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Sumit Agarwal, Sergio Mayordomo,
María Rodríguez-Moreno and Emanuele Tarantino

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Sumit Agarwal (**)

NUS

Sergio Mayordomo (***)

BANCO DE ESPAÑA

María Rodríguez-Moreno (****)

BANCO DE ESPAÑA

Emanuele Tarantino (*****)

LUISS, EIEF, CEPR, AND EUROPEAN COMMISSION

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(**) ushakri@yahoo.com
(***) sergio.mayordomo@bde.es
(****) maria.rodriguezmoreno@bde.es
(*****) etaranti@gmail.com

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Abstract

This paper examines how monetary policy affects corporate lending through its impact on household balance sheets, bridging the gap between the cash flow and bank lending channels. When policy rates rise, households with variable-rate debt face higher monthly payments, prompting early mortgage repayments, particularly among high-income borrowers. Exploiting the monetary tightening between July 2022 and September 2023 as a policy experiment, we show that banks that are more exposed to variable-rate mortgages granted to higher-income households increase their supply of corporate credit, especially to micro and small firms. However, no variation is observed in the balance of household credit or in other investment items on the banks' balance sheets. Indeed, banks facing higher liquidity constraints tend to extend more corporate credit as their exposure to early redemptions increases. Our findings provide new evidence on how household financial constraints shape monetary policy transmission, offering novel insights into the interplay between household debt dynamics and corporate credit allocation.

Keywords: floating-rate mortgages, early redemption, monetary policy tightening, monetary policy transmission, corporate lending, bank liquidity.

JEL classification: D14, E43, E52, G21.

Resumen

Este artículo analiza cómo la política monetaria influye en la oferta de crédito a través de su impacto en la situación financiera de los hogares. Así, cuando los tipos de interés de referencia aumentan, las familias con hipotecas a tipo variable tienen que hacer frente a cuotas más elevadas. Esto lleva a que muchas de ellas, especialmente las de mayor renta, decidan realizar anticipadamente amortizaciones parciales de sus hipotecas. Usando el endurecimiento de la política monetaria que se produjo entre julio de 2022 y septiembre de 2023 como un experimento, se encuentra evidencia de que los bancos más expuestos al crédito hipotecario a tipo variable concedido a hogares de mayor renta aumentan su oferta de crédito corporativo, especialmente a las empresas de menor tamaño. Sin embargo, no se observa variación en el saldo del crédito a hogares ni en otras partidas de inversión en el balance de los bancos. Además, los bancos con mayores restricciones de liquidez muestran una mayor propensión a aumentar el crédito a medida que su exposición a las amortizaciones anticipadas se incrementa. Estos resultados ofrecen nuevas perspectivas sobre la interacción entre la dinámica de la deuda de los hogares y la asignación de crédito corporativo. En concreto, este artículo aporta una dimensión novedosa al debate sobre la transmisión de la política monetaria al unir las dos corrientes de la literatura referentes a los canales de flujo de caja y de préstamos bancarios, que hasta ahora se habían estudiado de manera separada.

Palabras clave: hipotecas a tipo variable, amortizaciones anticipadas, endurecimiento de la política monetaria, transmisión de la política monetaria, crédito corporativo, liquidez bancaria.

Códigos JEL: D14, E43, E52, G21.

1. Introduction

Identifying the mechanisms driving monetary policy transmission from households to firms is an open question in macroeconomics and finance. A large body of research has examined how changes in interest rates affect credit supply, with particular attention to the bank lending channel operating through financial intermediaries' funding conditions and capital structure. Separately, recent work in macro-finance has documented the cash-flow channel, which highlights how monetary policy influences household spending by altering debt service costs, particularly for borrowers with variable-rate obligations. While both channels have been studied in isolation, their interaction and joint effect on credit supply remain underexplored. It requires observing household data on mortgage exposure with banks and banks' lending choices to the primary credit segments.

This paper examines how monetary policy affects bank lending through its impact on household balance sheets. Households with variable-rate debt face higher monthly payments when policy rates rise, leading to consumption and savings behavior shifts. Particularly among wealthier households, this results in early mortgage repayments, increasing the liquidity available to banks. The question is whether these liquidity boosts influence banks' lending decisions, possibly expanding their supply of corporate loans, consumer credit, or new mortgages. Establishing this empirical link would document a novel link between the cash flow and bank lending channels of monetary policy, suggesting that household exposure to financial shocks plays a crucial role in shaping how monetary policy affects credit dynamics.

Empirically, we exploit the interest rate rise of the second quarter of 2022 as a policy experiment. Between July 2022 and the end of 2023, the European Central Bank (ECB) policy rate increased by about 450bp. This episode provides a unique setting to analyze how monetary policy shifts translate into heterogeneous household responses and, consequently, differential bank lending behavior. It was the most significant policy rate increase since the Euro was introduced and came largely unexpectedly. The Banco de España Central Credit Registry allows us to construct a unique dataset with granular monthly information on all households, firms, banks, and their respective credit relationships before and after the monetary policy tightening period. This dataset enables us to quantify bank-specific exposure to floating-rate mortgages before the shock, particularly in areas where households are more prone to early redemptions. Spanish banks had the highest exposure to floating-rate mortgages in the euro area at the onset of the tightening period. Over 70% of the outstanding mortgage stock in Spain carried floating rates, compared to approximately 25% in the rest of the euro area.

Our findings document that the transmission of the shock to bank credit was not uniform across banks. Instead, it depended on the composition of banks' mortgage portfolios. Due to the abrupt policy change, households with floating-rate mortgages faced higher monthly payments on their debt service. Reacting to the shock, these households repaid their mortgages without drawing on their deposits' liquidity at the mortgage-issuing banks. The cumulative early redemptions in the six quarters following June 2022 amounted to 9% of the total outstanding mortgages, representing a significant share compared to the six semesters preceding June 2022 (3.7%). This suggests that households' early repayments represented a significant net liquidity shock originating in the household credit segment for the more exposed banks. We also document that the banks that received a more substantial liquidity influx were those more exposed to floating-rate mortgages in high-income areas before the policy change. However, they were otherwise largely comparable with respect to solvency, ROA, and business model, except for size (i.e., larger banks received larger volume of redemptions)[1].

The affected banks reallocated their credit primarily to non-financial corporations (NFCs), not to consumer credit, nor to new mortgages. Using data from the European Central Bank Bank Lending Survey (BLS) we document that, during the period we consider, Spanish banks reported a contraction in mortgage demand that nearly doubled that for loans by non-financial corporations, which may explain why they did not redirect the liquidity inflow to the household segment. Moreover, banks did not redirect this liquidity towards alternative bank balance-sheet investment components, such as fixed-income securities, investment funds, other investments, cash, or reserves. These findings are consistent across different model specifications and robustness checks. By establishing a direct link between the cash flow and bank lending channels, we provide novel insights into the traditional view of the bank lending channel by highlighting how banks' credit supply decisions depend on their mortgage portfolios and, ultimately, on household debt servicing adjustments.

Examining the characteristics of firms receiving new credit from exposed banks and the associated contractual terms, we find that credit reallocation was more pronounced toward firms resembling household-segment borrowers. Specifically, exposed banks were more likely to extend credit to micro and small firms with risk weights similar to those in their household portfolios. Moreover, the probability of default among firms receiving credit does not differ

[1]We perform several robustness tests to ensure that our findings are attributed to banks' exposure to early redemptions rather than their size.

between more and less exposed banks. Finally, while interest rates and maturities remain similar, more exposed banks extend smaller loan amounts (reflecting borrower size) and exhibit a slightly higher likelihood of requiring collateral.

Finally, we examine whether banks' liquidity constraints influence the reallocation of the liquidity influx due to households' early redemptions. We use the Liquidity Coverage Ratio (LCR) as a proxy for liquidity constraints. Reporting the value of the LCR is mandatory for banks in the EU since 1 October 2015. Our regression analyses show that banks with low LCR (indicating higher liquidity constraints in the baseline) extend more credit as their exposure to early redemptions increases. Intuitively, for these banks early redemptions relax liquidity constraints, allowing for a reallocation of credit. Instead, the relationship becomes not statistically significant when considering high-LCR banks. These results confirm that our main results are driven by banks' differential exposure to the shock.

The paper contributes to several strands of the literature. First, by bridging the gap between the cash flow and bank lending channels of monetary policy, our study provides a novel dimension to the broader debate on the financial and real effects of monetary policy. Previous work has documented the consumption response to changes in household monthly payments (Hughson et al., 2016; Di Maggio et al., 2017; Cloyne et al., 2020; Foldén et al., 2021) and how bank funding structure affects lending to firms (e.g., among many others, Bernanke and Blinder, 1988; Kashyap and Stein, 2000; Jiménez et al., 2014; García-Posada and Paz, 2024). The findings of this paper contribute to the understanding of how monetary policy affects corporate lending through its impact on household balance sheets. By integrating detailed datasets and empirical evidence, this study offers valuable insights into the mechanisms through which banks reallocate liquidity from household mortgage repayments to corporate credit supply. Our results highlight the importance of considering household financial constraints when assessing monetary policy transmission through the banking system.

Second, the paper contributes to the literature on the role of financial intermediaries in the transmission of monetary policy. While previous research has documented the impact of bank characteristics on lending behavior (e.g., Jiménez et al., 2012; Altavilla et al., 2017), this study highlights the importance of banks' exposure to household cash flows in shaping their credit allocation decisions. The findings suggest that banks' liquidity management strategies are influenced not only by their funding and capital structures but also by the cash-flow dynamics of their household clients during periods of monetary tightening.

Third, the paper provides new insights into the heterogeneity of credit reallocation across different types of firms. The evidence that micro and small firms benefit more from the reallocation of credit during periods of monetary tightening adds to the growing body of literature on the differential impact of monetary policy on firms of varying sizes (e.g., Gertler and Gilchrist, 1994; Crouzet and Mehrotra, 2020). This finding has important policy implications, as it suggests that substantial and rapid increases in policy rates could lead to early mortgage repayments, thus weakening the transmission of monetary policy. However, this transmission mechanism assists in alleviating the challenges that micro firms face in accessing financing.

Finally, the study contributes to the understanding of the broader economic implications of monetary policy adjustments. By documenting the link between household cash flows and corporate credit supply, the paper sheds light on a new channel through which monetary policy can influence economic activity. This channel, which operates through the interaction of household and corporate financial behavior, underscores the interconnectedness of different sectors of the economy and highlights the need for a holistic approach to monetary policy analysis.

In conclusion, this paper advances the literature on monetary policy transmission by integrating the cash-flow and bank lending channels, highlighting the role of financial intermediaries, and providing new evidence on the heterogeneity of credit reallocation across firms. The findings hinge on the' complex and multifaceted nature of monetary policy effects, offering valuable insights for policymakers and researchers alike.

