The unequal distribution of credit: Is there any role for monetary policy? *

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January 2024

Abstract

Is current monetary policy making the distribution of credit more unequal? Using french household-level data, we document credit volumes along the income distribution. Our analysis centers on assessing the impact of surprises in monetary policy on credit volumes at different income levels. Expansionary monetary policy surprises lead to a surge in mortgage credit exclusively for households within the top 20% income bracket. Monetary policy then does not impact mortgage credit volume for 80% of households, whereas its effect on consumer credit exists and remains consistent across the income distribution. This result is notably associated with the engagement of this particular income group in rental investments. Controlling for bank decision factors and city dynamics, we attribute these results to individual demand factors. Mechanisms related to intertemporal substitution and affordability drive the impact of monetary policy surprises. They manifest through the policy's influence on collaterals and a larger down payment.

JEL classification: E41 E52 G21 G23 G28

*The authors have benefitted greatly from exchanges with Julien Fouquau and Catherine Lubochinsky. We gratefully acknowledge financial support from the University of Strasbourg and the National Bank of Belgium. We are grateful to Christophe Boucher, Jérôme Héricourt, Paul Hubert, Clément Mathonnat, and Adrian Pop, as well as participants at various conferences and seminars (AFSE 2021 in Lille, University of Lorraine, and University of Strasbourg, Workshop on Banking and Society 2023 in Strasbourg, University Paris-Saclay Seminar CEPS in 2024) for very useful comments and discussions on earlier versions of this paper. The usual disclaimer applies. Besides, we are very grateful for the technical support and data access supplied by the Banque de France. The data on firms, households and financial institutions made available to researchers in the Banque de France Open Data Room are anonymised granular data and aggregate series collected or produced by the Banque de France. These data are not marketable. Any use and processing of these data, by any method or on any medium whatsoever, carried out as part of the research work with a view to publication or otherwise, is the sole responsibility of the author. The results of the research work carried out using the data made available in the Open Data Room belong to the author and cannot be considered as representing any opinion or position of the Banque de France. Under no circumstances can the Banque de France be held liable for the consequences - financial or otherwise - resulting from the use of the data or information provided in its Open Data Room.

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Keywords: monetary policy, credit distribution, inequality

1 Introduction

Monetary policy has two types of financial effects: on income and on wealth. First, when the central bank cuts rates or buys assets, there is an inevitable redistribution of financial income across economies, and among different sectors and households within those economies, according to their net financial position. [...]
Still, the distributional picture also has to take into account the second type of effects – wealth effects – which capture the impact of monetary policy on the value of financial assets. Are those effects accruing mainly to the rich and so worsening wealth inequality? (Mario Draghi, 2016, 2^{nd} *DIW Europe Lecture)*

Since the Great Recession, monetary policy and inequality have become closely intertwined. The distributional consequences of monetary policy have been recently studied, with empirical research utilizing individual-level data spanning over long periods and encompassing all households in the country. Holm et al. (2021), Andersen et al. (2022), and Amberg et al. (2022) have shed light on the relationship between monetary policy and income changes, sparking debates regarding its impact on inequality. In the Danish context, the effect on income varies monotonically with income level (Andersen et al., 2022). In contrast, Norway (Holm et al., 2021) and Sweden (Amberg et al., 2022) have experienced U-shaped effects on income. Additionally, Holm et al. (2021) has delved into the role of household liquid asset distribution and its interaction with monetary policy and inequality. The presence of illiquid assets like rental investment can influence how households respond to monetary policy surprises.

These articles analyze various dimensions of heterogeneity among households, highlighting the different channels through which monetary policy operates. Each channel presents either gains or costs resulting from monetary policy, and these effects are not evenly distributed. Andersen et al. (2022) analyze the *indirect* and *direct* channels of monetary policy. The indirect channels reflects the effect on the labor income, on the business income and on the stock income, while the direct focusing on interest rate gains and losses, and emphasizes debt service (for borrowers) or interest income from deposits and bonds (for savers). Recognizing the potential significance of household debt, they differentiate the effects of monetary policy based on income distribution and the size of the debt-to-income ratio. As highlighted by Andersen et al. (2022), understanding the relationship between monetary policy and income inequality hinges significantly on interest rate expenses. An expansionary monetary policy creates winners through reduced interest rate expenses and losers through diminished interest income. In addition, Andersen et al. (2022) show that net beneficiaries in terms of interest tend to belong to the higher income strata. However, these papers do *not* explore the effect of monetary policy on the distribution of credit itself. In other words, while the initial debt size influences the distributional consequences of monetary policy, there is limited literature on access to credit.

To address this gap, we investigate the role of monetary policy in the distribution of household credit, particularly its potential impact on facilitating increased mortgage access for higher-income individuals and various mortgage purposes. Household incomes and the mechanisms associated with monetary policy are intricately linked to credit access. Hence, the impact of monetary policy on credit can either reinforce or counteract both the effects on interests and access to credit itself. If an expansionary monetary policy promotes credit availability primarily for higher-income individuals, the gains favoring interest recipients will become even more unequal. Conversely, if an expansionary monetary policy predominantly enhances credit accessibility for the middle and lower-income classes, the benefits accrued by interest recipients will be more evenly distributed.

This paper provides novel evidence on the heterogeneous effects of monetary policy on the credit distribution among households. Drawing from individual-level data in France, our findings reveal that expansionary monetary policy affects only the mortgage credit of the highest-income households. There is no apparent impact of such a policy on mortgage credit for lower-income and middle-class households, while it does stimulate mortgage credit for the top-income and upper-middle-class segments. In more concrete terms, it only affects the top 20% of French households, specifically those with net annual incomes at least 50,000 euros. Then, the monetary policy of the European Central Bank does not have a discernible impact on mortgage credit volume for 80% of the French population, whereas it does have an effect on consumer credit across all households. This observation raises concerns, particularly in the context of homeownership and opportunities for property investment when considering income and wealth inequalities. Quantitatively, an expansionary monetary surprise of 25 basis points stimulates credit for households as a homogeneous group. However, when considering the income distribution of households, there is no significant impact on mortgage credit volume for the bottom 80%, an effect of 0.9% for the top-income households between the 80^{th} and 100^{th} income percentiles.

To isolate such an impact of monetary policy, we initially identify the credit distribution among households. We utilize a French microeconomic dataset (the French Credit Registry) covering the period from 2012:Q4 to 2019:Q3, encompassing 35% of the country's credit data. All loans within this dataset provide comprehensive information about both borrowers and lenders. The dataset is representative of the population with access to credit in terms of income and encompasses all cities with a bank branch. We have details about the lender, the bank branch location, and the city. Furthermore, we possess information about credit specifics, including the exact purpose of the credit, any collaterals involved, the interest rate level, and the debt service. The critical differentiation between credits for primary residence, secondary residence, rental investment, and consumer credit enables us to disentangle associated mechanisms. This distinction extends to primary loans, bridging loans, and loans for home improvements. Additionally, we determine the precise position of borrowers in the household income distribution through their net annual income levels. By controlling for these multiple determinants, we can pinpoint the role of income levels and confirm the unequal distribution of credit in France. For each mortgage, households observed their credit amount increase by an additional 19% for the 2nd income quantile and by an additional 81% for the top 80-95% of the income distribution compared to the 1st quantile. This disparity is even more pronounced at 115% for the top 95-100%.

The heterogeneous impact of monetary policy can be driven by both supply and demand considerations. To isolate this monetary policy effect, we should also account for the distribution of credit among households, which may be influenced by both bank decisions, aggregate and individual household choices. Our econometric strategy captures factors related to both bank decisions on one hand and aggregate household decisions (i.e. local dynamics) on the other. First, bank decisions refer to there credit standard, and more specifically there perception of risks, there risk tolerance, there cost of founds and balance sheet constraints, among others. Banks possess the most robust capabilities to differentiate between sound and risky credit, whether it pertains to consumer loans or mortgages. They evaluate the likelihood of non-repayment by considering factors such as income, employment status, and individual or family characteristics. Key determinants include the prospects of job advancement and the potential for future layoffs, while local bank branches have a nuanced understanding on the quality of the local economy. These bank-related decisions are related to the risk-taking channel and interest rate risk exposure. These bank decision-related factors are captured by interacting dummies, including bank*biannual dummies and bank branch*biannual dummies. These dummies absorb all time-varying, observed, and unobserved bank heterogeneity on a biannual basis, following a similar approach as Degryse et al. (2019). Quarterly variables related to non-performing loans and other quarterly ratios aligned with banking regulatory logic capture any additional elements. Thus, our econometric strategy separates monetary policy surprise from bank (supply) decision factors.

The heterogeneous impact of monetary policy can also be driven by both aggregate demand and individual demand considerations. The distribution of credit is undeniably influenced by the demand from households, following Ringo (2023), among others. Aggregate shocks at the city or district levels compel households to seek loans. The life cycle hypothesis leads households to consider their first home purchases, relying on stable employment and settling into family life. Decisions regarding residential locations sometimes lead to investments in secondary homes. Additionally, portfolio investment decisions may lead to considerations of rental properties (Kaplan et al., 2020; Achou et al., 2023) . In other words, household decisions regarding loans and their volume depend significantly on their intertemporal substitution choices and affordability considerations. Our econometric strategy will distinguish between elements of aggregate demand and individual demand. On the *aggregate* level, employment and career prospects at the local level are captured by other interacting dummies, namely city*biannual dummies. Potential differences in dynamics can also be captured by the bank branch* biannual dummies. Alongside bank decisions, our econometric strategy accounts for aggregate household decisions.

Then, individual household demand drives our results. It is this heterogeneity of individuals that takes the spotlight, as the transmission of monetary policy varies along the income distribution. It affects only households with the highest incomes, but this effect completely disappears for consumer credit. This important phenomenon for understanding the channels of monetary policy transmission needs to be rationalized. Through our econometric strategy, this mechanism cannot be captured by factors related to bank or *aggregate* household decisions. Monetary policy, in this scenario, must operate through individual demand factors, linked to intertemporal substitution and affordability. Three mechanisms of monetary policy may play a complementary role, namely (i) the impact on collateral's value, (ii) the impact on down payments, and (iii) the impact on debt service-to-income constraints. We find that the heterogeneity in the transmission of monetary policy on mortgage credit volume is related to the dynamics of rental investment. It directly implicates the proposed mechanisms related to collateral and down payments. The consequences of monetary policy on the value of their collateral, therefore, have a heterogeneous impact on individuals in the same city or neighborhood, in a given bank, at a given bank branch. The highlighted mechanisms connects to the population that has obtained credit, and our sample represents the French population with credit, which may not necessarily reflect the entire French population. As we do not consider our mechanism as a formal closure of access to credit for the most vulnerable households. However, we highlight that an expansionary monetary policy only enhances access to credit for top 20% of households.

A substantial part of the paper explores the sensitivity of our results to alternative empirical strategies. We confirm the existence of the heterogeneous transmission of monetary policy in a setup accounting for many relevant determinants of household credit, including loan characteristics (proxy of risk, first or second home, for new or old residence, or for home renovation), local economic developments and bank balance sheets. Our results hold for various combinations of lags, dummies, clusters, and different measures of monetary policy surprises.

Our work has important policy implications regarding monetary policy mandate. While the literature intensively discusses the distributional consequences of monetary policy, for policymakers this question seems very distant. The *average* household's access to credit and associated interest rates do affect the central bank's objectives, but the central bank governors are generally silent on the question of credit distribution *across* households. The notable exception is the issue of financial stability, where we see a puzzling rate of defaults and residential real estate vulnerabilities. The allocation of household credit is treated in the central bank's reports under the heading of risk, and not as regards its potential effects on income and consumption inequalities, which in turn affect economic growth. By contrast, our results point out that expansionary monetary policies trigger the inequalities relative to credit, and especially improve the size of rental investment.

Our work has additional policy implications regarding the dynamics of income and wealth inequalities. The debate on the gap between the interest rate and the growth rate as the key driver of inequality is still ongoing (Piketty, 2014, Acemoglu and Robinson, 2015). It is well known that the distribution of housing capital can affect the dynamics of wealth, namely through the mechanisms of housing prices, rents, and the dwelling costs saved by homeowners. The relative importance of housing in the dynamics of capital has been the focus of study by Bonnet et al. (2021), but the question of access to credit has not yet been sufficiently analyzed.

