Monetary Policy Transmission Through Adjustable-Rate Mortgages in the Euro Area*

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Abstract

This paper studies the role of adjustable-rate mortgages (ARMs) in monetary policy transmission within the Euro Area. Conventional wisdom holds that ARMs are relevant *per se*. This study finds that the presence of liquidity-constrained households strongly influences their impact. Using Euro Area survey data, I document that transmission is stronger in countries that exhibit both high ARM shares *and* sizable shares of liquidity-constrained households. To interpret this finding, I develop a heterogeneous-agent model featuring: (i) heterogeneity in marginal propensities to consume (MPCs), (ii) agents making both housing and mortgage choices, and (iii) a fraction of households with ARMs. In the model, MPCs determine the extent to which changes in mortgage payments translate into changes in consumption, making ARMs an important transmission vehicle only when paired with high MPCs. These results highlight that accounting for household heterogeneity in MPCs is essential to assess the strength of transmission through ARMs.

JEL classification: D14, E21, E52, E58
Keywords: Adjustable-rate mortgages, Euro Area, household heterogeneity, marginal propensity to consume, monetary policy

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1 Introduction

The transmission of monetary policy varies considerably across Euro Area economies (Calza, Monacelli and Stracca, 2013; Slacalek, Tristani and Violante, 2020; Corsetti, Duarte and Mann, 2022; Lenza and Slacalek, 2024). Spanish consumption, for instance, is three times more responsive to monetary policy shocks than German consumption. The disparity is even more pronounced between Ireland and France, where Irish consumption reacts up to ten times more than French consumption.[1] These differences pose a challenge to the European Central Bank, as the effects of its policy measures differ widely among member states. To address these challenges effectively, it is critical to understand the underlying reasons driving this heterogeneity.

This paper studies the transmission of monetary policy through mortgages in the Euro Area, focusing on the role played by the share of adjustable-rate mortgages (ARMs). Mortgages are a crucial component of household balance sheets, accounting for approximately 75% of total household debt in the Euro Area.[2] Moreover, ARMs account for approximately 48% of total mortgages in the Euro Area, making mortgage interest payments very sensitive to changes in monetary policy.[3] Consequently, differences in mortgage characteristics across Euro Area economies are likely to play an important role in shaping the observed heterogeneity in transmission.

The existing literature has explored how variations in the prevalence of ARMs influence monetary pass-through, emphasizing that higher ARM shares lead to stronger transmission in the Euro Area (Calza, Monacelli and Stracca, 2013; Pica, 2021; Corsetti, Duarte and Mann, 2022). This paper makes two contributions. First, I empirically document that the presence of liquidity-constrained households strongly influences the strength of transmission through ARMs. Using Euro Area survey data, I show that ARMs are important for transmission primarily when matched with a high fraction of liquidity-constrained households. Second, I develop a quantitative heterogeneous-agent model to rationalize this finding. In the model, a larger fraction of liquidity-constrained households implies a higher marginal propensity to consume (MPC) in the economy. After a recessionary monetary policy shock, households with ARMs experience increased mort-

[1]Figure 2 shows the estimated peak consumption effects of a contractionary monetary policy shock. Appendix B.1 displays complete IRFs estimated using equation (1).

[2]This figure uses data from the ECB Distributional Wealth Accounts, and it refers to the average ratio of mortgages over total liabilities of Euro Area households during the period 2012-2018.

[3]This figure uses data from the second wave of the Eurosystem Household Finance and Consumption Survey, computing the fraction of ARMs within outstanding mortgages in the Euro Area.

gage payments. The impact that these payments have on consumption critically depends on the MPC of the affected households, with higher MPC households adjusting their consumption more sharply. As a result, ARMs substantially amplify monetary transmission only when paired with high marginal propensities to consume (MPCs), consistent with the empirical evidence. By calibrating the model to Euro Area economies, I find that it captures 46% of the observed differences in transmission across these countries.

In the first part of the paper, I analyze the empirical relationship between the strength of monetary pass-through and the share of ARMs, investigating the influence that MPCs have on this relationship. Due to the lack of MPC estimates for individual Euro Area countries, I proxy each economy's MPC with its fraction of households that are hand-to-mouth (HtM).[4] The proxy is constructed using data from the Eurosystem Household Finance and Consumption Survey, in which households are classified as HtM following the methodology introduced by Kaplan, Violante and Weidner (2014). Since HtM households are characterized by limited liquid savings relative to their income, HtM shares measure the fraction of liquidity-constrained households in each economy.

The empirical analysis proceeds in two steps. First, I use local projections to estimate the response of individual countries to a contractionary monetary policy shock. I proxy the strength of transmission in each country with their peak consumption responses and then correlate these with: (i) the share of ARMs, and (ii) the share of agents that are both HtM and have ARMs.[5] Two key findings emerge. First, consistent with findings in Corsetti, Duarte and Mann (2022), transmission is stronger in countries with higher ARM shares. Further, the correlation is stronger where the prevalence of agents that are both HtM and have ARMs is larger, providing initial evidence of ARMs being a more effective transmission vehicle when paired with liquidity-constrained households.

Second, I directly incorporate ARMs and their interaction with HtM shares into a regression to estimate their correlations with the strength of monetary transmission. Using panel local projections, I find that transmission is particularly strong when a high share of ARMs is matched with a high share of HtM agents: the interaction effect is as large as the individual effect of ARMs and is statistically significant. This result indicates that in Euro Area economies with a large share of liquidity-constrained households, the impact of ARMs on transmission is twice as strong as in economies with low shares

[4] Kaplan, Violante and Weidner (2014) show that HtM households have significantly larger MPCs than non-HtM households, making HtM shares a good proxy for MPCs.

[5] While my baseline results proxy the strength of transmission with the peak consumption response, in Appendix B.3 I show that the results are robust to using average responses as proxies.

of constrained households. This finding highlights that HtM households play a significant role in shaping how ARMs influence transmission, and suggests that a high share of liquidity-constrained households is an important condition for ARMs to amplify monetary pass-through.

Overall, the empirical evidence establishes that the interaction between the shares of ARMs and HtM households is positively correlated with the strength of monetary policy transmission in the Euro Area. Motivated by this empirical fact, the second part of the paper develops a quantitative heterogeneous-agent model that accommodates different levels of ARMs and MPCs. The model is used to: (i) rationalize the empirical finding, (ii) study the mechanism through which ARMs and MPCs shape the transmission of monetary policy through mortgages, and (iii) quantify the extent to which it can account for the observed cross-country differences in transmission.

The model has three key features. First, households face idiosyncratic uncertainty, leading to income heterogeneity. This results in a distribution of MPCs across households, which allows me to study monetary transmission in economies with different MPC levels. Second, households make decisions regarding the size of their housing stock and the amount of mortgage they want to take on. This allows the model to accommodate transmission through the mortgage channel. Third, the model distinguishes between households with ARMs and households with fixed-rate mortgages (FRMs). The former see their mortgage payments fluctuate following changes in monetary policy, while the latter do not experience payment fluctuations. This distinction allows me to use the model to analyze how different ARM shares influence the strength of monetary policy transmission.

The core intuition from the model on how ARMs and MPCs interact to shape monetary policy transmission through mortgages is as follows. Households experience idiosyncratic productivity shocks, leading to income heterogeneity that affects both their MPCs and their mortgage choices: poorer households have higher MPCs and tend to opt for mortgages with higher loan-to-value ratios. When a monetary policy shock occurs, the mortgage payments of households with ARMs are immediately impacted due to the swift pass-through of short-term interest rates to mortgage rates, which affects the households' available resources for consumption. Wealthier households, whose mortgage payments constitute a small fraction of their overall income, barely change their consumption choices. In contrast, poorer households, which have higher MPCs and more burdensome mortgage payments, need to make significant adjustments. As a result, powerful transmission through mortgages requires: (i) a high fraction of households with ARMs, as they experience changes in mortgage payments, and (ii) a high prevalence of high-MPC households, as they make larger consumption adjustments. This mechanism rationalizes the empirical relation between the strength of monetary transmission and the interaction between ARMs and liquidity-constrained households highlighted in the first part of the paper.

I calibrate the model to the Spanish economy, following other studies that have analyzed monetary policy transmission through mortgages in the Euro Area (Corsetti, Duarte and Mann, 2022). The model accurately mirrors the distributions of liquid assets and housing wealth in the population. It also reproduces the empirical hump-shaped profile of the distribution of mortgage debt, where the bottom and top quartiles of the liquid asset distribution hold less mortgage debt than the middle quartiles. Importantly, in the model as in the data, lower-income households carry higher levels of debt relative to their resources: the ratio between mortgage debt and total wealth displays a decreasing pattern along the liquid asset distribution.

Using the Spanish calibration, I assess the impact of ARMs and MPCs on monetary policy transmission through counterfactual exercises. In the first exercise, I calibrate a counterfactual economy with an MPC half that of Spain and compare transmission under two different ARM rates: 20% and 80%. Following an expansionary monetary policy shock, the peak consumption response increases by 5.6% in the low-MPC economy as the ARM share rises from 20% to 80%. In the Spanish economy, the response increases by 39%. Consistent with the empirical evidence, these findings suggest a significant interaction between ARMs and MPCs: as the MPC level increases, the effect of increasing the share of ARMs on monetary policy transmission becomes higher.

Afterwards, I use the model to investigate how the distribution of ARMs across the population affects the strength of monetary policy transmission. Holding the economy-wide MPC level and ARM share constant, I modify the distribution of ARMs: in one scenario, ARMs are concentrated among lower-income (high-MPC) households, while in the other, they are concentrated among higher-income (low-MPC) households. The results show that monetary policy transmission is significantly stronger when ARMs are concentrated among lower-income households, suggesting that the distribution of ARMs across income levels is an important variable to take into account in order to anticipate the effects of monetary policy interventions.

Next, I evaluate how much of the empirical cross-country heterogeneity in transmission can be captured by a framework that isolates transmission through ARMs. In the model, this transmission channel depends on two key ingredients: the share of ARMs in the economy and the level of household MPCs. By varying these two inputs to match Euro Area data, the model reproduces 46% of the overall differences in transmission relative to Spain. Of this, 9% is accounted for by differences in ARM prevalence, 26% by differences in MPCs, and 11% by their interaction. Given the prominent role played by MPCs, these findings highlight the importance of accounting for household income heterogeneity when evaluating transmission through ARMs in the Euro Area.

Finally, I use the model to assess the welfare effects of contractionary monetary policy shocks on the economy as a whole and across different income groups. My results indicate that welfare declines are more severe in economies with higher ARM shares and greater MPC levels, as these conditions lead to larger consumption drops. Moreover, the adverse effects are disproportionately felt by households at the lower end of the income distribution, who experience larger welfare losses compared to higher-income households due to their high MPCs. These findings suggest that, during periods of prolonged interest rate hikes, policies that alleviate the burden of mortgage payments for lower-income families can be particularly effective in mitigating welfare losses. More broadly, the analysis reveals a tension: in economies with high ARM shares and high MPCs, monetary policy is highly effective at reducing aggregate consumption, but it does so by imposing the largest welfare costs on financially vulnerable households.

Related literature This study contributes to the literature studying how the efficacy of monetary policy is influenced by mortgage market characteristics by showing, both empirically and quantitatively, that the interaction between ARMs and MPCs is an important amplifier of monetary transmission.

From an empirical standpoint, the significance of housing institutions for monetary policy transmission has been investigated by studies such as Slacalek, Tristani and Violante (2020), Cloyne, Ferreira and Surico (2020), Flodén et al. (2021), Corsetti, Duarte and Mann (2022), Cumming and Hubert (2023), Battistini et al. (2025), and De Stefani and Mano (2025). The findings in Di Maggio et al. (2017) are particularly relevant for this study: in the United States, interest rate transmission to consumption is more pronounced in areas with a higher proportion of ARMs and low-income households. Caspi, Eshel and Segev (2024) exploit an exogenous variation in the exposure to ARMs due to a regulatory shift in Israel and unveil a similar pattern: households with a higher fraction of their mortgage being subject to adjustable rates decrease their consumption after a monetary policy tightening, with this effect being predominant across lower-income households.[6] Pica (2021) and Almgren et al. (2022) document similar findings for the Euro Area. Pica (2021) shows stronger monetary policy transmission in those Euro Area countries where ARMs are more widespread, while Almgren et al. (2022) find that the impact of monetary policy shocks is positively correlated with the proportion of HtM households in the economy. This paper contributes to this literature by showing that the interaction between the share of ARMs and the fraction of HtM households matters for the strength of monetary pass-through in the Euro Area, with transmission being particularly pronounced when both variables are elevated.

From a theoretical standpoint, monetary policy transmission through housing and mortgage markets has been explored extensively. Important contributions include Iacoviello (2005), Calza, Monacelli and Stracca (2013), Hedlund et al. (2016), Garriga, Kydland and Šustek (2017, 2021), and Greenwald (2018). Among these contributions, Pica (2021) and Corsetti, Duarte and Mann (2022) develop representative-agent open-economy New-Keynesian models to show that, within the Euro Area, stronger transmission takes place where homeownership rates and ARM shares are higher. This paper contributes to this literature by developing a heterogeneous-agent model that allows explorations of the role of MPCs in transmission through ARMs. Consistent with the empirical evidence, the model predicts that the ability of ARMs to amplify transmission depends on the level of the MPC in the economy, with these being particularly effective when MPCs are high.

The model developed in this paper builds on studies that incorporate heterogeneous agents into housing models, such as Beraja et al. (2019), Wong (2020), McKay and Wieland (2021), Eichenbaum, Rebelo and Wong (2022), and Berger et al. (2023).[7] In particular, the household block of the model used in this paper is based on Eichenbaum, Rebelo and Wong (2022), with two important distinctions. First, given the prominent role of ARMs in the Euro Area, the model incorporates this mortgage feature and disregards the refinancing option, which is much more widespread in the United States. Second, unlike Eichenbaum, Rebelo and Wong (2022), which uses an overlapping generations (OLG) model, this paper adopts a more conventional infinitely-lived household framework.

[6]Note that mortgage features in Israel are such that households have a *fraction* of their overall mortgage debt which is subject to adjustable rates.

[7]Other important studies with heterogeneous agents investigating housing and mortgage institutions, albeit with lower emphasis on monetary policy transmission, are: Kaplan, Mitman and Violante (2020), Berger et al. (2018), and Guerrieri, Lorenzoni and Prato (2020).

Structure of the paper The rest of the paper is organized as follows. Section 2 presents the empirical findings on the effects of ARMs and HtM households on monetary policy transmission. Section 3 describes the model, its calibration, and empirical fit. Section 4 analyzes the mechanism by which ARMs and MPCs shape the transmission of monetary policy through mortgages and presents the quantitative results. Finally, Section 5 concludes.

2 Motivating facts

This section studies the empirical relationship between the strength of monetary pass-through and the share of ARMs across Euro Area countries, with a focus on how MPCs influence this relationship.

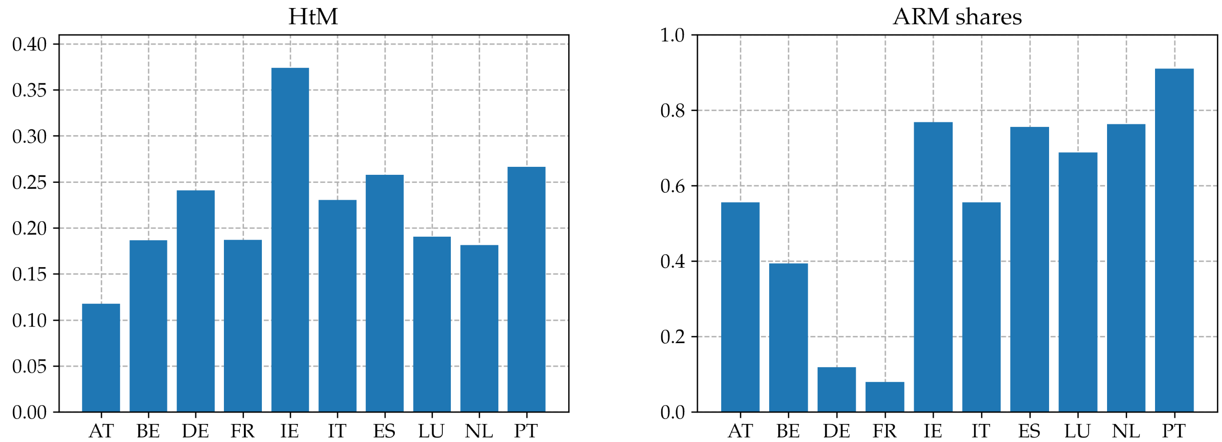
Since country-level MPC estimates are unavailable, they are proxied by the share of HtM households in each economy. I construct the proxy classifying households as HtM following the methodology by Kaplan, Violante and Weidner (2014), as detailed in Appendix B.2. HtM households are characterized by low liquid savings relative to income, and their prevalence offers a measure of the fraction of liquidity-constrained households in the economy. This is a suitable proxy for MPCs because Kaplan, Violante and Weidner (2014) show that HtM households exhibit MPCs more than twice as high as those of non-HtM households.

The main source of data is the second wave of the Eurosystem Household Finance and Consumption Survey (HFCS). By providing harmonized information on the share of ARMs and HtM households across several European economies, the HFCS allows me to leverage cross-country variation in these two variables to estimate their relationship with the potency of monetary pass-through. I compute the share of ARMs as the fraction of outstanding mortgages with an adjustable rate, based on household-level responses.[8] Figure 1 shows the cross-country variation in HtM and ARM shares in the Euro Area.

The empirical analysis proceeds in two steps. First, following the approach in Almgren et al. (2022), I document unconditional correlations between the strength of monetary policy transmission and the prevalence of ARMs and HtM households. I show that transmission is most strongly correlated with the share of households who are both HtM and have an ARM, namely those directly exposed to interest rate changes and with lim-

[8]Appendices B.3 and B.5 present robustness exercises using alternative definitions of ARM prevalence and data from other HFCS waves.

Figure 1: Shares of HtM households and ARMs in the data



Notes: The left panel shows the fraction of HtM households in Euro Area countries. The right panel displays the shares of ARMs across Euro Area countries. The source of the data is the HFCS.

ited ability to smooth consumption.

Second, I estimate a panel local projection regression that directly tests whether the interaction between HtM and ARM shares amplifies monetary policy transmission. By exploiting cross-country differences in these shares, I show that the strength of transmission is significantly higher in economies where both are elevated.[9]

Overall, the empirical evidence presented in this section highlights a positive correlation between the interaction of ARMs and HtM households and the strength of monetary policy transmission across Euro Area countries, suggesting that ARMs and MPCs interact to shape the strength of monetary policy pass-through.

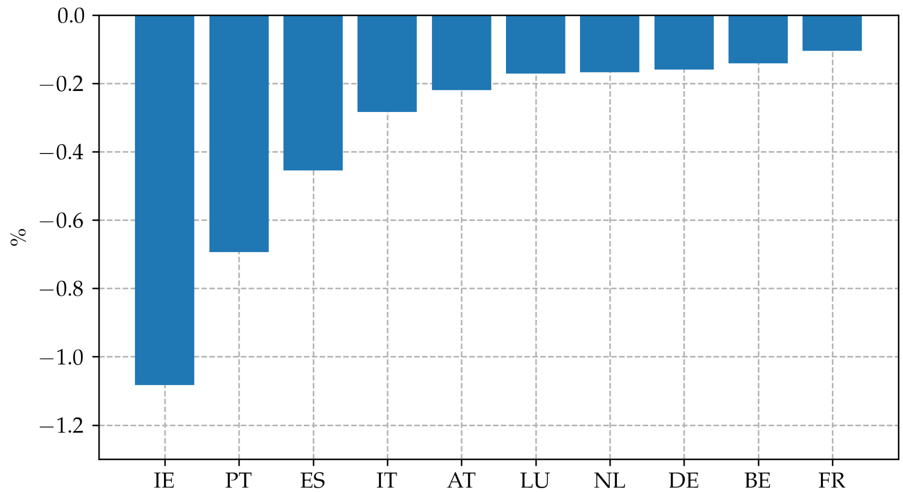
2.1 Unconditional correlations

My analysis uses data from the following Euro Area countries: Austria, Belgium, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Spain.[10] The sample covers the period 1999Q1–2019Q4, ending before the Covid-19 pandemic. For each country c in the sample, my goal is to estimate the strength of monetary policy pass-through across Euro Area countries. To do so, I estimate the response of consumption

[9]To address concerns about potential unobserved country-level confounders, Appendix B.6 presents a robustness exercise based on time-series variation within a single country: Italy.

[10]These represent ten of the eleven early adopters of the Euro. Finland, the eleventh, is excluded from the main analysis due to the lack of data on its ARM share in the HFCS.

Figure 2: Maximum effect of a contractionary monetary policy shock on consumption



Notes: Responses to a one standard deviation contractionary monetary policy shock. Each bar represents the maximum response of consumption within a 12-quarter period after the shock estimated using equation (1).

to monetary policy shocks using local projections (Jordà, 2005). Specifically, I run the following regression:

$$y^c_{t+h} = \alpha^{h,c} + \beta^{h,c}\epsilon^{MP}_t + \sum_{j=1}^{p} \Gamma^{h,c}_j X_{t-j} + u^c_{t+h}, \qquad h = 0, 1, 2, \ldots \tag{1}$$

where y^c is the logarithm of consumption in country c, ϵ^{MP} is the monetary policy shock series by Jarociński and Karadi (2020), and X is a set of lagged controls. I set $p = 2$ in the baseline. X includes two lags of the dependent variable, the monetary policy shock, country-level GDP and CPI, and Euro Area GDP, CPI, and the short-term interest rate.[11] The coefficient of interest, $\beta^{h,c}$, captures the response of consumption to the monetary policy shock at horizon h.[12]

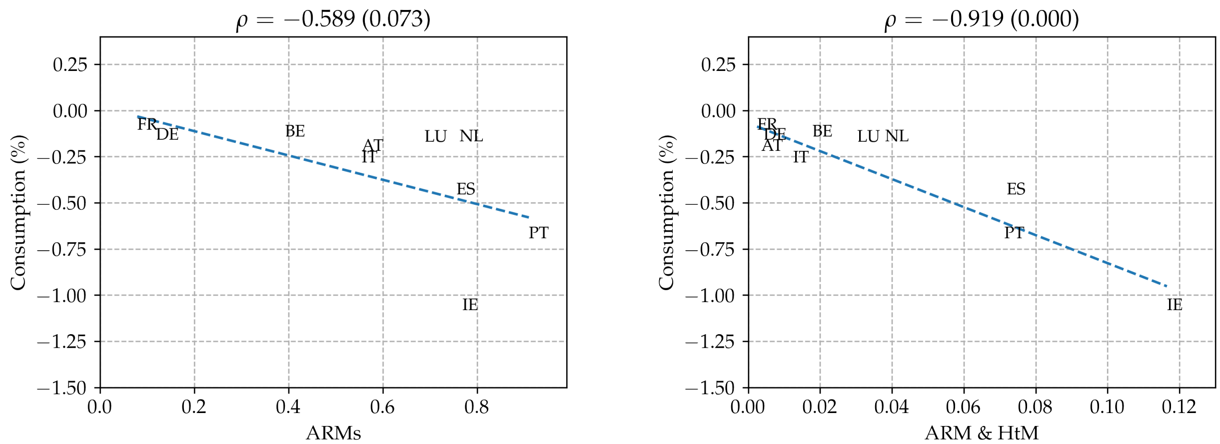
Figure 2 displays the peak consumption response within 12 quarters following a contractionary shock, which I use as a proxy for the strength of monetary policy transmission. As documented in earlier work (e.g. Corsetti et al., 2022; Almgren et al., 2022), the figure shows that transmission is highly heterogeneous across Euro Area countries.