2. Data and variable definition

2.1. Datasets

Our primary dataset is the credit registry of the Banco de España (*Central de Información de Riesgos del Banco de España* or CIRBE). This registry provides monthly information on all loans, credits, bank endorsements and general risks that financial institutions have with their customers. This detailed information is reported at contract level and includes both contract and borrower characteristics at origination and over the life of the contract. Specifically, contract characteristics include the loan amount at origination, maturity, interest rate setting (floating vs fixed)[2], interest rate or the bank

[2] A floating rate contract refers to a loan with a variable interest rate. This type of contract may initially have a fixed interest rate for a certain period. After this period, the interest rate on the outstanding balance resets periodically, which can be annually, semiannually or even monthly. The reset interest rate is based on a benchmark or index, commonly the Euribor, plus an additional margin known as the spread.

granting the loan. Borrower characteristics include the type of borrower (households and non-financial corporations), zip-code of their domicile and 4-digit sector code for non-financial corporations. The evolution of the contract includes the actual balance, loan performance, interest rate or early repayments.

We combine this data with the average income per consumption unit at the zip-code level as of 2021 to classify households by income. This information is collected by the *Instituto Nacional de Estadística* (INE). The household's income per unit of consumption is calculated by dividing the total disposable income of the household by the number of units of equivalent consumption that compose it, and the value of this ratio is assigned as income per unit of consumption equal to all members of that household. This dataset enable us to classify zip-codes as low or high-income areas within a given province based on the distribution across zip-codes (weighted by population) within the province.

We complement the information about the non-financial corporations with the *Central de Balances* (CB). The CB is managed by the Banco de España and contains publicly available financial statements mandatorily filed by Spanish firms. In addition, we employ the information available in CB to compute the firm probability of default following Blanco et. al (2023).

Finally, we merge our dataset with comprehensive balance sheet information on Spanish deposit-taking institutions (i.e., commercial banks, savings banks, and credit cooperatives) collected by the Banco de España. Our sample of banks covers 65 institutions that represent more than 96% of total mortgage credit and 94% of total credit to non-financial corporations granted by deposit-taking institutions (hereafter referred to as banks) as of December 2020.[3]

2.2. Floating rate mortgages and early repayments

The monetary policy tightening in July 2022 significantly increased mortgage reference rates, such as the Euribor 12m, consequently raising the mortgage costs for households with floating rate mortgages. According to Banco de España (2024), during the tightening cycle, floating rate mortgages experienced cumulative interest rate increases of 450 b.p. This led to an increase in early mortgage redemption by households. Figure 1 illustrates this phenomenon, showing that quarterly early redemptions relative to the stock of mortgage credit as of December 2020 tripled with the tightening of monetary policy. Additionally,

[3] To deal with bank mergers, we aggregate the credit balances of a firm/household in t of those entities that will operate -due to a mergers- as a single entity by the end of year $t+1$. In addition, for the pre-merger period we construct a synthetic bank by weighting the bank characteristics by the relative size of each single bank.

early redemptions were predominantly concentrated in floating rate mortgages, accounting for 90% of the redemptions. The cumulative early redemptions in the six quarters following June 2022 amounted to 9% of the total amount outstanding, representing a significant share compared to the six semesters preceding June 2022 (3.7%).

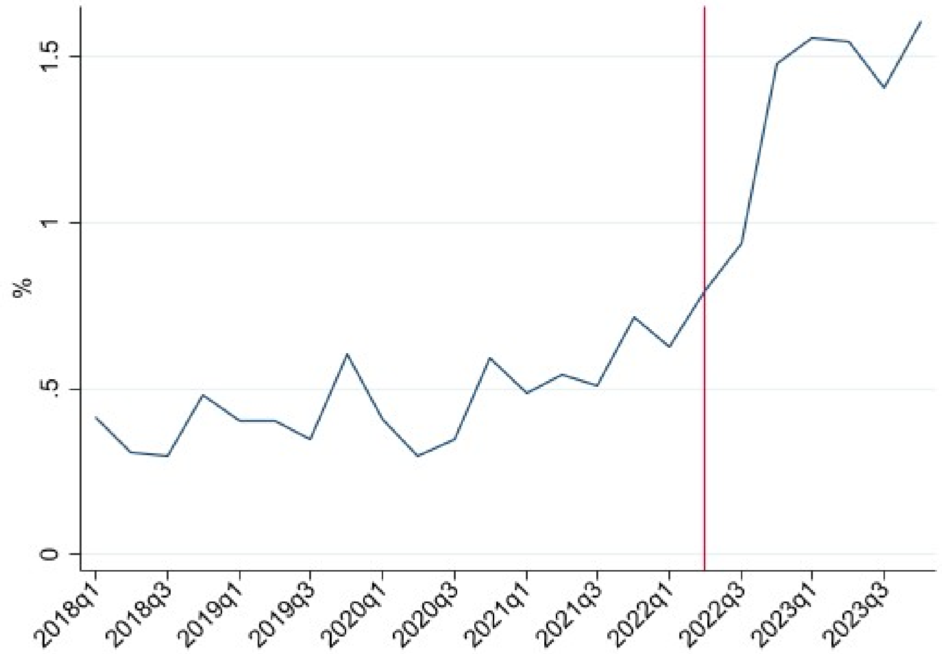

Figure 1: Quarterly Early Redemptions Relative to the Stock of Mortgages

This figure depicts the quarterly early repayments from mortgage contracts received by Spanish financial institutions relative to the stock of mortgage credit as of December 2020. The sample spans from 2018Q1 to 2023Q4.

Previous evidence indicates that monetary policy tightening incentivize early redemptions. However, not all households may be equally positioned to partially or totally repay their mortgages. To investigate this, we construct two metrics to illustrate the distribution of floating rate mortgages and the early repayments based on the households income. First, we define banks' exposure to floating rate mortgages within an income area relative to the stock of mortgages in that income area as of December 2020. Next, we define the total early redemptions received by each bank at the income area level from July 2022 to December 2023, relative to the stock of mortgages as of December 2020 in that income area.

Panel A of Table I presents the averages of these metrics using two different thresholds: 50^{th} and 75^{th} percentiles. On average, and consistently across income thresholds, 88% of the mortgage stock in each income area is classified as floating rate as of December 2020[4]. However, early redemptions are more intense in high income areas (i.e., zip codes in which the income of is above the 50^{th} or the 75^{th} percentiles) .

To provide additional evidence on the relationship between the early redemptions and floating rate mortgages in high-income areas we examine the growth rate of the mortgage stock between December 2021 and December 2023 at zip-code level. We aggregate the mortgage stock at the zip code level for each household with an active mortgage before December 2021 and compute the growth rate. The distribution by different income areas is depicted in Figure 2. It shows that the mortgage stock in high-income zip codes (above the 75^{th} percentile) decreased more significantly than in medium- (between the 50^{th} and 50^{th} percentiles) or low-income (below the 50^{th} percentile) zip codes. This suggests that early redemptions were more frequent in relatively wealthier areas.

We then compare early repayments by households and non-financial corporations to analyze whether these two groups exhibit different behaviors. We calculate the net early repayment for each household and non-financial corporation as the sum of early repayments from July 2022 to December 2023, net of new loans received during this period, relative to the maximum credit exposure during this timeframe. Figure 3 depicts the distribution of net early repayments. Consistent with the previous evidence, households are found to repay their mortgages partly or fully without taking out new mortgages whereas more than 50% of non-financial corporations that made early repayments obtained new loans during the period of interest.

In sum, Panel A of Table I and Figures 2 and 3 document that floating rate mortgages were distributed similarly across zip codes, regardless of household income. However, early repayments were substantially higher in high-income zip codes and significantly higher than those observed for non-financial corporations. Based on this evidence, we construct our primary explanatory variable of interest, $\text{FRM}_{b,pj}$, defined as the exposure of banks to floating rate mortgages in high-income areas (i.e., those more exposed to early redemptions)

[4]The Spanish residential mortgage market has historically been dominated by floating-rate mortgages, with over 95% of loans linked to the 12-month Euribor or other variable rates until 2015. However, since then, fixed-rate mortgage loans have gained significant traction. This shift can be attributed to several factors, including persistently low interest rates, economic uncertainty, and the need to mitigate finance costs in the event of rising Euribor. In fact, changes in monetary policy and higher interest rates have further accelerated this trend. For instance, around 63% of new mortgages were fixed-rate loans in 2021, and this proportion increased to 71% in 2022 and decreased in 2023 and 2024 to 60% and 58%, respectively. This shift is also observed in the amount outstanding of floating-rate mortgages, which decreased from 95% in 2015 to 60% in 2024. This transition is influenced not only by the generation of new fixed-rate mortgages but also by the early repayment of floating-rate mortgages by high-income households.

Table I: Banks' exposure to floating rate mortgages, early redemptions and other characteristics.

Panel A reports the average at bank level of the proportion of floating rate mortgages within different income areas as of December 2020 and the average early redemptions for the period July 2022 to December 2023 (i.e., the monetary tigthening period) relative to the stock of mortgage at income area level as of December 2020. Income areas are based on the distribution at province level of the average income at zip-code level as of December 2021 weighted by population. We compute four income areas depending on whether they are below or above the 50^{th} or the 75^{th} percentiles: Below P50, Above P50, Below P75 and Above P75. Panel B reports the descriptive statistics of the exposure of banks to floating rate mortgages in high-income areas (i.e., those more exposed to early redemptions) over the stock of mortgages (both as of December 2020) ($\text{FRM}_{b,pj}$). We consider three thresholds to define high-income zip codes depending on whether the income of that area is above the 50^{th}, the 75^{th}, or the 90^{th} percentiles. Panel C reports the descriptive statistics for banks' characteristics.

Panel A: Exposure Floating Rate Mortgages and Early Redemptions				
	Below P50	Above P50	Above P75	Above P90
Average Floating Rate Mortgages (Dec20)	0.8713	0.8845	0.8908	0.8925
Average Early Redemption (Jul22 - Dec23)	0.0537	0.0889	0.1097	0.0836

Panel B: Floating-Rate Mortgages in High-Income Zip Codes over the Stock of Mortgages						
	N	Mean	P50	SD	P10	P90
$\text{FRM}_{b,p50}$	65	0.5067	0.5101	0.2277	0.1460	0.8237
$\text{FRM}_{b,p75}$	65	0.2737	0.2540	0.1873	0.0437	0.5486
$\text{FRM}_{b,p90}$	65	0.1376	0.1148	0.1093	0.0117	0.3006

Panel C: Bank Characteristics						
	N	Mean	P50	SD	P10	P90
ROA (%)	65	4.7381	6.4260	7.1334	0.5668	10.0109
TIER 1 Capital Ratio (%)	65	23.9134	18.3598	29.2805	13.5448	32.0558
Loan to Deposits Ratio (%)	65	63.2463	60.7234	48.3896	27.5847	84.2670
Ln(Total Assets)	65	21.9975	21.8031	2.2181	19.5496	25.0195