Related Literature Our contributions are twofold and lie within three areas of literature. We introduce a new dimension of heterogeneity in monetary policy transmission, especially in the demand-side mechanisms. We also contribute to the causal analysis of monetary policy on income inequality.

Our primary contribution is to the extensive existing literature on the *transmission of monetary policy to credit* by enhancing it with an explanation of the diverse transmission of monetary policy among households. Since this literature commonly relies on multiple loan-bank relationships, researchers have long prioritized firm credit data and supply-side mechanisms. Various channels have been investigated, which can be classified in two categories. On the one hand, the bank lending channel of monetary policy puts emphasis on the strength of bank balance sheets as a determinant of credit availability (Jiménez et al., 2012; Drechsler et al., 2017, among others). On the other hand, the risk-taking channel highlights how the banks' appetite for risk is driven by policy interest rates and asymmetric information. Jiménez et al. (2014) and Dell'Ariccia et al. (2017) find that low interest rates increase the probability of extending loans to risky borrowers. Their measure of ex-ante risk-taking is based on credit history information on past loans (Jiménez et al., 2014) or on the bank's internal risk rating (Dell'Ariccia et al., 2017). Similarly, De Jonghe et al. (2020) explore the reallocation effects of the credit portfolio on firm credit. They highlight the key roles of the bank market shares in specific sectors and the risk level of the firm. Durante et al. (2022) emphasize the considerable heterogeneity in firms' reactions to monetary policy, particularly concerning the age and sector of the firm. A recent growing body of literature also examines the same impact on the supply of household credit. Gyöngyösi et al. (2022) highlight a bank lending channel for households by using Hungarian household-level data and performing a decomposition into domestic and foreign currency. Their strategy is based on the currency choice made by the borrower, while we investigate demand-related aspects and differentiate the mechanisms based on the purposes of mortgage credit. In the U.S. context, Peydró et al. (2020) demonstrate the role of funds, shadow banks, and fintech in the transmission of monetary policy. They differentiate between lenders (banks vs. nonbanks) and borrowers (firm credit vs. household credit). They illustrate how the substitution of bank credit with non-bank credit impacts the transmission of monetary policy to consumption and house prices by increasing the supply of credit to riskier borrowers.

We actively foster a second body of literature examining the *characteristics of demand in the channel of monetary policy transmission.* Various mechanisms have been proposed to explain differences in consumption responses to the same monetary policy and, consequently, different effects on real estate prices, durable consumption, and employment. In a nutshell, household balance sheets and mortgage markets matter. Having debt or not, as well as the variable or fixed nature of interest rates, are important contingent factors (Di Maggio et al., 2017; Flodén et al., 2021). The same holds true for opportunities for mortgage refinancing to take advantage of a lower interest rate on a new loan. Beraja et al. (2019) have demonstrated its significance as one of the primary transmission channels, linking refinancing incentives to movements in real estate prices, while Berger et al. (2021) connect them to interest rate incentives, the latter responding much more quickly to monetary policy. The distribution of the population and its demand mechanisms clearly plays a significant role in the transmission of monetary policy. Cumming and Hubert (2021) demonstrate that the distribution of household indebtedness also plays a pivotal role: the greater the share of highly-indebted households in the economy, the larger the consumption response to monetary policy. House price dynamics add to this picture, particularly concerning the share of highly-indebted households (Cumming and Hubert, 2022). Furthermore, more so than debt characteristics, the liquidity of household asset positions also directly influences the outcome (Kaplan et al., 2018; Holm et al., 2021). This is in direct alignment with the findings of Cloyne et al. (2020), who compare the transmission channels for monetary policy among three types of agents, namely renters, mortgagors, and outright homeowners. Their research underscores that the aggregate response of consumption to interest rate changes is primarily driven by mortgagors rather than outright homeowners or renters, emphasizing the importance of focusing on mortgage credit, as presented in our paper. Our work is closely related to Cloyne et al. (2020)'s study in distinguishing credit behavior between households financing their first real estate purchase and those venturing into the rental market. In a similar vein, Sodini et al. (2016) employ a quasi-experiment in Sweden to investigate how homeownership alters portfolio choices towards riskier investments.

We also contribute to a third literature, which examines the relationship between *monetary policy and income inequality.* The empirical literature focusing on the causal link between monetary policy and income inequality has recently shifted its conclusion, moving from survey data to comprehensive administrative data and household decomposable income. Survey-based analyses tended to show that tightening monetary policy leads to an increase in income inequality, and vice versa. This held true for both national surveys (Coibion et al., 2017) and cross-country analyses (Furceri et al., 2018; El Herradi and Leroy, 2021, among others). Recent papers based on comprehensive administrative data, in contrast, demonstrate that expansionary monetary policy increases income inequality, either by increasing income for each income decile (Andersen et al., 2022) or by producing U-shaped effects on income distribution according to income levels. Our paper is not the only ones identifying new heterogeneities in the transmission of monetary policy to households. Dolado et al. (2021) and Jašová et al. (2023) focus on the diverse impact of monetary policy on employment and wages, particularly through firm credit. We explore another connection by examining the differential impact of monetary policy on the distribution of credit among households. Surveys conducted by Colciago et al. (2019) and McKay and Wolf (2023) highlight the roles of various other channels, such as interest rate exposure (Auclert, 2019), income composition, or portfolio composition, as seen in Coibion et al. (2017). Lower interest expenses resulting from expansionary monetary policy generate varying gains among households (Andersen et al., 2022; Holm et al., 2021; and Amberg et al., 2022). The beneficiaries of lower interest rates on debts are primarily high-income households, regardless of the country considered, as reiterated by McKay and Wolf (2023). We complement this literature by adding a reinforcing effect on credit demand from households with higher incomes, which amplifies the initial unequal impact on lower interest expenses. With this result, we align with the recent empirical literature linking expansionary monetary policy to increased income inequality. We inform the theory (Kaplan et al., 2018; Hohberger et al., 2020; Alves et al. (2020), among others) regarding the importance of these real estate assets for rental investment. This aligns with the valuation of asset prices and the capital adjustment costs in Alves et al. (2020)'s model. It is indeed plausible to assume that there exist varying capital adjustment costs depending on the purpose of the real estate credit.

Finally, studies on access to credit and potential banking segregation are not new. Our paper is closely related to complementary work in Ringo (2023). It demonstrates how an increase in the interest rate negatively impacts the share of low and middle-income classes among real estate buyers. Their results, initially contrary to ours, actually pertain to a supply-side effect, whereas we present demand effects. Initially, in the absence of specific identifications of banks and their branches, it appears that the risk-taking channel serves as the primary mechanism elucidating these observations. Secondly, it focuses on local inequalities within a region rather than national inequalities, which Coibion et al. (2020) also link to supply-side effects[1].

[1] Income inequalities are perceived in Ringo (2023) through the area median family income, rather than national income inequalities. Therefore, local inequality mechanisms can be different from those presented in our paper. Indeed, Coibion

The remainder of the paper is structured as follows. Section 2 presents the data and the stylized facts. Section 3 describes the empirical strategy and the results, while section 4 concludes.

2 Data and stylized facts

2.1 Data

This paper uses French confidential loan-level data from France covering the period between 2012:Q4 and 2019:Q3. We match each loan to both bank balance sheet variables and household characteristics, including income level. We distinguish between loan type, more specifically mortgage and consumer credit provided by banks.

The French Credit Registry Our primary database originates from the French Credit Registry, known as CONTRAN, administered by the Bank of France. This repository contains confidential information regarding all forms of credit extended by financial intermediaries operating in France. The dataset is representative of the population with access to credit in terms of income and encompasses all cities with a bank branch. Delatte et al. (2020) also employ this dataset for corporate borrowers and local governments, whereas our focus is on household credit. The Bank of France's classification by the Bank of France enables us to identify and differentiate various lenders and borrowers.

On the lender's side, the French Credit Registry comprehensively lists all financial institutions operating in France, totaling 191 credit institutions. This dataset accounts for 35% of bank credit. Our sample encompasses 3,989 bank branches located in 1,745 French cities.[2] Given our knowledge of the bank branch locations and the cities involved in the bank-credit relationship, we link bank credit to the bank branch location. Regardless of whether it is for rental investment, a primary residence, or a secondary home, we assume that households are unlikely to venture beyond their own city in search of a loan.

et al. (2020) highlight how low-income households in highly unequal regions have accumulated a lower debt-to-income ratio than in less unequal regions. They rationalize their results with supply-side mechanisms rather than demand-side ones, which align with our interpretation of the supply-side effects. Finally, there are some minor differences in our paper. They limit their data sample to a combination of two datasets and focus solely on the existing real estate market. Our dependent variable, namely the credit volume per household used in this paper, and the share of poor households in an area cannot be directly translated. The potential differences between the USA and France also need to be considered.

[2] It is worth nothing that the cities Paris and Marseille are disaggregated by district, called *arrondissements*. However, the number of cities with bank branches may not remain constant. According to Scharfstein and Sunderam (2016) and Célerier and Matray (2019), the concentration of bank branches could potentially influence the credit distribution channel.

On the borrower's side, we distinguish between mortgage credit and consumer credit, considering various key characteristics. We break these down into 15 cases of household credit based on whether they pertain to mortgage or consumer credit, primary or bridge loans, credit for first or second homes, rental investments, new or existing residences, or home renovations. Because the French Credit Registry lacks a longitudinal tracking system for individuals, we leave out bridging loans from our analysis. We also incorporate consumer credit while excluding overdraft facilities and revolving credit to ensure comparability with mortgage credit.

The specificities of the credit arrangements are well-documented, encompassing aspects like interest rate levels, debt servicing, and repayment periods. Firstly, we include the fundamental credit characteristics, such as the different cases of mortgage credit and the distinction between fixed and variable interest rates. Table 1 provides information on the type of interest and the presence of collateral across all credits. For cases involving variable interest rates, which constitute less than 5% of the credit, we also consider the type of financial index used (e.g., EONIA, EURIBOR 1 month, EURIBOR 3 months) and the percentage of fixed interest rate over the entire loan contract period. Secondly, the individual demand mechanism depends on the use of collaterals[3]. Approximately 85% of our mortgage credit sample and nearly all consumer credit cases involve at least one form of collateral. Non-real estate collaterals secure a majority of loans.

Table 1: The distribution of collaterals

	Existence of collaterals (Shares in %)			
	No collaterals	Mortgage collaterals	Other collaterals	Both
First house	11.9%	23.6%	60.8%	3.7%
Second house	18%	26.6%	53.3%	2.1%
Rental investment	20.2%	26.5%	51.8%	1.5%
Consumer credit	99.2%	0%	0.8%	0%
	Fixed interest rate (Shares in %)			
	First house	Second house	Rental Inv.	Consumer
	98.5%	97.8%	98.2%	94.3%

We determine the net annual income of the entire family, serving as another proxy for individual portfolio and affordability. It allows us to ascertain their position within the national income distribution.[4] To avoid potential outliers, we apply certain thresholds: (i) the credit amount must be at least 10,000

[3]Unfortunately, the French Credit Registry does not specify the collateral amoint.

[4]The net annual income of the family does not include the wealth, which explains some credit relationship with low annual income. The correlation between income and wealth exists, but it is not perfect. That is why we will only address the links to income inequality in the article

euros for mortgage credit, (ii) the maximum amount for consumer credit is 40,000 euros, and (iii) the debt-service-to-income ratio (DSTI) for mortgage credit must be reasonable, with a maximum value of 60%. Until 2021, the French rule of thumb, approximated at 40%, was not a requirement. Some banks may accept higher DSTI, particularly for high-net-worth households. This can be attributed to sufficient income for acceptable living expenses or the presence of credit collateral. Finally, we have a total of 432,242 pairs of household-mortgage-bank relationships and 317,324 of household-bank relationship for consumer credit. Table 2 provides information on these credit types. The credit amount and the effective interest rate vary significantly between mortgage and consumer credit. Additionally, there is a notable distinction in the income distribution of borrowers. By examining income means and other thresholds, one observes an uneven distribution of income for various credit purposes. The utilization of mortgage credit, particularly for second homes or rental investments, is more common among middle and high-income classes.