Figure 3 explores how these differences in transmission relate to the prevalence of ARMs and HtM households. The left panel shows a strong negative correlation between

[11] Appendix A provides full details on the data sources used.

[12] Impulse responses for all countries are shown in Appendix B.1.

Figure 3: Correlation between the response of consumption, ARMs, and the share of HtM households with ARMs



Notes: The y-axes show the peak responses of consumption to a one standard deviation contractionary monetary policy shock in each Euro Area country, estimated using equation (1). The x-axis of the left panel is the share of outstanding ARMs in each Euro Area country in the HFCS; the x-axis of the right panel is the share of households in the population who are both HtM and have an ARM in the HFCS. On top of each chart I show ρ, the correlation coefficient, together with its p-value in parenthesis.

the peak consumption response and the ARM share ($\rho = -0.589$, $p < 0.10$), consistent with Pica (2021). The right panel shows that the correlation is even stronger when focusing on the share of households who are both HtM and have an ARM ($\rho = -0.919$, $p < 0.01$).[13] This group is directly exposed to interest rate changes and has limited ability to smooth consumption, which may help explain the stronger observed correlation and points to a potential interaction between rate exposure and household liquidity constraints in amplifying transmission.

These results suggest that the ability of ARMs to amplify monetary pass-through can be influenced by the presence of liquidity-constrained households. Accordingly, I explore this interaction more formally in the next section using panel regressions that control for a range of economic variables.

[13] Appendix B.3 shows that the results are robust to using the average response instead of the peak, as well as to alternative definitions of ARM shares.

2.2 Evidence from panel local projections

In my second exercise, I advance the analysis by directly estimating the effects of the interaction between ARMs and HtM households on the strength of monetary policy transmission. Unlike the first analysis, which focused on unconditional correlations, this specification controls for a range of macroeconomic variables. I estimate a fixed-effects panel local projection regression using quarterly data from 1999Q1 to 2019Q4 for the same Euro Area countries as before.[14] The estimated regression is:

$$\begin{aligned} y^c_{t+h} =& \beta_0^{h,c} + \beta_1^h \epsilon_t^{MP} + \beta_2^h \epsilon_t^{MP} ARM^c + \beta_3^h \epsilon_t^{MP} ARM^c HtM^c + \\ &+ \beta_4^h \epsilon_t^{MP} HtM^c + \Gamma^h X^c + u^c_{t+h}, \qquad h = 0, 1, 2, \ldots \end{aligned} \tag{2}$$

where y^c is the logarithm of consumption in country c, ϵ_t^{MP} is the monetary policy shock from Jarociński and Karadi (2020), ARM^c and HtM^c denote, respectively, the standardized shares of ARMs and HtM households in country c, and X^c includes a set of lagged control variables. These include two lags of the dependent variable, the monetary policy shock, GDP and CPI in country c, and Euro Area GDP, CPI, and the short-term interest rate.[15] The key coefficient of interest is β_3^h, which captures whether the interaction between ARM and HtM shares amplifies the transmission of monetary policy shocks.

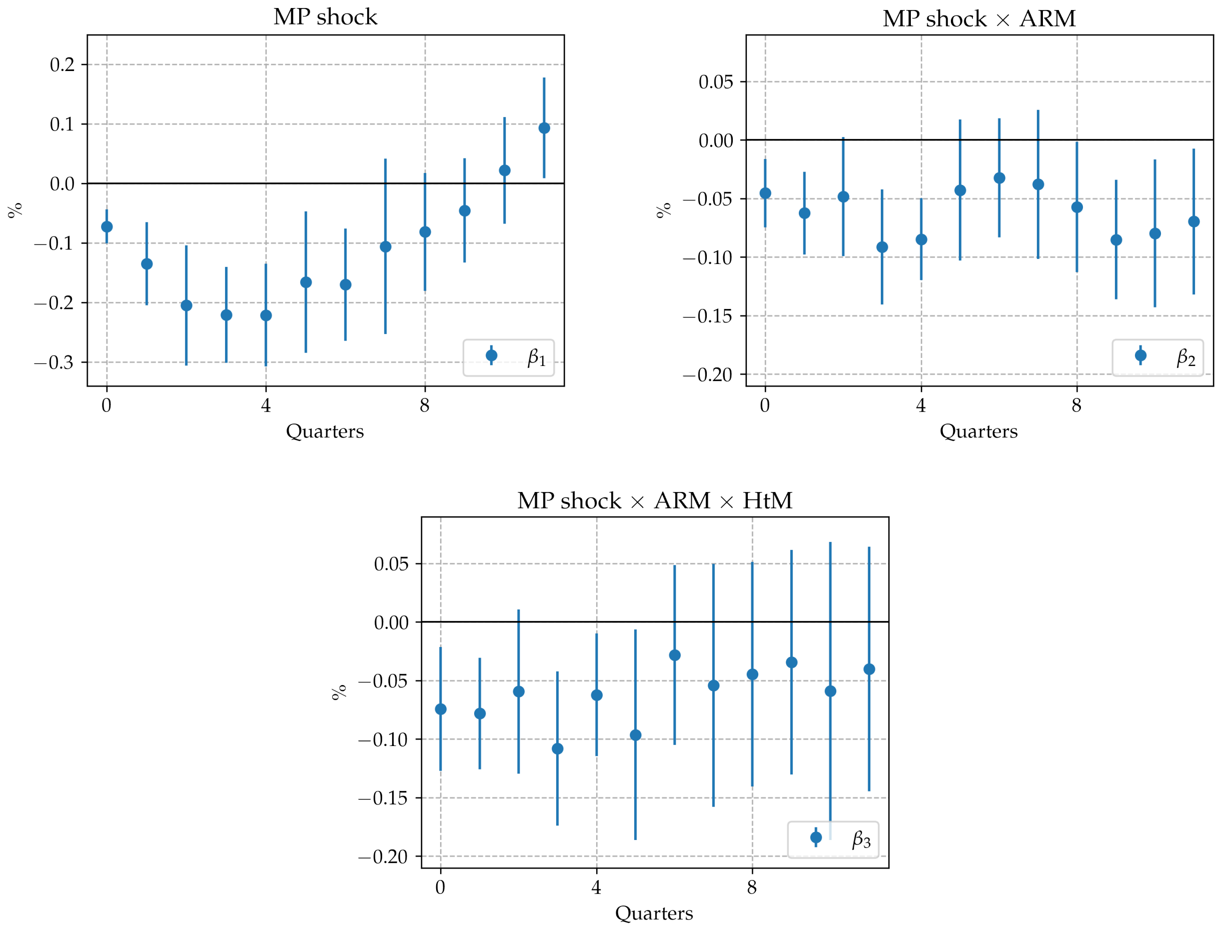
Figure 4 shows the impulse response functions for the coefficients β_1 to β_3. The left panel confirms that, on average across Euro Area countries, a contractionary monetary policy shock leads to a statistically significant decline in consumption, peaking at approximately -0.22 percentage points. The middle panel shows that this effect becomes more pronounced in economies with a higher prevalence of ARMs: when the ARM share is one standard deviation above the Euro Area average, the impact of the shock increases by an additional -0.09 percentage points at its peak. This supports prior findings that monetary transmission is more powerful when a the share of ARMs is larger.

Finally, the right panel displays the effect of the interaction between ARM and HtM on the effectiveness of monetary policy pass-through. When both ARM and HtM are one standard deviation above their Euro Area averages, a recessionary monetary policy shock is associated with an even larger decline in consumption. The coefficient has a magnitude

[14] Appendix B.4 presents results using an alternative specification where the interaction term is replaced with $ARMxHtM$, the share of households who are both HtM and have ARMs. The findings confirm that transmission is stronger in economies with higher $ARMxHtM$ shares, supporting the main results presented in this section.

[15] Appendix B.5 presents robustness checks using alternative survey waves and alternative measures of ARM prevalence.

Figure 4: Response of consumption to a monetary policy shock



Notes: Response of consumption to a one standard deviation contractionary monetary policy shock. The blue dots in each panel show the evolution, over a 12-quarter horizon, of coefficients β_1 to β_3 estimated using equation (2). The vertical blue lines represent 90% confidence intervals.

similar to that of the coefficient on the effect of high ARM (coefficient β_3 peaks at -0.11 percentage points, coefficient β_2 peaks at -0.09 percentage points), and it is statistically significant for approximately six quarters. The size of these coefficients indicates that when the HtM share increases from the Euro Area average to one standard deviation above it, the impact of the interaction between the monetary policy shock and the ARM share nearly doubles. This is a crucial result: across Euro Area countries, the strength of transmission is particularly pronounced in economies that display both a high share of ARMs *and* a high fraction of liquidity-constrained households.[16]

[16] Appendix B.6 provides a robustness exercise using time-series variation within Italy. By holding

Summary of empirical facts The analysis in this section provides empirical evidence that the interaction between the shares of ARMs and liquidity-constrained households is positively correlated with the strength of monetary policy transmission in the Euro Area. Motivated by this finding, the remainder of the paper develops a quantitative model to rationalize this empirical relationship.

3 Model

This section presents the model I developed to explore how ARMs and MPCs interact in the transmission of monetary policy. The model builds on the household block developed in Eichenbaum, Rebelo and Wong (2022), where households are allowed to make housing and mortgage decisions. Two important features distinguish it from Eichenbaum, Rebelo and Wong (2022): first, given the prominent role of ARMs in the Euro Area, the model incorporates this mortgage feature and disregards the refinancing option; second, instead of overlapping generations, the model relies on an infinitely-lived household framework.

Three key elements characterize the model. First, households face idiosyncratic uncertainty due to exogenous productivity shocks, generating income heterogeneity that results in varying MPCs across households. This feature enables the study of how different MPC levels influence monetary policy transmission through mortgages. Second, households decide on the size of their housing stock and on the amount of mortgage they want to take on. This feature allows the model to accommodate transmission through the mortgage channel, which is central to this study. Third, the model distinguishes between households with ARMs and those with fixed-rate mortgages (FRMs). Households with ARMs experience fluctuating mortgage payments in response to monetary policy changes, while FRM holders have mortgage payments that are insulated from interest rate fluctuations. This distinction enables the investigation of how different shares of ARMs affect the potency of monetary policy transmission.

This section is organized as follows. First, I describe each of the model blocks in turn. Second, I present the model calibration. Third, I discuss the performance of the model in matching some important untargeted moments. Appendix C.1 describes the algorithm I developed to solve the model.

country-level characteristics fixed, this exercise helps address concerns about unobserved confounders and provides additional support for the cross-country results.

3.1 Model blocks

In this section, I first describe the variables affecting the decisions that households make, and then introduce the value functions associated with such decisions.

Preferences Time is discrete and the economy is populated by a unit mass of infinitely-lived households indexed by i. Households discount the future at rate β. The momentary utility of a household is given by:

$$u(c,h) = \frac{\left(c^{\alpha}h^{1-\alpha}\right)^{1-\sigma}}{1-\sigma} \tag{3}$$

where $\sigma > 0$. c and h denote flexible consumption and the stock of housing, respectively. This specification assumes that the service from housing is equal to its stock, in line with Eichenbaum, Rebelo and Wong (2022). Households cannot freely adjust their housing stock, but may always freely adjust the other consumption good.

Housing stock Households enter each period with a stock of housing inherited from the previous period. The law of motion for the housing stock is

$$h' = (1-\delta)h, \tag{4}$$

which dictates that the stock that households inherit is $(1-\delta)h$, where h is the previous period's housing stock and δ is the rate of depreciation.

Each period, households must choose whether to change their house or remain in their current one. In either case, their updated housing stock h' will be the relevant one for the period's utility. If households decide to change, they have to sell the house they inherited. Revenues from the sale are $(1-f)p(1-\delta)h$, where p is the price of a unit of housing stock and f is a proportional adjustment cost which captures the loss that households incur when they decide to change their house.[17] Households then purchase a new house of size h' at unit price p.

[17] This is a standard feature of housing models (see, e.g., Kaplan and Violante, 2014, Kaplan et al., 2018, Berger et al., 2018, Wong, 2020, Eichenbaum et al., 2022) which captures the closing fees and costs that are associated with the sale of a house. In addition, the presence of adjustment costs implies that households change their housing stock infrequently, which is a realistic feature of the model.

Income process Households are subject to idiosyncratic uncertainty. In particular, income of household i at time t is

$$y_{i,t} = we_{i,t} \tag{5}$$

where w is the real wage in the economy and $e_{i,t}$ is the household's current productivity. Following standard practice in the literature (e.g., Guerrieri and Lorenzoni, 2017; Auclert et al., 2020, 2021, 2023), I assume that $e_{i,t}$ behaves according to the following AR(1) process:

$$\log e_i' = \rho_e \log e_i + \epsilon_i \tag{6}$$

where $|\rho_e| < 1$ and ϵ_i is an idiosyncratic shock drawn from a normal distribution with standard deviation σ_e. Accordingly, at each point in time, households will vary in their productivity level $e_{i,t}$. This feature of the model, together with the presence of borrowing constraints, implies that households have different MPCs. Since the aim of this study is to analyze how the effectiveness of ARMs depends on MPCs, this is a crucial feature of the model.

Risk-free assets Households can invest in one-period ahead risk-free assets. A household's position in these assets is denoted by a'. These assets pay interest rate r. I introduce incomplete markets in the economy by constraining households to save in these assets, that is, $a' \geq 0$.

Mortgages Households may take out loans with their house as collateral. These loans are modelled as a proportional repayment plan: each period, households pay back a fixed proportion μ of the remaining balance. Accordingly, households entering the period with an outstanding mortgage balance of b will see their mortgage balances evolve as follows:

$$b' = (1 - \mu)b. \tag{7}$$

Households can open a mortgage only to finance part of their housing purchase:

$$b' \in [0, \lambda ph'] \tag{8}$$

where λ is a pre-specified loan-to-value cap, p is the price of a housing unit and h' is the level of the housing stock a household wants to purchase. Hence, households cannot use mortgages as a saving device (the mortgage amount needs to be positive) and can borrow up to a fraction λ of the value of the house they wish to buy.

The mortgage interest rate r^b is defined as

$$r^b = r + \Delta^b \tag{9}$$

where r is the risk-free rate and Δ^b is a constant spread that creates a positive wedge between r^b and r.

Households entering the period with an outstanding mortgage balance of b must make a mortgage payment, M, which includes both interest and principal repayment, as follows:

$$M = (r^b + \mu)b. \tag{10}$$

Equation (10) captures the main transmission channel of ARMs. Following a monetary shock that leads to a change in r, the mortgage rate r^b adjusts according to the dynamics in equation (9). As a result, households with ARMs experience changes in their mortgage payments, M, while those with FRMs see no impact on their payments from changes in r^b. Within the economy, the fraction of ARMs is captured by the parameter γ.

Taxes At each point in time, household i, with idiosyncratic productivity level e_i, pays a time-invariant tax to the government, denoted $\tau(e_i)$. While the individual amount $\tau(e_i)$ remains constant over time, it is proportional to the household's idiosyncratic productivity level e_i, ensuring that wealthier households pay higher taxes than poorer ones.[18]

Value functions The household's state vector is $s = e, h, b, a$, which records productivity e, housing stock h, outstanding mortgage balance b, and liquid assets a at the beginning of the period. Each period, households face a discrete decision: they can either remain in their current home or move and potentially take on a new mortgage. The corresponding value functions are $V^{\text{stay}}(s)$ and $V^{\text{buy}}(s)$, respectively, and the household's overall value function is

$$V(e, h, b, a) = \max\{V^{buy}(e, h, b, a), V^{stay}(e, h, b, a)\}. \tag{11}$$

As is standard in models with discrete choices, the *max* operator introduces kinks and discontinuities that complicate the numerical solution. To smooth the problem, I follow

[18]Note that since $\tau(e_i)$ is constant over time across productivity levels, taxes will not play a role in the analysis.

the approach of Iskhakov et al. (2017), Bardóczy (2022), and Beraja and Zorzi (2024), and add i.i.d. type-I extreme value taste shocks, ϵ_b and ϵ_s, to the two alternatives:

$$V(e,h,b,a) = \max\{V^{buy}(e,h,b,a) + \sigma_\epsilon \epsilon_b, V^{stay}(e,h,b,a) + \sigma_\epsilon \epsilon_s\} \tag{12}$$

where σ_ϵ is a scale parameter. Further implementation details are provided in Appendix C.2.

Finally, I define the value functions associated with the two discrete choices.

Buyers. Households that decide to purchase a new home solve:

$$\begin{aligned} V^{\text{buy}}(e,h,b,a) = &\max_{c,h',b',a'} \ u(c,h') + \beta \mathbb{E}\left[V(e',h',b',a') \mid e\right] \\ \text{s.t.} \quad & c + a' + ph' - b' \leq y + (1+r)a - (1+r_b)b + (1-f)p(1-\delta)h - \tau, \\ & b' \in [0, \lambda p h'], \\ & a' \geq 0. \end{aligned} \tag{13}$$

These households choose consumption c, next-period housing h', new mortgage balance b', and liquid savings a'. Before purchasing a new home, they must settle any outstanding mortgage debt $(1+r_b)b$ and sell their current property, receiving $(1-f)p(1-\delta)h$ in proceeds.

Stayers. Households that remain in their current home solve:

$$\begin{aligned} V^{\text{stay}}(e,h,b,a) = &\max_{c,a'} \ u(c,h) + \beta \mathbb{E}\left[V(e',h',b',a') \mid e\right] \\ \text{s.t.} \quad & c + a' \leq y + (1+r)a - M - \tau, \\ & M = (r_b + \mu)b, \\ & h' = (1-\delta)h, \\ & b' = (1-\mu)b, \\ & a' \geq 0. \end{aligned} \tag{14}$$

These households face a standard consumption–saving problem with mortgage repayments M. Their housing stock depreciates at rate δ, and they repay a fixed proportion μ of their outstanding mortgage balance each period.

3.2 Calibration

The model is calibrated to a reference country, Spain, following other studies that have analyzed monetary policy transmission through mortgages in the Euro Area (Corsetti, Duarte and Mann, 2022). Most parameters are calibrated using European data sources that provide information for the Spanish economy. For parameters that have not been estimated for Spain or other European countries, which I discuss below, I rely on U.S. estimates.

Two parameters are particularly critical for the analysis: the discount factor β, which controls the household MPCs, and γ, the share of ARMs in the economy. Since the objective is to study the role of ARMs and MPCs in monetary policy transmission, these parameters are first calibrated to the Spanish economy and then modified in counterfactual exercises. This approach allows me to investigate how differences in ARM prevalence and household MPCs affect monetary policy pass-through across Euro Area economies.

Table 1 summarizes the parameter values and their sources.

Households. The model is calibrated at a quarterly frequency. The coefficient of relative risk aversion, σ, is set to 2, a standard value in the literature.

The discount factor β is set to match the ratio of liquid asset holdings (net of mortgage debt) to annual GDP, equal to 0.53 on average between 2012 and 2018.[19,20] The parameter α, determining the weight of non-durable consumption in the utility function, is calibrated to match the average housing-to-consumption ratio ($H/C = 5.96$) over the same period.[21] These targets yield $\beta = 0.984$ and $\alpha = 0.714$.

The short-term nominal interest rate r is set to the average annual Eonia rate over 2003–2018 (1.05%). Following standard practice (e.g., McKay, Nakamura and Steinsson, 2016; Wong, 2020), the borrowing constraint on liquid assets is set to zero, restricting household borrowing to mortgages only. The real wage w is normalized to one, so that income heterogeneity arises solely from idiosyncratic productivity differences.

The persistence and variance of the productivity process, ρ_e and σ_e^2, are taken from McKay, Nakamura and Steinsson (2016), who rely on the U.S. estimates of Floden and Lindé (2001). Specifically, $\rho_e = 0.967$ and $\sigma_e^2 = 0.033$.[22] The process is discretized into five

[19] The time period 2012–2018 corresponds to the sample available in the ECB Distributional Wealth Accounts (DWA), which harmonize the Quarterly Sector Accounts with the HFCS. See here for documentation.

[20] To compute liquid assets, I match the categories in Guerrieri and Lorenzoni (2017) and McKay, Nakamura and Steinsson (2016), which provide a definition of liquid assets for the United States, in the DWA. In particular, I sum the following entries: *Deposits*, *Debt Securities*, *Listed Shares*, and *Investment Fund Shares*. The entry *Mortgage Debt* accounts for mortgages in the calculation of net assets.

[21] The ratio is computed using *Housing Wealth* from the DWA to measure H, and private consumption from Eurostat National Accounts for C.

[22] While ρ_e follows the estimate in Floden and Lindé (2001), their evidence would imply $\sigma_e^2 = 0.017$.

Table 1: Parameter values

Parameter	Explanation	Value	Target/Source
Households			
β	Discount factor	0.984	Net assets/GDP=0.53
σ	Inverse EIS	2	Standard value
α	Consumption share	0.714	H/C ratio=5.96
r	Short-term interest rate	1.05%	Mean Eonia rate 2003-2018
w	Real wage	1	Standard value
ρ_e	Persistence, productivity	0.967	McKay, Nakamura and Steinsson (2016)
σ_e^2	Variance, productivity	0.033	McKay, Nakamura and Steinsson (2016)
σ_ε	Scale parameter	0.1	Beraja and Zorzi (2024)
$\underline{a}$	Borrowing constraint	0	McKay, Nakamura and Steinsson (2016)
Housing			
γ	ARM share	75.6%	HFCS
Δ^b	Mortgage rate spread	1.95%	Mean mortgage rate 2003-2018
f	Adjustment cost	0.1	OECD (2012)
λ	Mortgage borrowing limit	0.85	Pica (2021)
δ	Yearly housing depreciation	2%	BEA estimate (Fraumeni, 1997)
μ	Mortgage repayment speed	0.015	Mortgage maturity $=$ 25 years
$\bar{H}$	Housing stock	19.58	$p^{ss} = 1$

Notes: See text for a discussion on the sources and targets.

states using the Rouwenhorst method.

The scale parameter σ_ε in equation (12) is set to 0.1, following the analysis in Beraja and Zorzi (2024).[23]

McKay, Nakamura and Steinsson (2016) argue that such a value understates earnings volatility relative to the more recent evidence in Guvenen, Ozkan and Song (2014) and therefore consider an alternative calibration with $\sigma_e^2 = 0.033$. Since subsequent studies, such as Ganong et al. (2025), document even higher volatility, I adopt this higher value in the baseline calibration.

[23] Beraja and Zorzi (2024) provide a set of reasonable values for σ_ε, ranging from 0.1 to 0.45. I choose to use the value 0.1 because the authors find it to be reasonable based on the evidence in Bachmann et al. (2021) which, using European data, is particularly relevant for the present study.