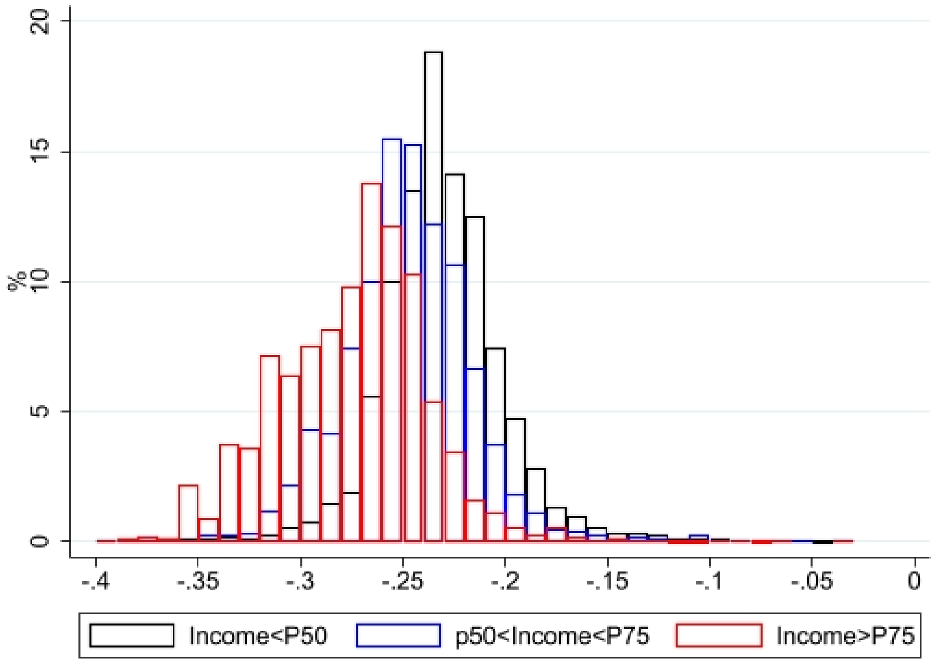

Figure 2: Growth rate in the stock of mortgages

This figure depicts the distribution of the growth rate of the mortgage stock from December 2021 to December 2023 at zip-code level. For each household with an active mortgage before December 2021, we aggregate the mortgage stock at the zip code level and calculate the growth rate. We then illustrate three distributions for three different areas: zip codes with income below the 50^{th} percentile, zip codes with income between the 50^{th} and the 75^{th} percentile and zip codes with income above the 75^{th} percentile.

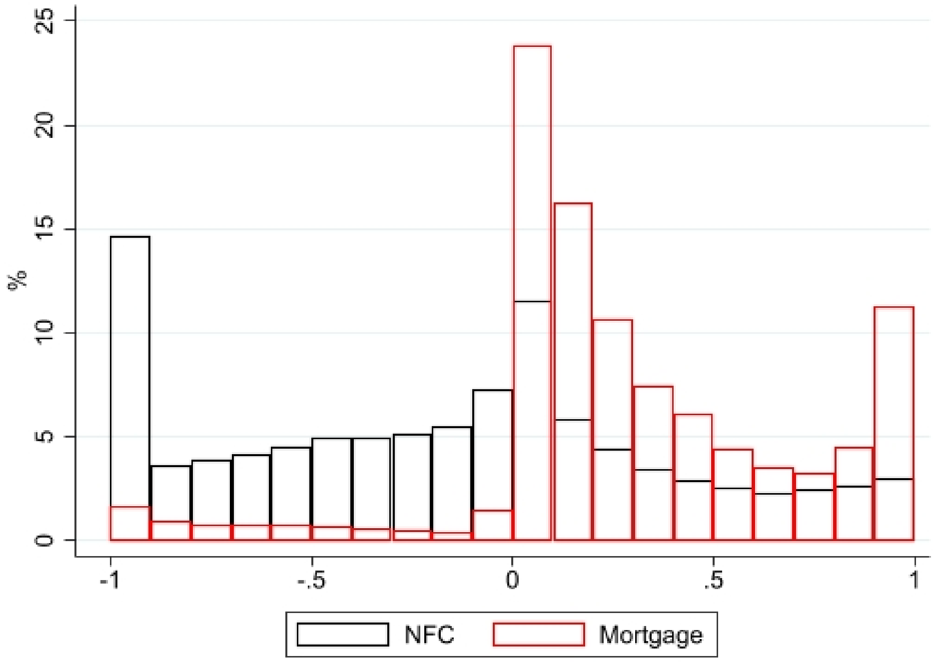

Figure 3: Net Early Redemptions

This figure depicts the distribution of net early redemptions for mortgages and loans to non-financial corporations. For each household and non-financial corporation we compute the sum of early repayments from July 2022 to December 2023, net of new loans received during this period, relative to the maximum credit exposure during this timeframe.

over the stock of mortgages (both as of December 2020):

$$\text{FRM}_{b,pj} = \frac{\text{Stock of Floating Rate Mortgages in High Income Areas}_{b,pj}}{\text{Stock of Mortgages}_b}. \tag{1}$$

This measure proxies the "extra liquidity" banks receive through the early mortgage redemptions. Panel B of Table I presents the main descriptive statistics for this variable. Similar to the previous metrics, we distinguish three thresholds of zip codes' income (pj) to define high- and low-income areas: the 50^{th}, 75^{th}, and 90^{th} percentiles. Banks extend more floating-rate mortgages to households in zip codes with higher incomes. On average, 27% of the floating rate mortgage stock is located in areas whose income is above the 75^{th} percentile ($\text{FRM}_{b,p75}$). However, there is significant variation among banks: the 10^{th} percentile of the distribution at bank level of the ratio of floating rate mortgages in zip codes with income above the the 75^{th} percentile ($\text{FRM}_{b,p75}$) is equal to 4% whereas the 90^{th} percentile is equal to 55%. This pattern is consistent across different thresholds.

Panel C of Table I contains the descriptive statistics of several banks' characteristics including proxies for the profitability (ROA), solvency (distance to minimum Tier 1 capital ratio), size (logarithm of the total assets), and business model (loan to deposits ratio). The distance to minimum Tier 1 Capital ratio is computed as the difference between the Tier 1 Capital ratio and the minimum Tier 1 capital requirements, including the Pillar 2 and the macroprudential buffers. For confidentiality, we report the Tier 1 capital ratio instead of the distance to minimum Tier 1 capital ratio. The banks in our sample exhibit significant variability in the four previously mentioned variables. Notably, during this period, banks demonstrate strong profitability and solvency, with deposits emerging as a crucial source for financing credit.

Finally, we conduct a regression analysis to examine how bank characteristics correlate with their exposure to early mortgage redemptions. We run one regression where the dependent variable is the share of floating-rate mortgages of each bank in high-income zip codes, defined as those with households' income above the 75^{th} percentile of the distribution. The explanatory variables are those described in Panel B. The results are reported in Table A1. They indicate that the proxy for the bank's exposure to early redemptions is uncorrelated with all characteristics except for loan size. In other words, larger banks are more exposed to early redemptions, but apart from that, there are no other significant differences between banks. Based on this result, we will later propose several regression analyses to confirm that the cross-sectional variation in the credit supply to NFC is attributed to exposure to early redemptions rather than other bank characteristics.

2.3. Descriptive evidence on the characteristics and credit of non-financial corporations

We next describe the main characteristics of non-financial corporations joint with their bank credit exposures and dynamics. The main dependent variable in our analysis is the semiannual credit growth ($\Delta\text{Credit}_{f,b,t}$) for firm f with bank b in semester t and it is defined as follows:

$$\Delta\text{Credit}_{f,b,t} = \frac{\text{BankDebt}_{f,b,t} - \text{BankDebt}_{f,b,t-1}}{\frac{\text{BankDebt}_{f,b,t} + \text{BankDebt}_{f,b,t-1}}{2}} \tag{2}$$

where $\text{BankDebt}_{f,b,t}$ denotes firm f stock of bank credit with bank b in semester t. This growth rate is constructed for the semesters spanning our sample period between December 2020 and December 2023. Following previous literature (e.g., Arce et al., 2021), the growth rate is defined relative to the average debt between the two periods of interest to limit the impact of extreme values.

We construct a panel that contains information on $433,604$ firms, $827,362$ bank-firm relations, and $3,693,497$ bank-firm-time observations between December 2020 and December 2023.

Panel A of Table II presents the descriptive statistics of $\Delta\text{Credit}_{f,b,t}$ for the entire sample period, as well as for the period before and after the monetary policy rate hike in June 2022. A general deleveraging trend is observed throughout the sample period, with a median growth rate of -6.5%. This trend is more pronounced after the interest rate hike, with a growth rate of -8.7% compared to -4.2% before the hike.

Panel B of Table II summarizes the characteristics of the firms in the sample for the pre- and post-hike period.[5] Large firms account for 3% of the sample, 6% of the firms are medium-sized, 21% are small, and 70% are micro-sized. Of these firms, 35% operate in the commerce and hospitality sector, 19% in construction, and 11% in manufacturing. This table also summarizes firms' Net Ordinary Income, Equity to Total Assets, and Cash to Total Assets and Probability of Default, which we will use as firm controls in our regressions. Based on this information, we conclude that the median firm in the sample is solvent and profitable, with a default probability of 1.06% corresponding to a BB (CQS5) rating.

3. Analysis of bank credit reallocation across segments

After documenting the large inflows experienced by banks in the form of early redemptions of their mortgages, we next study whether we observe a link between such early redemptions and the allocation of new credit to three different segments: the mortgage and consumer-credit segment for households, and the segment of loans to non-financial corporations. We compute the monthly new credit to these three segments and the monthly early redemptions at bank level during the tightening period (July 2022 to December 2023). Corporations repeatedly demand credit over time, often renewing existing exposures. In contrast, households typically request credit only once during our study period, particularly for mortgages. Examining credit change over time at the bank-zip-code level enables us to compare the evolution of new credit across these segments using similar aggregation units.

We first perform a descriptive analysis of banks' credit reallocation over business segments and then turn to a regression analysis. We finally address the potential

[5]We exclude duplicates of firms operating with multiple banks.

Table II: Descriptive Statistics of NFC

Panel A contains the descriptive statistics of the semiannual credit growth (Equation 2) for the entire sample period, as well as for the period before and after the monetary policy rate hike in June 2022. Panel B reports the characteristics of the firms in the sample. We report information on firms' Net Ordinary Income, Equity to Total Assets, Cash to Total Assets and Probability of Default.

	Panel A: $\Delta\text{Credit}_{f,b,t}$					
	N	Mean	P50	SD	P10	P90
Full sample	3,693,497	-0.0613	-0.0652	0.7194	-0.4951	0.3716
Before June 2022	1,835,381	-0.0116	-0.0421	0.7455	-0.4506	0.5802
After June 2022	1,858,116	-0.1103	-0.0870	0.6893	-0.5507	0.2162

	Panel B: Firm Characteristcs					
	N	Mean	P50	SD	P10	P90
Net Ord Income (000€)	433,604	47.511	6.545	183.642	-35.025	135.235
Equity/TA (%)	433,604	26.999	33.526	66.307	-8.673	78.779
Cash/TA (%)	433,604	18.680	11.180	20.508	0.563	48.662
Probability of Default (%)	433,604	1.895	1.058	6.884	0.270	2.394

reallocation towards different investments.

3.1. Descriptive analysis

Figure 4 relates, for the three segments, the average monthly new credit generated by each bank over the period July 2022 - December 2023 relative to the bank stock of credit as of December 2020 and the average monthly early redemptions over the same period relative to the bank stock of mortgages as of December 2020. More specifically, we depict the bin-scatter that relates the monthly averages of the early redemptions relative to the stock of credit (x-axis) and the monthly average of the new credit relative to the bank stock of credit (y-axis). Panel A shows a positive and significant association between new credit to non-financial corporations and early redemptions. However, most observations fall below the 45-degree line, suggesting that not all redemptions were reallocated to firms. Banks facing a surge in mortgage redemptions tend to issue more new mortgages (Panel B), although the relationship is weaker than for credit to non-financial corporations and non-statistically significant. Finally, there is no credit reallocation of early redemptions to consumer credit (Panel C).