Table 2: The distribution of income and credit - Descriptive statistics on household credit

	Mean	Min	Bottom 1%	1^{st} quartile	Median	3^{rd} quartile	Top 1%	Max	Nbr
				Mortgage credit - First house					
Credit amount	112,400	10,000	10,000	53,500	91,970	145,600	435,000	6.2m.	334,562
Annual income	52,300	5,015	14,800	29,600	41,340	56,600	186,900	76m.	334,562
Interest Rate (in %)	3.1	0.64	1.65	2.3	2.9	3.7	5.9	9.6	334,562
				Mortgage credit - Second house					
Credit amount	104,400	10 000	14,500	48,100	78,000	128,400	500,000	2.8m.	14,042
Annual income	81,600	6,570	16,500	40,000	58,000	87,200	448,000	55m	14,042
Interest Rate (in %)	3.1	0.85	1.64	2.3	2.9	3.7	5.3	6.6	14,042
				Mortgage credit - Rental investment					
Credit amount	104,500	10,000	10,000	50 000	83,500	139,900	376,000	2,1m.	83,638
Annual income	78,500	5,000	16,100	39,500	58,900	86,200	356,800	48m	83,638
Interest Rate (in %)	3	0.8	1.61	2.2	2.8	3.7	5.5	9.2	83,638
				Consumer credit					
Credit amount	8,670	20	262	3,100	6,000	12,000	33,600	40,000	317,324
Annual income	44,800	5,000	8,400	19,500	32,500	55,500	121,900	13m	317,324
Interest Rate (in %)	4.56	0.03	0.93	2.8	3.6	5.3	19.1	20.9	317,324

Note: The data here are described in terms of the entire set of credits considered and are examined in their distribution by variable. This does not pertain to the distribution of income.

Financial institutions: key characteristics The recent financial reforms stemming from Basel III, with a particular focus on the tightening of capital requirement regulations, have resulted in a reduction in the supply of credit (Aiyar et al., 2016). Additionally, heterogeneity in bank size and asset composition is also an issue for credit availability, as highlighted by Jiménez et al. (2012). This situation is mirrored in the case of non-performing loans, which have the potential to further exacerbate credit constraints. Then, we introduce controls for the size, composition, and profitability of financial institution balance sheets. We have gathered quarterly data encompassing the entire balance sheet of financial institutions, along with semi-annual income statements, to construct the variables conventionally used in this literature. Following Jiménez et al. (2012), Dell'Ariccia et al. (2017), and Gyöngyösi et al. (2022), we incorporate a range of financial characteristics, namely (i) the logarithm of total bank assets, (ii) the bank capital ratio (defined as capital divided by total assets), (iii) the liquidity ratio (computed as liquid assets divided by total assets), (iv) the returns on assets (ROA), and (v) the non-performing loans ratio, which is the ratio of non-performing loans to total loans. Table 3 shows the summary statistics relative to these variables.

We employ proxies for capital and liquidity ratios, with these computations being commonly found in the literature (see Table A.1 in Appendix for details). We do not use the Minimum Tier 1 capital, the Liquidity Coverage Ratio (LCR), and the Net Stable Funding Ratio (NSFR).[5] This decision does not necessarily constitute a weakness, as these official ratios were not universally adopted, particularly during the period 2012-2019. Consequently, concerns regarding comparability and data quality may have arisen.

Table 3 underscores the strength of the French banking system, as indicated by the low levels of non-performing loans and relatively high returns on assets, in line with the ACPR's annual summary statistics. It is worth noting that the reported bank capital ratios might appear relatively modest, averaging at 1.4%. This figure, however, should be assessed in the context of the Minimum Tier 1 capital, which can reach up to 6% as of January 2022. Nonetheless, it is essential to recognize that the latter represents a ratio of regulatory capital to risk-weighted assets, and we currently lack information concerning the precise level of these risks. Examining the numerator, no substantial increase in common equity Tier 1 is evident. Similarly, the liquidity ratio may not precisely mirror the LCR or NSFR ratios.

Table 3: Descriptive statistics on financial institutions

	Mean	Min	Bottom 1%	1^{st} quartile	Median	3^{rd} quartile	Top 1%	Max
Total Assets (bn.)	104	0.28	1.9	16.7	29.4	187	484	500
Returns on Assets (in %)	0.4	-1.3	0.1	0.2	0.3	0.5	1.1	1.8
Equity/Total Assets (in %)	1.4	0.2	0.3	0.6	1.1	1.9	4.7	15.7
Liquidity/Total Assets (in %)	1.8	0.01	0.2	0.4	0.6	1.4	20.9	32.3
Non Performing Loans (in %)	2.4	0.6	0.65	1.1	2.3	2.9	8.2	31.5

[5] The current dataset from the Bank of France does not include the confidential data held by the French financial regulator (Prudential Supervision and Resolution Authority, abbreviated as ACPR in French), which includes consolidated data by financial group and certain computations such as risk-weighted assets or the stock of high liquidity assets.

Monetary policy Our study incorporates monetary policy surprises as defined by Jarociński and Karadi (2020). We use the 64 monetary policy announcements from the European Central Bank and their potential associated surprises between 2012:Q4 and 2019:Q3.

Jarociński and Karadi (2020) investigate both the U.S. and European contexts by examining the relation between monetary policy interest rates and stock market reactions. In cases where the monetary policy surprise proves effective, an unexpected increase in interest rates leads to a decrease in stock prices. Consequently, Jarociński and Karadi (2020) refer to these instances of negative co-movement shocks as true monetary policy shocks. Conversely, all instances of positive co-movement shocks are defined as central bank information shock. Altavilla et al. (2019), on the other hand, differentiate between surprises related to both conventional and unconventional monetary policies, identifying two distinct events, namely the press release and the press conference. Altavilla et al. (2019) compute four distinct monetary policy surprises. The "Target" surprise is derived from the press release, while press conferences give rise to surprises related to "Timing", the "Forward Guidance", and the "Quantitative Easing".

We adopt monetary policy surprises as proposed by Jarociński and Karadi (2020). These surprises, alongside the central bank information shock from Jarociński and Karadi (2020) and the surprises from Altavilla et al. (2019), serve as complementary results. It is important to note that these diverse monetary policy surprises have gained wide acceptance and usage in the literature. Amberg et al. (2022) leverage the concept of negative or positive co-movement between monetary policy interest rates and stock prices to assess the relationship between monetary policy and income inequality. In a similar vein, Jašová et al. (2023) utilize the same dataset to scrutinize the effects of monetary policy surprises on labor market outcomes.

It is worth mentioning that these studies employ daily data, while we calculate our monetary policy surprises on a quarterly basis. Our approach assumes that if monetary policy does not respond to changes in household credit within the quarter, causality remains valid. However, it is important to acknowledge that this strategy treats all monetary policy changes within the same time frame uniformly, implying that a positive monetary policy surprise within a quarter could potentially be entirely offset by a negative one.

Income inequality The household income data utilized in the French Credit Registry encompasses all forms of income, encompassing both labor-related income and non-labor income sources such as pensions, benefits, investments, and transfers. This comprehensive dataset allows for easy comparability with income inequality data. To obtain income inequality data, we rely on the *"Enquêtes Revenus fiscaux et sociaux"* from INSEE, which standds as one of the most reliable sources for French income inequality data. The INSEE dataset takes into account the entire spectrum of household income distributions and provides annual income thresholds for each decile. What distinguishes this dataset is its foundation in a longitudinal microeconomic study that encompasses a variety of household types, including information regarding the number of children. The annual income thresholds computed by INSEE factor in this information, along with the associated average number of children. It is worth noting, however, that the French Credit Registry lacks individual-level details for each credit, such as information regarding the presence of children and the age of the household members, as illustrated by Cumming and Hubert (2021). Nevertheless, given that our credit data offers comprehensive insights at the level of each bank branch, we make the assumption that these national income thresholds are reasonably comparable to the annual net household incomes within our dataset.

For each loan, we conduct a comparison between the current net household income and these income thresholds. This matching process yields valuable insights into the distribution of credit among different households. To ensure robustness in our analysis, we aggregate the data into quantiles rather than deciles. This is motivated by the potential issue of having a relatively low number of loans at the decile level on a quarterly basis, which could introduce bias into the econometric model. We further differentiate the top income earners into two distinct categories: the top 95-100% and the top 80-95% of the income distribution. This segmentation allows for a more nuanced examination of the credit distribution across different income brackets.

Data representativeness is a crucial element in illustrating the heterogeneous impact of monetary policy. The French Credit Registry, developed by the Banque de France, serves as a database aiming to be representative of household credit data. It incorporates credit presence in all French cities where there is indeed a bank branch. The French population with credit appears, *a priori*, different from the overall French population, with the former likely having a higher proportion of affluent individuals.

Table 4 displays income distributions by income quantile, separating the top 5% of households for the entire French population according to INSEE. Additionally, it presents the distribution within our database for each credit type, offering insights into the specific characteristics of the population utilizing these credits.

Table 4: Annual income thresholds in household distributions - Median

	Bottom 20%	Bottom 40%	Middle 60%	Top 80%	Top 95%
French Population	17,500	25,500	35,300	50,000	81,500
First home - credit	27,000	36,800	46,300	61,800	101,800
Second home - credit	36,200	51,000	66,900	97,600	198,400
Rental investment - credit	35,500	51,000	67,800	95,900	175,000
Consumer credit	18,000	26,000	40,200	55,600	68,100

The credit distributions are depicted here by income thresholds for each quantile. These thresholds are markedly different from those of the entire French population. Predictably, mortgage loans represent a top-income population, but this discrepancy is particularly pronounced for households seeking loans for secondary homes. This pattern of mortgage lending, less focused on the financial profitability of the investment compared to rental investments, is thus predominantly sought after by those with higher incomes. The income distribution of households applying for consumer credit is relatively similar to that of the overall French population, except in the case of top-income households. Throughout the upcoming analysis, we will adhere to the distribution of households by quantile corresponding to that of the French population. The relative positioning of households in relation to other credit-holding households pertains to other questions. Coibion et al. (2017), among others, analyze the inequality-credit nexus by separating local inequalities from national inequalities.

2.2 Stylized facts

Table 5 below illustrates the distribution of new credit issued by banks for both mortgage and consumer credits. This distribution is based on the mortgage volumes originating from individuals with low, middle, and top incomes. The message conveyed by this table closely aligns with the one presented in Table 2: individuals in the upper-middle classes and those with top incomes account for the majority of mortgage loans in France, while access to consumer credit is more evenly distributed among different income groups. In addition, the table highlights the distinction between first homes, second houses, and rental investments. Top income individuals hold a significantly larger share of rental investment credit, as indicated by Piketty (2014). Drawing from Norwegian administrative data, Holm et al. (2021) also examine the distribution of both mortgage and consumer credit, revealing quantitative disparities between

Norway and France. In Norway, without distinguishing between types of mortgage loans, the top 20% of households hold less than 20% of all mortgage credit. In contrast, in France, the top 20% of households hold approximately 45% of credit for first homes, 75% for second homes, and 70% for rental investment properties. Beyond income distribution and measures of income inequality, Norway also appears to have a more equitable access to credit compared to France. In summary, there is a clear disparity in access to credit, which is contingent upon the type of credit being considered.

Table 5: Credit shares (in %) by borrowers and credit category- Quarterly median

	Bottom 0-20	Bottom 20-40	Middle 40-60	Middle 60-80	Top 80-95	Top 95-100
First house	1.7	8.2	14.9	26.9	30.6	18.6
Second house	0.8	3.3	7	13.6	30.8	45.6
Rental investment	0.1	4	8.1	14.5	31.7	40.1
Consumer credit	12.1	17.6	15.4	16.7	32.8	4.8

We expand upon this approach by introducing variability across different banks. In Figure 1, we provide additional data illustrating the distribution of new credit among financial institutions for each quarter. We continue to apply the same breakdown by income quantiles. Each box plot represents households within their respective income quantiles, with the exception of the top 80-95% and top 95-100% of the income distribution, which are depicted separately at the end of the figure. These box plots are relatively compact, indicating that credit distribution among income quantiles is fairly consistent across various financial institutions. In some instances, there is noticeable specialization for certain income groups, primarily within the top 95-100% of the income distribution. This specialization is likely influenced by differences in bank characteristics, such as geographical location and strategies. Figure 1 highlights an increasing share of mortgage credit as income rises, particularly for second homes and rental investments. This underscores the participation of middle and high-income groups in these credit arrangements, while consumer credit remains generally uniform. Among the top 20% of income earners, they hold approximately 40% of consumer credit, while the share for all other households quantiles remains relatively consistent. This outcome can be attributed to a decreasing debt burden in line with income distribution, potentially indicating a significant debt load for lower-income households, which might imply a debt overhang issue for the most financially vulnerable households.

