed accounts	Bonds	Other financial asset
1	4.21	80.91	1.93	2.98	0.98	1.49	0.22	0.31	0.67
2	47.77	91.60	6.53	11.94	4.63	6.76	0.87	1.72	2.25
3	86.15	93.45	8.76	16.60	6.61	9.09	1.40	2.69	3.74
4	94.89	96.01	14.26	26.29	12.47	14.77	1.99	4.37	5.51
5	96.37	98.06	31.56	47.59	31.60	28.44	6.38	8.04	11.31

Notes: Property includes all types of real estate.

Table G.1 shows the percentage of households with different asset ownership from each wealth quintile. There is large heterogeneity among different assets and different wealth quintiles. Deposits, including sight accounts and deposit accounts, have the highest coverage among households. Properties, or real estate, are also common among middle and high wealth groups. Households have much lower rates of ownership in non-publicly traded businesses and risky financial assets in the Euro area. Meanwhile, for all types of assets, the ownership rate increases as the wealth quintile increases.