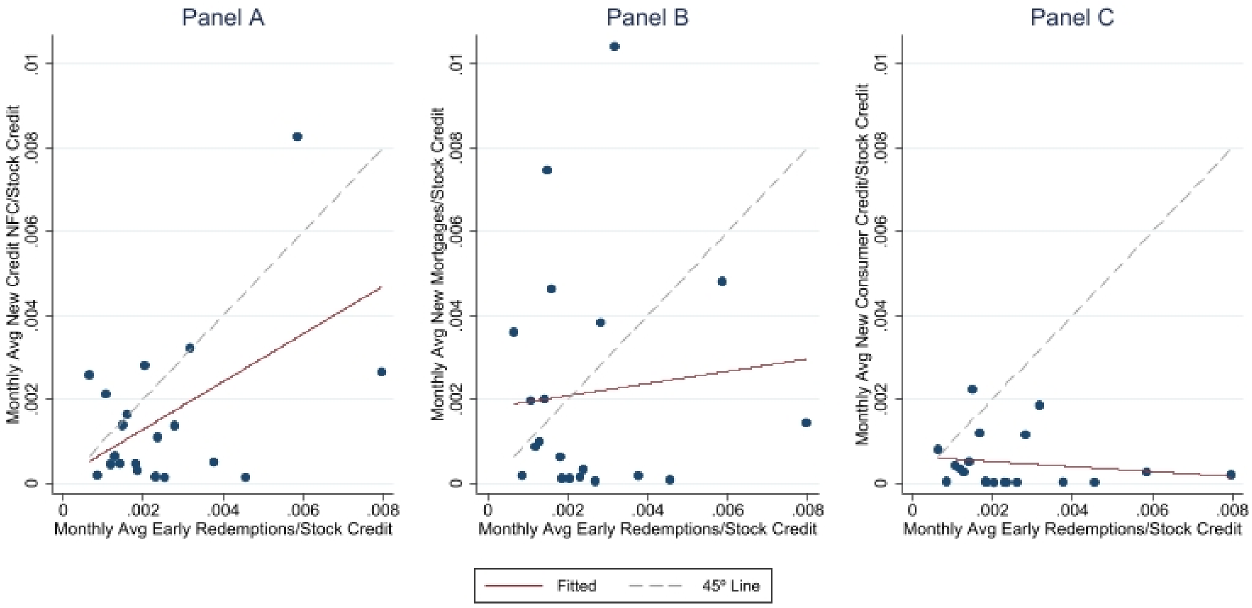

Figure 4: Early Redemptions and New Credit to Different Credit Segments

This figure depicts the bin-scatter that relates the monthly averages of the early redemptions relative to the stock of credit (x-axis) and the monthly average of the new credit relative to the bank stock of credit (y-axis). The dash line represents the 45º line and the solid line represents the fitted linear regression. Panel A refers to the credit to non-financial corporations and Panels B and C to mortgages and consumer credit, respectively.

The evidence in the figure suggests that the "extra liquidity" from early mortgage redemptions, in a context of significant interest rate increases and portfolios tilted towards floating rate mortgages, led banks to extend more mortgages and loans to non-financial corporations. This could be influenced by both supply and demand factors.

The more significant increase in loans compared to mortgages may be due to the substantial shrinkage of demand in the mortgage segment, as documented by Spanish banks' responses to the Bank Lending Survey (BLS). Figure 5 depicts the cumulative net percentage of banks reporting increased demand for mortgages, consumer credit, and loans for non-financial corporations. For each quarter, we calculate the net percentage obtained as the difference between the sum of the share of banks responding "increased considerably" and "increased somewhat" and the sum of the shares of banks responding "decreased somewhat" and "decreased considerably". Positive values indicate an increase in demand, whereas negative values indicate a decrease in demand. Finally, we cumulate the net percentage changes in demand across segments from June 2022 (coinciding with the monetary policy tightening under investigation) onward.

The contraction in mortgage demand, as reported by Spanish banks, was more than double that observed for non-financial corporations. Taken together, the evidence in Figures 4 and 5 suggests that, although banks may have been eager to reallocate the liquidity accrued from early redemptions within the mortgage segment, the significant drop in mortgage demand forced them to redirect funds to firms. Finally, the high level of risk of the consumer credit segment, especially in a period of monetary policy tightening, and its relatively small size in bank portfolios may explain the negative relation between early redemptions and new consumer credit.[6]

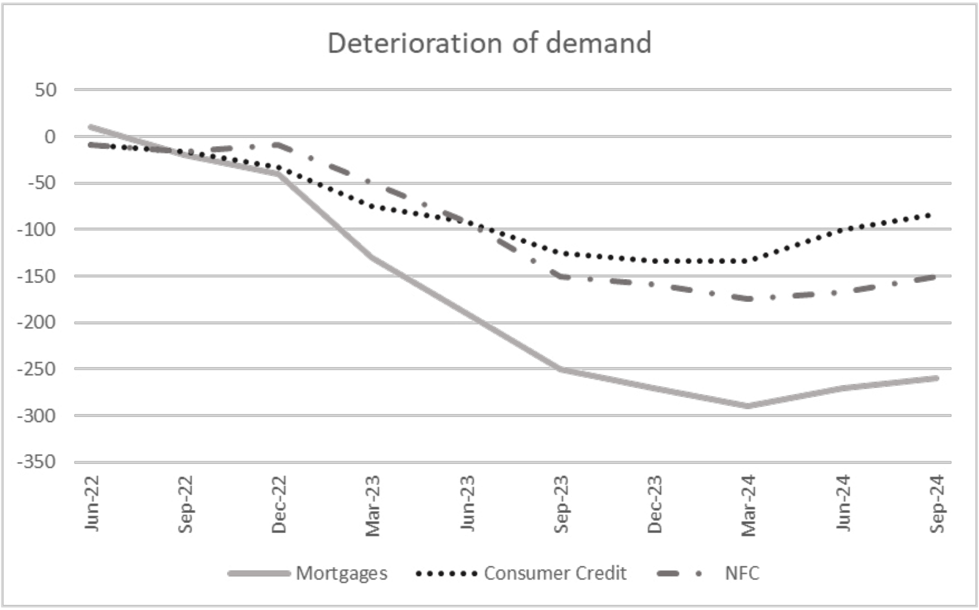

Figure 5: Cumulative net percentage of banks reporting an increase in demand

This figure depicts the cumulative net percentage of banks reporting an increase in demand in loans for house purchase (solid line), consumer credit (dot line) and in loans for non-financial corporations (NFC, dash-dot line). Each quarter we calculate the net percentage defined as the difference between the sum of the share of banks responding "increased considerably" and "increased somewhat" and the sum of the share of banks responding "decreased somewhat" and "decreased considerably". Positive values indicate an increase in demand whereas negative values indicate a decrease in demand. Finally, we cumulate the net percentages from June 2022 onward.

3.2. Regression analysis

We now turn to a multivariate analysis of bank credit reallocation to the three main business segments. Based on the descriptive evidence reported above, we conjecture that

[6]Consumer credit represents around 15% of total credit as of December 2022.

there is a reallocation of credit from the mortgage to the business segment by those banks with more significant exposure to the floating rate mortgages in high-income areas as defined in Equation 2, that is, the ones with a larger likelihood of receiving early redemptions. The analysis that follows aggregates information at the bank-zip-code-time level. This level of aggregation enables us to examine the relationship between the exposure to early redemptions through the share of floating rate mortgages granted in high-income areas and the evolution of credit, while controlling for the demand in each credit segment. To this aim, we assume that demand patterns within a given zip code are similar across households.

We use the following regression:

$$\text{Credit}_{b,zc,t} = \beta \text{Post}_t \times \text{FRM}_{b,p75} + \Gamma \text{BankControls}_{b,t} + \alpha_{zc,t} + \alpha_b + \varepsilon_{zc,b,t}. \tag{3}$$

We employ two alternative dependent variables. To measure the variation of the stock of credit, we use the semiannual credit growth at zip-code-bank level ($\Delta\text{Credit}_{b,zc,t}$). This variable is constructed analogously to Equation 2, with the difference that here it uses information on the stock of credit for each segment in a given zip code instead of the stock of credit of each firm. Given that the variation of the stock of credit is influenced by the early repayments, the second dependent variable we use is the amount of new credit extended in each semester in each zip code by a given bank relative to the bank size ($\text{NewCredit}_{b,zc,t}/\text{TA}_b$). Our explanatory variable of interest, $\text{FRM}_{b,p75}$, measures the exposure of banks to floating rate mortgages in high-income areas as of December 2020, where high-income areas are defined according to the 75^{th} percentile of the distribution of income within a given province. We interact $\text{FRM}_{b,p75}$ with the variable Post_t, which equals one for the period July 2022 – December 2023. Since it is predetermined, our exposure variable ($\text{FRM}_{b,p75}$) is unaffected by the lending activity during the tightening of the monetary policy we analyze.

$\text{BankControls}_{b,t}$ is a vector that contains bank proxies for the profitability (ROA), solvency (distance to minimum Tier 1 capital ratio), size (logarithm of the total assets), and business model (loan to deposits ratio). We take the value of these controls as of December 2020 for the semiannual credit variations between December 2020 and June 2022, and that as of December 2021 for the credit between June 2022 and December 2023. We also use zip-code-time fixed effects ($\alpha_{zc,t}$) to control for the demand for credit. Finally, the bank fixed-effects (α_b) allow us to control for time-invariant bank characteristics. Standard errors are clustered at the zip-code-bank level.

Table III reports the results obtained for the three credit segments. A positive and significant relationship exists between our explanatory variable and the credit to non-financial corporations for both credit growth and new credit. The reallocation towards firms is more substantial than the potential repayments done by corporations. On the contrary, we find a negative relation for mortgages when we look at the credit growth, meaning that for this sector, early repayments may be higher than the allocation of new credit. However, the relationship is positive and significant when considering the new credit. This supports the idea that banks have tried to reallocate the liquidity accruing from the early redemptions to extend new mortgages. In the case of consumer credit, we find a negative and significant effect for both dependent variables. In line with the descriptive evidence above (Figure 4), these results suggest that the credit extended by those banks with "extra liquidity" generated from early redemptions was mainly redirected toward non-financial corporations.

Additionally, banks could allocate the "extra liquidity" gathered from early mortgage repayments to purposes other than credit, such as accumulating cash, increasing reserves, or investing in financial assets. To explore this hypothesis, we estimate a regression analysis at the bank level in which the dependent variable is the change from June 2022 to December 2023 of specific bank's balance-sheet items relative to the bank's total assets as of June 2022 which is regressed on several bank characteristics as of December 2021. The main explanatory variable of interest is the exposure of banks to floating rate mortgages in high-income areas as of December 2020, with high-income areas defined by the 75^{th} percentile of the income distribution within a given province ($\mathrm{FRM}_{b,p75}$). We consider the change in five balance-sheet items relative to total assets to define the dependent variable: (i) fixed-income securities, (ii) investment funds, (iii) other investments, (iv) cash and cash equivalents and (v) reserves. Our sample consists of 65 banks and results are reported in Table IV. We found no significant relationship between our variable of interest and all the alternative uses of the liquidity generated by the households' mortgages early redemptions. Therefore, these results rule out the possibility that banks allocate the cash received from early redemptions to investments in segments other than credit.