We can further enhance our analysis by adopting a more granular approach, focusing on individual bank branches. For comparative purposes, Figure 2 follows the same distribution as Figure 1 and is

Figure 1: Credit shares (in %) by lenders, borrowers, and credit category - Distribution by bank-quarter pairs

Note: Authors' calculations. Period from 2012:Q4 to 2019:Q3. Each point represents a bank-quarter pair. Table 5 and this Figure follow the same distribution by income groups, namely 0-20, 20-40, 40-60, 60-80, 80-95 and 95-100.

divided into four panels. Figure 2 reveals a similar pattern to Figure 1, indicating that banks' strategies are generally consistent across the entire geographical expanse of France. The box plots for the lower and middle segments of the income distribution are notably high for first house credit, indicating significant variations among bank branches. This suggests that bank branches cater to different customer profiles, likely influenced by their geographical locations. Several unobservable factors in the credit distribution may be associated with specific cities, city districts, or even individual bank branches within a given city district. In summary, Figure 2 plays a pivotal role in our clustering strategy, as it provides valuable insights into the heterogeneity of bank branches and their relationships with different income groups and credit types.

Using this dataset, we subsequently validate the unequal distribution of credit among households. The majority of mortgage credit is concentrated among the upper-middle class and high-income individuals, whereas access to consumer credit is more evenly distributed among various household groups. This trend

Figure 2: Credit shares (in %) by lenders, borrowers, and credit category - Distribution by bank branch-quarter pairs

Note: Authors' calculations. Period from 2012:Q4 to 2019:Q3. Each point represents a bank branch-quarter pair. Table 5 and this Figure follow the same distribution by income groups, namely 0-20, 20-40, 40-60, 60-80, 80-95 and 95-100.

persists when we adopt a more detailed perspective by considering individual bank branches.

3 Empirical strategy and results

3.1 Empirical strategy

Armed with the household credit data, financial institution characteristics, and household characteristics, we delve into the credit distribution across households and its relationship with monetary policy. We begin by outlining our identification strategy and subsequently present our specification.

Our identification strategy is twofold. First, we ensure the exogeneity of monetary policy. Second, we differentiate the factors related to bank and household decisions from those unrelated to these decisions. This separation allows us to distinguish between direct and indirect (general equilibrium) mechanisms.

Endogeneity One potential concern is the possibility of our results being influenced by an endogenous relationship between monetary policy, banks, and household behavior. In essence, we need to distinguish between credit supply and credit demand. We utilize monetary policy surprises as documented by Altavilla et al. (2019) and Jarociński and Karadi (2020). While individual fixed effects are commonly employed in the literature examining the correlation between monetary policy and firm credit (Jiménez et al., 2012; Jiménez et al., 2014; Dell'Ariccia et al., 2017), extending the same approach to household credit presents significant challenges. In studies focusing on firm credit, it is common practice to consider multiple firm-bank relationships. Specifically, a firm might have various loan applications simultaneously with the same bank or different banks. Then, the literature controls for both observable and unobservable time-varying factors, as well as firm and bank heterogeneity, using firm fixed effects.

To the best of our knowledge, Gyöngyösi et al. (2022) is the only study that has implemented a strategy involving multiple household-bank relationships to analyze household credit. They utilized households' choice of currency denomination for their mortgage credit to control for demand-side mechanisms. Specifically, they considered the two loans taken by the same household from the same bank but in different currencies. We are unable to employ the same methodology for several reasons. Firstly, the dual-currency loan choice is not a prevalent option in France. Secondly, the French Credit Registry lacks the necessary longitudinal data to track households over time[6]. Finally, information regarding unsuccessful loan applications is not available. An alternative approach could have involved comparing mortgage loans and bridging loans, but the required data is unavailable. Moreover, it is reasonable to assume that the decision to use a bridging loan is influenced by factors distinct from those guiding the choice of a primary mortgage loan.

Bank and household decision factors: use of interacted dummies Our identification strategy incorporates all decision factors at both bank and city levels, allowing room for individual demand factors. We separate bank decisions and household decisions using a set of control variables and interacted dummies, specifically bank branch*semi-annual and city*semi-annual dummies. This represents a more stringent set of dummies compared to options like bank*year, city*annual, city, bank branch dummies, for example. We employ semi-annual or annual dummies instead of quarterly dummies since monetary policy surprises are measured at the quarterly level in our dataset. This isolates the impact of monetary

[6]Consequently, our analysis relies on cross-sectional regression models, employing dummies rather than fixed effects.

policy from factors external to household and bank decisions.

We control for banks' decisions regarding their loan portfolios, whether at the national or local branch level in France. Banks can adjust various risk and interest rate exposure variables. National objectives for credit reallocation among different branches may also come into play. These diverse elements are captured by interacted bank*biannual dummies. Similarly, the interacted bank branch*biannual dummies control for bank branch strategies and potential changes. We account for changes, whether observable or unobservable, in local-level bank strategies. In other words, the degree of decentralization/centralization in bank decision-making and its implications for our identification are considered. The bank branch*semi-annual dummies encompass all forms of bank branch heterogeneity, be it time-varying, observable, or unobservable. This comprehensive set of interacted dummy variables assists in capturing a wide range of heterogeneity across banks over time. For instance, banks may reallocate credit towards riskier households, a phenomenon associated with the risk-taking channel described in Dell'Ariccia et al. (2017) and Gyöngyösi et al. (2022). This reallocation is analyzed in the literature through interaction terms between the monetary policy measure and bank capital ratios. Our interacted bank*biannual dummies already encompass these risk relationships. In addition, we utilize quarterly variations in traditional banking ratios, commonly employed in the literature, to further enhance our capture of bank decisions. Specifically, we employ capital ratios, liquidity ratios, profitability ratios, non-performing loans, and quarterly changes in bank size. Consequently, our extensive set of variables encompasses all factors related to bank decisions.

We also incorporate *aggregated* household decision factors by employing interacted dummies, particularly city*biannual dummies. Even though we cannot track *individual* household-level demand, the use of such dummies enables us to capture the effects of household decisions at an *aggregated* level by city and city district. Consequently, the city's demographic structure, including age-related considerations, family dynamics, and residential patterns, is embedded within these dummies. The city's dynamism, including house prices, labor market conditions and wage growth prospects, is also considered. Additionally, the simultaneous use of bank branch*biannual dummies and city*biannual dummies allows us to control for variations specific to certain city districts. The branch location strategy may also be related to distinct customer segments specific to each district.

Our identification strategy allows us to capture the heterogeneity of monetary policy transmission through individual demand effects. To isolate individual demand mechanisms as effectively as possible, we saturate the model with multiple control variables at the individual and loan-specific levels. The mere act of taking out a loan in a given bank branch at a particular time is already informative, as the banks' strategies make this choice non-random. The presence of collaterals, whether these collaterals are on mortgages, other assets, or both types of assets, contributes to capturing individual-level decisions. Concerning this individual aspect, Daysal et al. (2023) aptly demonstrates the significance of intergenerational wealth transmission, both in real estate and non-real estate assets. The preference for new or existing residences adds to the individualization of choices and preferences. Furthermore, the use of fixed or variable interest rates, the portion of the contract with a fixed interest rate over the entire loan term, and the utilization of a specific financial index are factors that differentiate individuals.

This model saturation enables the isolation of heterogeneous and individual effects of monetary policy. At least three mechanisms are possible: (i) the individual value of collateral, (ii) the individual value of down payments, and (iii) debt service-to-income constraints. They will be studied through interaction terms with the monetary policy surprise variable.

First, the value of collateral is unique to each individual, depending on their decisions regarding real estate and financial investment. Expansionary monetary policy will thus favor the value of collateral and differentiate households. The consequences of monetary policy on the value of their collateral, therefore, have a heterogeneous impact on individuals in the same city or neighborhood, at a given bank branch. Our specification does not account for the impact of monetary policy on the value of collateral, which can indirectly affect the credit amounts. Since assets are predominantly owned by households with the highest incomes, this indirect effect of monetary policy on credit amounts would apply only to the latter.

Second, down payments are also specific to individuals who can afford them. Monetary policy, by affecting the value of real estate and stock assets, can again enable individuals to modify their level of mortgage prepayment. An expansionary monetary policy surprise allows them to receive larger loans. This echoes findings in Beraja et al. (2019) regarding incentives for U.S. households to refinance their mortgage loans in response to changes in real estate prices.

Third, individual income constraints can affect household demand. As demonstrated by Ringo (2023), expansionary monetary policy inevitably impacts the debt service-to-income constraints of lower-income households and prompts them to seek mortgage or non-mortgage credit. Monetary policy can also impact firm credit, thereby affecting the future heterogeneous dynamics of wages and hiring, following Jašová et al. (2023). However, our specification and data do not allow us to identify such mechanisms relative to debt service-to-income constraints.

Models Our initial investigation centers on the relationship between the household credit level and the stance of monetary policy. This serves as the initial step in distinguishing the impact on both the level and composition of credit. The dependent variable in this analysis is the logarithm of the credit amount, which could pertain to either mortgage or consumer credit, provided by a bank. The basic model is as follows:

$$log(credit)_{kBbct} = \alpha + \beta MP_{t-2} + \delta^{'} Quantile_{kt} + \gamma^{'} Bank_{B,t-1} + \Theta^{'} CreditCat_{kt} + \xi^{'} X_{kt} + \eta_{bT} + \eta_{cT} + \epsilon_{kBbct} \quad (1)$$

The variable $credit_{kBbct}$ represents the credit granted by bank B in city c at bank branch b during a quarter t. MP_{t-2} signifies the monetary policy surprise, while $Quantile_{kt}$ indicates the precise income group to which the household belongs based on contemporaneous income at time t. Six dummy variables are used, taking the value of one in their corresponding income group and zero otherwise. The classification mirrors the previous figures, distinguishing top-income households from the top 80-95% and the top 95-100% of the income distribution. $Bank_{B,t-1}$ represents a set of bank-specific control variables. $CreditCat_{kt}$ is a dummy variable that categorizes credit into first house, second house, and rental investment, while X_{kt} includes other credit-specific control variables, such as 15 types, fixed or variable interest rates, types of variable interest rates, and the number of collaterals. Due to the substantial number of dummy variables and the quarterly variation in monetary policy surprises, we saturate the specification with semi-annual dummies. Therefore η_{bT} are bank branch*semi-annual dummies and η_{cT} city*semi-annual dummies, with T used for this bi-annual designation rather than quarterly. We simultaneously employ bank branch*semi-annual dummies and quaterly banking control variables to capture the maximum variations associated with supply-side effects. Our coefficient of interest is here β, which is expected to be negative with respect to the monetary policy surprise measures. Given the challenge of tracking the speed of credit response to monetary policy, we typically use 6-month lags for the monetary policy measure.

Subsequently, to analyze the heterogeneous effects of monetary policy on the credit distribution among households, we extend model 1 by introducing interaction terms between monetary policy measures and the various income group dummies:

$$\begin{aligned} log(credit)_{kBbct} = \alpha \quad &+ \quad \beta MP_{t-2} + \delta^{'} Quantile_{kt} + \theta^{'} MP_{t-2} * Quantile_{kt} \\ &+ \quad \gamma^{'} Bank_{B,t-2} + \Theta^{'} CreditCat_{kt} + \xi^{'} X_{kt} + \eta_{bT} + \eta_{cT} + \epsilon_{kbct} \end{aligned} \tag{2}$$

Our coefficient of interest will now be denoted as θ since it captures the heterogeneous changes in credit resulting from exogenous variations in monetary policy. These coefficients may vary across different segments of the household distribution, suggesting the emergence of a new channel through which monetary policy affects credit. To assess the overall impact, we shall complement this marginal effect θ with β.