Housing The share of ARMs in the total mortgage stock, γ, is taken from the HFCS, where it stands at 75.6% for Spain.[24] In the counterfactual exercises, γ is adjusted to match the ARM shares observed in other Euro Area countries according to the HFCS.[25]

The spread between the mortgage rate and the risk-free rate, $\Delta^b = r_b - r$, is set to 1.95%, consistent with the average difference between the mean annual mortgage rate (3%) and the Eonia rate (1.05%) in Spain over 2003–2018. The annual depreciation rate of the housing stock, δ, is set to 2%, the midpoint of the Bureau of Economic Analysis estimates (Fraumeni, 1997). The parameter governing mortgage repayment speed, μ, is set to 0.015, implying an average mortgage maturity of twenty-five years, in line with the evidence in van Hoenselaar et al. (2021).[26]

The housing transaction cost parameter, f, is set to 0.10, following OECD (2012). This value exceeds the 5% commonly used in U.S.-based studies (e.g., Berger et al., 2018; Wong, 2020; Diaz and Luengo-Prado, 2010), reflecting the higher transaction costs typically observed in European housing markets.

The maximum loan-to-value ratio, λ, is set to 0.85, based on Pica (2021). This value is slightly higher than the standard 0.8 used in the literature (e.g., Berger, Guerrieri, Lorenzoni and Vavra, 2018; McKay and Wieland, 2021), consistent with the empirical LTV ratios across Euro Area economies. Finally, the aggregate housing stock $\bar{H}$ is chosen to normalize the steady-state housing price to one.

3.3 Model fit

This section shows that the model is able to match important untargeted moments in the data.

Figure 5 compares the distribution of assets and mortgage debt in the model and in the HFCS data.[27] The model successfully replicates the upward trends in the distribution

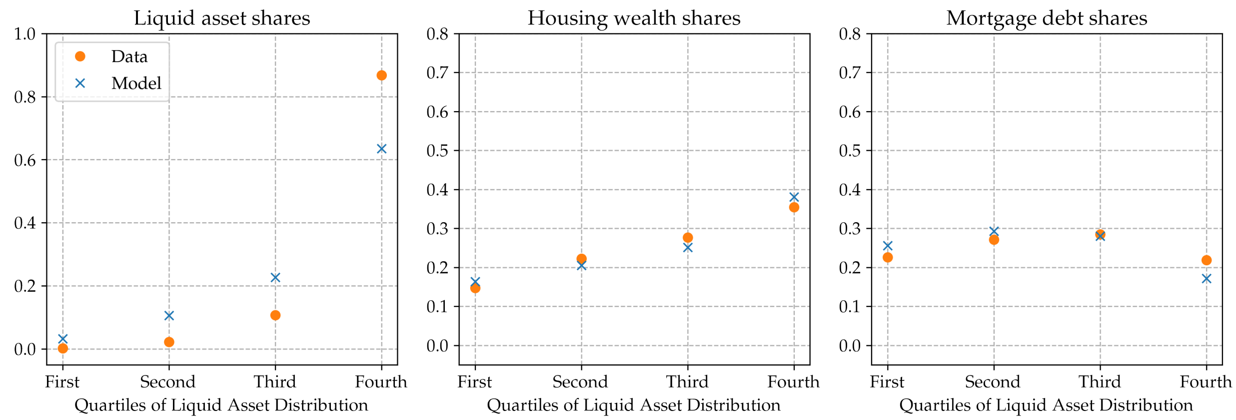
[24] To replicate the share of ARMs in the total mortgage stock, I proceed as follows. Among households with positive mortgage balances in steady state, a fraction γ holds ARMs, while the remaining $(1-\gamma)$ does not. Among households without outstanding mortgages, if they decide to borrow after a monetary policy shock, the same fractions γ and $(1-\gamma)$ apply.

[25] In line with the empirical analysis, where the variable of interest is the share of ARMs in the total mortgage stock, I target the share of ARMs in the total mortgage stock in the model. Appendix C.5 reports robustness exercises where I instead target the share of households with ARMs in the population of each economy.

[26] Appendix C.3 provides additional details on the calibration of μ.

[27] In the HFCS data, I calculate liquid assets using the definition provided by Almgren et al. (2022). Further details on the construction of this variable are available in Appendix B.2. To capture housing wealth, I

Figure 5: Distributions of assets and debt in the model and in the data



Notes: In each panel, households are ranked based on their position in the liquid asset distribution. Each dot represents the fraction of total liquid assets (left panel), housing wealth (middle panel), and mortgage debt (right panel) held by a specific quartile in the model (in blue) and in the Spanish HFCS data (in orange).

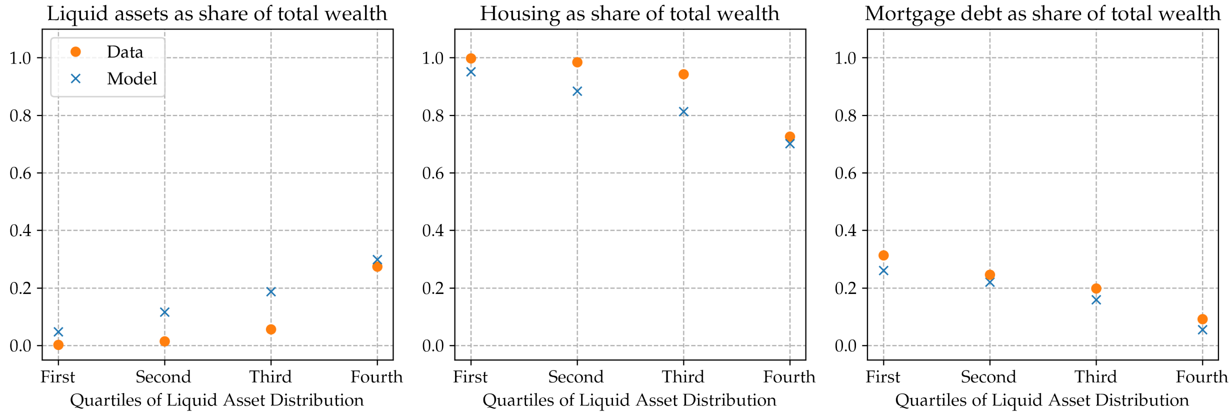
of liquid assets and housing wealth. Notably, the fourth quartile of the liquid asset distribution owns the vast majority of assets (approximately 80% in the data and above 60% in the model) and holds the largest share of housing wealth (around 40% in both cases). Additionally, the model mirrors the empirical hump-shaped profile of the mortgage debt distribution, where the fraction of total mortgage held by the bottom and top quartiles of the liquid asset distribution is slightly less the fraction held by the second and third quartiles.

Figure 6 compares the composition of household wealth in the model and in the data. The left panel of the figure displays the ratio of total liquid assets to total wealth across different quartiles, where total wealth is computed as the sum of liquid assets and housing wealth held by each quartile. Both in the model and the data, households in the lower quartiles hold very little of their wealth in liquid assets: as shown in the middle panel, most of their wealth is concentrated in housing. In addition, the right panel of Figure 6 shows the ratio between mortgage debt and total wealth along the liquid asset distribution. The model accurately captures the declining pattern of this ratio in the data, where debt represents a lower fraction of total wealth as households increase their holdings of liquid assets.

Overall, both in the data and in the model, lower income households primarily accu-

use the variable *da1110* ("Value of household's main residence"), and to measure the amount of outstanding mortgages, I use the variable *dl1110* ("Outstanding balance of household's main residence mortgages").

Figure 6: Composition of total wealth in the model and in the data



Notes: In each panel, households are ranked based on their position in the liquid asset distribution. Each dot represents the ratio between total liquid assets and total wealth (left panel), total housing wealth and total wealth (middle panel), and total mortgage debt and total wealth (right panel) in the four quartiles in the model (in blue) and in the Spanish HFCS data (in orange).

mulate wealth in the form of housing and carry substantial mortgage debt relative to their assets. This is important, since it indicates that fluctuations in mortgage conditions are especially significant for this cohort of households, which is characterized by high MPCs.

4 Results

This section presents the quantitative results on the role of ARMs and MPCs in monetary policy transmission. The analysis is conducted in the partial equilibrium framework introduced in Section 3, where consumption adjusts solely in response to changes in the short-term interest rate r and the mortgage rate r^b. This setting is ideal to study how varying levels of ARMs and MPCs affect transmission through mortgages in isolation.

The analysis proceeds in two parts. First, I examine the response of consumption to changes in the mortgage rate r^b alone, focusing on transmission through the mortgage channel exclusively. The analysis has two main objectives: (i) to investigate the role of MPCs in amplifying transmission through ARMs, and (ii) to show that, in line with the empirical evidence of Section 2, transmission is stronger when high ARMs are paired with high MPCs in the model. In addition, I present an important model prediction: for a given fraction of ARMs in the economy, transmission through mortgages is stronger when ARMs are concentrated among low-income (high-MPC) households.

Second, I consider a monetary policy shock in which both r and r^b move. I use the model to: (i) assess how much of the observed cross-country heterogeneity in transmission can be captured by it, and (ii) explore the welfare effects of monetary policy shocks across different income cohorts.

The model delivers the following intuition on the roles of ARMs and MPCs in transmission. Income heterogeneity affects both households' MPCs and their mortgage choices: poorer households tend to have higher MPCs and take out loans with higher loan-to-value ratios. When interest rates rise, those with ARMs face an immediate increase in mortgage payments, reducing their available resources for consumption. Wealthier households are less affected, as mortgage payments represent a smaller share of their income. In contrast, poorer households, with higher MPCs and more burdensome mortgage payments, adjust consumption more sharply. As a result, transmission through the mortgage channel is stronger when a larger fraction of households hold ARMs and when those households have high MPCs.[28]

4.1 Changes in the mortgage rate r^b

This subsection analyzes how ARMs and MPCs shape monetary transmission through the mortgage channel by examining consumption responses to changes in the mortgage rate r^b, holding the short-term interest rate r fixed.

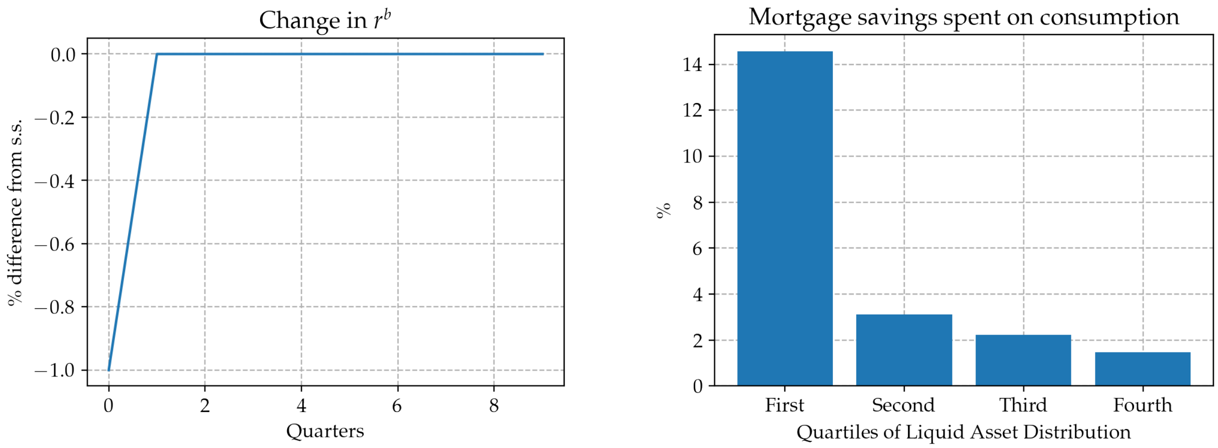
4.1.1 The role of the MPC

To examine how MPCs influence the transmission of monetary policy through mortgages, I simulate a one-time reduction in the mortgage interest rate r^b in an economy where all households hold ARMs ($\gamma = 1$). As shown in the left panel of Figure 7, the mortgage rate decreases by 100 basis points on impact, leading to a temporary drop in mortgage payments for all households with outstanding balances. I then analyze how the consumption response varies with households' MPCs.

The right panel of Figure 7 displays the share of mortgage savings that is passed through to consumption across the MPC distribution. Households with higher MPCs exhibit a stronger consumption response to the same reduction in mortgage payments. This result illustrates the core mechanism of the model: ARMs amplify transmission more

[28] Robustness results for all exercises in this section are provided in Appendix C.5, where I target the share of households with ARMs in the population rather than the share of ARMs in the outstanding mortgage stock.

Figure 7: Consumption response to mortgage rate shock by asset quartile



Notes: The left panel shows the dynamics of the mortgage rate. In the right panel, households are ranked by quartile in the liquid asset distribution. Each bar shows the average fraction of mortgage savings from a one-time reduction in r^b that is spent on consumption.

effectively when they affect households with high MPCs, who are more responsive to changes in disposable income.

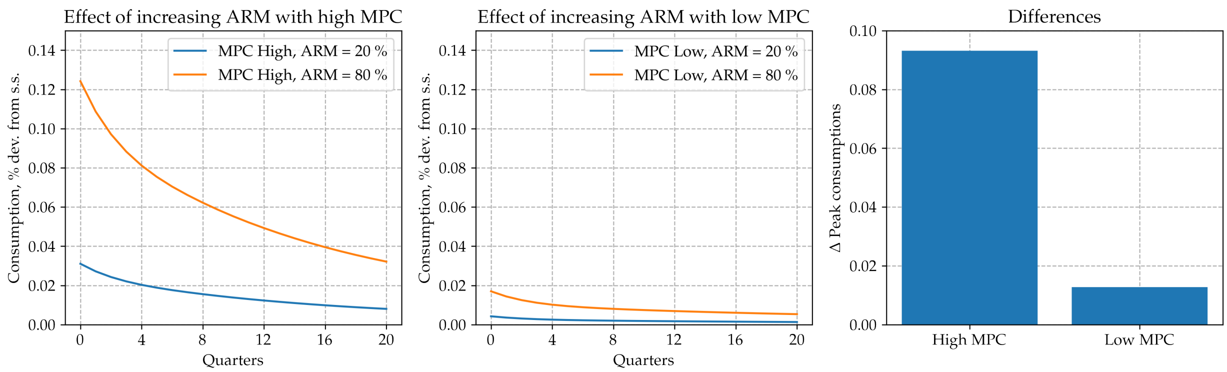
4.1.2 The interaction between ARMs and MPCs

Building on the previous exercise, I now examine how ARMs and MPCs interact in shaping transmission through the mortgage channel. The analysis compares two economies that differ in both their ARM shares and MPC levels. The first is the Spanish baseline. The second is calibrated identically except for a higher discount factor β, which generates an MPC half that of Spain.

In each economy, I simulate a 100 basis point reduction in the mortgage rate r^b and analyze the consumption response under two scenarios: one with an ARM share of 20%, and another with 80%. Figure 8 presents the results. The left and middle panels show that, within each economy, higher ARM shares lead to larger consumption responses, in line with our expectations. The right panel highlights the interaction effect: as the ARM share rises from 20% to 80%, the increase in peak consumption is much larger in the high-MPC economy.

This pattern reflects the amplification mechanism discussed earlier: while higher ARM shares expand the set of affected households, higher MPCs increase the sensitivity of their consumption to the shock. As a result, the model predicts stronger transmission when

Figure 8: Interaction between ARMs and MPCs after a mortgage rate shock



Notes: The left and middle panels show the consumption response, in percentage deviations from steady state, to a mortgage rate shock in the high-MPC and low-MPC economies, respectively. In each, the blue line corresponds to a 20% ARM share and the orange line to an 80% ARM share. The right panel shows the difference in the peak consumption response as the ARM share increases from 20% to 80%. The mortgage rate shock is calibrated to reduce r^b by 100 basis points on impact and follows an AR(1) process with a persistence of 0.75.

high ARM shares are paired with high MPCs, in line with the empirical evidence from Section 2.

4.1.3 The distribution of ARMs

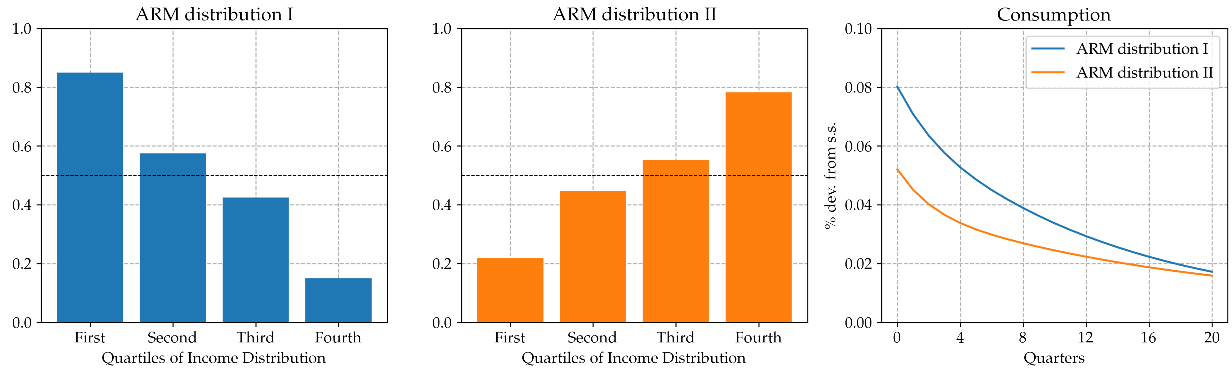
I next examine how the distribution of ARMs across the population affects the strength of transmission through the mortgage channel. Using the Spanish calibration with an overall ARM share of 50%, I compare two economies with identical MPC levels and ARM shares but differing distributions of ARMs across the income distribution.

The left and middle panels of Figure 9 display the two scenarios. In *Distribution I*, ARMs are concentrated among low-income (high-MPC) households, while in *Distribution II*, ARMs are concentrated among high-income (low-MPC) households. The dashed line marks the constant overall ARM share in both cases.[29]

The right panel shows the consumption response to a 100 basis point reduction in the mortgage rate r^b. In the economy with *Distribution I*, the response peaks at approximately 0.08%. In contrast, the response in the economy with *Distribution II* peaks at about 0.05%. Concentrating ARMs among lower-income households thus leads to a signifi-

[29]The two distributions are not perfectly symmetric because the amount of mortgage debt differs across income quartiles.

Figure 9: Transmission of mortgage rate shock under alternative ARM distributions



Notes: The left and middle panels display the share of ARMs across income quartiles. The horizontal dashed line marks the overall ARM share in both simulations, equal to 50%. The right panel shows the resulting consumption response to a mortgage rate shock. The shock is calibrated to reduce r^b by 100 basis points on impact and follows an AR(1) process with a persistence of 0.75.

cantly stronger transmission effect, with the peak response roughly 1.6 times larger.

This result builds on previous analyses, which highlighted the importance of high MPCs for strong transmission through mortgages, to provide a key insight: for a given share of ARMs, transmission is more effective when these mortgages are concentrated among low-income (high-MPC) households. This finding underscores the importance for policymakers of monitoring the distribution of ARMs in the population to better anticipate the strength of transmission through the mortgage channel.

The mortgage rate exercises show how ARMs and MPCs interact in the transmission of monetary policy through mortgages. While ARMs determine the share of households directly affected by changes in mortgage rates, MPCs govern the sensitivity of consumption to those changes. Strong transmission through the mortgage channel requires both a high ARM share, so that many households are exposed to the shock, and high MPCs, so that their consumption responds strongly. Accordingly, transmission is particularly strong when high ARM shares are matched with high MPCs, consistent with the empirical evidence on their interaction discussed in Section 2.

4.2 Monetary policy shocks with changes in both r and r^b

After establishing the mechanism through which ARMs and MPCs shape the transmission of monetary policy through mortgages, I now allow both the short-term interest rate

r and the mortgage rate r^b to respond to the monetary policy shock. Changes in r lead to changes in r^b in line with the dynamics described in equation (9). Since this extended framework is used to compare model-generated consumption responses to the empirical estimates from Section 2, I allow both r and r^b to affect household decisions in order to capture as much of the monetary policy transmission as the structure of the model permits.

In this setting, I first assess how much of the observed cross-country heterogeneity in transmission can be accounted for by the model. I then evaluate the welfare consequences of contractionary monetary policy shocks, both in the aggregate and across different household cohorts.[30]

4.2.1 The role of ARMs in explaining transmission heterogeneity

To assess how much of the observed cross-country heterogeneity in monetary policy transmission can be captured by the model, I proceed in three steps.

First, I calculate the empirical differences in monetary policy transmission across Euro Area countries. In Section 2, I estimated the strength of transmission for each country using local projections (equation 1). Based on these estimates, I compute the difference in the peak consumption response of each country relative to Spain, the reference economy.

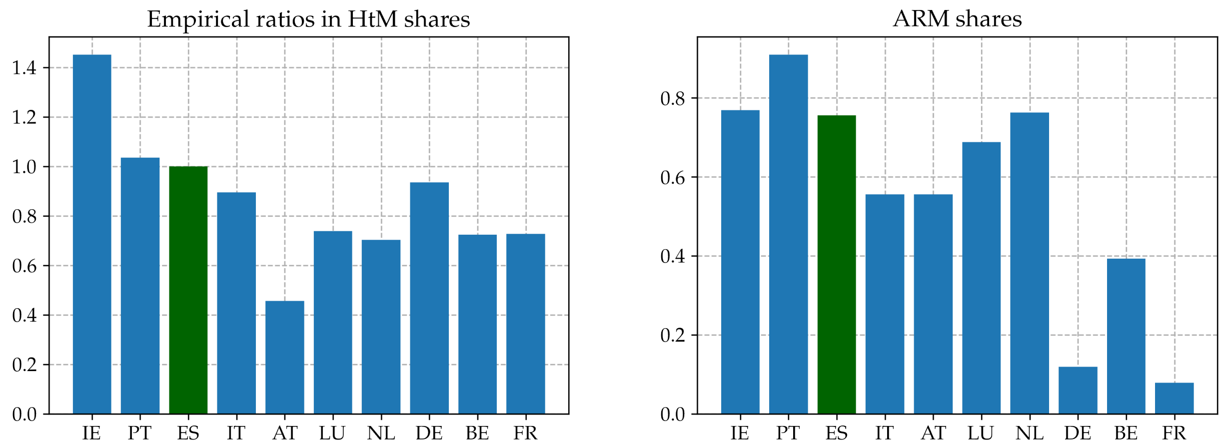
Second, I use the model to quantify how much of these differences in transmission the framework can generate through variation in ARM shares and MPC levels. I begin by calibrating the monetary policy shock so that the model's peak consumption response for Spain matches the data.[31] Then, for each Euro Area country, I construct a counterfactual Spanish economy in which I adjust two parameters: the discount factor β, to match the country's inferred MPC level, and the share of ARMs γ, to match the observed ARM share in the HFCS.

Since MPCs are not directly observed, I approximate them using the share of HtM households. Specifically, I assume that the ratio of Spain's MPC to country c's MPC equals the ratio of their HtM shares: $MPC^{ES}/MPC^{c} = HtM^{ES}/HtM^{c}$. For each country, I adjust β to reproduce this MPC ratio and calibrate γ to the observed ARM share. Figure 10 shows the relative HtM shares and ARM shares used in this calibration. This procedure

[30] As a robustness check, Appendix C.6 shows that the interaction between ARMs and MPCs continues to amplify transmission when both r and r^b move, consistent with the findings in Section 4.1.2.