3.3. The role of deposits

Our mechanism of reallocating excess liquidity to different credit segments holds if households repaying their mortgages early do not utilize the deposits available in the banks where they repay their debt. Although we lack a deposit register at the bank household level to confirm this behavior, we can test the hypothesis using bank-level

Table III: Allocation of New Credit by Segments

This table reports the estimation of Equation (3) for different credit segments: non-financial corporations (Columns (1)-(2)), mortgages (Columns (3)-(4)) and household consumer credit (Columns (5)-(6)). We employ two alternative dependent variables. Columns (1), (3), and (5) report the results obtained when the dependent variable is the semiannual growth in the stock of credit at zip-code-bank level ($\Delta \text{Credit}_{b,zc,t}$) whereas Columns (2), (4) and (6) report the results obtained when we use the total amount of new credit operations generated by a given bank in each semester relative to bank's total assets ($\text{NewCredit}_{b,zc,t}/\text{TA}_b$) as the dependent variable. Our explanatory variable of interest is the interaction of two terms ($\text{Post}_t \times \text{FRM}_{b,p75}$). The first term ($\text{FRM}_{b,p75}$) is the exposure of banks to floating rate mortgages in high-income areas as of December 2020, where high-income areas are defined according to the 75^{th} percentile of the distribution of income within a given province. The second term (Post_t) is a dummy variable that takes value one during the tightening period of monetary policy (i.e., July 2022 – December 2023). We include bank controls, bank fixed effects and zip-code-time fixed effects. Standard errors, clustered at the zip-code-bank level, are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Credit Segment	NFC		Mortgages		Consumer Credit	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	ΔCredit	NewCred	ΔCredit	NewCred	ΔCredit	NewCred
$\text{Post}_t \times \text{FRM}_{b,p75}$	0.065***	0.004**	-0.025*	0.003*	-0.391***	-0.004*
	[0.022]	[0.002]	[0.014]	[0.002]	[0.024]	[0.002]
Observations	334,370	334,370	342,516	342,516	360,574	360,574
R-squared	0.283	0.223	0.193	0.285	0.196	0.295
Bank Controls	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES
Location-Time FE	YES	YES	YES	YES	YES	YES

Table IV: Alternative Investments

This table presents the results obtained from the estimation of a regression analysis at the bank level in which the dependent variable is the change from June 2022 to December 2023 of specific bank's balance-sheet items relative to the bank's total assets as of June 2022 which is regressed on several bank characteristics as of December 2021. The main explanatory variable of interest is the exposure of banks to floating rate mortgages in high-income areas as of December 2020, with high-income areas defined by the 75^{th} percentile of the income distribution within a given province ($\text{FRM}_{b,p75}$). The dependent variables used in this regression analysis refer to the change in five balance-sheet items relative to total assets to define the dependent variable: fixed-income securities (Column 1), investment funds (Column 2), other investments (Column 3), cash and cash equivalents (Column 4) and reserves (Column 5). Bank controls include bank characteristics such as ROA, distance to minimum tier 1 capital ratio, loan to deposits ratio and the logarithm of the total assets. Standard errors, robust to heteroskedasticity, are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dep Variable	ΔDebt	ΔInvFund	ΔOther Equity	ΔCash	ΔReserves
$\text{FRM}_{b,p75}$	9.859	-0.129	-0.611	0.017	0.013
	[10.863]	[0.439]	[0.551]	[0.109]	[0.639]
Observations	65	65	65	65	65
R-squared	0.174	0.352	0.058	0.010	0.493
Bank Characteristics	YES	YES	YES	YES	YES

information on household deposits and their relationship with early repayments.

We first perform a simple mean test comparing the evolution of bank's household deposits for two types of banks, depending on whether they experienced high or low early mortgage repayments. We assume that a bank experienced a high level of early repayments if the repayments it receives from July 2022 to December 2023 relative to its total assets are above the median of the distribution of all banks in our sample. Otherwise, we say that banks faced low early repayments. We observe that the change in deposits relative to total assets is -2% for banks with more repayments and -1.7% for banks with fewer repayments, and the difference is not statistically significant.

Moreover, we conduct a simple regression analysis where the dependent variable is the change in household deposits between June 2022 and December 2023 relative to total assets as of June 2022. The explanatory variable of interest is the share of early mortgage repayments relative to total assets over the same period. We include additional bank controls as in Equation (3). The results (not reported) show no significant association between early repayments and deposits.

To ensure that households did not repay their mortgages using extra liquidity from deposit accounts, which could impact banks' ability to intermediate, we provide additional descriptive evidence. Firstly, the decline in Spanish households' outstanding loans during the second half of 2022 and 2023 was accompanied by a decrease in illiquid financial assets. Conversely, there were inflows into liquid financial assets, including deposits, and the reduction in sight deposits was offset by an increase in term deposits (for more evidence, see Banco de España, 2024).

Furthermore, INE data indicates that consumption expenditures have grown at a slower rate for households in the top quintile of expenditure distribution since 2021, which corresponds to the highest income households. Moreover, the Spanish Survey of Household Finances (EFF) reveals a decline in households' marginal propensity to consume, particularly among higher-income households. This evidence suggests that high-income households are reducing consumption and saving more from their salaries (e.g., Flodén et al., 2020). In fact, the difference between the income and total consumption expenditures of high-income households in 2022-2023, according to INE, amounts to 12,000 euros per year, which is sufficient to cover the average repayments made by households in the top quartile of income distribution (11,900 euros).

All this evidence documents that early repayments represent a liquidity shock for banks that originated in the household credit segment. This liquidity appears to be mainly reallocated to the non-financial corporations segment, indicating a new channel of monetary policy tightening transmission across segments, leading to an increased credit supply to the corporate sector. Hereafter, we examine this channel by restricting our analysis to the credit to non-financial corporations and control for demand saturating the specification with industry-location-size-time fixed effects such that we can isolate the reallocation driven by supply.

4. Anatomy of credit reallocation to non-financial corporations

4.1. Baseline analysis

4.1.1. Methodology

We conjecture that there is a reallocation of credit from the mortgage to the business segment by those banks with more substantial exposure to the floating rate mortgages in high-income areas as defined in Equation 1. These were the banks with a larger likelihood of receiving early redemptions. We formally analyze this question using granular information at the bank-firm level based on the following regression:

$$\begin{aligned} \Delta\text{Credit}_{f,b,t} \quad = \quad & \beta\text{Post}_t \times \text{FRM}_{b,pj} + \Gamma\text{BankControls}_{b,t} + \Phi\text{FirmControls}_{f,t} \\ & + \alpha_{i,l,s,t} + \alpha_b + \varepsilon_{f,b,t} \end{aligned} \tag{4}$$

where the dependent variable, Δ Credit$_{f,b,t}$ is the semiannual growth rate in the stock of financial credit (Equation (2)). The independent variable, FRM$_{b,pj}$, measures banks' exposure to floating rate mortgages in high-income areas. We distinguish three thresholds of zip codes' income to define high-income areas, taking the 50^{th}, 75^{th}, and 90^{th} percentiles of the income distribution at the province level. We interact our explanatory variable with Post$_t$, a dummy variable that takes during the period of monetary policy tightening (July 2022 – December 2023).

The vector of controls comprises bank and firm characteristics. Specifically, BankControls$_{b,t}$ contains information on bank ROA, Distance to minimum Tier 1 Capital ratio, Loan to Deposits ratio, and the logarithm of the Total Assets. FirmControls$_{f,t}$ contains the firm characteristics: Net Ordinary Income, Equity to Total Assets, and Cash to Total Assets. We use the information of bank and firm controls as of December 2020 for the credit variations between December 2020 and June 2022 and as of December 2021 for the semiannual credit growth between June 2022 and December 2023. We also use industry-location-size-time fixed effects ($\alpha_{i,l,s,t}$) to control for firm demand of credit under the assumption that firms with similar size operating in the same sector and zip code should exhibit similar demand of credit in a given semester. We consider this set of fixed effects instead of firm-time fixed effects because 54% of the firms in our sample operate with a single bank. Moreover, a more saturated specification based on firm-time fixed effects would prevent us from using a high proportion of firms. Industry is measured at the NACE 2-digit level, location at the zip-code level, size corresponds to micro, small, medium-sized, or large firms according to the European Commission classification, and time refers to semester. Finally, α_b denotes the bank fixed effects to control for time-invariant bank characteristics. Standard errors are clustered at the bank and firm level.

4.1.2. Results

Table V presents the baseline analysis for three different thresholds used to classify high-income areas. Column (1) shows the results when we use the median of the within-province income distribution to define the high-income zip codes. We find that the greater the banks' exposure to floating rate mortgages in these areas, the more they reallocate credit to non-financial corporations. Columns (2) and (3), which use the 75^{th} and 90^{th} percentiles of within-province income distribution respectively, confirm that the intensity of credit reallocation increases as higher percentiles in the income distribution are used to define high-income areas.

Based on the results reported in Column (2), a bank with 4.4% of floating-rate mortgages in high-income areas as of December 2020 (corresponding to the 10th percentile of the distribution as shown in Table I) increases its semiannual credit growth to average non-financial corporations by 1.7% during the period of monetary policy tightening. Conversely, a bank with similar characteristics but with exposure to floating rate mortgages in high-income areas equivalent of 54.9% (equivalent to the 90^{th} percentile of the distribution in Table I) would increase its credit to the average firm in our sample by 20.7% on a semiannual basis over the same period.