To account for the potential dependence of observations across banks and cities, we cluster the standard errors at the bank branch level. The monetary policy stance varies by local economic conditions, and unobservable factors affecting households' credit within the same bank branch could be correlated (Moulton, 1990). Figure 2 above indeed highlights significant heterogeneity across bank branches, and each bank branch can be located in various city districts. An alternative clustering approach could involve clustering at the level of the year-city group, similar to the approach used by Andersen et al. (2022). However, due to the large set of interacted dummies, there may be questions about the necessity of double, as suggested by Cameron and Miller (2015) and Abadie et al. (2023). In summary, we cluster at the bank branch level for our primary analysis and ensure the robustness of our results by also clustering standard errors at the city level.

3.2 The transmission of monetary policy along the income distribution

We first discuss the estimated impact of monetary policy on credit and, second, the estimated coefficients of the interaction between monetary policy and the income inequality measures.

Table 6 reports our baseline results for model 1 without considering the distributional role of monetary policy. We investigate here bank relationships by examining both bank decisions and household choices. On the supply side, we consider bank characteristics at the national level, as well as bank branch dummies at the local level. On the demand side, we incorporate multiple income groups of borrowers, and various loan characteristics. Our approach is line with previous research by Cloyne et al. (2020), Cumming and Hubert (2021), and Gyöngyösi et al. (2022). We extend this literature by adding factors such as the motive of the mortgage credit, options related to variable interest rates and associated financial indices, as well as various collaterals. In contrast, Gyöngyösi et al. (2022) focus on the presence of a guarantor and the risk of non-performing loans based on delinquencies occurring within the 6 years following the loan. We focus on the two main categories of household credit: mortgage (columns (1) to (4)) and consumer credit (columns (5) to (8)).

Regarding our identification strategy, all of these specifications first utilize the primary indicator of monetary policy surprises widely used in the literature, namely the one from Jarociński and Karadi (2020). Second, table 6 progressively saturates the specifications with city*semi-annual dummies and bank branch*semi-annual dummies. Columns (1) and (4) introduce fixed effects for bank, city, bank branch, and years. To capture the seasonality of credit, columns (2) and (5) replace the yearly fixed effects with semi-annual ones. Given the demand mechanisms mentioned earlier, columns (3) and (7) include city*year and bank*year dummies, while columns (4) and (8) employ city*semi-annual and bank branch*semi-annual dummies. Importantly, the coefficients for monetary policy surprises exhibit a high degree of stability across these specifications. This consistency indicates that these surprises are not influenced by local variations, nor by variations in banks, whether they are observed or unobserved.

Changes in monetary policy, such as lower interest rates or an expansion of the ECB's balance sheet, have a global impact on mortgage volumes. Loosening monetary conditions tend to lead to an increase in outstanding mortgage credit. While changes in monetary policy can be potentially influenced by local or national conditions, the pattern remains consistent with respect to monetary policy surprises. Through our analysis of the French case, we confirm the initial findings of Cloyne et al. (2020), Altavilla et al. (2020), and Gyöngyösi et al. (2022). In line with the methodology of Amberg et al. (2022) and Jašová et al. (2023), the monetary policy surprise is standardized, and all reported results correspond to a 25 basis point surprise. A 25 basis point expansionary monetary policy surprise results in a 0.3% increase in the amount of mortgage credit. Importantly, monetary policy surprises also have a notable impact on both types of household credit, with a similar increase of 1% in the amount of consumer credit.

Columns (4) and (8) present the most restrictive specifications, saturating the variations of supply-side effects and aggregate demand effects to the maximum. This most stringent econometric strategy will be our benchmark approach. The lack of statistical significance for the mortgage credit variable in column (4) highlights the potential heterogeneity of monetary policy effects on households. It supports the relevance of interaction terms that we propose in equation 2.

Table 6 also corroborates the insights from Table 2 regarding the credit distribution. It emphasizes that credit distribution is not uniform and is contingent upon household income. Top-income households (beyond the 8^{th} decile) hold a substantially higher amount of credit compared to other households, particularly in the case of mortgages. For each mortgage, households in the 2^{nd} quantile see their credit amount increase by an additional 19%, while those in the top 80-100% of the income distribution experience a 89% increase compared to the 1^{st} quantile. Similar trends are observed for consumer credit, with increases of 14%, and 40%, respectively. These findings underscore the unequal distribution of credit. Furthermore, there are significant differences in the amount of credit between middle-class and low-income households for mortgages, but not for consumer credit. This aligns with the notion of relative impoverishment among the middle classes, which implies only marginal differences in credit amounts across social classes, as discussed in Bazillier et al. (2021).

Table 6: Baseline specification: the overall effect of monetary policy

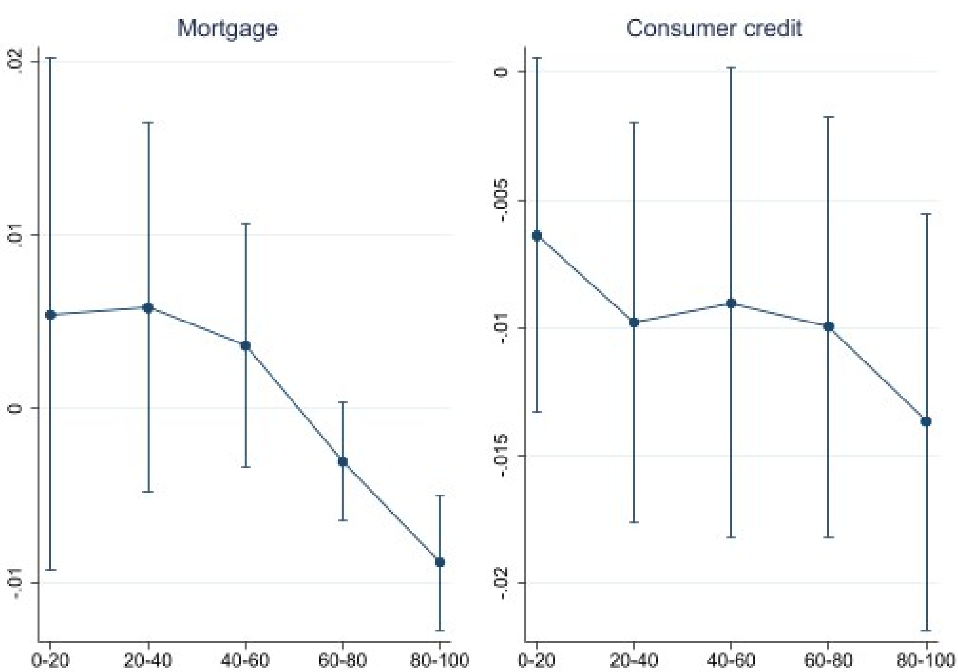
Dep. Var.	Mortgage				Consumer Credit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Monetary Policy Surprise (MPS) $_{t-2}$	-0.003**	-0.003**	-0.005**	-0.003	-0.008***	-0.012***	-0.006**	-0.010***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Bottom 20-40	0.191***	0.190***	0.194***	0.195***	0.141***	0.141***	0.138***	0.142***
	(0.025)	(0.025)	(0.025)	(0.027)	(0.006)	(0.006)	(0.006)	(0.006)
Middle 40-60	0.385***	0.385***	0.391***	0.392***	0.267***	0.266***	0.263***	0.268***
	(0.043)	(0.043)	(0.043)	(0.045)	(0.007)	(0.007)	(0.008)	(0.008)
Middle 60-80	0.572***	0.571***	0.580***	0.583***	0.391***	0.390***	0.386***	0.390***
	(0.053)	(0.053)	(0.052)	(0.054)	(0.008)	(0.008)	(0.009)	(0.009)
Top 80-100	0.887***	0.886***	0.899***	0.899***	0.409***	0.408***	0.405***	0.405***
	(0.061)	(0.062)	(0.059)	(0.063)	(0.011)	(0.011)	(0.011)	(0.011)
Second House	0.887***	0.886***	0.899***	0.899***	0.409***	0.408***	0.405***	0.405***
	(0.061)	(0.062)	(0.059)	(0.063)	(0.011)	(0.011)	(0.011)	(0.011)
Rental Investment	0.887***	0.886***	0.899***	0.899***	0.409***	0.408***	0.405***	0.405***
	(0.061)	(0.062)	(0.059)	(0.063)	(0.011)	(0.011)	(0.011)	(0.011)
Other control variables								
Fixed/variable interest rate	Y	Y	Y	Y	Y	Y	Y	Y
Type of financial index	Y	Y	Y	Y	Y	Y	Y	Y
Type of collateral	Y	Y	Y	Y	Y	Y	Y	Y
Other bank controls	Y	Y	Y	Y	Y	Y	Y	Y
New/old residence	Y	Y	Y	Y				
Fixed effects								
City	Y	Y			Y	Y		
Bank	Y	Y			Y	Y		
Bank branch	Y	Y			Y	Y		
Year	Y				Y			
Semi-annual		Y				Y		
City x Year dummies			Y				Y	
Bank x Year dummies			Y				Y	
City x Semi-annual dummies				Y				Y
Bank branch x Semi-annual dummies				Y				Y
Obs.	432,242	432,242	432,242	432,242	317,324	317,324	317,324	317,324
$Adj.R^2$	0.517	0.518	0.523	0.518	0.530	0.530	0.534	0.544

Robust standard errors are in parentheses and are clustered at the bank branches level. The dependent variable is the log of credit amount. *, **, and *** denote, respectively, significance at the 10%, 5%, and 1% levels. The monetary policy surprise comes from Jarociński and Karadi (2020).

Because monetary policy can simultaneously impact both the volume and composition of credit, our primary focus here centers on understanding their distributional implications. Figure 3 and Table 7 display equation 2, which delves into the heterogeneous effect of monetary policy by incorporating the interaction between monetary policy surprises and quantile dummies. The earlier findings remain consistent, particularly with regard to the characteristics of bank and income distribution. This also reaffirms the heterogeneous effect of monetary policy on credit volume along the income distribution, occurring in the case of mortgage credit but not for consumer credit.

Figure 3 illustrates a total effect, and not a marginal effect. In other words, a non-statistically significant coefficient indicates that monetary policy has no effect on the credit volume. From a qualitative perspective, these coefficients lend support to the notion of a credit reallocation in favor of higher-income individuals. The null coefficient highlights that monetary policy does not significantly impact mortgage credit for those situated at the lower income strata and at the middle-income strata. Expansionary monetary policy surprises, however, lead to an increase in the volume of mortgage credit primarily for the top income brackets (80-100%). A quantitative analysis reveals that an unexpected 25 basis points decrease in interest rates results in approximately a 0.9% increase in mortgage credit for the top income earners. The dynamics are distinct for consumer credit. Monetary policy does not influence the credit volume of the poorest households (0-20%) and a portion of the middle-income groups (40-60%). Yet, it has a positive impact on other segments of the population, namely the lower-middle class (20-40%), the upper-middle class (60-80%), and the top income group (80-100%). For these latter three groups, an unanticipated 25 basis points reduction in interest rates results in a 1% increase in consumer credit volume.

Figure 3: Effects of monetary policy on the volume of credit by credit category - Distribution



Note: Authors' calculations. This figure presents the distributive effects of a expansionary monetary policy surprise. Each point represents a coefficient estimate from the Equation 2 for each bin of the distribution. The point estimates and the 95% confidence intervals are plotted. Robust standard errors are clustered at the bank branches level.

Table 7 presents the marginal effects and the associated decomposition of interaction terms. Columns (1) to (4) consistently show that the effect of monetary policy exists only for top income group. Columns

(5) to (8) on consumer credit occasionally reveal significant interaction terms for top income group, but only if the specification includes semi-annual effects (columns (6) and (8)) rather than annual effects. Nevertheless, these effects quantitatively less robust compared to the effect on mortgage credit.