[31] This corresponds to a 170 basis point reduction in r on impact. The shock follows an AR(1) process with persistence 0.75.

Figure 10: Empirical shares of HtM households and ARMs, used to calibrate the counterfactual exercises



Notes: The left panel shows the ratios of HtM households in Euro Area countries relative to Spain, while the right panel displays the shares of ARMs across Euro Area countries. Countries are ranked by the strength of monetary policy transmission, from Ireland (strongest) to France (weakest), in line with estimates from equation (1) shown in Figure 2. The source of the data is the HFCS.

allows me to compute the peak consumption response in each counterfactual economy.

Importantly, MPCs affect transmission through two channels: the standard interest rate channel via r and the mortgage channel via r^b. To isolate the role of MPCs in shaping mortgage-driven transmission, I exclude their effect on consumption through r and focus solely on their impact through r^b.[32] This ensures that differences in the model's counterfactual consumption responses relative to Spain reflect only variation in transmission through ARMs, which is the focus of this analysis.

As a third and final step, I compare the empirical and model-implied differences in transmission to assess how much of the observed heterogeneity in transmission can be captured by the model.[33]

Table 2 displays the results. The *Difference* section reports, for each country, the empirical peak consumption response relative to Spain (*Data*), the model-implied counterpart (*Model*), and the share of the empirical difference captured by the model (% *Captured*). The *Contribution* section breaks down the model-implied difference into the roles played

[32] Appendix C.4 describes this decomposition.

[33] This section presents the baseline results, where ARMs and MPCs are assumed to be independent (i.e., the ARM share is constant across income levels). Appendix C.7 provides robustness results incorporating an exogenous correlation between ARMs and MPCs.

Table 2: ARM and MPC contributions to overall transmission

	Difference			Contribution		
	Data	Model	% Captured	ARM	MPC	Interaction
AT	0.236	0.148	63%	4%	71%	25%
BE	0.314	0.140	45%	21%	43%	40%
DE	0.295	0.150	50%	52%	8%	40%
FR	0.350	0.160	46%	26%	8%	66%
IE	-0.728	-0.225	34%	1%	97%	2%
IT	0.172	0.107	62%	20%	59%	21%
LU	0.284	0.122	43%	4%	87%	9%
NL	0.287	0.121	42%	−1%	102%	−1%
PT	-0.239	-0.078	32%	43%	47%	10%
Averages	0.311	0.139	46%	19%	57%	24%

Notes: For each country, the table shows the difference in percentage points in the peak consumption response to a monetary policy shock relative to Spain. This difference is presented both in the data (second column) and in the model (third column). The fourth column shows the fraction of this difference captured by the model. The last three columns report the fraction of the model-implied differences between each country and Spain that are attributable to differences in ARMs, MPCs, and their interaction. The last row presents the average values of the column variables across countries.

by ARMs, MPCs, and their interaction. To compute this decomposition, I conduct a series of counterfactual exercises in which I vary either ARMs or MPCs individually while holding the other fixed, and attribute the remaining difference to their interaction.[34]

The model captures between 32% and 63% of the observed cross-country transmission differences, with an average of 46%. On average, 19% of the model-implied differences are attributable to variation in ARMs, with their contribution ranging from –1% to 52% across countries. This channel is especially relevant in economies such as Portugal and Germany, where ARM prevalence differs significantly from Spain while MPC levels are relatively close. MPCs explain 57% of the variation on average, with the largest contributions in countries such as Ireland and the Netherlands, where differences in MPCs are

[34]For example, the observed peak consumption response difference between Spain and Austria is 0.236. The model generates a difference of 0.148, implying it captures 63% of the empirical gap. By varying ARMs and MPCs separately, I identify the contribution of each channel to this 0.148. Any remaining component is attributed to their interaction.

more substantial than differences in ARMs relative to Spain. Finally, interactions between ARMs and MPCs account for the remaining 24% of the explained variation.

These results highlight the critical importance of accounting for MPC heterogeneity when evaluating monetary policy transmission through mortgages. The 19% ARM contribution implies that a model with heterogeneity in ARMs alone would explain roughly 9% of the empirical heterogeneity in transmission (i.e., 19% of the 46% captured). Including MPC heterogeneity, both through its direct impact and through its interaction with ARMs, allows the model to account for an additional 37% of the overall empirical differences, bringing the total to 46%.

The Netherlands (NL) offers a particularly illustrative example of the importance of accounting for differences in MPCs. Despite having a higher ARM share than Spain, the Netherlands exhibits lower transmission in the data, which is reflected in a negative ARM contribution of –1% in the decomposition. Once the model additionally incorporates the Netherlands' lower MPC, it is able to replicate the country's weaker consumption response.

Overall, this analysis yields two key takeaways. First, a model that isolates transmission through ARMs can account for a substantial share of the empirical differences in monetary policy pass-through across Euro Area economies. Second, heterogeneity in MPCs plays a central role in shaping transmission through ARMs and must be accounted for to explain these differences.

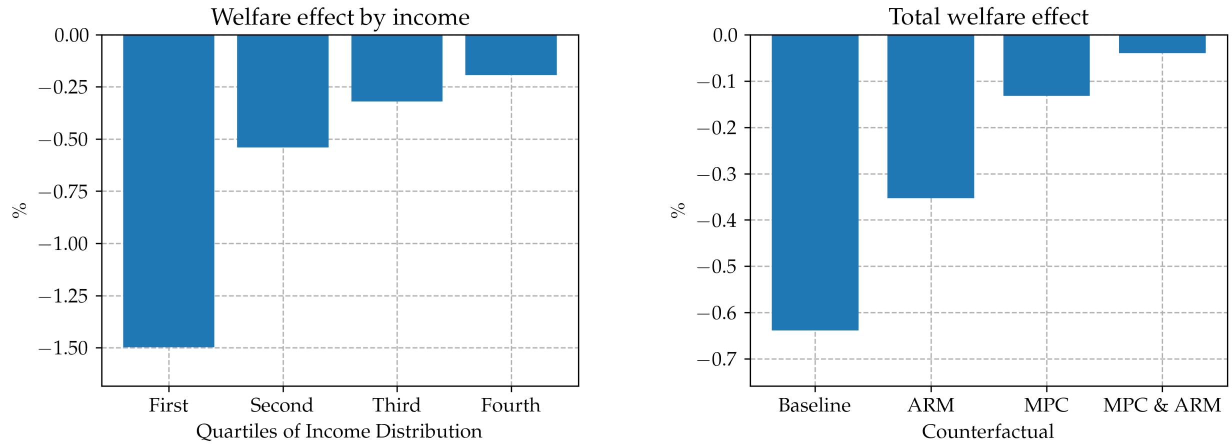
4.2.2 Welfare effects

In this section, I use the model to examine the welfare effects of contractionary monetary policy shocks across income groups and in the aggregate. Welfare is measured as the average percentage change in household utility over a 12-quarter period following the shock, with larger declines indicating greater welfare losses.

The left panel of Figure 11 shows the distribution of welfare losses across income quartiles in the Spanish economy. Households in the lowest income quartile experience the most severe welfare decline, as limited savings and high MPCs force them to make sharp consumption adjustments when mortgage payments rise. Moving up the income distribution, welfare losses diminish as households have greater financial buffers and lower MPCs, allowing them to better smooth consumption.

The right panel reports aggregate welfare effects under several counterfactuals. The first bar reflects the welfare loss in the baseline Spanish economy. The *ARM* scenario

Figure 11: Welfare consequences of a contractionary monetary policy shock



Notes: The left panel shows the average welfare drop after a recessionary monetary policy shock for households in different quartiles of the income distribution in the baseline Spanish calibration. The right panel shows the total welfare drop in the baseline Spanish calibration, in a counterfactual calibration with ARM share half that of Spain (*ARM*), in a counterfactual calibration with MPC half that of Spain (*MPC*), and in a counterfactual calibration with ARM share and MPC level half those of Spain (*MPC & ARM*). The welfare effect is computed as the average percentage change in utility that households experience over a 12-quarter period following the shock. The shock follows an AR(1) process with persistence 0.75 and is calibrated to lead to an increase in r of 170 basis points on impact. The shock is identical to the one used in Section 4.2.1, except that it is contractionary rather than expansionary.

holds MPC constant but halves the ARM share. The *MPC* scenario holds the ARM share fixed and halves the MPC. The final bar (*MPC & ARM*) reduces both MPC and ARM share by half. In all cases, welfare losses decline when fewer households face immediate payment increases or when households are less financially constrained, consistent with previous findings.

Overall, welfare declines are larger in economies with both high ARM shares and high MPCs. In these settings, interest rate hikes effectively curb aggregate consumption. However, they impose the greatest costs on financially vulnerable households, whose welfare contracts most sharply. This unequal burden reveals a key tension in mortgage-based transmission and suggests that, during tightening cycles, targeted support for low-income households may be particularly effective in mitigating welfare losses.[35]

[35] In response to recent rate hikes, the Spanish government introduced targeted mortgage relief for low-income households, including lowering the applicable ARM rate from Euribor + 0.25% to Euribor – 0.10%. See International Monetary Fund (2024) for background and the official policy summary here.

5 Conclusion

This paper shows that the role of ARMs in monetary policy transmission is strongly influenced by the fraction of liquidity-constrained households in the economy. Through a set of empirical exercises, I document a key empirical fact: monetary policy transmission is stronger in Euro Area countries where high shares of ARMs are matched with high shares of HtM households. To account for this finding, I build a heterogeneous-agent model with housing and mortgage choices that flexibly accommodates different ARM shares. The model illustrates how ARMs and MPCs interact in monetary transmission: while higher ARM shares imply that more households experience changes in mortgage payments following a monetary shock, it is the MPC that determines the sensitivity of consumption to these changes. Accordingly, ARMs effectively enhance monetary transmission only in economies characterized by high MPCs.

These findings carry important policy implications. First, the distribution of ARMs across the population is a key variable to predict the strength of monetary policy transmission. In economies with high ARM uptake, transmission is particularly potent when ARMs are concentrated among low-income, high-MPC households. Second, while a larger share of constrained households enhances transmission, it also exacerbates the negative welfare effects these households experience after contractionary monetary shocks. Therefore, the analysis suggests that it is essential to consider measures to mitigate these welfare losses, especially in the context of sizable and prolonged contractionary monetary policy interventions.

Finally, expanding the analysis in this paper along two key dimensions would be particularly valuable. First, the Euro Area literature has highlighted the importance of homeownership rates in shaping monetary policy transmission, making it particularly interesting to incorporate this dimension of heterogeneity. Second, the current model operates within a partial equilibrium framework; extending it to a general equilibrium model would allow for a deeper exploration of whether the partial equilibrium effects hold when incorporating a more comprehensive supply side.

References

Almgren, M., Gallegos, J.-E., Kramer, J. and Lima, R. (2022). Monetary Policy and Liquidity Constraints: Evidence from the Euro Area, *American Economic Journal: Macroeconomics* **14**(4): 309–340.

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

Auclert, A., Bardóczy, B., Rognlie, M. and Straub, L. (2021). Using the Sequence-Space Jacobian to Solve and Estimate Heterogeneous-Agent Models, *Econometrica* **89**(5): 2375–2408.

Auclert, A., Rognlie, M. and Straub, L. (2020). Micro Jumps, Macro Humps: Monetary Policy and Business Cycles in an Estimated HANK Model, *Working Paper* .

Auclert, A., Rognlie, M. and Straub, L. (2023). The Intertemporal Keynesian Cross, *Journal of Political Economy (Forthcoming)* .

Bachmann, R., Born, B., Goldfayn-Frank, O., Kocharkov, G., Luetticke, R. and Weber, M. (2021). A Temporary VAT Cut as Unconventional Fiscal Policy, *NBER Working Papers 29442, National Bureau of Economic Research, Inc* .

Bardóczy, B. (2022). Spousal Insurance and the Amplification of Business Cycles, *Working Paper* .

Battistini, N., Falagiarda, M., Hackmann, A. and Roma, M. (2025). Navigating the housing channel of monetary policy across euro area regions, *European Economic Review* **171**.

Beraja, M., Fuster, A., Hurst, E. and Vavra, J. (2019). Regional Heterogeneity and the Refinancing Channel of Monetary Policy, *The Quarterly Journal of Economics* **134**(1): 109–183.

Beraja, M. and Zorzi, N. (2024). Durables and Size-Dependence in the Marginal Propensity to Spend, *Working Paper* .

Berger, D., Guerrieri, V., Lorenzoni, G. and Vavra, J. (2018). House Prices and Consumer Spending, *Review of Economic Studies* **85**(3): 1502–1542.

Berger, D., Milbradt, K., Tourre, F. and Vavra, J. (2023). Refinancing Frictions, Mortgage Pricing and Redistribution, *Working Paper* .

Calza, A., Monacelli, T. and Stracca, L. (2013). Housing Finance and Monetary Policy, *Journal of the European Economic Association* **11**(1): 101–122.

Carroll, C. (2006). The Method of Endogenous Gridpoints for Solving Dynamic Stochastic Optimization Problems, *Economics Letters* **91**(3): 312–320.

Caspi, I., Eshel, N. and Segev, N. (2024). The Mortgage Cash-Flow Channel: How Rising Interest Rates Impact Household Consumption, *Working Paper* .

Cloyne, J., Ferreira, C. and Surico, P. (2020). Monetary Policy when Households have Debt: New Evidence on the Transmission Mechanism, *The Review of Economic Studies* **87**(1): 102–129.

Corsetti, G., Duarte, J. B. and Mann, S. (2022). One Money, Many Markets, *Journal of the European Economic Association* **20**(1): 513–548.

Cumming, F. and Hubert, P. (2023). The Distribution of Households' Indebtedness and the Transmission of Monetary Policy, *The Review of Economics and Statistics* **105**(5): 1304–1313.

De Stefani, A. and Mano, R. (2025). Long-Term Debt and Short-Term Rates: Fixed-Rate Mortgages and Monetary Transmission, *IMF Working Paper No. 2025/024* .

Di Maggio, M., Kermani, A., Keys, B. J., Piskorski, T., Ramcharan, R., Seru, A. and Yao, V. (2017). Interest Rate Pass-Through: Mortgage Rates, Household Consumption, and Voluntary Deleveraging, *American Economic Review* **107**(11): 3550–3588.

Diaz, A. and Luengo-Prado, M. J. (2010). The Wealth Distribution with Durable Goods, *International Economic Review* **51**(1): 143—170.

Eichenbaum, M., Rebelo, S. and Wong, A. (2022). State Dependent Effects of Monetary Policy: the Refinancing Channel, *American Economic Review* **112**(3): 721–761.

Floden, M. and Lindé, J. (2001). Idiosyncratic Risk in the United States and Sweden: Is There a Role for Government Insurance?, *Review of Economic Dynamics* **4**(2): 406–437.

Flodén, M., Kilström, M., Sigurdsson, J. and Vestman, R. (2021). Household Debt and Monetary Policy: Revealing the Cash-Flow Channel, *The Economic Journal* **131**(636): 1742–1771.

Fraumeni, B. M. (1997). The Measurement of Depreciation in the U.S. National Income and Product Accounts, *Survey of Current Business* **77**: 7–23.

Ganong, P., Noel, P., Patterson, C., Vavra, J. and Weinberg, A. (2025). Earnings Instability, *Working Paper* .

Garriga, C., Kydland, F. E. and Šustek, R. (2017). Mortgages and Monetary Policy, *The Review of Financial Studies* **30**(10): 3337–3375.

Garriga, C., Kydland, F. E. and Šustek, R. (2021). MoNK: Mortgages in a New-Keynesian model, *Journal of Economic Dynamics and Control* **123**: 104059.

Greenwald, D. L. (2018). The Mortgage Credit Channel of Macroeconomic Tranmission, *Working Paper* .

Guerrieri, V. and Lorenzoni, G. (2017). Credit Crises, Precautionary Savings, and the Liquidity Trap, *Quarterly Journal of Economics* **132**(2): 1427–1467.

Guerrieri, V., Lorenzoni, G. and Prato, M. (2020). Slow Household Deleveraging, *Journal of the European Economic Association* **18**(6): 2755–2775.

Guvenen, F., Ozkan, S. and Song, J. (2014). The Nature of Countercyclical Income Risk, *Journal of Political Economy* **122**(3): 621–60.

Hedlund, A., Karahan, F., Mitman, K. and Ozkan, S. (2016). Monetary Policy, Heterogeneity, and the Housing Channel, *Working Paper* .

Iacoviello, M. (2005). House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle, *American Economic Review* **95**(3): 739– 764.

International Monetary Fund (2024). Chapter 2: Feeling the Pinch?, *World Economic Outlook (April 2024)* .

Iskhakov, F., Jørgensen, T. H., Rust, J. and Schjerning, B. (2017). The endogenous grid method for discrete-continuous dynamic choice models with (or without) taste shocks, *Quantitative Economics* **8**(2): 317–365.

Jarociński, M. and Karadi, P. (2020). Deconstructing Monetary Policy Surprises—The Role of Information Shocks, *American Economic Journal: Macroeconomics* **12**(2): 1–43.

Jordà, O. (2005). Estimation and Inference of Impulse Responses by Local Projections, *American Economic Review* **95**(1): 161–182.

Kaplan, G., Mitman, K. and Violante, G. L. (2020). The Housing Boom and Bust: Model Meets Evidence, *Journal of Political Economy* **128**(9).

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

Kaplan, G. and Violante, G. (2014). A Model of the Consumption Response to Fiscal Stimulus Payments, *Econometrica* **82**(4): 1199–1239.

Kaplan, G., Violante, G. L. and Weidner, J. (2014). The Wealthy Hand-to-Mouth, *Brookings Papers on Economic Activity* (1): 77–138.

Lenza, M. and Slacalek, J. (2024). How does monetary policy affect income and wealth inequality? Evidence from quantitative easing in the euro area, *Journal of Applied Econometrics* pp. 1–20.

McFadden, D. (1973). Conditional Logit Analysis of Qualitative Choice Behavior, *Institute of Urban and Regional Development, University of California* .

McKay, A., Nakamura, E. and Steinsson, J. (2016). The Power of Forward Guidance, *American Economic Review* **106**(10): 3133–3158.

McKay, A. and Wieland, J. F. (2021). Lumpy Durable Consumption Demand and the Limited Ammunition of Monetary Policy, *Econometrica* **89**(6): 2717–2749.

OECD (2012). OECD Economic Surveys: European Union 2012, *OECD Economic Surveys: European Union 2012, OECD Publishing, Paris* .

Pica, S. (2021). Housing Markets and the Heterogeneous Effects of Monetary Policy Across the Euro Area, *Technical report SSRN Electronic Journal* .

Slacalek, J., Tristani, O. and Violante, G. L. (2020). Household balance sheet channels of monetary policy: A back of the envelope calculation for the euro area, *Journal of Economic Dynamics and Control* **115**: 103879.

van Hoenselaar, F., Cournède, B., Pace, F. D. and Ziemann, V. (2021). Mortgage Finance Across OECD Countries, *OECD Economics Department Working Paper No. 1693, OECD Publishing, Paris* .

Wong, A. (2020). Refinancing and the Transmission of Monetary Policy to Consumption, *Working Paper* .

A Data sources

The following are the sources of the data used in the analyses.

Gross Domestic Product: *Gross Domestic Product at Market Prices*, chain linked volumes, seasonally and calendar adjusted, quarterly frequency. Source: Eurostat, table NAMQ 10 GDP.

Consumption: *Final Consumption Expenditure of Households and NPISH at Market Prices*, chain linked volumes, seasonally and calendar adjusted, quarterly frequency. Source: Eurostat, table NAMQ 10 GDP.

Consumer Price Index: *All-items HICP*, monthly frequency averaged to convert into quarterly frequency. Source: Eurostat, table PRC HICP MIDX.

Short-term interest rate: *Euro Area day-to-day rate*, quarterly frequency. Source: Eurostat, table IRT ST Q.

Share of ARM households: Entry DL1110 ("Outstanding balance of HMR mortgage") filtered using entry DL1110ai ("Has adjustable interest rate HMR mortgage"). Source: Eurosystem Household Finance and Consumption Survey (HFCS), waves one, two and three.

Share of hand-to-mouth households: This variable is constructed following the procedure detailed in Almgren et al. (2022) (see appendix B.2 for more details). Source: Eurosystem Household Finance and Consumption Survey (HFCS), waves one, two and three.

Outstanding amount of ARMs - Italy: *Consistenze di prestiti per l'acquisto di abitazioni famiglie consumatrici a tasso variabile*, quarterly frequency. Source: Bank of Italy.

Share of hand-to-mouth households - Italy, time series: Provided by the ECB on the basis of the series constructed for the analysis in Slacalek, Tristani and Violante (2020), quarterly frequency.

Mortgage interest rate - Italy: *Cost of borrowing for households for house purchase*, monthly frequency averaged to convert into quarterly frequency. Source: ECB SDW, MIR dataset.

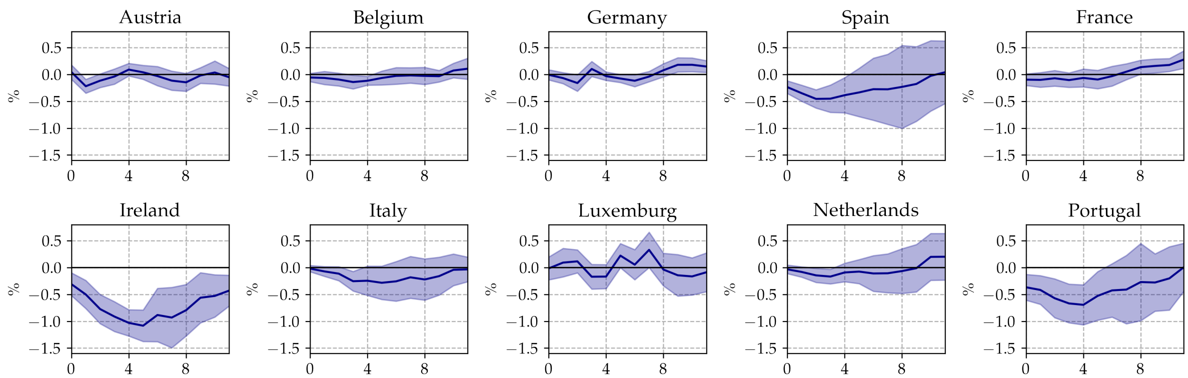
Monetary policy shocks: Monetary policy shocks by Jarociński and Karadi (2020), series updated until October 2022, monthly frequency summed up to convert into quarterly frequency. Source: Marek Jarocinski's website: https://marekjarocinski.github.io.

B Empirics – Additional figures

B.1 Euro Area impulse response functions

Figure B.1 shows the IRFs for each Euro Area country in the sample estimated using equation (1).

Figure B.1: IRFs of consumption to a contractionary monetary policy shock



Notes: Responses to a one standard deviation recessionary monetary policy shock. The shaded blue areas are 90% confidence intervals.