Table VI presents a battery of robustness tests. Column (1) reports the results obtained for the baseline analysis, where high-income areas are defined using the 75^{th} percentile of the income distribution (Column (2) of Table V). In Column (2) we saturate the model with firm-time fixed effects to control for demand instead of using the industry-location-size-time

Table V: Baseline Analysis. Reallocation of Credit to NFC

This table presents estimation of Equation 4, which examines the reallocation of credit towards NFC. The dependent variable is the semiannual growth rate in the stock of credit (Equation 2). The primary explanatory variable, $\text{FRM}_{b,pj}$ as defined in Equation 1, measures banks' exposure to floating rate mortgages in high-income areas. Column (1) reports results obtained when high-income zip-codes within a given province are those with an average income above the the 50^{th} percentile of the distribution, while Columns (2) and (3) use the 75^{th} and 90^{th} percentiles, respectively. This variable is interacted with Post_t, a dummy variable that takes value one for the period July 2022 – December 2023. Bank controls include bank characteristics such as ROA, distance to minimum tier 1 capital ratio, loan to deposits ratio and the logarithm of the total assets. Firm controls include firm characteristics like net ordinary income, equity to total assets and cash to total assets. The model includes industry-location-size-time (ILST) fixed effects and bank fixed effects. Standard errors, clustered at the bank and firm level, are in brackets.***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Dep Variable		$\Delta\text{Credit}_{f,b,t}$	
High-Income Area (pj)	50^{th} percentile	75^{th} percentile	90^{th} percentile
$\text{Post}_t \times \text{FRM}_{b,pj}$	0.358**	0.378***	0.573**
	[0.170]	[0.138]	[0.278]
Observations	3,693,497	3,693,497	3,693,497
R-squared	0.196	0.196	0.196
Bank Controls	YES	YES	YES
Bank FE	YES	YES	YES
Firm Controls	YES	YES	YES
ILST FE	YES	YES	YES

fixed effects. As a consequence, the number of observations drops by around 1 million (corresponding to the number of single-bank firms in a given semester). The results for multi-bank firms in each semester reveal an even stronger reallocation of credit to firms by banks more exposed to early redemptions. In Columns (3) and (4) we estimate weighted panel regressions where the weights are defined by the stock of mortgages at bank level as of December 2020 and the stock of mortgages at bank-zip-code level, respectively. The results align with previous findings, confirming that using equal weights for our banks is a conservative approach. This is due to the fact that larger banks can reallocate credit more easily across their clients, and the coefficient increases when we assign a greater weight to them in our estimation approach. In Columns (5) and (6) we employ an alternative dependent variable. In Column (5) we use the semiannual log change of the stock of financial credit. We observe a positive and significant relationship, with the coefficient's magnitude being substantially larger due to the greater variability of this alternative dependent variable (the standard deviation of this variable is 3.19 whereas the one of our baseline dependent variable is equal to 0.72). In Column (6) we use a dummy variable that takes value one when the semiannual growth rate is positive and zero otherwise. This variable allows us to examine the relationship between banks' exposure to floating-rate mortgages in high-income areas and the flow of new credit, rather than relying on changes in the stock of credit. The probability of extending new credit to firms is significantly higher when a bank has greater exposure to floating-rate mortgages in high-income areas compared to when its exposure is low.

Previous evidence indicated that the proxy for the bank's exposure to early redemptions was uncorrelated with all characteristics except for loan size. We now propose several regression analyses to confirm that the cross-sectional variation in the credit supply to NFC is attributed to exposure to early redemptions rather than bank size. Thus, in Table VII, we replicate the baseline analysis, which appears in column (1) for comparability, for alternative sample of banks depending on their size. Thus, in column (2) we provide the results obtained when we remove from our analysis the three largest banks in our sample, in column (3) we remove the three smallest banks and in column (4) we remove the three largest and the three smallest banks. We observe that our results hold for the three alternative samples of banks.

Finally, we analyze the dynamics of credit reallocation before and after the tightening of monetary policy through an additional regression analysis. Instead of using the Post coefficient, we interact the variable $\mathrm{FRM}_{b,p75}$ with a series of time dummies. We include

Table VI: Robustness Test for Credit Reallocation Analysis. Alternative Specifications
This table presents robustness tests for the estimation of Equation (4). Column (1) presents the baseline analysis, which is analogous that that in Column (2) of Table V. Column (2) introduces firm-time fixed effects to control for demand. Columns (3) and (4) report weighted panel regressions, with weights corresponding to the stock of mortgages as of December 2020 at bank and at bank-zip-code level, respectively. The dependent variable in Columns (1) - (4) is the semiannual growth rate in the stock of financial credit (Equation 2). In Columns (5) and (6) we employ alternative dependent variables. Column (5) uses the semiannual log change of the stock of financial credit whereas in Column (6) we use a dummy variable that takes value one if the semiannual growth rate in the stock of financial credit is positive and zero otherwise. The primary explanatory variable in all columns, $\text{FRM}_{b,pj}$ as defined in Equation 1, measures banks' exposure to floating rate mortgages in high-income areas, those zip-codes with income above the 75^{th} percentile of the distribution of income within a given province. This variable is interacted with Post_t, a dummy variable that takes value one for the period July 2022 – December 2023. Bank controls include bank characteristics such as ROA, Distance to minimum Tier 1 Capital ratio, Loan to Deposits ratio and the logarithm of the Total Assets. Firm controls include the following firm characteristics Net Ordinary Income, Equity to Total Assets and Cash to Total Assets. The model is saturated with industry-location-size-time (ILST) fixed effects (except in Column (2) which uses firm-time fixed effects) and bank fixed effects. Standard errors, clustered at the bank and firm level, are in brackets.***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_t \times \text{FRM}_{b,p75}$	0.378***	0.455***	0.799*	0.594***	1.637***	0.188**
	[0.138]	[0.132]	[0.416]	[0.197]	[0.561]	[0.074]
Observations	3,693,497	2,603,124	3,693,497	3,615,216	3,693,497	3,693,497
R-squared	0.196	0.413	0.266	0.227	0.191	0.197
Bank Controls	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES
Firm Constrol	YES	YES	YES	YES	YES	YES
ILST FE	YES	YES	YES	YES	YES	YES
Firm-Time FE	NO	YES	NO	NO	NO	NO
Dependent variable	Baseline	Baseline	Baseline	Baseline	Log Change	Dummy
Weights	No	No	Bank	Bank-ZC	No	No

Table VII: Robustness Test for Credit Reallocation Analysis. Dealing with Bank Size

This table presents robustness tests for the estimation of Equation (4). Column (1) presents the baseline analysis, which is analogous that that in Column (2) of Table V. Column (2) excludes the three largest banks whereas Column (3) excludes the three smallest banks. Column (4) excludes the three largest and three smallest banks. The primary explanatory variable in all columns, $\text{FRM}_{b,pj}$ as defined in Equation 1, measures banks' exposure to floating rate mortgages in high-income areas, those zip-codes with income above the 75^{th} percentile of the distribution of income within a given province. This variable is interacted with Post_t, a dummy variable that takes value one for the period July 2022 – December 2023. Bank controls include bank characteristics such as ROA, Distance to minimum Tier 1 Capital ratio, Loan to Deposits ratio and the logarithm of the Total Assets. Firm controls include the following firm characteristics Net Ordinary Income, Equity to Total Assets and Cash to Total Assets. The model is saturated with industry-location-size-time (ILST) fixed effects (except in Column (2) which uses firm-time fixed effects) and bank fixed effects. Standard errors, clustered at the bank and firm level, are in brackets.***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep Variable		$\Delta\text{Credit}_{f,b,t}$		
Sample	Baseline	Excl. Large Banks	Excl. Small Banks	Excl. Large/Small Banks
$\text{Post}_t \times \text{FRM}_{b,p75}$	0.378***	0.296**	0.379***	0.297**
	[0.138]	[0.139]	[0.139]	[0.141]
Observations	3,693,497	1,482,679	3,692,887	1,482,094
R-squared	0.196	0.259	0.196	0.259
Bank Controls	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Firm Controls	YES	YES	YES	YES
ILST FE	YES	YES	YES	YES

three time dummies for the period corresponding to the monetary policy tightening (one for each semester) and one time dummy for the semester immediately before the ECB began increasing the deposit facility rate (DFR) (i.e., the first semester of 2022). We use the two semesters of 2021 as the reference period to eliminate any seasonal effects caused by credit activity in a particular semester. Figure 6 reports the estimated coefficients. We find that the effect is not significant in the first semester of 2022, which supports the time period split used in our analyses. The effect becomes significant in the second semester of 2022, peaks in the first semester of 2023, and shows a slight decrease in the second semester of 2023, when the reference rate began to decline in anticipation of future decreases in the ECB policy rate.

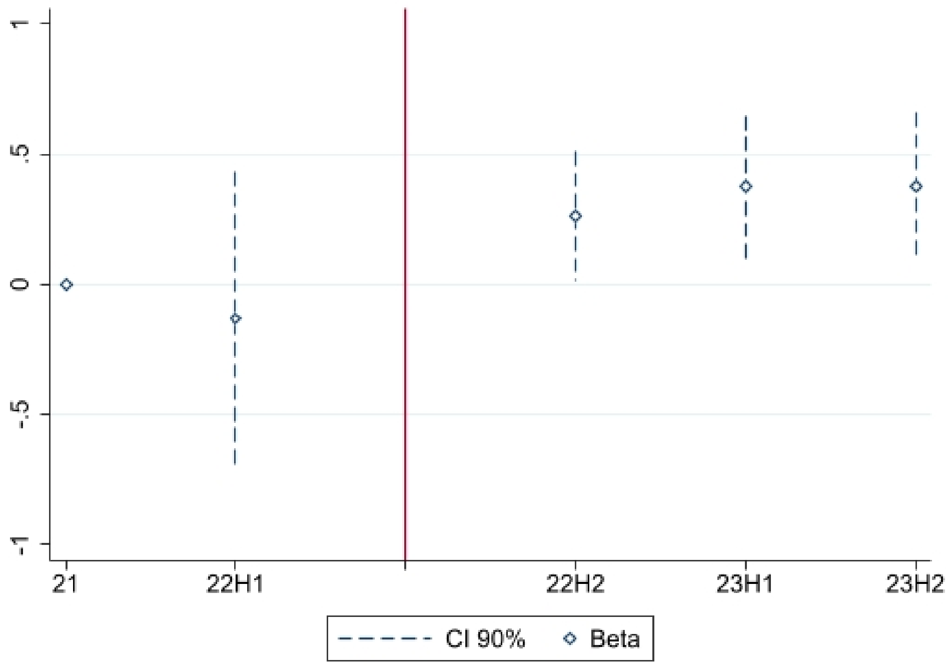

Figure 6: Time-varying analysis

This figure depicts the estimated coefficients of a variation of Equation 4 where we interact the variable $FRM_{b,p75}$ with three time dummies for the period corresponding to the monetary policy tightening (22H2, 23H1 and 23H2) and one time dummy for the semester immediately before the ECB began increasing the deposit facility rate (DFR) (22H1).The 2021 serves as the reference period for interpreting the coefficients. Bars represent the confidence interval at 90%.

4.2. Credit reallocation and firms' characteristics

4.2.1. Banks' risk taking

We next study whether the reallocation of credit towards non-financial corporations by banks that are more exposed to early mortgage repayments is linked to a risk-taking strategy (e.g., search for yield). We expand the regression analysis in Equation (4) by incorporating the firm probability of default ($\text{PD}_{f,t}$) and two additional interaction terms: $\text{Post}_t \times \text{PD}_{f,t}$ and $\text{Post}_t \times \text{PD}_{f,t} \times \text{FRM}_{b,pj}$. This will help us determine if there are differences in the credit reallocation depending on the firm riskiness following the tightening of monetary policy and whether banks with higher exposure to early repayments exhibit a distinct stance towards credit reallocation to riskier firms.

$$\begin{aligned}\Delta\text{Credit}_{f,b,t} \quad = \quad & \beta_1\text{PD}_{f,t} + \beta_2\text{Post}_t \times \text{PD}_{f,t} + \beta_3\text{Post}_t \times \text{FRM}_{b,pj} + \beta_4\text{Post}_t \times \text{PD}_{f,t} \times \text{FRM}_{b,pj} + \\ & + \Gamma\text{BankControls}_{b,t} + \Phi\text{FirmControls}_{f,t} + \alpha_{i,l,s,t} + \alpha_b + \varepsilon_{f,b,t}. \qquad (5)\end{aligned}$$

Table VIII provides the results obtained when we estimate Equation (5) using alternative definitions of the variable $\text{FRM}_{b,pj}$ depending on the thresholds used to define high-income areas. We observe that firms' risk measure is negatively associated with credit growth, indicating that banks are adhering to prudent lending policies. We do not observe any difference in lending policies during the period of monetary policy tightening compared to the period before the tightening. Moreover, in line with previous finding, we observe that banks with larger exposure to floating rate mortgages in high-income areas significantly increase the credit allocation to firms, independently of the threshold used to define them. Notably, we do not find a differential effect based on firms' level of risk. This suggests that banks are not taking on additional risk when reallocating the extra liquidity obtained from early repayments.