Table 7: The heterogeneous effect of monetary policy on credit volume

Dep. Var.	Mortgage				Consumer Credit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Monetary Policy Surprise (MPS) $_{t-2}$	0.003	0.003	0.005	0.005	-0.004	-0.008**	-0.003	-0.006*
	(0.005)	(0.005)	(0.005)	(0.007)	(0.003)	(0.003)	(0.003)	(0.004)
Bottom 20-40	0.191***	0.191***	0.194***	0.195***	0.141***	0.140***	0.137***	0.142***
	(0.025)	(0.025)	(0.025)	(0.027)	(0.006)	(0.006)	(0.006)	(0.006)
Middle 40-60	0.386***	0.385***	0.391***	0.394***	0.266***	0.266***	0.262***	0.267***
	(0.043)	(0.043)	(0.042)	(0.044)	(0.007)	(0.007)	(0.007)	(0.007)
Middle 60-80	0.571***	0.571***	0.579***	0.584***	0.390***	0.389***	0.385***	0.390***
	(0.052)	(0.053)	(0.052)	(0.053)	(0.008)	(0.008)	(0.009)	(0.009)
Top 80-100	0.885***	0.885***	0.897***	0.813***	0.408***	0.407***	0.403***	0.403***
	(0.061)	(0.062)	(0.059)	(0.065)	(0.011)	(0.011)	(0.011)	(0.012)
MPS × Bottom 20-40	0.003	0.003	-0.001	0.001	-0.004	-0.004	-0.002	-0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
MPS × Middle 40-60	-0.000	0.000	-0.003	-0.001	-0.004	-0.004	-0.002	-0.003
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
MPS × Middle 60-80	-0.006	-0.006	-0.010	-0.008	-0.003	-0.003	-0.003	-0.004
	(0.006)	(0.006)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)
MPS × Top 80-100	-0.013**	-0.012**	-0.016**	-0.014**	-0.006	-0.007*	-0.007	-0.007*
	(0.006)	(0.006)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)
Second House	0.527***	0.528***	0.526***	0.524***				
	(0.017)	(0.017)	(0.016)	(0.018)				
Rental Investment	0.734***	0.733***	0.730***	0.698***				
	(0.046)	(0.047)	(0.047)	(0.052)				
Other control variables								
Fixed/variable interest rate	Y	Y	Y	Y	Y	Y	Y	Y
Type of financial index	Y	Y	Y	Y	Y	Y	Y	Y
Type of collateral	Y	Y	Y	Y	Y	Y	Y	Y
Other bank controls	Y	Y	Y	Y	Y	Y	Y	Y
New/old residence	Y	Y	Y	Y				
Fixed effects								
City	Y	Y			Y	Y		
Bank	Y	Y			Y	Y		
Bank branch	Y	Y			Y	Y		
Year	Y				Y			
Semi-annual		Y				Y		
City x Year dummies			Y				Y	
Bank x Year dummies			Y				Y	
City x Semi-annual dummies				Y				Y
Bank branch x Semi-annual dummies				Y				Y
Obs.	432,242	432,242	432,242	432,242	317,324	317,324	317,324	317,324
Adj.R^2	0.517	0.518	0.523	0.528	0.530	0.530	0.534	0.544

Robust standard errors are in parentheses and are clustered at the bank branches level. The dependent variable is the log of credit amount. *, **, and *** denote, respectively, significance at the 10%, 5%, and 1% levels. The monetary policy surprise comes from Jarociński and Karadi (2020).

3.3 Inspecting the mechanisms

In this section, we delve into the dynamics of mortgage-bank relationships, which exhibit greater heterogeneity across the household income distribution when compared to bank relationships for consumer credit.

Table 8 provides an initial explanatory element, underscoring the influence of rental investment in the heterogeneous response of credit volume to monetary policy. We propose triple interaction terms involving both the position in the income distribution and this specific credit usage motive, namely, rental investment. In the Table, all dummies related to income distribution and the motives behind mortgage credit are included as controls. Column (1) of Table 8 replicates the analyses previously conducted in Table 7 and Figure 3. The interaction term in column sheds light on this heterogeneity, underscoring its significance for the top income bracket. The subsequent columns of Table 8 present our findings for Model 2, and gradually introduce additional interaction terms. In a nutshell, the motive behind obtaining a mortgage plays a pivotal role. Column (2) introduces a novel interaction term between monetary policy surprise and rental investment. Here, a 25 basis point expansionary monetary policy surprise corresponds to an 0.8% increase in rental investment credit, with no discernible impact on credit for primary or secondary residences. In addition, column (3) employs the two previous interaction terms with monetary policy surprise. The results remain robust and suggest complementary mechanisms between these two elements. Column (4) goes one step further by adding another interaction term to column (3), multiplying rental investment by the top income dummy. This new interaction term will reinforce the validity of the earlier relationship. Consequently, the heterogeneous transmission of monetary policy is not determined by the size of mortgage credit for top income households or the proportion of rental investment credit in the mortgage market. The robust correlation between rental investment and income distribution suggests that this new mechanism could be expanded upon.

The heterogeneous transmission of monetary policy operates through top-income households (column (2)) and rental investment (columns (3) and (4)). Are these mechanisms complementary or substitutes? To confirm that the channel functions with both mechanisms, column (5) takes into account all the interaction terms, including the triple interaction term involving monetary policy surprise, the top income group, and rental investment. Column (5) involves four interaction terms: First, the interaction term between monetary policy surprise and the top income group remains statistically significant. The quantitative impact closely resembles the one observed in column (2). Second, the interaction term between rental investment and the top income group is once again significant. Higher-income households will obtain smaller loans for their rental property investments than for their primary or secondary residences, likely due to a demand effect from these households. Third, the interaction term between monetary policy surprise and rental investment is now statistically irrelevant, suggesting that the results from columns (3) and (4) are primarily driven by the top income group. Fourth, the triple interaction term is statistically significant and suggests an amplification effect of the rental investment.

In summary, rental investment plays a relevant role in the heterogeneous transmission of monetary policy, complementing the previous effects on top incomes. Column (5) underscores that both components of the underlying mechanisms are at work. A 25 basis point expansionary monetary policy surprise results in a 1% increase in credit for top-income households, but only when it is associated with a primary or secondary residence. The same surprise is associated with a 2.8% increase in credit when it pertains to rental investment by top-income households.

Table 8: The heterogeneous effect of monetary policy - the role of rental investment

Dep. Var.			Mortgage		
	(1)	(2)	(3)	(4)	(5)
Monetary Policy Surprise (MPS) $_{t-2}$	0.008*	-0.002	0.009*	-0.003	0.006
	(0.005)	(0.002)	(0.005)	(0.002)	(0.006)
MPS $_{t-2}$ × Top 80-100	-0.014***		-0.014***		-0.010*
	(0.004)		(0.004)		(0.005)
MPS $_{t-2}$ × Rental Investment		-0.008***	-0.007***		-0.007
		(0.003)	(0.003)		(0.013)
Rental Investment × Top 80-100				-0.102***	-0.103***
				(0.007)	(0.007)
MPS $_{t-2}$ × Rental Investment × Top 80-100					-0.018***
					(0.005)
Other control variables					
Quantiles	Y	Y	Y	Y	Y
Fixed/variable interest rate	Y	Y	Y	Y	Y
Type of financial index	Y	Y	Y	Y	Y
Type of collateral	Y	Y	Y	Y	Y
Other bank controls	Y	Y	Y	Y	Y
New/old residence	Y	Y	Y	Y	Y
City x Semi-annual dummies	Y	Y	Y	Y	Y
Bank branch x Semi-annual dummies	Y	Y	Y	Y	Y
Obs.	432,242	432,242	432,242	432,242	432,242
$Adj.R^2$	0.518	0.518	0.518	0.519	0.519

Robust standard errors are in parentheses and are clustered at the bank branches level. The dependent variable is the log of credit amount. *, **, and *** denote, respectively, significance at the 10%, 5%, and 1% levels. The monetary policy surprise data comes from Jarociński and Karadi (2020).

Table 9 delves into these mechanisms ostensibly linked to rental investment. The household's portfolio decision implies an individual choice by the agent, and our specification encompasses all effects related to supply and aggregate demand. Regarding individual demand, households may have opted for such a purchase based on an adequate collateral level. Alternatively, they might have chosen to enhance portfolio returns by allocating a portion of their financial portfolio to rental investment. We deliberately utilize information concerning collateral existence and differentiate between financial and real estate collaterals. Monetary policy can influence the value of collateral and the associated down payment by each household in a loan. This, in turn, affects the household's decision to apply for a loan or not. Consequently, Table 9 introduces interaction terms between monetary policy surprise and collaterals.

Table 9: The heterogeneous effect of monetary policy - the role of collateral

Dep. Var.	Mortgage			
	(1)	(2)	(3)	(4)
Monetary Policy Surprise (MPS) $_{t-2}$	0.008*	0.031***	0.041***	0.017***
	(0.005)	(0.004)	(0.005)	(0.006)
MPS $_{t-2}$ × Top 80-100	-0.014***		-0.013***	0.021***
	(0.004)		(0.003)	(0.007)
MPS $_{t-2}$ × Real estate collateral		-0.040***	-0.040***	0.006
		(0.014)	(0.013)	(0.020)
MPS $_{t-2}$ × Financial collateral		-0.042***	-0.041***	-0.023***
		(0.004)	(0.004)	(0.006)
MPS $_{t-2}$ × Both collaterals		-0.044***	-0.044***	-0.022*
		(0.008)	(0.008)	(0.012)
MPS $_{t-2}$ × Top 80-100 × Real estate collateral				-0.039***
				(0.014)
MPS $_{t-2}$ × Top 80-100 × Financial collateral				-0.029***
				(0.006)
MPS $_{t-2}$ × Top 80-100 × Both collaterals				-0.034***
				(0.011)
Other control variables				
Quantiles	Y	Y	Y	Y
Fixed/variable interest rate	Y	Y	Y	Y
Type of financial index	Y	Y	Y	Y
Type of collateral	Y	Y	Y	Y
Other bank controls	Y	Y	Y	Y
New/old residence	Y	Y	Y	Y
City x Semi-annual dummies	Y	Y	Y	Y
Bank branch x Semi-annual dummies	Y	Y	Y	Y
Obs.	432,242	432,242	432,242	432,242
$Adj.R^2$	0.518	0.513	0.513	0.513

Robust standard errors are in parentheses and are clustered at the bank branches level. The dependent variable is the log of credit amount. *, **, and *** denote, respectively, significance at the 10%, 5%, and 1% levels. The monetary policy surprise data comes from Jarociński and Karadi (2020).

Similar to the previous table, Table 9 introduces interaction terms. Column (1) serves as a benchmark, while column (2) adds interaction terms between monetary policy and the use of specific collateral in the credit contract. The coefficient associated with monetary policy without interaction terms represents the effect of a monetary policy surprise for a household without any collateral. The interaction terms show that the heterogeneous expansionary impact of a monetary surprise leads to an increase in the volume of credit only in the presence of collateral. The monetary surprise thus influences the value of collateral, impacting the volume of credit through this channel. This holds true for both financial and real estate collaterals, as well as for the dual use of these two types of collaterals. In quantitative terms, a 25 basis point expansionary monetary policy surprise increases the volume of credit by approximately 1% when at least one type of collateral is present. While the collateral value, missing in the database, would have been relevant, column (2) already provides an indicative marker of the heterogeneous effect of monetary policy.

Columns (3) and (4) delve into these interaction terms. Column (3) adds to column (2) the interaction term between monetary policy and top-income households, to once again capture the complementary or substitutable nature of this mechanism. The results remain qualitatively and quantitatively stable. The use of column (4) allows for the consideration of both mechanisms. Accounting for multiple interaction terms, a 25 basis point expansionary monetary surprise is associated with an increase in credit of around 0.3% for households with collaterals[7]. The same shock will conditionally increase credit for top 20% income households with collaterals. The total effect for the latter will be -0.5% (real estate collateral), -1.5% (financial collateral), and -1.8% (combined two types of collaterals).