B.2 Methodology to construct HtM shares

I construct the share of HtM households in each Euro Area economy using data from the HFCS and applying the methodology by Kaplan and Violante (2014), adjusted for the analysis using Euro Area data by Almgren et al. (2022). In particular, letting y_i denote monthly income, m_i denote liquid wealth, and $\underline{m_i}$ denote a credit limit for household i in the HFCS, a household is categorized as being HtM if:

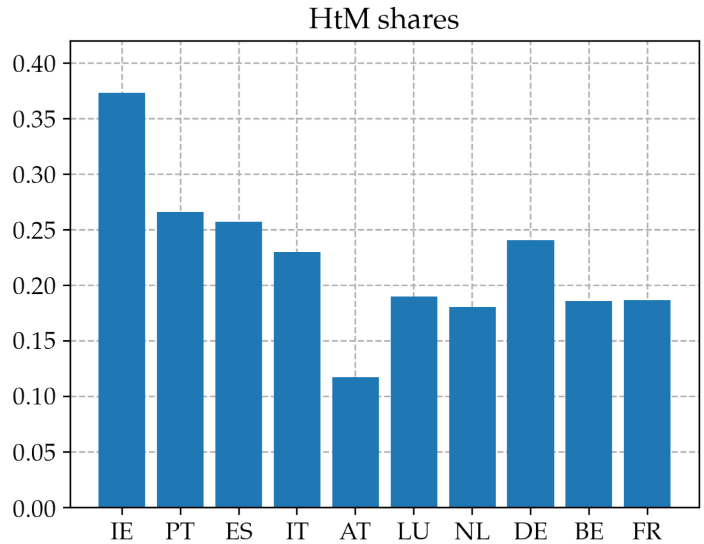
$$0 \leq m_i \leq \frac{y_i}{2}$$

or:

$$m_y \leq 0 \quad \text{and} \quad m_i \leq \frac{y_i}{2} - \underline{m_i}.$$

The first condition highlights that if households have positive liquid wealth, they are classified as HtM if this wealth is less than half their monthly income. The second condition states that if households have negative liquid wealth, then they are classified as HtM if this wealth is less than half of their monthly income minus their credit limit, which is set equal to the household's monthly income. The idea behind this last condition is that household can use a credit card that needs repayment once a month. In line with the analysis in Almgren et al. (2022), very few households are classified as HtM based on this second condition. Figure B.2 shows the fraction of HtM households in each Euro Area economy considered in the analysis (note that this chart shows the same values as in the left panel of Figure 1, with the only difference being the ranking of the countries).

Figure B.2: Shares of HtM households in Euro Area countries



Notes: See text for the methodology used to construct these shares. Countries are ranked by the strength of monetary policy transmission, from Ireland (strongest) to France (weakest), in line with the estimates from equation (1) shown in Figure 2.

Classification of assets in ECB HFCS I follow Almgren et al. (2022) to categorize variables in the ECB HFCS. In particular, *liquid wealth* is computed as *liquid assets* minus *liquid debt*. The variables included in *liquid assets* are:

1. **hd1110**: value of sight accounts (scaled by 1.0556 to adjust for cash missing in the HFCS)
2. **da2102**: mutual funds, total
3. **da2103**: bonds
4. **da2105**: shares, publicly traded
5. **hd1210**: value of saving accounts

The variables included in *liquid debt* are:

1. **hc0220**: amount if outstanding credit line/overdraft balance
2. **hc0320**: amount of outstanding credit cards balances.

B.3 Alternative correlations

Tables B.1 and B.2 show the correlation coefficients and p-values under alternative specifications relative to the one considered in Section 2.1. Each column shows the metric used to proxy the potency of monetary policy transmission: maximum response of consumption over a two year period (*Max 2Y*), maximum response of consumption over a three year period (*Max 3Y*), average response of consumption over a two year period (*Mean 2Y*), and average response of consumption over a three year period (*Mean 3Y*). Each row shows the specification considered. *Baseline* refers to the baseline specification in Section 2.1. *Before 2012* cuts the sample for the estimation of regression (1) to the period before 2012, the one considered in Almgren et al. (2022). *After 2007* starts the sample in 2007, following Corsetti, Duarte and Mann (2022) and Pica (2021). *3 Lags* shows the alternative correlations in a specification of regression (1) where the controls have 3 lags instead of 2. *Other shock* shows the correlations where the shock in equation (1) is the one constructed in Altavilla et al. (2019) (2-year OIS change). Relative to Section 2, Table B.1 reports the correlations with the share of HtM households exclusively, which confirm the results in Almgren et al. (2022): the strength of monetary policy is positively correlated with the fraction of HtM agents in the Euro Area.

Table B.1: Correlations with HtM and ARM in alternative specifications

	HtM				ARM			
	Max 2Y	Max 3Y	Mean 2Y	Mean 3Y	Max 2Y	Max 3Y	Mean 2Y	Mean 3Y
Baseline	-0.865	-0.865	-0.879	-0.869	-0.589	-0.589	-0.538	-0.593
	(0.001)	(0.001)	(0.001)	(0.001)	(0.073)	(0.073)	(0.108)	(0.071)
Before 2012	-0.667	-0.680	-0.708	-0.723	-0.634	-0.689	-0.472	-0.555
	(0.035)	(0.030)	(0.022)	(0.018)	(0.049)	(0.027)	(0.168)	(0.095)
After 2007	-0.577	-0.697	-0.842	-0.830	-0.479	-0.525	-0.296	-0.308
	(0.080)	(0.025)	(0.002)	(0.003)	(0.160)	(0.119)	(0.406)	(0.387)
3 Lags	-0.798	-0.796	-0.816	-0.732	-0.706	-0.727	-0.669	-0.755
	(0.006)	(0.006)	(0.004)	(0.016)	(0.023)	(0.017)	(0.034)	(0.012)
Other shock	-0.806	-0.810	-0.774	-0.768	-0.625	-0.619	-0.614	-0.671
	(0.005)	(0.005)	(0.009)	(0.009)	(0.053)	(0.056)	(0.059)	(0.034)

Notes: Each line shows the correlation coefficient and p-value (in parenthesis) of the response of consumption to a one-standard deviation recessionary shock.

Table B.2: Correlations with HtM & ARM households in alternative specifications

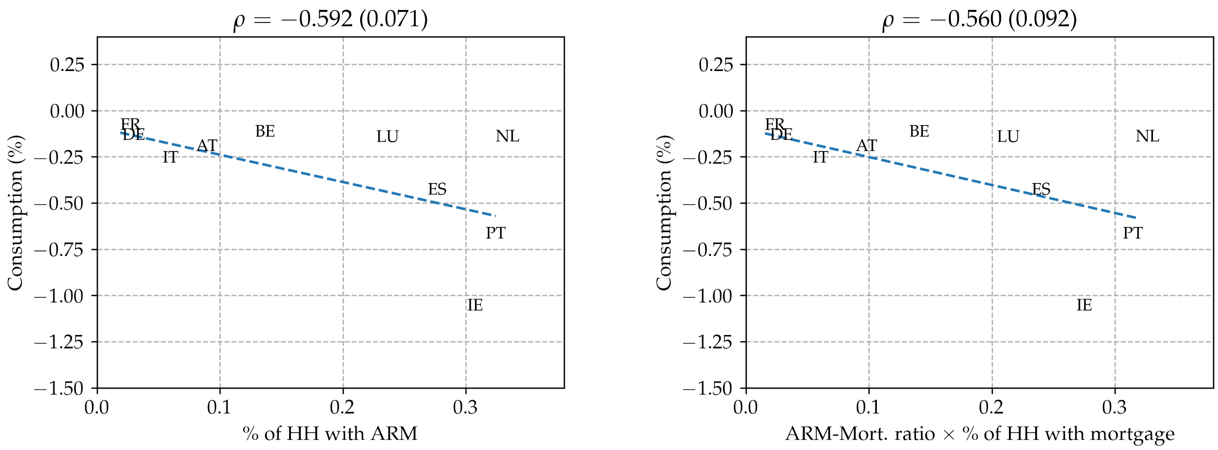
	HtM & ARM			
	Max 2Y	Max 3Y	Mean 2Y	Mean 3Y
Baseline	-0.888	-0.919	-0.909	-0.920
	(0.000)	(0.000)	(0.000)	(0.000)
Before 2012	-0.691	-0.721	-0.730	-0.767
	(0.026)	(0.018)	(0.016)	(0.001)
After 2007	-0.793	-0.874	-0.861	-0.835
	(0.006)	(0.001)	(0.001)	(0.003)
3 Lags	-0.918	-0.910	-0.915	-0.893
	(0.000)	(0.000)	(0.000)	(0.001)
Other shock	-0.885	-0.889	-0.865	-0.892
	(0.000)	(0.000)	(0.001)	(0.000)

Notes: Each line shows the correlation coefficient and p-value (in parenthesis) of the response of consumption to a one-standard deviation recessionary shock.

Figure B.3 shows the alternative correlations that would arise considering different ARM shares. The left panel shows the correlation with the product between the share of outstanding ARMs and the fraction of households that have a mortgage in each country in the HFCS. The idea is that this variable is high not only when most mortgages have an ARM, but also when mortgages are widespread in the economy. The right panel shows the correlation with the fraction of households in the population that have an ARM instead of the share of ARMs within the total mortgage stock. The figure shows that the results from Section 2.1 are robust to these alternative measures of the ARM share.

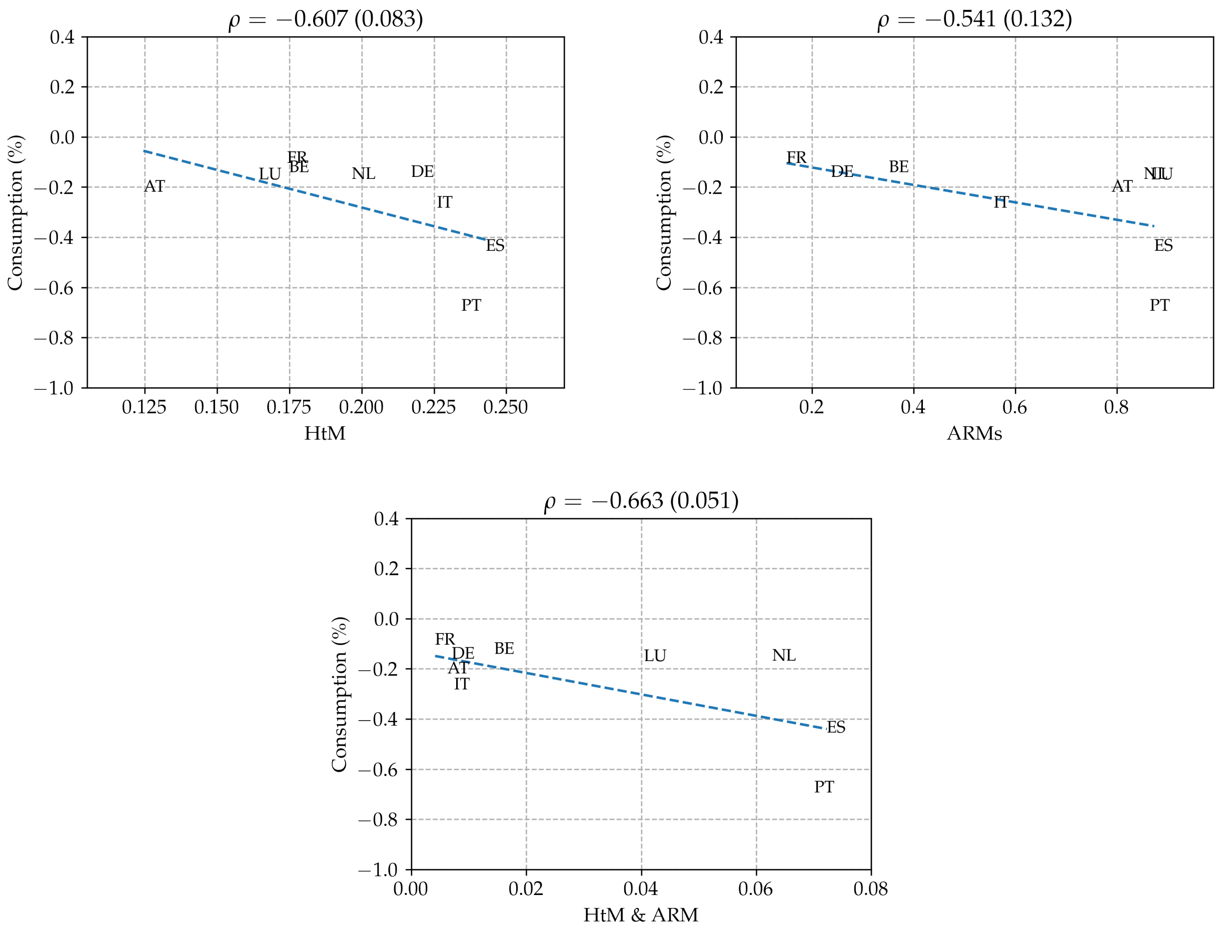
Figures B.4 and B.5 show the alternative correlations of the two variables of interest computed in different waves of the HFCS, which are consistent with the main ones in Section 2.1.

Figure B.3: Alternative correlations between the potency of transmission and HtM and ARM shares: Alternative ARM shares



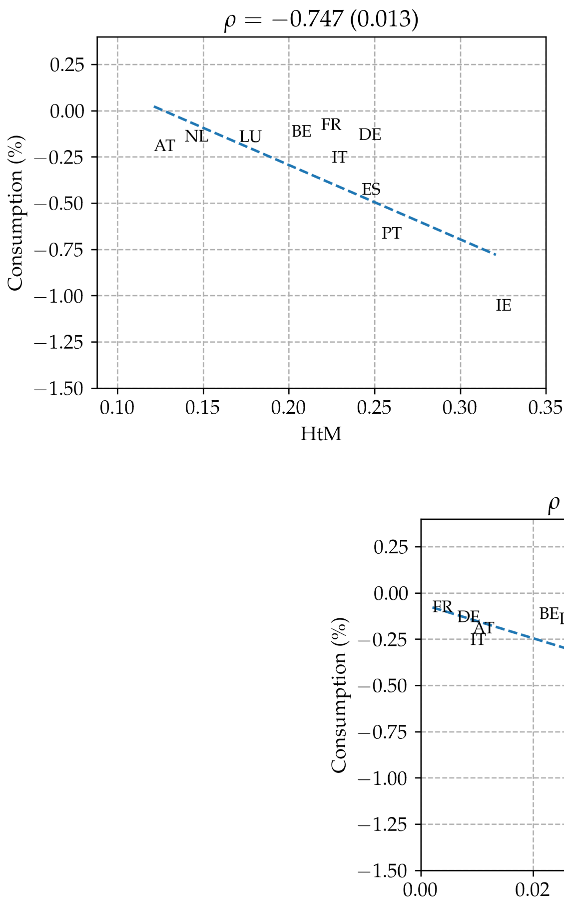
Notes: The y-axes show the peak response of consumption to a one standard deviation recessionary monetary policy shock estimated using equation (1). On top of each chart I show ρ, the correlation coefficient, together with its p-value in parenthesis.

Figure B.4: Alternative correlations between the potency of transmission and HtM and ARM shares: HFCS wave 1



Notes: The y-axes show the peak response of consumption to a one standard deviation recessionary monetary policy shock estimated using equation (1). On top of each chart I show ρ, the correlation coefficient, together with its p-value in parenthesis.

Figure B.5: Alternative correlations between the potency of transmission and HtM and ARM shares: HFCS wave 3



Notes: The y-axes show the peak response of consumption to a one standard deviation recessionary monetary policy shock estimated using equation (1). On top of each chart I show ρ, the correlation coefficient, together with its p-value in parenthesis.

B.4 Panel local projections – Effect of higher share of HtM households with ARMs

This section provides alternative evidence on the relevance of HtM households with ARMs for the strength of monetary policy transmission in the Euro Area, mirroring the empirical evidence provided in the scatterplots of Section 2.1. While the main results in Section 2.2 focus on the separate and interactive effects of the aggregate ARM share (ARM) and HtM share (HtM), here I estimate the additional amplification arising specifically from economies where the share of households that are both HtM and have ARMs is high.

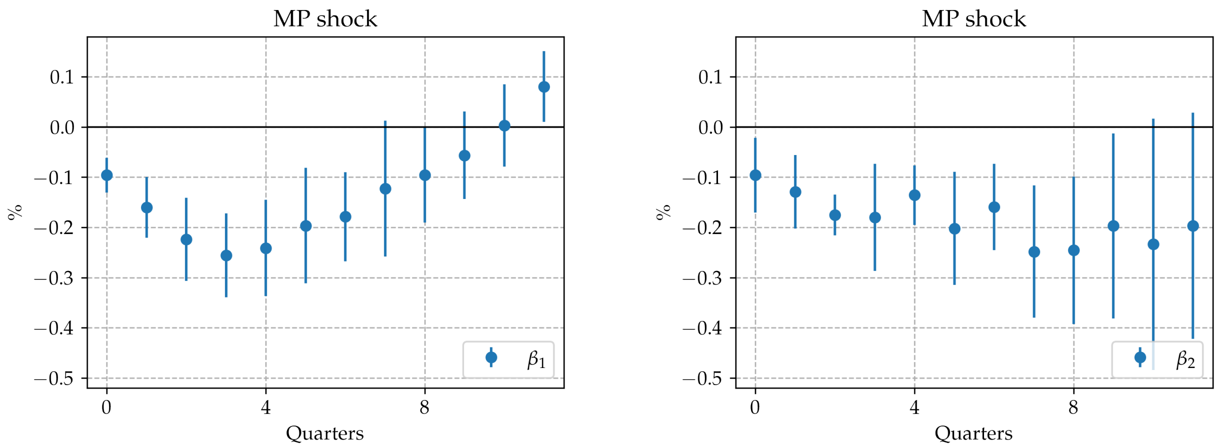
Specifically, I estimate the following fixed-effects panel local projection regression (Jordà, 2005):

$$\begin{aligned} y^c_{t+h} =& \beta^h_0 + \beta^h_1 \epsilon^{MP}_t + \beta^h_2 \epsilon^{MP}_t ARMxHtM^c + \beta^h_3 \epsilon^{MP}_t ARM^c + \\ & \beta^h_4 \epsilon^{MP}_t HtM^c + \Gamma^h X^c + u^c_{t+h}, \qquad h = 0, 1, 2, \ldots \end{aligned} \tag{15}$$

where y^c is the logarithm of consumption in country c, ϵ^{MP}_t is the monetary policy shock from Jarociński and Karadi (2020), $ARMxHtM^c$ is the standardized share of households in country c who are both HtM and have ARMs, and X^c includes the same set of lagged control variables as in equation (2). The key coefficient of interest is β^h_2, which captures the additional effect of a monetary policy shock in economies where the share of HtM households with ARMs is one standard deviation above the Euro Area average.

The results are presented in Figure B.6. The left panel shows the baseline response to a recessionary monetary policy shock (β^h_1), indicating a statistically significant decline in consumption when $ARMxHtM$ is at its Euro Area average. The right panel shows the additional amplification effect captured by β^h_2: the coefficient is consistently negative and statistically significant over the horizon, suggesting that monetary policy transmission is stronger in countries with a high prevalence of households that are simultaneously liquidity-constrained and directly exposed to interest rate changes. This evidence aligns with the strong correlation patterns documented in Section 2.1.

Figure B.6: Response of consumption to a monetary policy shock, results from equation (15)

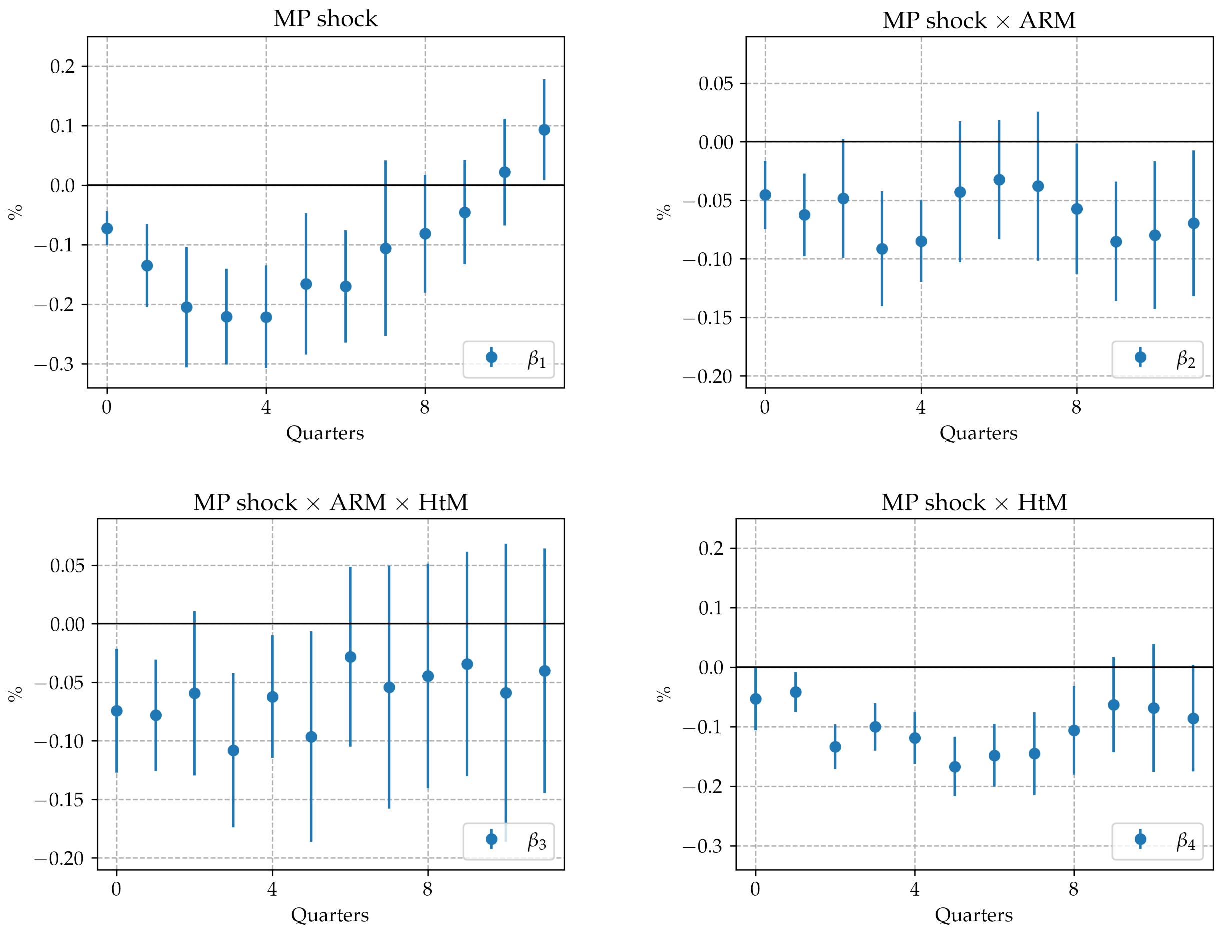


Notes: Responses to a one standard deviation recessionary monetary policy shock. The vertical blue lines represent 90% confidence intervals.