We aim to confirm that these lending practices are not influenced by the risk level of loan applications received by banks, regardless of their exposure to floating rate mortgages in high-income areas. While we control for demand in Equation (5), we aim to further demonstrate that the reallocation is not demand-driven. To achieve this, we use an additional dataset containing information on banks' requests for information from the Banco de España through CIRBE regarding the credit situation of potential customers who applied for new credit. These can be considered loan applications, at least for firms without previous lending relationships with a given bank. We merge the data on firm

Table VIII: Reallocation of Credit to NFC by firm risk

This table reports the estimates of Equation 5, which examines the reallocation of credit towards NFC depending on the firm riskiness. We expand the regression analysis in Equation 4 by incorporating the firm probability of default ($\mathrm{PD}_{f,t}$) and two additional interaction terms: $\mathrm{Post}_t \times \mathrm{PD}_{f,t}$ and $\mathrm{Post}_t \times \mathrm{PD}_{f,t} \times \mathrm{FRM}_{b,pj}$. The dependent variable is the semiannual growth rate in the stock of financial credit (Equation 2). The primary explanatory variable, $\mathrm{FRM}_{b,pj}$ as defined in Equation (1), measures banks' exposure to floating rate mortgages in high-income areas. Column (1) reports results using the 50^{th} percentile, while Columns (2) and (3) use the 75^{th} and 90^{th} percentiles, respectively. $Post_t$ is a dummy variable that takes value one for the period July 2022 – December 2023. Controls include bank characteristics such as ROA, distance to minimum tier 1 capital ratio, loan to deposits ratio and the logarithm of the total assets as well as firm characteristics like net ordinary income, equity to total assets and cash to total assets. The model includes industry-location-size-time (ILST) fixed effects and bank fixed effects. Standard errors, clustered at the bank and firm level, are in brackets.***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Dep. Variable		$\Delta\mathrm{Credit}_{f,b,t}$	
High-Income Area (pj)	50^{th} percentile	75^{th} percentile	90^{th} percentile
$\mathrm{PD}_{f,t}$	-0.111***	-0.111***	-0.111***
	[0.014]	[0.014]	[0.014]
$\mathrm{Post}_t \times \mathrm{PD}_{f,t}$	0.064	0.001	-0.048
	[0.069]	[0.057]	[0.043]
$\mathrm{Post}_t \times \mathrm{FRM}_{b,pj}$	0.361**	0.378***	0.568**
	[0.170]	[0.138]	[0.278]
$\mathrm{Post}_t \times \mathrm{PD}_{f,t} \times \mathrm{FRM}_{b,pj}$	-0.126	-0.010	0.327
	[0.144]	[0.196]	[0.261]
Observations	3,693,497	3,693,497	3,693,497
R-squared	0.196	0.196	0.196
Bank Controls	YES	YES	YES
Bank FE	YES	YES	YES
Firm Controls	YES	YES	YES
ILST FE	YES	YES	YES

applications with firm-level information, including the probability of default, and bank-level data. This allows us to restrict the sample to firms for which we can estimate the probability of default and to firm-bank pairs without an existing credit relationship before the applications. Next, we calculate the average probability of default for each bank in each semester based on the individual probabilities of default of the firms applying for credit. Finally, we regress this variable on our explanatory variable of interest, $\text{Post}_t \times \text{FRM}_{b,pj}$, using bank characteristics and bank fixed effects as controls, given that this analysis is conducted at the bank-semester level. The [untabulated] results indicate no differences in the risk profiles of firms applying for credit to banks, irrespective of the proportion of floating rate mortgages in high-income areas within their portfolios. This confirms that the previously presented evidence originates from a supply channel and is not influenced by variations in the riskiness of firms seeking credit from different banks.

4.2.2. Firm size

Next, we investigate whether the reallocation of credit towards firms by banks with higher exposure to early mortgage repayments is associated with firms of specific sizes. Firm size is crucial factor in determining the risk weights of bank credit exposures, which in turn determine the cost of capital of the operation. According to the European Banking Authority report published in 2022 on the 2021 credit risk benchmarking exercise, the average risk weight under the Internal Based Model (IRB) approach for banks' risk management and capital calculation for mortgages was 12%. Similarly, credit exposures to retail SME have risk weights ranging between 14.5% and 23%,[7] depending on whether the Avanced IRB or Foundation IRB approach is used. In contrast, exposures to corporate SME and corporates are significantly higher, with risk weights ranging from 38% to 54% for the corporate SME and from 45% to 57% for corporates. These differences may incentivize banks to allocate the extra liquidity accruing from early redemptions towards exposures with risk weights closer to those of mortgages, such as those for retail SME. Furthermore, besides being closer substitutes for mortgages in terms of risk weights, the average size of new loans to SMEs, particularly to micro firms, is more comparable to the average size of new mortgages ($83,700$ vs. $85,706$, respectively). Multiple credit exposures of relatively small size allows banks to maintain a diversification strategy.

We formally test the relationship between size and credit reallocation by extending our regression analysis splitting the variable of interest in Equation (4) through four interaction

[7] Retail SME is a category corresponding to SME with total exposures, including the ones of the parent and its subsidiaries, below 1 million €. SME with larger exposures are classified as corporate SME.

terms between our variable of interest ($\text{Post}_t \times \text{FRM}_{b,pj}$) and four different dummy variables denoting micro, small, medium-sized and large corporations (Micro_f, Small_f, Medium_f and Large_f, respectively) based on the European Commission definition of firm sizes:

$$\begin{aligned}\Delta\text{Credit}_{f,b,t} \;=\;& \beta_1\text{Post}_t \times \text{Micro}_f \times \text{FRM}_{b,pj} + \beta_2\text{Post}_t \times \text{Small}_f \times \text{FRM}_{b,pj} + \\ & +\beta_3\text{Post}_t \times \text{Medium}_f \times \text{FRM}_{b,pj} + \beta_4\text{Post}_t \times \text{Large}_f \times \text{FRM}_{b,pj} \\ & +\Gamma\text{BankControls}_{b,t} + \Phi\text{FirmControls}_{f,t} \\ & +\alpha_{i,l,s,t} + \alpha_b + \varepsilon_{f,b,t}. \qquad (6)\end{aligned}$$

The results presented in Table IX indicate that banks with greater exposure to floating rate mortgages in high-income areas reallocated more credit to micro firms. This finding holds true across all definitions of the explanatory variable, regardless of the percentile used to define high-income zip codes. Our evidence suggests a cascade effect, where banks reallocated more credit to SMEs, particularly to micro firms, but the extent of reallocation decreases as firm size increases, ultimately resulting in no reallocation to large corporations. This could also mean that large corporations have access to alternative financing sources, such as fixed-income securities. However, the lack of credit reallocation to medium-sized firms when high-income areas are defined using the 90^{th} percentile confirms that firm size influenced banks' lending decisions.

The capacity of banks to redirect liquidity from household mortgage repayments to corporate lending is vital for the survival of micro and small firms, which depend more heavily on bank financing. This reallocation could have contributed to support the liquidity needs of these firms during the recent period of monetary tightening.

4.3. The characteristics of the new corporate credit granted by banks more exposed to early redemptions

Previous subsections have indicated that micro firms benefited the most from the reallocation of credit and that banks did not engage in increased risk-taking. In this subsection, we delve deeper into the characteristics of credit granted by banks exposed to the shock. We construct a new panel at the contract level based on all new operations of financial credit granted from December 2020 to December 2023. The panel contains information on $155,932$ firms, $252,344$ bank-firm relations, and $2,934,577$ bank-firm-operation-time observations between December 2020 and December 2023. We propose a regression analysis considering four alternative contract characteristics as

Table IX: Reallocation of Credit to Non-Financial Corporation by Firm Size

This table reports the estimates of Equation 6, which examines the reallocation of credit towards non-financial corporations depending on their size. We expand the regression analysis in Equation 4 by splitting the variable of interest into four through the interaction between the variable ($\text{Post}_t \times \text{FRM}_{b,pj}$) and four different dummy variables denoting micro, small, medium-sized and large corporations (Micro_f, Small_f, Medium_f and Large_f, respectively) based on the European Commission definition of firm sizes. $\text{FRM}_{b,pj}$ measures banks' exposure to floating rate mortgages in high-income areas, and Post_t is a dummy variable that takes value one for the period July 2022 – December 2023. The dependent variable is the semiannual growth rate in the stock of financial credit (Equation 2. Column (1) reports the results obtained using the 50^{th} percentile of the distribution of income within a given province to define high-income zip codes, whereas Columns (2) and (3) use the 75^{th} and 90^{th} percentiles, respectively. Bank controls include bank characteristics such as ROA, distance to minimum tier 1 capital ratio, loan to deposits ratio and the logarithm of total assets. Firm controls include firm characteristics like net ordinary income, equity to total assets, and cash to total assets. The model includes industry-location-size-time (ILST) fixed effects and bank fixed effects. Standard errors, clustered at the bank and firm level, are in brackets.***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Dep. Variable		$\Delta\text{Credit}_{f,b,t}$	
High-Income Area (pj)	50^{th} percentile	75^{th} percentile	90^{th} percentile
$\text{Post}_t \times \text{FRM}_{b,pj} \times \text{Micro}_f$	0.374**	0.420***	0.686**
	[0.169]	[0.133]	[0.270]
$\text{Post}_t \times \text{FRM}_{b,pj} \times \text{Small}_f$	0.353*	0.373**	0.547*
	[0.187]	[0.156]	[0.298]
$\text{Post}_t \times \text{FRM}_{b,pj} \times \text{Medium}_f$	0.345*	0.313*	0.424
	[0.183]	[0.168]	[0.320]
$\text{Post}_t \times \text{FRM}_{b,pj} \times \text{Large}_f$	0.252	0.193	0.211
	[0.161]	[0.160]	[0.302]
Observations	3,693,497	3,693,497	3,693,497
R-squared	0.196	0.196	0.196
Bank Controls	YES	YES	YES
Bank FE	YES	YES	YES
Firm Controls	YES	YES	YES
ILST FE	YES	YES	YES

dependent variables: interest rate (in %), maturity at origination (logarithm of the maturity in months), size (logarithm of the total amount granted in euros), and the presence of collateral (represented as a dummy variable):

$$\begin{aligned}\text{Characteristic}_{l,f,b,t} \quad &= \quad \beta_1 \text{Post}_t \times \text{FRM}_{b,pj} + \Gamma \text{BankControls}_{b,t} + \Phi \text{FirmControls}_{f,t} \\ &\quad + \alpha_{i,l,s,t} + \alpha_b + \alpha_c + \varepsilon_{l,f,b,t}. \qquad (7)\end{aligned}$$

As in previous regression analyses, the explanatory variable of interest is the interaction between banks' exposure to floating-rate mortgages in high-income areas and a dummy variable that equals one for the period from July 2022 to December 2023 ($\text{Post}_t \times \text{FRM}_{b,pj}$). We also use the same set of bank and firm controls, along with industry-location-size-time fixed effects and bank fixed effects. Since this regression is conducted at the loan level, we include fixed effects for the type of contract (α_c). These contract types include standard loans (75% of the operations), credit accounts (20%), and other residual contract types (5%).[8]

The results presented in Table X align with the findings from previous sections. Confirming the absence of differential risk-taking behavior, we observe that banks with higher exposure to early redemptions offer interest rates similar to those with lower exposure. Additionally, there are no differences in the maturity of the contracts. Consistent with the larger supply of credit to micro firms, we find that the average loan granted by banks more exposed to floating rate mortgages in high-income areas during the monetary policy tightening period is smaller. Finally, the credit granted by these banks during the rate-hike period is more likely to be collateralized. The evidence regarding the size and collateral of the loans supports the previous findings and their interpretation, suggesting that banks are willing to offer loans that are substitutes for mortgages. This lending activity is consistent with banks' efforts to diversify their credit portfolio to non-financial corporations and optimize risk weights through the demand for collateral in new credit relationships.