3.4 Robustness tests

Decomposing the top income classes: top 80-95 vs top 95-100. Our primary finding is that the heterogeneous transmission of monetary policy is influenced by both the top income group and rental investment. The objective of Table 10 is to facilitate the differentiation between income distribution among the top earners. It is common practice to distinguish between the top 80-95% and the top 95-100% of the income distribution. Many of the previously identified mechanisms could be attributed to systemic practices among the highest-income segment of the population, which, in turn, implies a professional approach to capital accumulation. Table 10 follows the same spirit as Table 8 but provides a breakdown

[7] In this analysis, we use those with financial collaterals or those with both types of collaterals

across different top income groups.

Column (1) introduces the distinction between top income groups. The most substantial level difference in average credit compared to bottom 20% is observed for the top 95-100% of the income distribution, with a 115% level difference. The interaction terms between monetary policy and these groups fully capture the effects of monetary policy surprises. Quantitatively, the impact of such surprises appears to be nearly two times higher for the top 95-100% of households (0.5%) compared to the top 80-95% (1.2%). Moving on to Column (2) in this table, it follows the same approach as Column (5) in Table 8 and introduces all interaction terms. The interaction terms between monetary policy and the top income groups, as well as the one between rental investment and the latter, remain statistically significant, with similar quantitative differences between the top 80-95% and the top 95-100%. Interestingly, the triple interaction term involving monetary policy tells a consistent story as observed in Table 8 for the top 80-95%, but not for the highest-income households. According to Table 10, an expansionary monetary policy surprise is associated with an increase in credit when it is related to rental investment and top income groups. Concerning the magnitude of the effects, it triggers a 2.3% rise in mortgage activity for rental investment among middle and lower-income groups. It suggests a credit reallocation between first home, second home, and rental investment for these groups. The impact of the surprise for the top 80-95% of the income distribution is significantly larger for rental investment (5.4%) than for other credit motivations. However, the triple interaction term and the associated reinforcing effect do not appear to have an impact on the top 5% of households. Finally, the earlier results regarding the existence of collateral remain quantitatively equivalent.

Econometric strategy. To account for household decision factors, we saturate our baseline specification with a large set of interacted dummies. Specifically, we employ bank branch* semi-annual dummies and city*semi-annual dummies, deliberately opting for the most restrictive approach that does not encompass quarterly variations in the monetary policy surprise.

Then, Table 11 incorporates various sets of fixed effects and introduces an alternative clustering strategy. Table 11 reproduces the specification with triple interaction terms as seen in Tables 8 and 10. Columns (1) and (4) employ city, bank, and bank branch fixed effects, while columns (2), (3), (6), and (7) make use of city*annual and bank*annual dummies. Finally, columns (4) and (8) use city*semi-

Table 10: Robustness: Decomposing the top income groups

Dep. Var.		Mortgage	
	(1)	(2)	(3)
Monetary Policy Surprise (MPS) $_{t-2}$	0.008*	0.005	0.041***
	(0.005)	(0.006)	(0.005)
Bottom 20-40	0.195***	0.194***	0.197***
	(0.027)	(0.026)	(0.029)
Middle 40-60	0.393***	0.351***	0.395***
	(0.044)	(0.043)	(0.047)
Middle 60-80	0.583***	0.495***	0.587***
	(0.053)	(0.051)	(0.057)
Top 80-95	0.814***	0.725***	0.904***
	(0.066)	(0.064)	(0.067)
Top 95-100	1.115***	0.828***	0.824***
	(0.075)	(0.076)	(0.077)
MPS $_{t-2}$ × Top 80-95	-0.013***		-0.012***
	(0.003)		(0.003)
MPS $_{t-2}$ × Top 95-100	-0.024***		-0.022***
	(0.008)		(0.008)
MPS $_{t-2}$ × Rental Investment		-0.023***	
		(0.008)	
Rental Investment × Top 80-95		-0.101***	
		(0.003)	
Rental Investment × Top 95-100		-0.335***	
		(0.009)	
MPS $_{t-2}$ × Rental Investment × Top 80-95		-0.031***	
		(0.009)	
MPS $_{t-2}$ × Rental Investment × Top 95-100		0.016	
		(0.010)	
MPS $_{t-2}$ × Real estate collateral			-0.040***
			(0.013)
MPS $_{t-2}$ × Financial collateral			-0.042***
			(0.004)
MPS $_{t-2}$ × Both collaterals			-0.045***
			(0.008)
Other control variables			
Fixed/variable interest rate	Y	Y	Y
Type of financial index	Y	Y	Y
Type of collateral	Y	Y	Y
Other bank controls	Y	Y	Y
New/old residence	Y	Y	Y
City x Semi-annual dummies	Y	Y	Y
Bank branch x Semi-annual dummies	Y	Y	Y
Obs.	437,242	432,242	432,242
$Adj.R^2$	0.528	0.530	0.523

Robust standard errors are in parentheses and are clustered at the bank branches level. The dependent variable is the log of credit amount. *, **, and *** denote, respectively, significance at the 10%, 5%, and 1% levels. The monetary policy surprise data comes from Jarociński and Karadi (2020).

annual and bank*semi-annual dummies, whereas the baseline specification use city*semi-annual and bank branch*semi-annual dummies. The inclusion of bank*time dummies helps account for supply-side effects arising from changes in bank strategy unrelated to monetary policy surprises. Regarding clustering strategy, standard errors are clustered at the city level in columns (3), (4), (7), and (8).

Throughout the model, we observe the expected signs with consistent quantitative effects: both parts of the transmission channel remain operational. The primary distinction between clustering and interacting dummy strategies pertains to the triple interaction term involving monetary surprise, rental investment, and the dummy variable representing the top 5% of households. The fluctuating significance of this term, once interacting dummies are introduced, aligns with Table 10. Monetary policy exhibits heterogeneous effects, impacting exclusively the 80-95% and 95-100% income distribution groups when it comes to first-time home purchases or secondary purchases. Monetary policy also affects rental investments across all income levels. Furthermore, through the triple interaction terms, we observe an additional effect of monetary policy on credit, particularly for investment property mortgages within the 80-95% income distribution range. However, no such stable effect is evident for households in the top 5% of the income distribution.

Table 11: Robustness: Fixed effects and clustering strategy

Dep. Var.	Mortgage							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Monetary Policy Surprise (MPS) $_{t-2}$	0.009	0.004	0.004	0.002	0.009	0.004	0.004	0.002
	(0.008)	(0.003)	(0.002)	(0.004)	(0.008)	(0.003)	(0.002)	(0.004)
MPS $_{t-2}$ × Top 80-100	-0.012**	-0.010*	-0.010**	-0.010**				
	(0.005)	(0.005)	(0.005)	(0.005)				
MPS $_{t-2}$ × Rental Investment	-0.007	-0.010	-0.010	-0.008	-0.031***	-0.029***	-0.029***	-0.024***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.008)	(0.007)	(0.007)	(0.008)
Rental Investment × Top 80-100	-0.129***	-0.131***	-0.131***	-0.130***				
	(0.007)	(0.007)	(0.008)	(0.008)				
MPS $_{t-2}$ × Rental Investment × Top 80-100	-0.020***	-0.022***	-0.022***	-0.018***				
	(0.005)	(0.004)	(0.004)	(0.004)				
MPS $_{t-2}$ × Top 80-95					-0.010**	-0.009**	-0.009**	-0.009**
					(0.004)	(0.005)	(0.004)	(0.004)
MPS $_{t-2}$ × Top 95-100					-0.024**	-0.018	-0.018*	-0.020*
					(0.012)	(0.012)	(0.011)	(0.010)
Rental Investment × Top 80-95					-0.099***	-0.101***	-0.101***	-0.101***
					(0.004)	(0.003)	(0.003)	(0.003)
Rental Investment × Top 95-100					-0.335***	-0.336***	-0.336***	-0.334***
					(0.010)	(0.009)	(0.010)	(0.010)
MPS $_{t-2}$ × Rental Investment × Top 80-95					-0.039***	-0.038***	-0.038***	-0.031***
					(0.009)	(0.009)	(0.009)	(0.008)
MPS $_{t-2}$ × Rental Investment × Top 95-100					-0.024**	-0.019*	-0.019**	-0.016*
					(0.010)	(0.010)	(0.009)	(0.009)
Other control variables								
Quantiles	Y	Y	Y	Y	Y	Y	Y	Y
Fixed/variable interest rate	Y	Y	Y	Y	Y	Y	Y	Y
Type of financial index	Y	Y	Y	Y	Y	Y	Y	Y
Type of collateral	Y	Y	Y	Y	Y	Y	Y	Y
Other bank controls	Y	Y	Y	Y	Y	Y	Y	Y
New/old residence	Y	Y	Y	Y	Y	Y	Y	Y
Fixed effects								
City	Y				Y			
Bank	Y				Y			
Bank branch	Y				Y			
Bank x Annual dummies		Y	Y			Y	Y	
City x Annual dummies		Y	Y			Y	Y	
Bank x Semi-annual dummies				Y				Y
City x Semi-annual dummies				Y				Y
Clusters								
Bank Branch	Y	Y			Y	Y		
City			Y	Y			Y	Y
Obs.	432,242	432,032	432,032	432,242	432,242	432,032	432,032	432,242
Adj.R^2	0.524	0.535	0.535	0.536	0.525	0.535	0.535	0.537

Robust standard errors are in parentheses and are clustered at various levels. The dependent variable is the log of credit amount.*, **, and *** denote, respectively, significance at the 10%, 5%, and 1% levels. The monetary policy surprise data comes from Jarociński and Karadi (2020).

Other Monetary Policy Surprises. In Table 12, we address concerns about monetary policy surprises measures. Table 12 provides five other indicators or monetary policy surprises widely used in the literature, namely the central bank information shock from Jarociński and Karadi (2020) (columns (1) and (2)), and the four indicators from Altavilla et al. (2019) (columns (3) to (10)). The latter disentangles the surprises from the press release ("Target" surprise) and the others from the press conference. They also distinguish "Timing", "Forward Guidance", and "Quantitative Easing" surprises. They capture the revision of policy expectations from market participants. The "Timing" component is informative about the short run for conventional monetary policy, while the "Forward Guidance" is relative to the medium run for the same policy. As expected, "Quantitative easing" captures the revision of policy expectations for unconventional monetary policy.

For each of the five types of monetary surprises, we disaggregate the analysis into two separate models, mirroring the two components of our previous analysis. Thus, the first column in each set examines the effect of monetary policy surprise on mortgage credit, while the second column concentrates on consumer credit. Monetary surprises have different effects on credit distribution among households. Capturing different elements, different responses are therefore reassuring. This also allows for a more precise decomposition of the elements associated with a monetary surprise and a more specific isolation of the mechanisms mentioned earlier.

Firstly, the central bank information shock, associated with a positive co-movement between interest rates and stock market prices, can be interpreted as an alternative monetary surprise. Columns (1) and (2) of Table 12 indeed shows an effect on credit distribution for mortgage credit but not for consumer credit, which can be interpreted as reassuring. Secondly, the Target and Timing surprises from Altavilla et al. (2019) provide information about the short-term window related to conventional monetary policies. Columns (3) and (4), as well as columns (5) and (6), demonstrate redistributive effects of these surprises in favor of lower and middle-income classes for consumer credit. Monetary policy surprise has an impact on mortgage credit, but this effect is consistent across the income distribution and is driven by the Target component rather than the Timing component (press release rather than press conference).

Regarding the last two components, the analysis of monetary surprises on Quantitative Economics goes beyond the time frame and replaces the analysis of non-conventional measures such as liquidity measures and asset purchase programs. Continuing a logic of medium and long-term, the forward guidance surprise has no effect on credit volume. This is likely explained by the fact that the effects of aggregate supply and demand are captured. Only the individual demand effects of households and their links to collateral value and the down payment amount remain. These elements are probably too distant from the anticipation and credibility logic inherent in forward guidance. Similarly, the Quantitative Easing surprise has no impact, as it is focused on the debts of private firms and states in the eurozone.