B.5 Panel local projections – Robustness

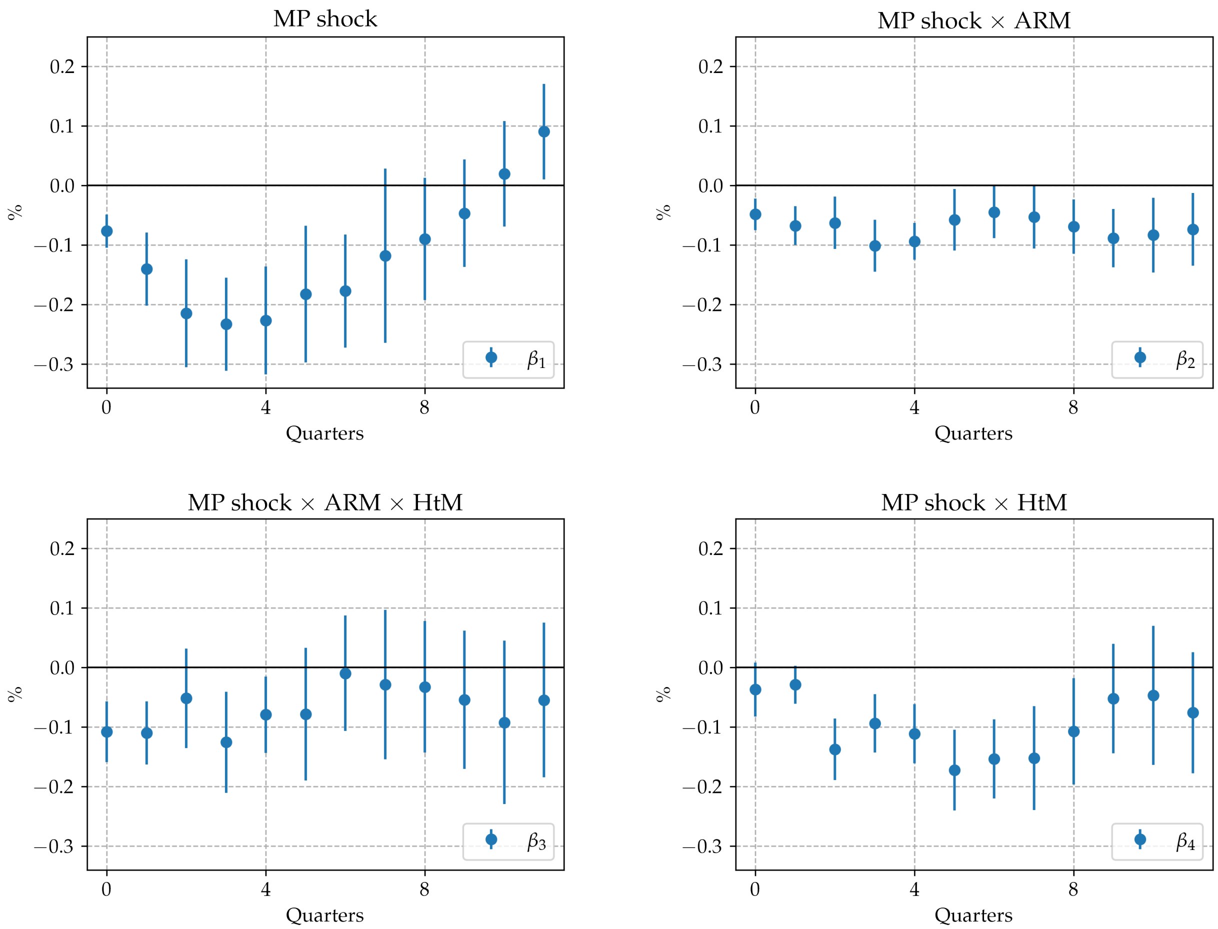
The results presented in Section 2.2 use data from the second wave of the HFCS. I here consider alternative specifications using data from the other two waves of the survey. Figure B.7 reproduces the main coefficients estimated using equation (2) for reference. As a first robustness exercise, Figure B.8 shows the IRFs of the coefficients of interest estimated using the specification in equation (2), where ARM and HtM are the average HtM and ARM shares across the three ECB HFCS survey waves, and using alternative definitions of the share of ARMs and the fraction of HtM households. As a second robustness exercise, I interpolate the HtM and ARM shares values between the three survey waves, and re-estimate the coefficients of interest using equation (2). The results are displayed in Figure B.9. As a third robustness exercise, I once again use the interpolated values of the HtM and ARM shares across survey waves, but I start the sample in 2010, when the first survey was conducted. The results of this exercise are shown in Figure B.10. Additionally, Figures B.11 and B.12 show robustness exercises where the variable ARM in specification (2) is replaced (i) with the product between ARM and the share of households with a mortgage, and (ii) with the fraction of households with an ARM in the population of each country. Finally, Figure B.13 presents a robustness exercise in which the variable HtM in specification (2) is replaced by $WHtM$, which represents the share of households in each economy classified as *wealthy* hand-to-mouth. These households are hand-to-mouth but possess positive amounts of illiquid wealth. Overall, the results are line with the ones presented in Section 2.2 across the different robustness exercises.

Figure B.7: Response of consumption to a monetary policy shock, baseline results from equation (2)



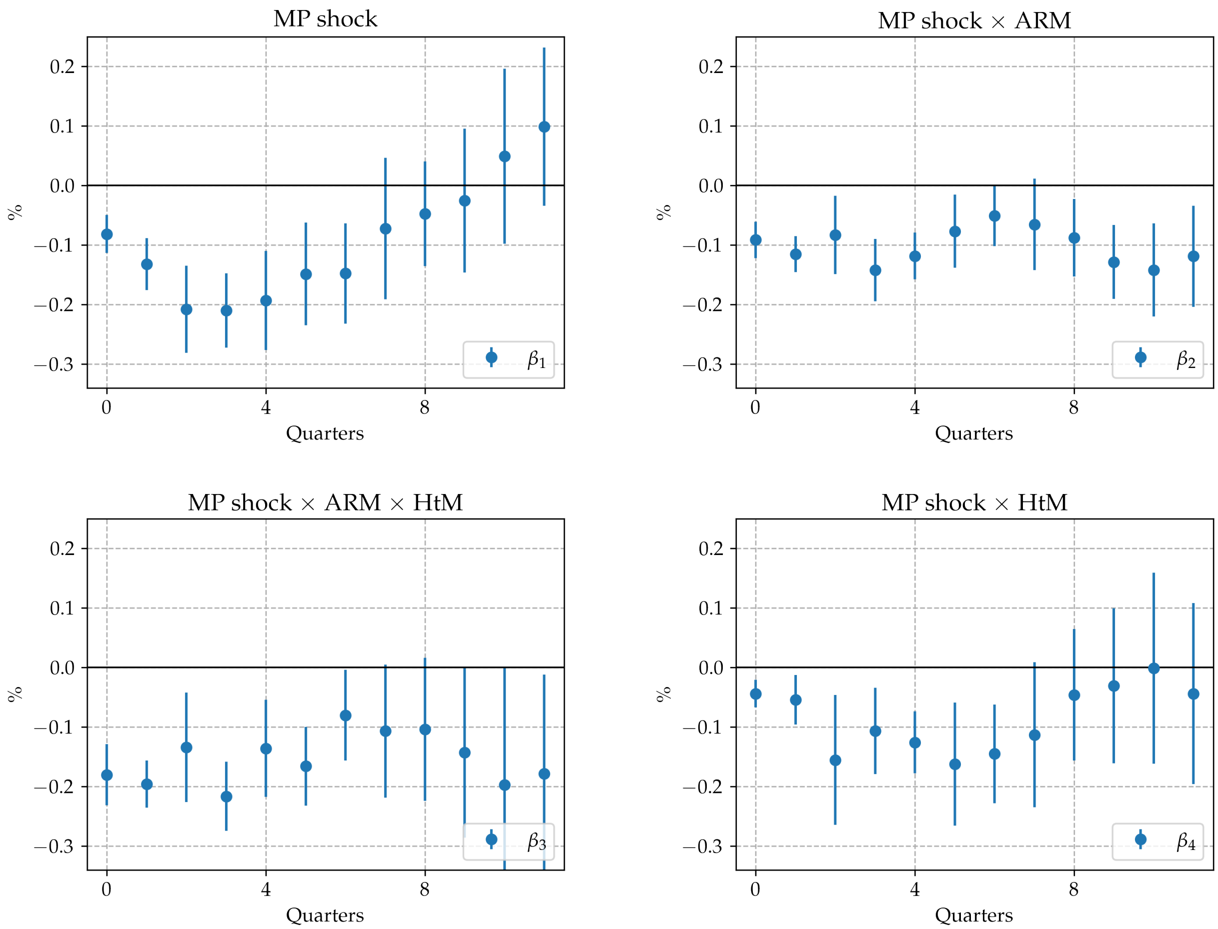
Notes: Response of consumption to a one standard deviation contractionary monetary policy shock. The vertical blue lines represent 90% confidence intervals.

Figure B.8: Response of consumption to a monetary policy shock, average HtM and ARM values across HFCS waves



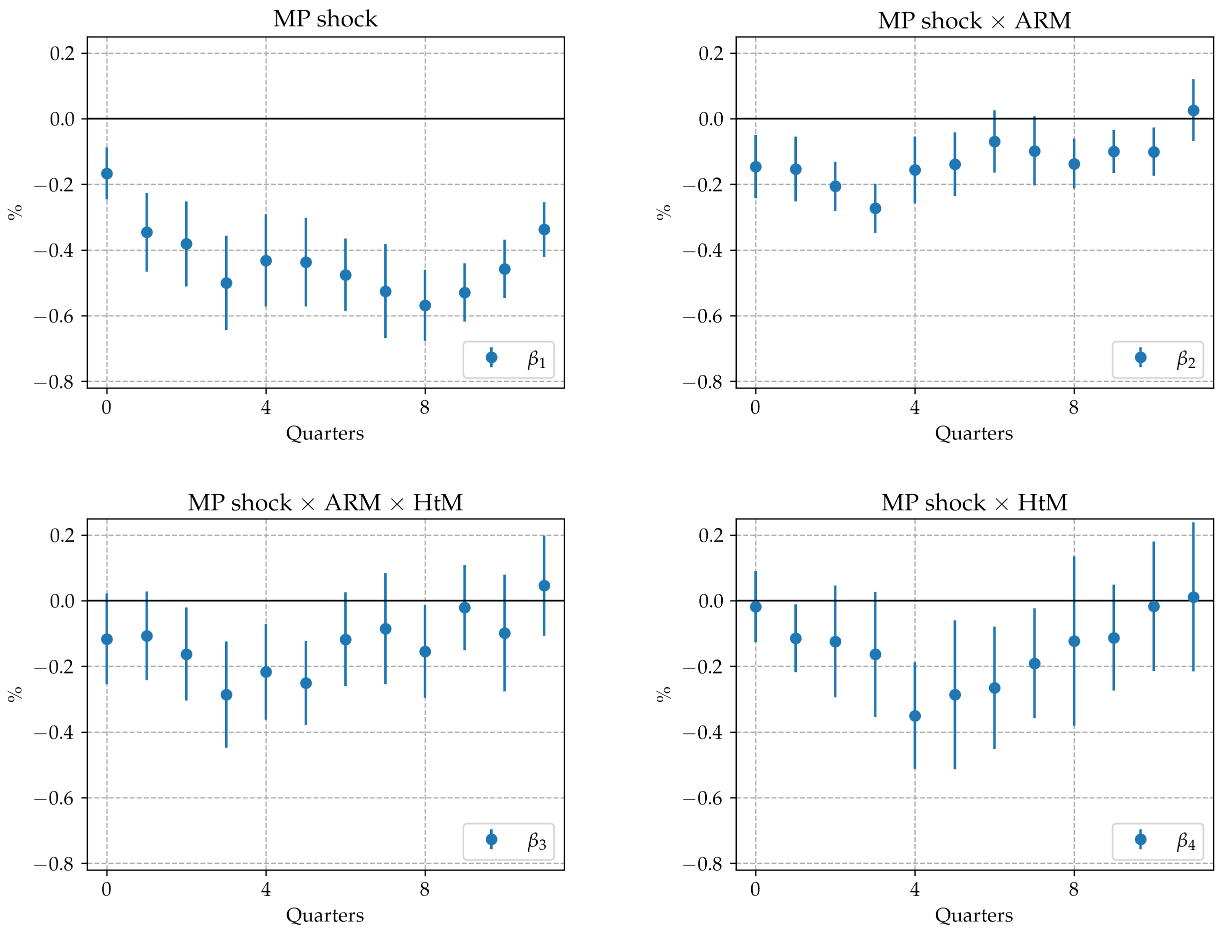
Notes: Response of consumption to a one standard deviation contractionary monetary policy shock. The vertical blue lines represent 90% confidence intervals.

Figure B.9: Response of consumption to a monetary policy shock, interpolated HtM and ARM values across HFCS waves



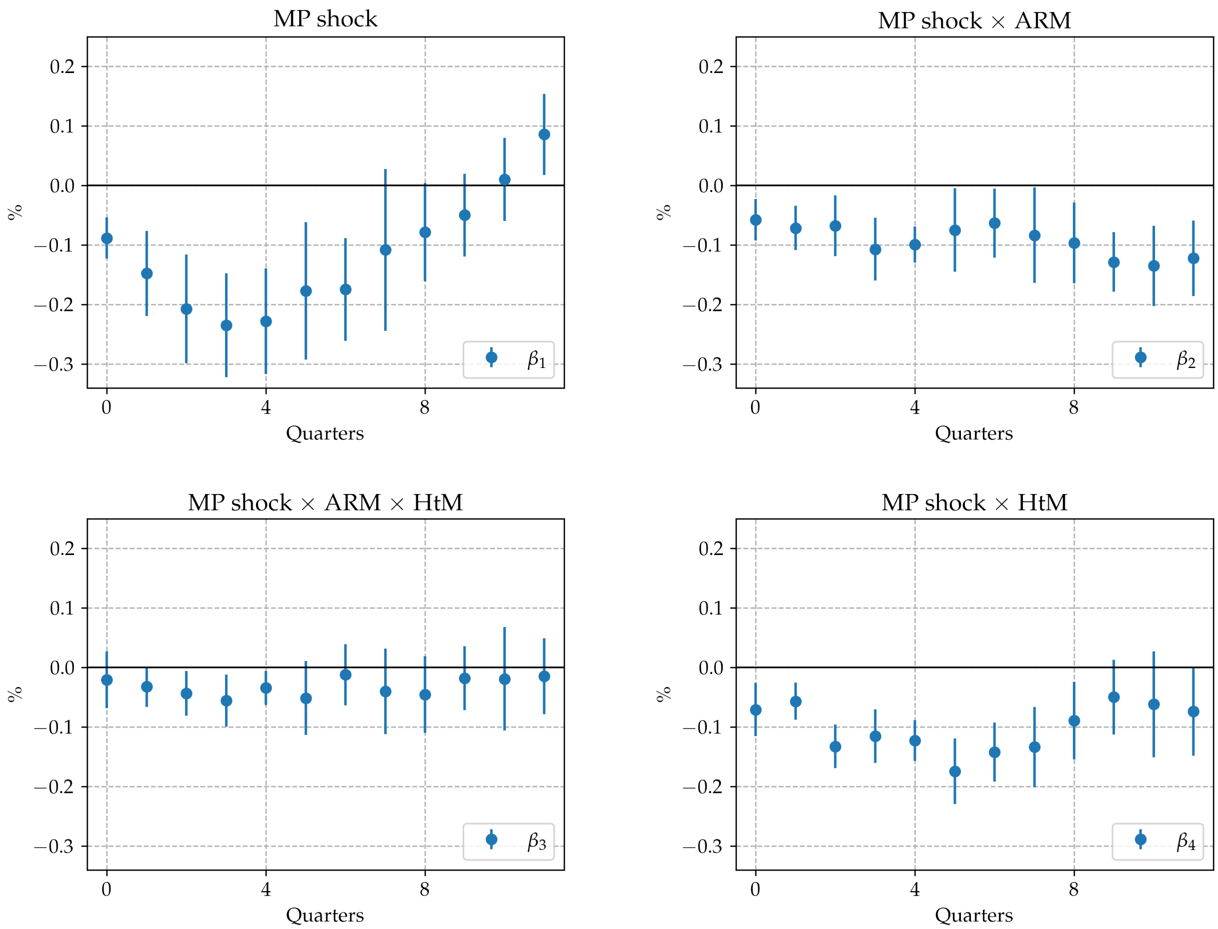
Notes: Response of consumption to a one standard deviation contractionary monetary policy shock. The vertical blue lines represent 90% confidence intervals.

Figure B.10: Response of consumption to a monetary policy shock, interpolated HtM and ARM values across HFCS waves and sample beginning in 2010



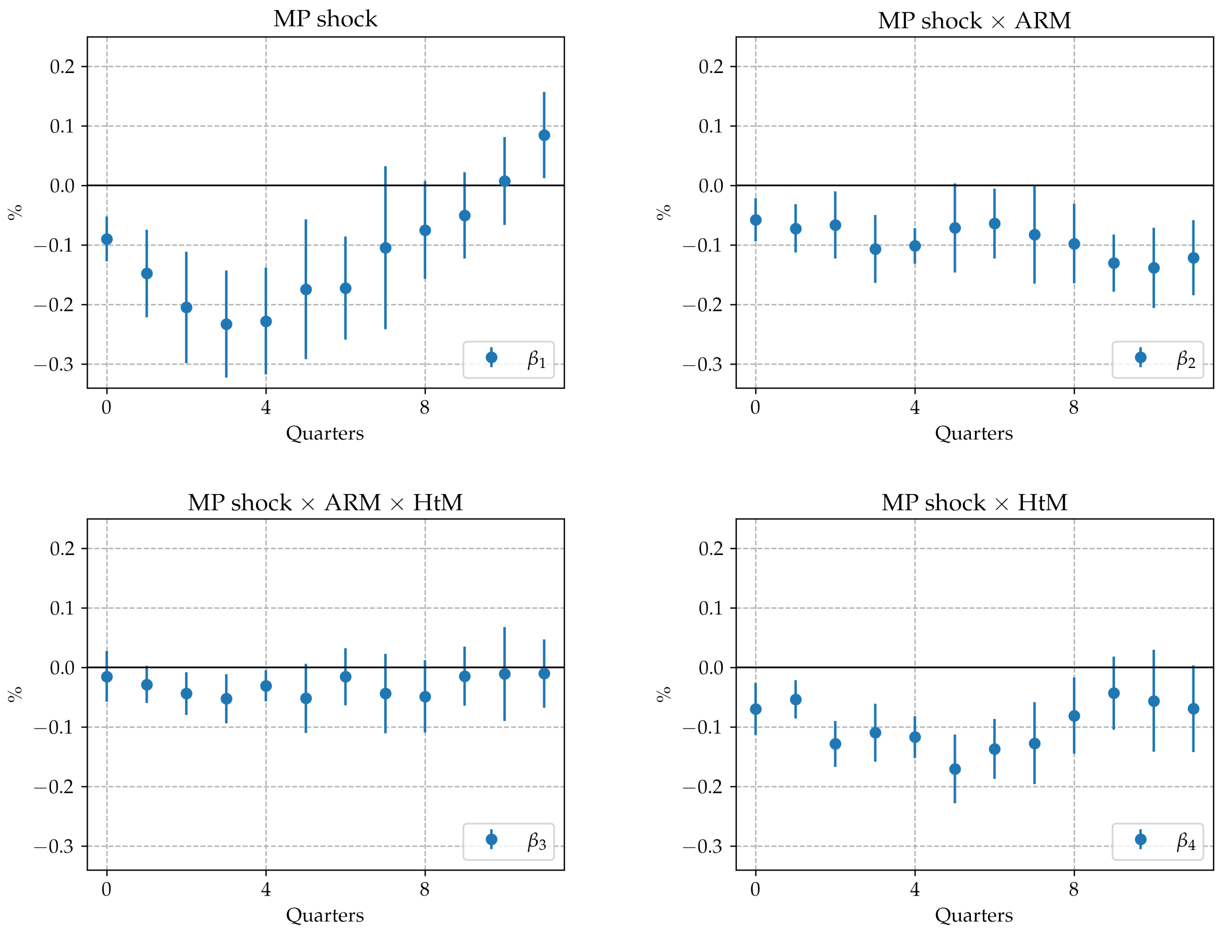
Notes: Response of consumption to a one standard deviation contractionary monetary policy shock. The vertical blue lines represent 90% confidence intervals.

Figure B.11: Response of consumption to a monetary policy shock, using *ARM* × *Share of mortgagors*



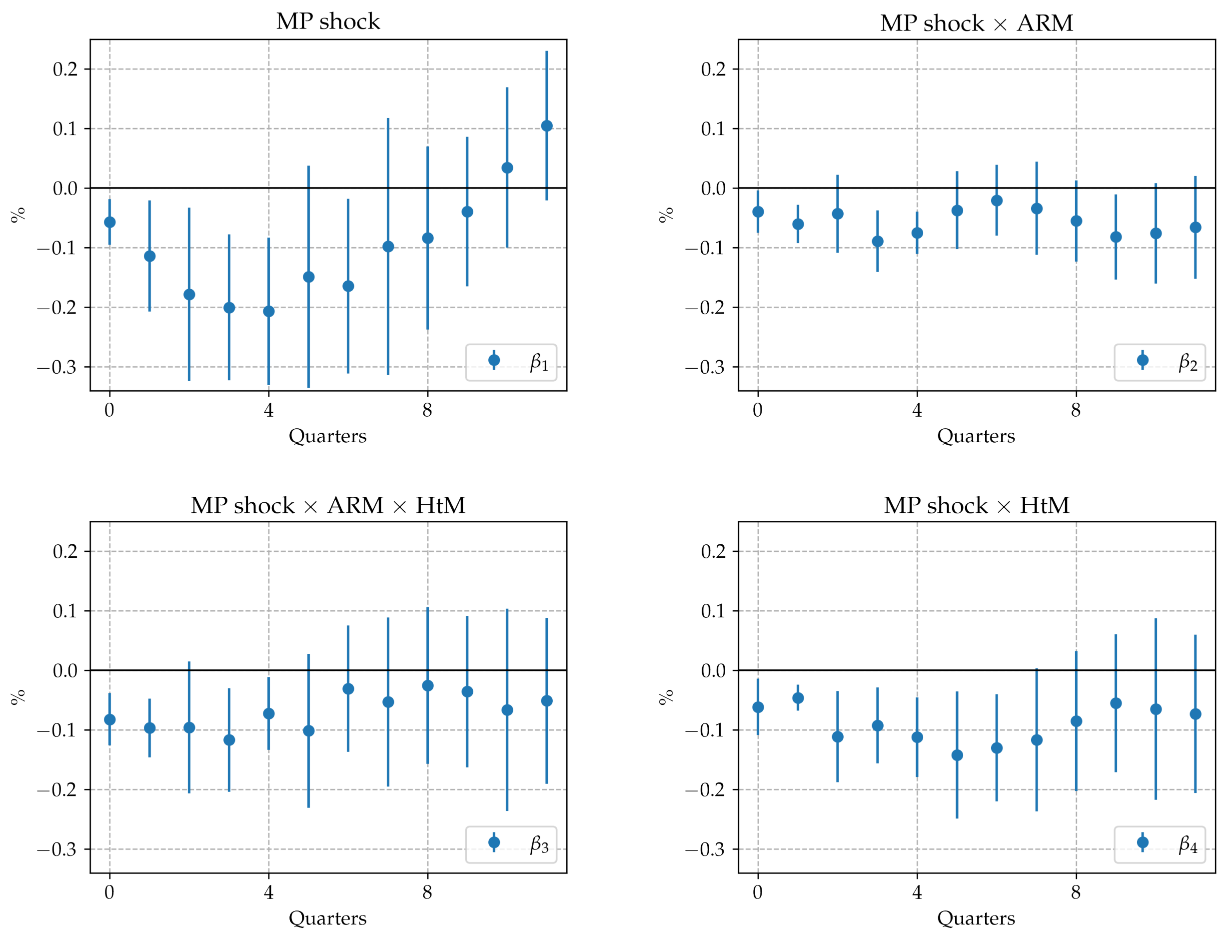
Notes: Response of consumption to a one standard deviation contractionary monetary policy shock. The vertical blue lines represent 90% confidence intervals.