[8] This residual category of loan contracts includes loans with staged disbursements, overdrafts, or financial leasing.

Table X: Loan Characteristics

This table presents the estimates of Equation (7), which analyzes the characteristics of new credit allocated to non-financial corporations. In Column (1), the dependent variable is the interest rate at origination (in %). Column (2) uses the maturity at origination (logarithm of the maturity in months). Column (3) reports the results using the size (logarithm of the total amount granted in euros). In Column (4), the dependent variable is a dummy variable that equals one if there is collateral and zero otherwise. The primary explanatory variable is the interaction between banks' exposure to floating rate mortgages in high-income areas (using the 75^{th} percentile) and a dummy variable that equals one for the period from July 2022 to December 2023 ($\text{Post}_t \times \text{FRM}_{b,p75}$). Bank controls include bank characteristics such as ROA, distance to minimum Tier 1 capital ratio, loan to deposits ratio, and the logarithm of the total assets. Firm controls include firm characteristics like net ordinary income, equity to total assets, and cash to total assets. The model includes industry-location-size-time (ILST) fixed effects, bank fixed effects, and contract-type fixed effects. Standard errors, clustered at the bank and firm level, are in brackets.***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Variable	(1) Interest rates	(2) Log(Maturity)	(3) Log(Amount)	(4) Collateral
$\text{Post}_t \times \text{FRM}_{b,p75}$	-1.349	-0.218	-1.069**	0.075***
	[1.100]	[0.261]	[0.528]	[0.024]
Observations	2,934,577	2,934,577	2,934,577	2,934,577
R-squared	0.960	0.756	0.740	0.869
Bank Controls	YES	YES	YES	YES
Firm Controls	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
ILST FE	YES	YES	YES	YES

5. The role of bank liquidity buffers

We investigate how banks reallocate credit, particularly examining whether liquidity constraints influence this reallocation. Our hypothesis posits that banks with a lower Liquidity Coverage Ratio (LCR), indicating higher liquidity constraints, are more likely to reallocate credit than banks with a higher LCR, which were better positioned to extend credit even before facing mortgage redemptions. The LCR has been mandatory in the EU since October 1, 2015, with full implementation at a minimum of 100% effective from January 2018. Due to confidentiality, we do not disclose specific LCR statistics, but according to the 2024 Banco de España Financial Stability Report, the overall LCR of Spanish banks was approximately 200% in December 2021. Banks operate significantly above the minimum regulatory thresholds to avoid potential negative market reactions and regulators' imposition of corrective measures if the minimum is breached. According to the BCBS (2021), banks manage their LCR to internal targets or other thresholds well above regulatory minima as part of their liquidity risk management frameworks.

To verify this hypothesis, we extend the regression analysis in Equation 4 by incorporating interaction terms that involve a dummy variable representing the bank's liquidity level ($\text{HLCR}_{t,b}$). This dummy variable equals one if a given bank has a LCR above the 33^{th} percentile of the distribution of the 65 banks of our sample as of December 2020. This dummy variable is interacted with our variable of interest ($\text{Post}_t \times \text{FRM}_{b,pj}$).[9]

$$\begin{aligned} \Delta\text{Credit}_{f,b,t} \quad = \quad & \beta_1 \text{Post}_t \times \text{FRM}_{b,pj} + \beta_2 \text{Post}_t \times \text{FRM}_{b,pj} \times \text{HLCR}_{t,b} + \beta_3 \text{Post}_t \times \text{HLCR}_b \\ & + \Gamma \text{BankControls}_{b,t} + \Phi \text{FirmControls}_{f,t} + \alpha_{i,l,s,t} + \alpha_b + \varepsilon_{f,b,t}. \end{aligned} \tag{8}$$

The results are reported in Table XI. As in previous tables, we distinguish three thresholds of zip codes' income to define high-income areas, using the 50^{th}, 75^{th}, and 90^{th} percentiles of the income distribution at the province level. The results for each threshold are presented in columns (1), (2), and (3), respectively. The coefficient β_1 estimates the sensitivity of credit supply by banks with low LCR to non-financial corporations based on their exposure to floating-rate mortgages in high-income areas. The results from the three columns indicate that banks with low LCR extend more credit as their exposure to early redemptions increases. Conversely, the coefficient β_2 represents the differential effect on

[9] Note that we cannot estimate the variable indicating whether the bank has a high LCR due to the use of bank fixed effects.

credit supply for banks with high LCR. We observe that, likely due to their high pre-existing liquidity buffers, these banks reallocate much less credit than banks with low LCR. The linear combination of coefficients β_1 and β_2, reported at the bottom of the table, is close to zero and not statistically significant in all columns, suggesting that banks with high LCR do not reallocate credit to non-financial corporations despite being potentially highly exposed to mortgage redemptions. This evidence confirms that our main results are driven by banks' differential exposure to the shock.

6. Concluding remarks

We shed light on a previously underexplored interaction between the cash flow and bank lending channels of monetary policy transmission. We document that unexpected monetary policy tightening, by inducing early mortgage repayments among wealthier households with floating-rate debt, generates a liquidity shock for mortgage-issuing banks. This shock, however, does not lead to an expansion in consumer credit or new mortgage lending but is instead reallocated towards non-financial corporations. Notably, the firms benefiting from this reallocation tend to resemble household borrowers for risk profile and size, suggesting that banks adjust their credit supply patterns based on pre-existing exposure to household credit markets. These results contribute to the existing debate on the bank lending channel by demonstrating that changes in household balance sheets, rather than just bank funding costs, play a crucial role in shaping credit supply responses to monetary policy shifts.

Beyond its contribution to macro-finance and banking literature, our study has important policy implications. The heterogeneous impact of monetary tightening on bank lending behavior suggests that central banks should consider the composition of banks' mortgage portfolios when assessing policy transmission. If credit reallocation occurs predominantly towards small firms with risk characteristics similar to household borrowers, monetary policy may have unintended distributional consequences for firm financing. Future research could explore how these dynamics evolve over different phases of the business cycle and whether similar mechanisms operate in financial systems with lower reliance on floating-rate debt. More broadly, our findings emphasize the importance of integrating household finance dynamics into models of bank credit supply, offering a richer understanding of how monetary policy shapes economic activity.

Table XI: Role of Liquidity Buffers

This table presents the estimates of Equation 8, which investigates the reallocation of credit towards NFC based on the bank's liquidity constraints. We expand the regression analysis in Equation 4 by including several interaction terms involving a dummy variable that equals one if a bank's Liquidity Coverage Ratio (LCR) is above the 33^{rd} percentile of the distribution of the 65 banks in our sample as of December 2020, and zero otherwise (HLCR_b). More specifically this variable is included through two interaction terms: $\text{Post}_t \times \text{HLCR}_b$ and $\text{Post}_t \times \text{FRM}_{b,pj} \times \text{HLCR}_b$. The dependent variable is the semiannual growth rate in the stock of financial credit (Equation 2). The explanatory variable $\text{FRM}_{b,pj}$, defined in Equation (1), measures banks' exposure to floating rate mortgages in high-income areas. $Post_t$ is a dummy variable that takes value one for the period July 2022 – December 2023. Column (1) reports results using the 50^{th} percentile, while Columns (2) and (3) use the 75^{th} and 90^{th} percentiles, respectively. Controls include bank characteristics such as ROA, distance to minimum tier 1 capital ratio, loan to deposits ratio and the logarithm of the total assets as well as firm characteristics like net ordinary income, equity to total assets and cash to total assets. The model includes industry-location-size-time (ILST) fixed effects and bank fixed effects. The bottom of the table reports the linear combination of the sum of the $\text{Post}_t \times \text{FRM}_{b,pj}$ and $\text{Post}_t \times \text{FRM}_{b,pj} \times \text{HLCR}_b$ coefficients (β_1 and β_2, respectively). Standard errors, are clustered at the bank and firm level, are in brackets.***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Dep Variable		$\Delta\text{Credit}_{f,b,t}$	
High-Income Area (pj)	50^{th} percentile	75^{th} percentile	90^{th} percentile
$\text{Post}_t \times \text{FRM}_{b,pj}$	0.432*	0.542**	1.025**
	[0.255]	[0.219]	[0.408]
$\text{Post}_t \times \text{FRM}_{b,pj} \times \text{HLCR}_{t,b}$	-0.381	-0.517*	-1.068**
	[0.332]	[0.275]	[0.462]
$\text{Post}_t \times \text{HLCR}_b$	0.275	0.232**	0.233***
	[0.189]	[0.097]	[0.083]
Observations	3,693,497	3,693,497	3,693,497
R-squared	0.196	0.196	0.196
Bank Characteristics	YES	YES	YES
Firm Characteristics	YES	YES	YES
Bank FE	YES	YES	YES
ILST FE	YES	YES	YES
$\beta_1 + \beta_2$	0.050	0.025	-0.042
	[0.114]	[0.102]	[0.153]

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A. Tables

Table A1: Floating-rate mortgages in high-income areas and bank characteristics
This table examines the relationship between banks' exposure to floating-rate mortgages in high-income areas and various bank characteristics. The dependent variable is the share of floating-rate mortgages held by each bank in high-income zip codes, defined as those with households' income above the 75^{th} percentile of the distribution ($FRM_{b,p75}$) as of December 2020. Explanatory variables include indicators of solvency (distance to minimum Tier 1 capital ratio), size (logarithm of the total assets), business model (loan to deposits ratio), and profitability (ROA) as of December 2020. Robust standard errors are in brackets.***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)
Dep Variable	$FRM_{b,p75}$
Distance TIER 1 Capital Ratio	0.002
	[0.002]
Ln(Total Assets)	0.015***
	[0.003]
Loan to Deposits Ratio	-0.002
	[0.001]
ROA (%)	0.004
	[0.004]
Observations	65
R-squared	0.600

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