Table 12: Robustness: Alternative measures of monetary policy surprises

Dep. Var.	Mortgage or Consumer credit									
Monetary Policy Surprise (MPS)	J&K (2020)		Altavilla et al. (2019)							
	Information		Timing		Target		Forward Guidance		QE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Monetary Policy Surprise (MPS) $_{t-2}$	0.004	-0.014***	0.005	-0.014**	-0.006**	-0.016***	0.009	-0.007	-0.000	-0.005**
	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.004)	(0.015)	(0.008)	(0.002)	(0.002)
MPS $_{t-2}$ $\times$ Top 80-100	-0.009***	0.006	0.001	0.017***	0.005	0.007**	-0.014	-0.005	-0.002	-0.001
	(0.003)	(0.004)	(0.006)	(0.006)	(0.004)	(0.003)	(0.011)	(0.007)	(0.002)	(0.002)
Sample										
Mortgage (M) vs Consumer (C)	M	C	M	C	M	C	M	C	M	C
Other control variables										
Quantiles	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fixed/variable interest rate	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Type of financial index	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Type of collateral	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Other bank controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
New/old residence	Y		Y		Y		Y		Y	
City x Semi-annual dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank branch x Semi-annual dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	431,272	317,254	410,176	295,328	410,176	295,328	410,176	295,328	410,176	295,328
$Adj.R^2$	0.528	0.544	0.526	0.545	0.526	0.545	0.526	0.545	0.526	0.545

Robust standard errors are in parentheses and are clustered at the bank branches level. The dependent variable is the log of credit amount. *, **, and *** denote, respectively, significance at the 10%, 5%, and 1% levels. The monetary policy surprise data comes from Jarociński and Karadi (2020) (columns (1) to (2)) and from Altavilla et al. (2019) (columns (3) to (10)).

4 Conclusion

Based on a French microeconomic credit dataset, we investigate the unequal distribution of credit among French households. Upper-middle-class and top-income households emerge as the primary drivers of mortgage credit. Our empirical approach dissects the pertinent decisions of banks and households. We incorporate bank and bank branch characteristics through balance sheet variables and a suite of interacted dummies, effectively capturing their distinct behavior. Besides, household-related factors, particularly on the individual portfolio (i.e., the presence of collaterals) and a finely grained classification of mortgage credits, mirror this pattern. Lastly, the use of city and bank branch*semi-annual dummies controls for demographic and local economic trends.

By estimating the impact of monetary policy on credit volumes across the income distribution, we ascertain that monetary policy has no substantial effect on mortgage credit volumes for lower and middle-income households. Only affluent households, notably those in the highest income quintile, witness an increase in credit with an expansionary monetary policy surprise. The impact on consumer credit is far more uniform along the income distribution and significantly affects credit volume across the board. This holds significant implications for understanding the transmission of monetary policy. This newly observed phenomenon, exclusive to mortgage credit, is notably rationalized by the impact of monetary policy on (i) collateral and (ii) the value of the down payment and can also be linked, in a future study, to (iii) individual wage impacts.

Our research bears implications concerning the prudential regulation of banks and the efficacy of monetary policy measures. Monetary policy can potentially stimulate household credit for high-income individuals and mortgage credit for investment in rental properties, which may, in turn, exacerbate income and wealth disparities. As noted in the survey by Bazillier and Hericourt (2017), inequality, household credit, and financial crises are intricately connected, and a more equitable distribution of credit among households could enhance financial stability.

This framework can be expanded by distinguishing between labor and capital income and incorporating wealth inequality. Moreover, it can be extended to encompass local income inequalities, not limited to national income inequality. Drawing from U.S. data, Coibion et al. (2020) underscore that the demand for household credit is influenced by local income inequality levels, beyond the overall level.

References

Abadie, A., Athey, S., Imbens, G. W., and Wooldridge, J. M. (2023). When should you adjust standard errors for clustering? *The Quarterly Journal of Economics*, 138(1):1–35.

Acemoglu, D. and Robinson, J. A. (2015). The rise and decline of general laws of capitalism. *Journal of economic perspectives*, 29(1):3–28.

Achou, B., d'Albis, H., and Iliopulos, E. (2023). House prices and rents: a reappraisal. *Macroeconomic Dynamics*, page 1–27.

Aiyar, S., Calomiris, C. W., and Wieladek, T. (2016). How does credit supply respond to monetary policy and bank minimum capital requirements? *European Economic Review*, 82:142–165.

Altavilla, C., Brugnolini, L., Gürkaynak, R. S., Motto, R., and Ragusa, G. (2019). Measuring euro area monetary policy. *Journal of Monetary Economics*, 108:162–179.

Altavilla, C., Laeven, L., and Peydró, J.-L. (2020). Monetary and macroprudential policy complementarities: evidence from european credit registers.

Alves, F., Kaplan, G., Moll, B., and Violante, G. L. (2020). A further look at the propagation of monetary policy shocks in hank. *Journal of Money, Credit and Banking*, 52(S2):521–559.

Amberg, N., Jansson, T., Klein, M., and Picco, A. R. (2022). Five facts about the distributional income effects of monetary policy shocks. *American Economic Review: Insights*, 4(3):289–304.

Andersen, A. L., Johannesen, N., Jørgensen, M., and Peydró, J.-L. (2022). Monetary policy and inequality. *Journal of Finance, Forthcoming.*

Auclert, A. (2019). Monetary policy and the redistribution channel. *American Economic Review*, 109(6):2333–67.

Bazillier, R. and Hericourt, J. (2017). The circular relationship between inequality, leverage, and financial crises. *Journal of Economic Surveys*, 31(2):463–496.

Bazillier, R., Héricourt, J., and Ligonnière, S. (2021). Structure of income inequality and household leverage: Cross-country causal evidence. *European Economic Review*, 132:103629.

Beraja, M., Fuster, A., Hurst, E., and Vavra, J. (2019). Regional heterogeneity and the refinancing channel of monetary policy. *The Quarterly Journal of Economics*, 134(1):109–183.

Berger, D., Milbradt, K., Tourre, F., and Vavra, J. (2021). Mortgage prepayment and path-dependent effects of monetary policy. *American Economic Review*, 111(9):2829–2878.

Bonnet, O., Chapelle, G., Trannoy, A., and Wasmer, E. (2021). Land is back, it should be taxed, it can be taxed. *European Economic Review*, 134:103696.

Cameron, A. C. and Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources*, 50(2):317–372.

Célerier, C. and Matray, A. (2019). Bank-branch supply, financial inclusion, and wealth accumulation. *The Review of Financial Studies*, 32(12):4767–4809.

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

Coibion, O., Gorodnichenko, Y., Kudlyak, M., and Mondragon, J. (2020). Greater inequality and household borrowing: New evidence from household data. *Journal of the European Economic Association*, 18(6):2922–2971.

Coibion, O., Gorodnichenko, Y., Kueng, L., and Silvia, J. (2017). Innocent bystanders? monetary policy and inequality. *Journal of Monetary Economics*, 88:70–89.

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

Cumming, F. and Hubert, P. (2021). The distribution of households' indebtedness and the transmission of monetary policy. *Review of Economics and Statistics*, pages 1–36.

Cumming, F. and Hubert, P. (2022). House prices, the distribution of household debt and the refinancing channel of monetary policy. *Economics Letters*, 212:110280.

Daysal, N. M., Lovenheim, M. F., and Wasser, D. N. (2023). The intergenerational transmission of housing wealth. Technical report, National Bureau of Economic Research.

De Jonghe, O., Dewachter, H., Mulier, K., Ongena, S., and Schepens, G. (2020). Some borrowers are more equal than others: Bank funding shocks and credit reallocation. *Review of Finance*, 24(1):1–43.

Degryse, H., De Jonghe, O., Jakovljević, S., Mulier, K., and Schepens, G. (2019). Identifying credit supply shocks with bank-firm data: Methods and applications. *Journal of Financial Intermediation*, 40:100813.

Delatte, A. L., Matray, A., and Pinardon Touati, N. (2020). Private credit under political influence: Evidence from france.

Dell'Ariccia, G., Laeven, L., and Suarez, G. A. (2017). Bank leverage and monetary policy's risk-taking channel: evidence from the United States. *the Journal of Finance*, 72(2):613–654.

Di Maggio, M., Kermani, A., Keys, B. J., Piskorski, T., Ramcharan, R., Seru, A., and Yao, V. (2017). Interest rate pass-through: Mortgage rates, household consumption, and voluntary deleveraging. *American Economic Review*, 107(11):3550–88.

Dolado, J. J., Motyovszki, G., and Pappa, E. (2021). Monetary policy and inequality under labor market frictions and capital-skill complementarity. *American Economic Journal: Macroeconomics*, 13(2):292–332.

Drechsler, I., Savov, A., and Schnabl, P. (2017). The deposits channel of monetary policy. *The Quarterly Journal of Economics*, 132(4):1819–1876.

Durante, E., Ferrando, A., and Vermeulen, P. (2022). Monetary policy, investment and firm heterogeneity. *European Economic Review*, 148:104251.

El Herradi, M. and Leroy, A. (2021). Monetary policy and the top 1%: Evidence from a century of modern economic history. *International Journal of Central Banking*, 18(5):237–277.

Flodén, M., Kilström, M., Sigurdsson, J., and Vestman, R. (2021). Household debt and monetary policy: revealing the cash-flow channel. *The Economic Journal*, 131(636):1742–1771.

Furceri, D., Loungani, P., and Zdzienicka, A. (2018). The effects of monetary policy shocks on inequality. *Journal of International Money and Finance*, 85:168–186.

Gyöngyösi, G., Ongena, S., and Schindele, I. (2022). Monetary policy and household loan supply: Volume and composition effects.

Hohberger, S., Priftis, R., and Vogel, L. (2020). The distributional effects of conventional monetary policy and quantitative easing: Evidence from an estimated dsge model. *Journal of Banking & Finance*, 113:105483.

Holm, M. B., Paul, P., and Tischbirek, A. (2021). The transmission of monetary policy under the microscope. *Journal of Political Economy*, 129(10):2861–2904.

Jarociński, M. and Karadi, P. (2020). Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics*, 12(2):1–43.

Jašová, M., Mendicino, C., Panetti, E., Peydró, J.-L., Supera, D., et al. (2023). Monetary policy, labor income redistribution and the credit channel: Evidence from matched employer-employee and credit registers. Technical report.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2012). Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. *American Economic Review*, 102(5):2301–26.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2014). Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? *Econometrica*, 82(2):463–505.

Kaplan, G., Mitman, K., and Violante, G. L. (2020). The housing boom and bust: Model meets evidence. *Journal of Political Economy*, 128(9):3285–3345.

Kaplan, G., Moll, B., and Violante, G. L. (2018). Monetary policy according to hank. *American Economic Review*, 108(3):697–743.

McKay, A. and Wolf, C. K. (2023). Monetary policy and inequality. *Journal of Economic Perspectives*, 37(1):121–144.

Moulton, B. R. (1990). An illustration of a pitfall in estimating the effects of aggregate variables on micro units. *The review of Economics and Statistics*, pages 334–338.

Peydró, J. L., Elliott, D., Meisenzahl, R., and Turner, B. C. (2020). Nonbanks, Banks, and Monetary Policy: US Loan-Level Evidence since the 1990s.

Piketty, T. (2014). Capital in the 21st century. *Harvard University Press*.

Ringo, D. (2023). Monetary policy and home buying inequality.

Scharfstein, D. and Sunderam, A. (2016). Market power in mortgage lending and the transmission of monetary policy.

Sodini, P., Van Nieuwerburgh, S., Vestman, R., and von Lilienfeld-Toal, U. (2016). Identifying the benefits from home ownership: A swedish experiment. Technical report, National Bureau of Economic Research.

Appendix 1: Data Appendix

Table A.1: Data sources on financial institutions

Variable	Formula	Code
Total Assets		S0H 0010
Bank Capital Ratio	$\frac{Equity}{Total\ Assets}$*100	$\frac{S05\ 0620}{S0H\ 0010}$*100
Liquidity Ratio	$\frac{Cash+Liquidity\ Reserves}{Total\ Assets}$*100	$\frac{S01\ 0020+S01\ 0180}{S0H\ 0010}$*100
Returns on Assets (ROA)	$\frac{Net\ Income}{Total\ Assets}$	$\frac{S07\ 1620}{S0H\ 0010}$*100
Non-Performing Loans Ratio	$\frac{Doubtful\ Accounts}{Client\ Transactions}$	$\frac{S02\ 0410}{S02\ 0020}$*100

Note: The codes are provided *here* and *here*.