Figure B.12: Response of consumption to a monetary policy shock, using *Share of HH with ARM*



Notes: Response of consumption to a one standard deviation contractionary monetary policy shock. The vertical blue lines represent 90% confidence intervals.

Figure B.13: Response of consumption to a monetary policy shock, using *Wealthy HtM*



Notes: Response of consumption to a one standard deviation contractionary monetary policy shock. The vertical blue lines represent 90% confidence intervals.

B.6 Evidence using Italian time series

This appendix provides a robustness check using time-series variation within a single country, Italy, to address concerns about potential unobserved country-specific factors driving the cross-country results presented in Section 2.2. While the main analysis focuses on cross-country differences, this within-country exercise allows me to control for fixed country-level characteristics and test whether the interaction between ARMs and HtM shares amplifies monetary policy transmission over time.

Due to data constraints, the time series spans the period 2007Q1 to 2019Q4. The series on the share of HtM households was reconstructed by the authors of Slacalek, Tristani and Violante (2020), while the share of outstanding ARMs was provided by economists at the Bank of Italy.[36]

I estimate the following local projection regression (Jordà, 2005):

$$
\begin{aligned}
y_{t+h} = & \beta_0^h + \beta_1^h \epsilon_t^{MP} + \beta_2^h \epsilon_t^{MP} ARM_{t-1} + \beta_3^h \epsilon_t^{MP} ARM_{t-1} HtM_{t-1} + \\
& + \beta_4^h \epsilon_t^{MP} HtM_{t-1} + \Gamma^h X + u_{t+h}, \qquad h = 0, 1, 2, \ldots
\end{aligned}
\tag{16}
$$

where y_t is the logarithm of Italian consumption, ϵ_t^{MP} is the monetary policy shock from Jarociński and Karadi (2020), and ARM_{t-1} and HtM_{t-1} are the lagged, standardized shares of ARMs and HtM households, respectively.[37] X_t includes a parsimonious set of controls, given the limited sample length: two lags of consumption, two lags of the monetary policy shock, two lags of Italian CPI, and two lags of the average Italian mortgage rate.[38]

Figure B.14 presents the impulse response functions. The left panel shows β_1, indicating that, on average, a contractionary monetary policy shock does not lead to a statistically significant change in consumption over this period. The middle panel shows β_2, capturing the effect when the ARM share is one standard deviation above its Italian average: the coefficient is initially negative and statistically significant but turns insignificant at longer horizons, suggesting limited amplification from ARMs alone.

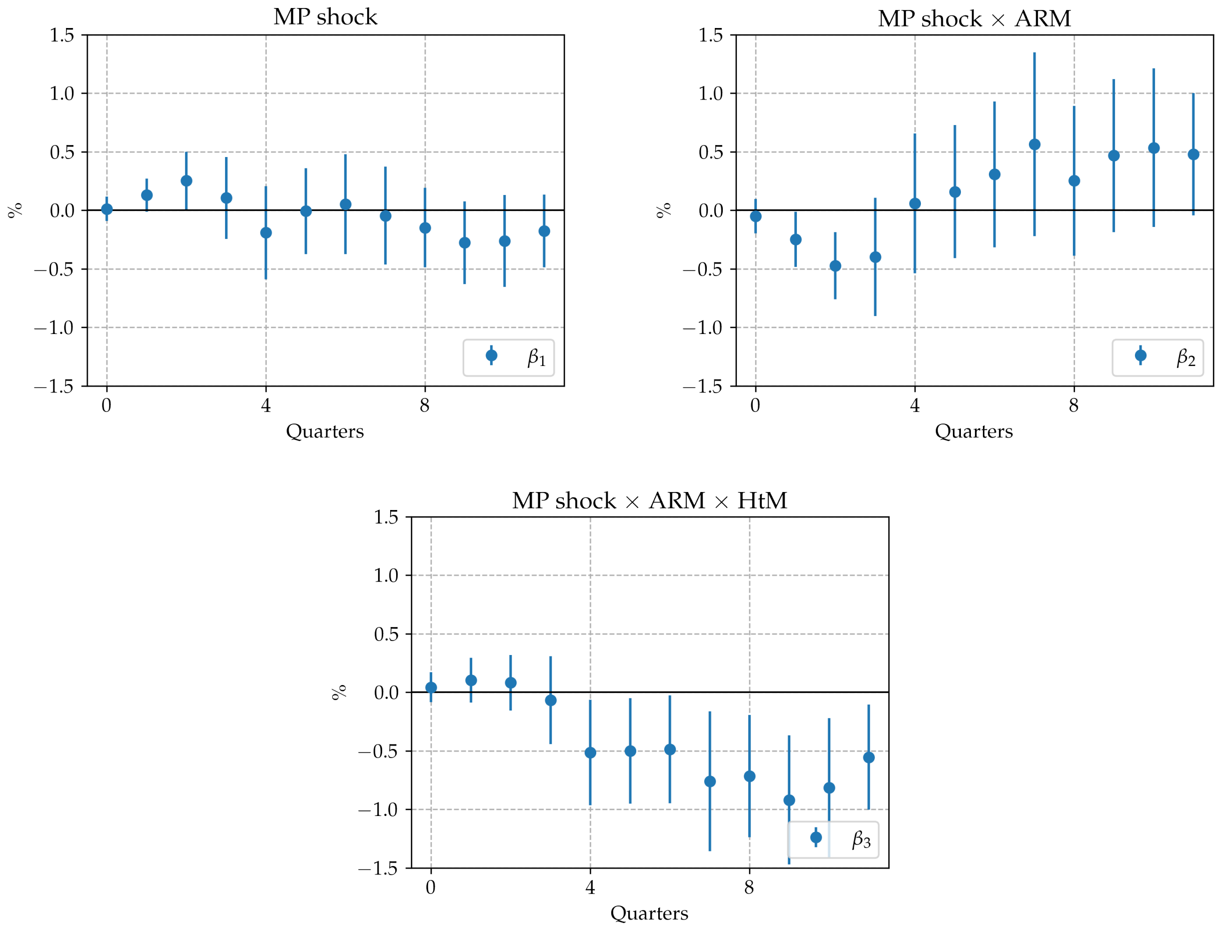
Finally, the right panel shows that when both ARM and HtM are one standard deviation above their means, the effects of a monetary policy shock are amplified, with a statistically significant peak impact of approximately -0.92 percentage points. This finding suggests that while ARMs alone may not have a substantial effect, their influence

[36] I am grateful to both for sharing these data.

[37] The lag ensures the regression estimates the differential effects of shocks conditional on prior-period ARM and HtM shares.

[38] Appendix B.7 provides robustness checks with alternative specifications.

Figure B.14: Response of consumption to a monetary policy shock in Italy



Notes: Response of consumption to a one standard deviation contractionary monetary policy shock. The blue dots in each panel show the evolution, over a 12-quarter horizon, of coefficients β_1 to β_3 estimated using equation (16). The vertical blue lines represent 90% confidence intervals.

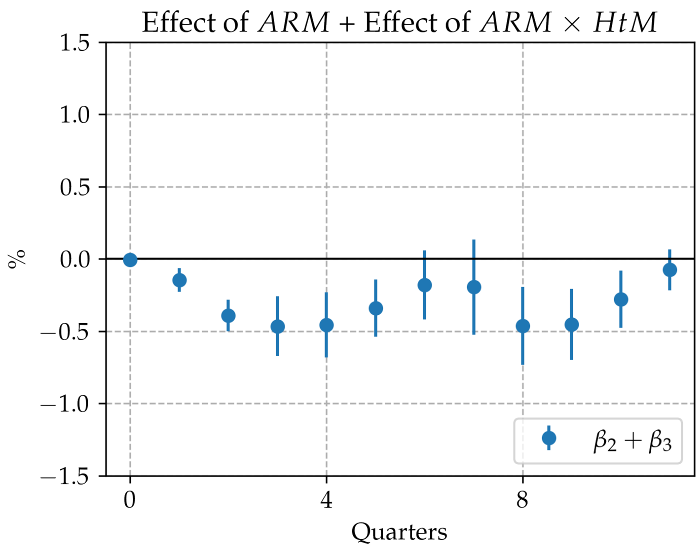
becomes critical when combined with a high share of HtM households, significantly enhancing monetary policy pass-through.[39]

By contrast, the right panel shows β_3, the effect of the interaction between ARMs and HtM shares. When both are elevated, the shock's impact on consumption is significantly amplified, with a peak effect of about -0.92 percentage points. This supports the idea that while ARMs alone may not strongly drive transmission, their effect becomes pronounced when combined with a high share of liquidity-constrained households, consistent with the main cross-country findings of Section 2.2. Figure B.15 shows that the combined effect,

[39] Figure B.15 shows that the sum of coefficients β_2 and β_3 is negative and statistically significant.

$\beta_2 + \beta_3$, is negative and statistically significant.

Figure B.15: Response of consumption to a monetary policy shock, baseline results from equation (16), sum of coefficients β_2 and β_3



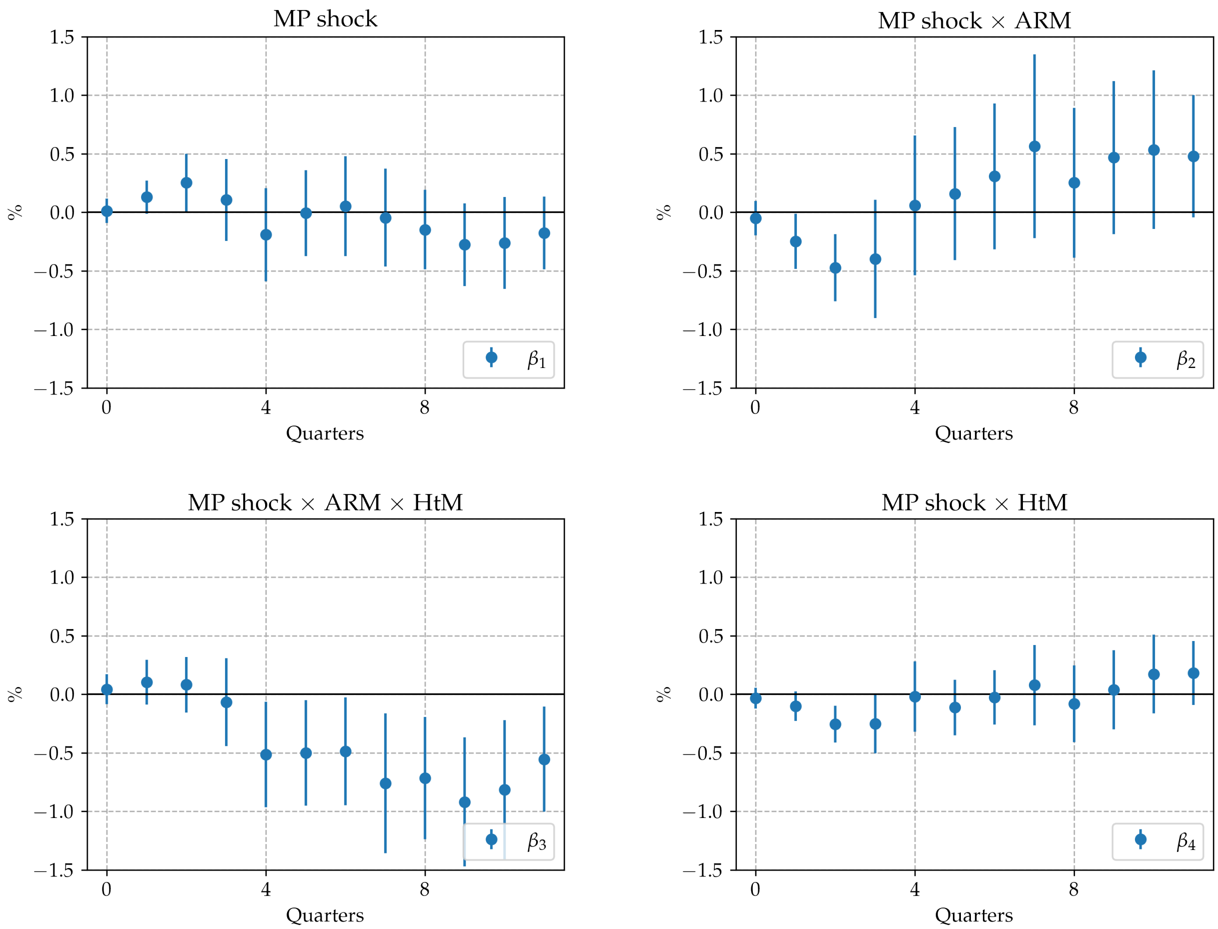
Notes: Responses to a one standard deviation recessionary monetary policy shock. The vertical blue lines represent 90% confidence intervals.

B.7 Italian local projections – Robustness

One main concern with the empirical exercise in Section (B.6) is that the coefficients estimated could be many relative to the observations available. In order to overcome this concern, the model in equation (16) contains a restricted number of control variables. This appendix provides a series of robustness exercises changing the variables included in the control vector X. The main message from this section is that the main coefficient of interest, β_3, the one capturing the effect of the interaction between ARM and HtM, remains negative and statistically significant throughout the different specifications.

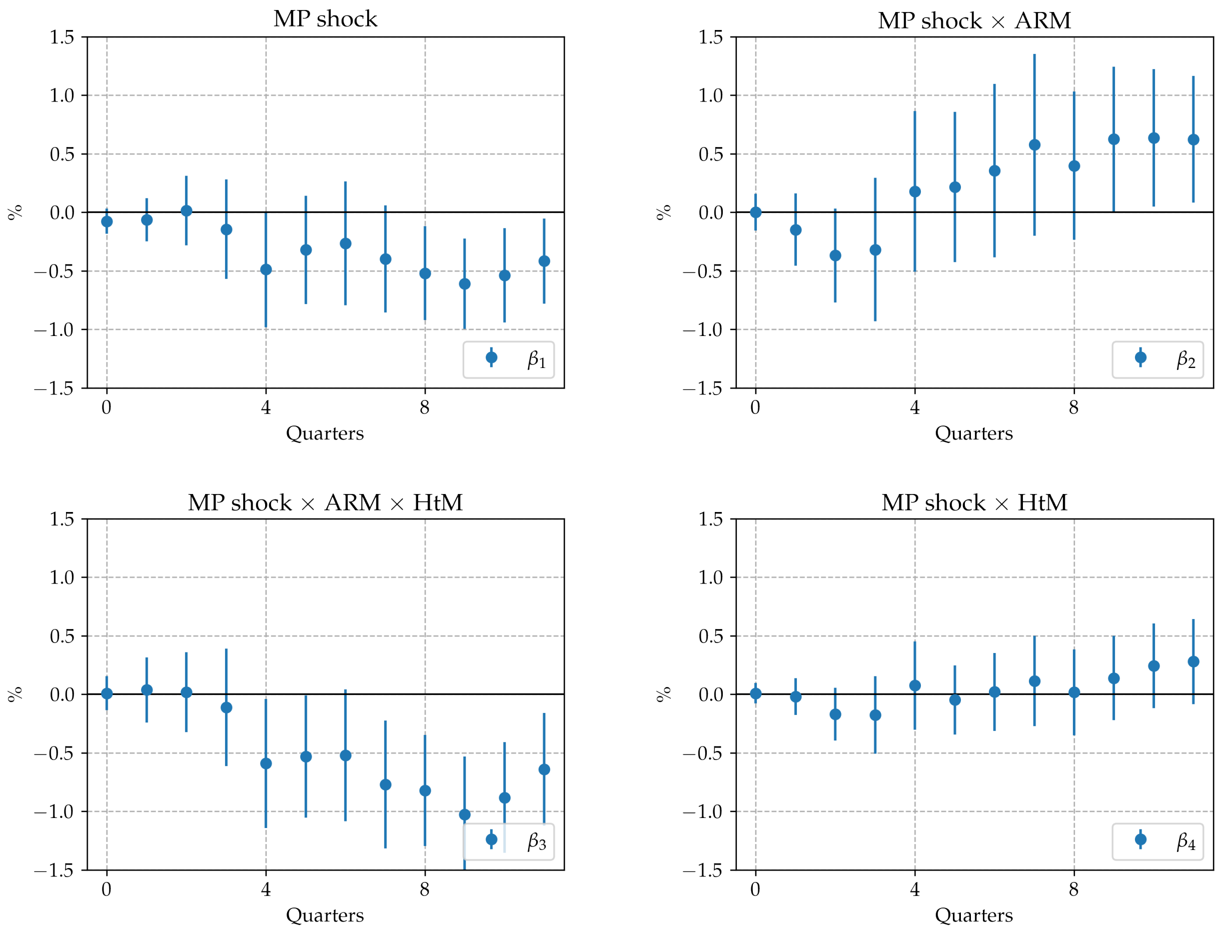
Figure B.16 shows the responses of regression (16) for comparison. Figure B.17 shows the responses where the set of controls X includes only the left-hand-side variable, consumption, and the average Italian mortgage rate. Figure B.18 shows the responses where only the left-hand-side variable and Euro Area variables are included in X, namely: Euro Area GDP, cpi and short-term interest rate. Finally, Figure B.19 shows the responses where X includes a large number of variables (more similar to the specification of the panel model in equation (2)): the left-hand-side variable, Italian cpi and average mortgage rate, as well as Euro Area GDP, cpi and short-term interest rate. Throughout the specifications, the coefficient of interest β_3 remains negative and statistically significant.

Figure B.16: Response of consumption to a monetary policy shock, baseline results from equation (16)



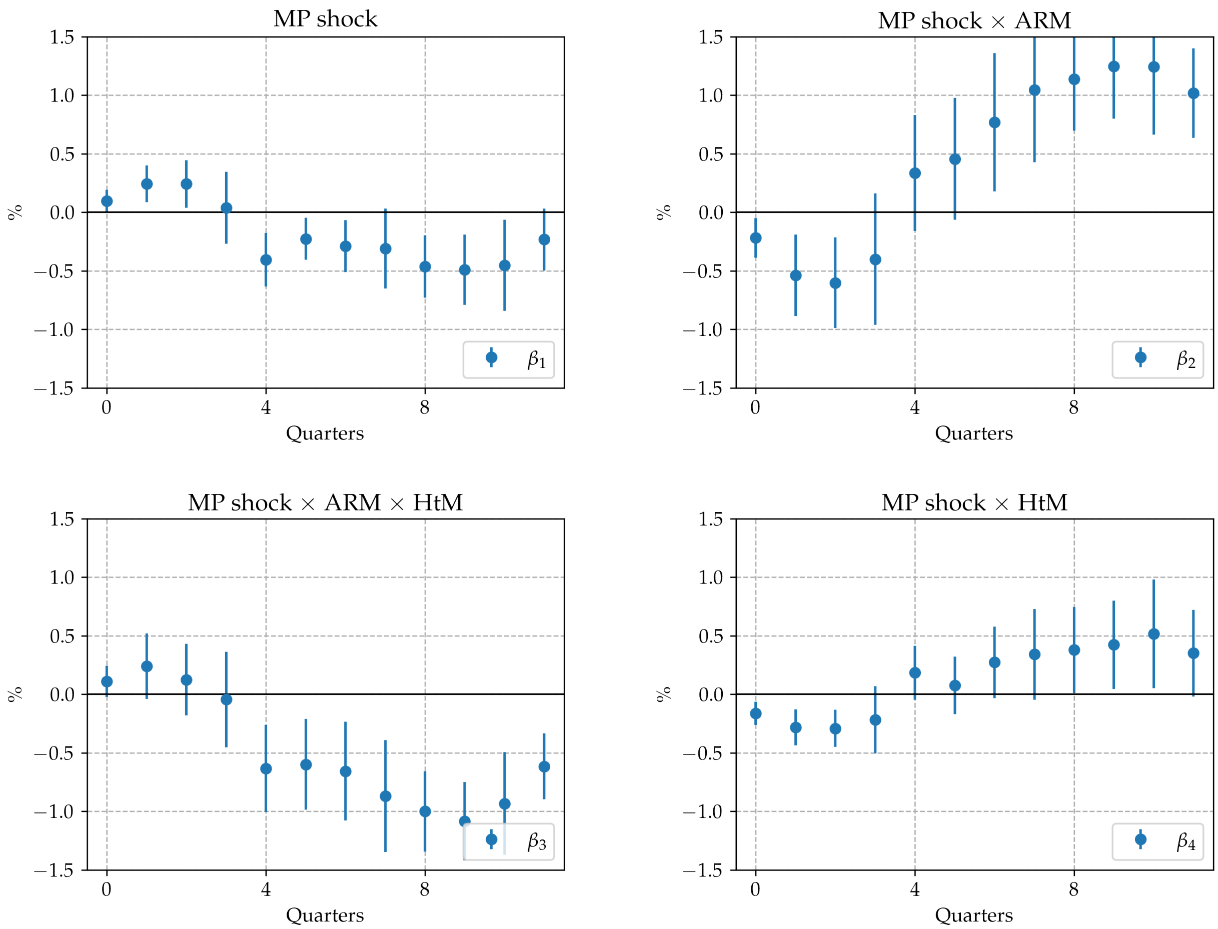
Notes: Response of consumption to a one standard deviation contractionary monetary policy shock. The vertical blue lines represent 90% confidence intervals.

Figure B.17: Response of consumption to a monetary policy shock, only consumption and Italian mortgage rate as controls



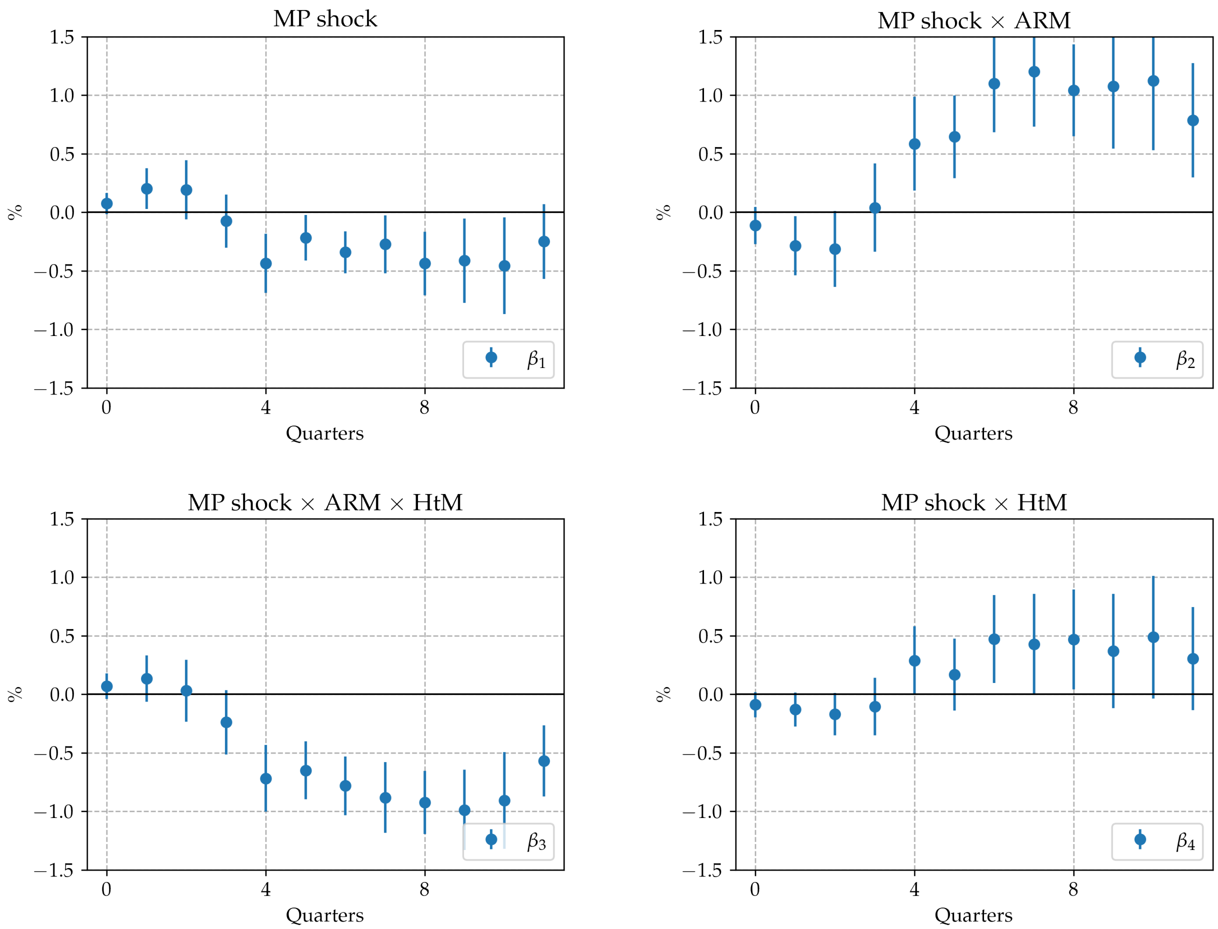
Notes: Response of consumption to a one standard deviation contractionary monetary policy shock. The vertical blue lines represent 90% confidence intervals.

Figure B.18: Response of consumption to a monetary policy shock, only Euro Area controls



Notes: Response of consumption to a one standard deviation contractionary monetary policy shock. The vertical blue lines represent 90% confidence intervals.

Figure B.19: Response of consumption to a monetary policy shock, both Euro Area and Italian controls



Notes: Response of consumption to a one standard deviation contractionary monetary policy shock. The vertical blue lines represent 90% confidence intervals.

C Model - Derivations and additional material

C.1 Algorithm to solve the household problem

This appendix describes the algorithm used to solve the household block of the model. Let s be the vector of household states $\{y, h, b, a\}$. The value functions associated with adjustment (*buyers* in S 3) and non-adjustment (*stayers* in the Section 3) are denoted by $V^a(s)$ and $V^n(s)$, respectively.

The non-adjuster's consumption and savings decisions are characterized by the following value function:

$$V^n(s) = \max_{c,a'} u(c, h') + \beta \mathbb{E}\left[V(s')|y\right] \tag{17}$$
$$\begin{aligned} \text{s.t. } c + a' &\leq y + (1+r)a - (r^b + \mu)b \\ h' &= (1-\delta)h \\ b' &= (1-\mu)b \\ a' &\geq 0 \end{aligned}$$

Similarly, the adjuster's decisions are characterized by:

$$V^a(s) = \max_{c,h',b',a'} u(c, h') + \beta \mathbb{E}\left[V(s')|y\right] \tag{18}$$
$$\begin{aligned} \text{s.t. } c + a' + ph' - b' &\leq y + (1+r)a + p(1-f)(1-\delta)d - (1+r^b)b \\ b' &\in [0, \lambda ph'] \\ a' &\geq 0 \end{aligned}$$

Note that, for notation convenience, I am disregarding the term τ, so that y in value functions (17) and (18) should be interpreted as post-tax income.

General set-up Before getting to the main algorithm, the above problem needs to be re-written to have households choosing a loan-to-value ratio, rather than the size of the loan directly. Without this modification, each household would need to have a grid for mortgages depend on the size of their durable choice. Now, let $\tilde{b} = \frac{b}{ph}$. The re-written value functions are then:

$$
\begin{aligned}
V^n(y,h,\tilde{b},a) &= \max_{c,a'} u(c,h') + \beta\mathbb{E}\left[V(y',h',\tilde{b}',a')|y\right] \\
\text{s.t. } c + a' &= y + (1+r)a - (r^b+\mu)\tilde{b}p^{-}h \\
a' &\geq 0 \\
\tilde{b}' &= \frac{(1-\mu)}{(1-\delta)}\frac{p^{-}}{p}\tilde{b} \\
h' &= (1-\delta)h
\end{aligned} \tag{19}
$$

and

$$
\begin{aligned}
V^a(y,h,\tilde{b},a) &= \max_{\{c,h',\tilde{b}',a'\}} u(c,h') + \beta\mathbb{E}\left[V(y',h',\tilde{b}',a')|y\right] \\
\text{s.t. } c + a' + (1-\tilde{b}')ph' &= y + (1+r)a + (1-f)(1-\delta)ph - (1+r^b)\tilde{b}p^{-}h \\
a' &\geq 0 \\
\tilde{b}' &\in [0,\lambda].
\end{aligned} \tag{20}
$$

First-order and envelope conditions For the non-adjustment problem, the first order condition with respect to a' is

$$
[a']\colon u_c(c,h') \geq \beta\mathbb{E}\left[V_a(y',h',b',a')|y\right], \tag{21}
$$

and the envelope conditions are

$$
V_a^n(y,h,\tilde{b},a) = (1+r)u_c\left(c,h'\right), \tag{22}
$$

$$
\begin{aligned}
V_h^n(y,h,\tilde{b},a) = (1-\delta)\Big(&u_h(c,h') + \beta\mathbb{E}\left[V_h(y',h',\tilde{b}',a')|y\right]\Big) \\
&- (r_b+\mu)\tilde{b}p^{-})u_c(c,h',n),
\end{aligned} \tag{23}
$$

$$
V_{\tilde{b}}^n(y,h,\tilde{b},a) = \frac{(1-\mu)}{(1-\delta)}\frac{p^{-}}{p}\beta\mathbb{E}\left[V_b(y',h',\tilde{b}',a')|y\right] + (r^b+\mu)u_c(c,h',n)p^{-}h. \tag{24}
$$

For the adjustment problem, the first order conditions for a', h', and b' are

$$
[a']\colon u_c(c,h') \geq \beta\mathbb{E}\left[V_a(y',h',\tilde{b}',a')|y\right], \tag{25}
$$

$$
[h']\colon u_d(c,h') + \beta\mathbb{E}\left[V_d(y',h',\tilde{b}',a')|y\right] = p(1-\tilde{b})u_c(c,h'), \tag{26}
$$

$$
[\tilde{b}']\colon \begin{cases} ph'u_c(c,h') + \beta\mathbb{E}\left[V_{\tilde{b}}(y',h',\tilde{b}',a')|y\right] = 0 & \text{if } \tilde{b}' \in (0,\lambda) \\ ph'u_c(c,h') + \beta\mathbb{E}\left[V_{\tilde{b}}(y',h',\tilde{b}',a')|y\right] > 0 & \text{if } \tilde{b}' = \lambda \\ ph'u_c(c,h') + \beta\mathbb{E}\left[V_{\tilde{b}}(y',h',\tilde{b}',a')|y\right] < 0 & \text{if } \tilde{b}' = 0 \end{cases}, \tag{27}
$$

and the envelope conditions are

$$V_a^a(y, h, \tilde{b}, a) = (1 + r)u_c(c, h') \tag{28}$$

$$V_h^a(y, h, \tilde{b}, a) = \Big((1 - f)(1 - \delta)p - (1 + r^b)\tilde{b}p^-\Big)u_c(c, h') \tag{29}$$

$$V_{\tilde{b}}^a(y, h, \tilde{b}, a) = -(1 + r^b)p^- h u_c(c, h'). \tag{30}$$

For the algorithm, I further rewrite the adjustment problem. Since the adjustment problem re-optimizes a', $\tilde{b}'$ and h', the household does not need to know the individual values for a, $\tilde{b}$ and h, but rather the total resources they contribute to their budget. To save time in the computation, I drop dependence on these states, and instead write the value function in terms of assets-on-hand defined as

$$z = (1 + r)a + (1 - f)(1 - \delta)ph - (1 + r^b)\tilde{b}p^- h. \tag{31}$$

Note that it is relatively easy to move from the solution in terms of the state variables y and z, and the solution in terms of the original state variables h, $\tilde{b}$, and a. For each combination $\{h, \tilde{b}, a\}$ there is a corresponding z, for which the solution is known.

For the algorithm, it is also convenient to re-express the adjustment problem as three staged problems

$$V^a(y, z) = \max_{h'} \underbrace{\left\{ \max_{\tilde{b}' \in [0, \lambda]} \underbrace{\left\{ \max_{a' \geq 0, c} u(y + z - p(1 - b')h' - a', h') + \beta \mathbb{E}\left[V(y', h', b', a')|y\right] \right\}}_{V^{a,(1)}(y,z,h',b')} \right\}}_{V^{a,(2)}(y,z,h')} \tag{32}$$

The innermost problem will solve for c and a', taking decisions for h' and $\tilde{b}'$ as given. This can be written as:

$$\begin{aligned} V^{a,(1)}(y, z, h', \tilde{b}') = \max_{c, a'} \; & u(c, h') + \beta \mathbb{E}\left[V(y', h', \tilde{b}', a')|y\right] \\ \text{s.t. } & c + a' = y + z - p(1 - \tilde{b}')h' \\ & a' \geq 0. \end{aligned} \tag{33}$$

This has first order condition for a'

$$[a']\colon u_c(c, h') \geq \beta \mathbb{E}\left[V_a(y', h', \tilde{b}', a')|y\right], \tag{34}$$

and envelope conditions

$$V_h^{a,(1)}(y,z,h',\tilde{b}') = u_h(c,h') + \beta\mathbb{E}\left[V_h(y',h',\tilde{b}',a')|y\right] - p(1-\tilde{b})u_c(c,h') \tag{35}$$

$$V_{\tilde{b}'}^{a,(1)}(y,z,h',\tilde{b}') = ph'u_c(c,h') + \beta\mathbb{E}\left[V_{\tilde{b}}(y',h',\tilde{b}',a')|y\right] \tag{36}$$

Given the solution for the inner problem, the middle problem will solve for $\tilde{b}'$ taking the decision for h' as given:

$$V^{a,(2)}(y,z,h') = \max_{\tilde{b}'} V^{a,(1)} \tag{37}$$
$$\text{s.t. } \tilde{b}' \in [0,\lambda].$$

Given the solution for the middle problem, the outer problem will take a decision for h':

$$V^a(y,z) = \max_{h'} V^{a,(2)} \tag{38}$$

Note that the first order conditions of the three stages collapse to the first order conditions written above. For convenience, I define the post-decision value function as $W(s) = \beta\mathbb{E}\left[V(s')|y\right]$.

Algorithm. I start with a guess for the value function and its partial derivatives, defined over a discretized grid. I then iterate backward until convergence. Π denotes the transition matrix of the exogenous income state, y.

0. **Preamble**. Create grids for a, $\tilde{b}$, h, and z, and discretize exogenous income process using the Rouwenhorst method.

1. **Initial guess**. Create guess for V, V_h, $V_{\tilde{b}}$, and V_a.

2. **Common** $\underline{y' \to y}$. By definition

$$W(y,h',\tilde{b}',a') = \beta\Pi V(y',h',\tilde{b}',a') \tag{39}$$

$$W_a(y,h',\tilde{b}',a') = \beta\Pi V_a(y',h',\tilde{b}',a') \tag{40}$$

$$W_h(y,h',\tilde{b}',a') = \beta\Pi V_h(y',h',\tilde{b}',a') \tag{41}$$

$$W_{\tilde{b}}(y,h',\tilde{b}',a') = \beta\Pi V_{\tilde{b}}(y',h',\tilde{b}',a') \tag{42}$$

3. **Non-adjustment problem**. Solve the non-adjustment problem, given guesses for V, V_h, $V_{\tilde{b}}$, and V_a. Note that I suppress the n superscript on all policy functions in this section for notation convenience. Thus, the $a'(y,h,\tilde{b},a)$ that I find below is the a' choice *conditional* on the choice of not adjusting.

(i) **Unconstrained** $\underline{a' \to a}$. Assume that the constraint on assets does not bind. Then (21) can be re-written to define c as

$$c(y,h',\tilde{b}',a') = u_c^{-1}\Big(W_a(y,h',\tilde{b}',a'),h'\Big). \tag{43}$$

Note that because the guess W_a is defined in terms of h' and $\tilde{b}'$, this problem will initially be defined in terms of these rather than h and $\tilde{b}$, which are the state variables of the problem. There is a one to one mapping between the two. Using the budget constraint, we get $a^{endo}(y,h',\tilde{b}',a')$, which is the a that implies the household chooses $\{c(y,h',\tilde{b}',a'),a'\}$. This is:

$$a^{endo}(y,h',\tilde{b}',a') = \frac{1}{1+r}\Big(c(y,h',\tilde{b}',a') + a' + \frac{p(\mu+r^b)}{1-\mu}\tilde{b}'h' - y\Big). \tag{44}$$

(ii) **Upper Envelope**. Let `agrid` denote the pre-computed grid for the discretized values of a. Normally, $a'(y,h',\tilde{b}',a)$ can be found via interpolation, putting $\big(a^{endo}(y,h',\tilde{b}',a'), \texttt{agrid}\big) \to \big(\texttt{agrid}, a'(y,h',\tilde{b}',a)\big)$.[40] However, because this problem features a discrete choice, there may be discontinuities in W_a that lead to non-unique solutions for the inversion.

To correct for this, I take the upper envelope of the solution. For each non-unique solution of the inversion, the upper envelope algorithm chooses the point for which the value function gives greater utility. The steps of the upper envelope algorithm are detailed below for the 'non-adjustment problem'. Please refer to those steps, simply substituting z^{endo} with a^{endo} and `zgrid` with `agrid`.

The algorithm delivers both the policy function $a'(y,h',\tilde{b}',a)$ as well as an updated value function $V^n(y,h',\tilde{b}',a)$. At the end of this step, it is possible to calculate $W_{\tilde{b}}(y,h',\tilde{b}',a)$ and $W_h(y,h',\tilde{b}',a)$ by interpolation, evaluating $W_{\tilde{b}}$ and W_h at the policy function $a'(y,h',\tilde{b}',a)$.

(iii) **Update state** $\underline{h' \to h}$. Using interpolation, re-write $a'(y,h',\tilde{b}',a)$, $V^n(y,h',\tilde{b}',a)$, $W_{\tilde{b}}(y,h',\tilde{b}',a)$ and $W_h(y,h',\tilde{b}',a)$ in terms of h rather than h'. Do this by evaluating each at $h' = (1-\delta)$.

(iv) **Update state** $\underline{\tilde{b}' \to \tilde{b}}$. Using interpolation, re-write $a'(y,h,\tilde{b}',a)$, $V^n(y,h,\tilde{b}',a)$, $W_{\tilde{b}}(y,h,\tilde{b}',a)$ and $W_h(y,h,\tilde{b}',a)$ in terms of $\tilde{b}$ rather than $\tilde{b}'$. Do this by evaluating each at at $\tilde{b}' = \frac{(1-\mu)}{(1-\delta)}\frac{p^-}{p}\tilde{b}$.

[40] This would be the standard procedure in the endogenous grid-point method by Carroll (2006).

(v) **Update guesses**. First calculate $c(y,h,\tilde{b},a)$ as

$$c(y,h,\tilde{b},a) = y + (1+r)a - (\mu + r^b)p^-\tilde{b}h - a'(y,h,\tilde{b},a) \tag{45}$$

Note that there will be some states for which it is impossible to have positive consumption. In particular, states with very low assets but very high durable consumption. For these states, force consumption to be a very low value, such as $1e-9$.

Then, use the envelope conditions to update guesses as follows:

$$V_a^n(y,h,\tilde{b},a) = (1+r)u_c\left(c(y,h,\tilde{b},a),(1-\delta)h\right), \tag{46}$$

$$\begin{aligned} V_h^n(y,h,\tilde{b},a) = {} & (1-\delta)\Big(u_h(c(y,h,b,a),(1-\delta)h) + W_h(y,h,\tilde{b},a)\Big) \\ & - (r^b+\mu)p^-\tilde{b}u_c(c(y,h,\tilde{b},a),(1-\delta)h), \end{aligned} \tag{47}$$

$$\begin{aligned} V_{\tilde{b}}^n(y,h,\tilde{b},a) = {} & \frac{(1-\mu)}{(1-\delta)}\frac{p^-}{p}W_{\tilde{b}}(y,h,\tilde{b},a) \\ & + (r^b+\mu)p^-hu_c(c(y,h,\tilde{b},a),(1-\delta)h). \end{aligned} \tag{48}$$

Note that $V^n(y,h,\tilde{b},a)$ was already obtained in previous steps, and does not need explicit updating in this step.

4. **Adjustment problem**. Solve the non-adjustment problem, given guesses for V, V_h, $V_{\tilde{b}}$, and V_a. Note that I suppress the a superscript on all policy functions in this section for notation convenience. Thus, the $a'(y,h,\tilde{b},a)$ that I find below (and analogous policy functions for h' and $\tilde{b}'$) is the a' choice *conditional* on the choice of adjusting.

   (i) **Unconstrained** $\underline{a' \to z|h',\tilde{b}'}$. Here we solve the first order condition of the 'inner' maximization problem, where we solve for c and a' taking the choice for h' and $\tilde{b}'$, as well as states y and z, as given.

   Assume that the constraint on assets does not bind. Then (25) can be re-written to define c as

$$c(y,h',b',a') = u_c^{-1}\Big(W_a(y,h',b',a'),h'\Big). \tag{49}$$

   Using the budget constraint, we get $z^{endo}(y,h',\tilde{b}',a')$, which is the z that implies the household chooses $\{c(y,h',\tilde{b}',a'),a'\}$. This is

$$z^{endo}(y,h',\tilde{b}',a') = a' + c(y,h',b',a') + p(1-\tilde{b}')h' - y$$

(ii) **Upper envelope**. Let `agrid` denote the pre-computed grid for the discretized values of a. We use the upper envelope to go from $\left(z^{endo}(y,h',\tilde{b}',a'),\texttt{agrid}\right) \rightarrow \left(\texttt{agrid},a'(y,z,h',\tilde{b}')\right)$. These are steps in the upper-envelope algorithm.

   i. **Initialize value function.** Initialize an empty value function at minus infinity:

   $$V^u(y,h',\tilde{b}',a') = -\infty$$

   ii. **Create endogenous segments.** Let $a(j)$ be j^{th} point on the grid for a. Conditional on all other states, $s = (y,h',\tilde{b}')$, create a segment $[z(s,j),z(s,j+1)]$. $z(s,j)$ and $z(s,j+1)$ represent the values of z for which households choose $a' = \texttt{agrid}[j]$ and $a' = \texttt{agrid}[j+1]$, respectively.

   iii. **Interpolate.** Find all values of $\texttt{zgrid} \in [z(s,j),z(s,j+1)]$. By knowing that $a' = \texttt{agrid}[j]$ when $z = z(s,j)$ and $a' = \texttt{agrid}[j+1]$ when $z = z(s,j+1)$, implement a standard interpolation to back out what a' is when $z \in [z(s,j),z(s,j+1)]$.

   iv. **Choose the solution that maximizes the value function.** Because of the discrete choice, it is possible that multiple values of `zgrid` fall in the segment $[z(s,j),z(s,j+1)]$. Accordingly, for each candidate a' obtained from the previous steps, compute its associated value function and choose the a' that maximizes it.

   v. **Enforce the constraint** For each candidate solution a', check that the constraint is not binding. If it is, substitute $a' = 0$. Fill the values of the initialized value function $V^u(y,h',\tilde{b}',a')$.

   The results of upper envelope step are a policy function $a'(y,z,h',\tilde{b}')$ and a value function $V^a(y,z,h',\tilde{b}')$ which are in terms of the state variables $\{y,z\}$ and the choice variables $\{h',\tilde{b}'\}$. At the end of this step, we can calculate $W_b(y,h',\tilde{b}',a)$ and $W_d(y,h',\tilde{b}',a)$ by interpolation, evaluating $W_{\tilde{b}}$ and W_d at the policy function $a'(y,z,h',\tilde{b}')$.

(iii) **Choose** $\tilde{b}'|h'$. For the next two stages of the adjustment problem, we can no longer employ endogenous grid-point method and must instead employ a root finding algorithm on the first order condition.

   The first order condition for $\tilde{b}'$ taking the choice of h' as given as well as the optimal solution for both c and a' is the envelope condition of the 'inner' problem with respect to $\tilde{b}'$, equation (27).

$$V^{a,(1)}_{\tilde{b}'} = ph' u_c(c(y,z,h',\tilde{b}'),h') + W_b(y,z,h',\tilde{b}') \tag{50}$$

There are three cases of solutions for the above equation. The first, if (50) is always positive, then $\tilde{b}'$ takes on the corner solution $\tilde{b}' = \lambda$. The second, if (50) is always negative, $\tilde{b}'$ takes the corner solution $\tilde{b}' = 0$. If the above equation crosses zero at least once, there is an interior solution. We use a root finding algorithm to find the grid points between which the equation crosses zero. If there are multiple inflection points, we use the value function to choose the true maximum and pick between multiple inflection points using the value function.

The root finding algorithm also exploits that for some state values of the problem (combinations $\{y,z,h'\}$), there is either no solution for $\tilde{b}'$ such that cash on hand is strictly positive, or there is a further restricted set of $\tilde{b}'$ values for which $\tilde{b}'$ is positive. It searches over this restricted set, and sets $\tilde{b}'$ to its maximum possible value for areas of the state space where there is no solution.

The resulting policy function is $\tilde{b}'(y,z,h')$. At the end of this step, we can calculate $V^a(y,z,h')$, $W_d(y,z,h')$ and $a'(y,z,h')$ by evaluating $V^a(y,z,h',\tilde{b}')$, $W_d(y,z,h',\tilde{b}')$ and $a'(y,z,h','\tilde{b}')$ at the policy function $b'(y,z,h')$. $c(y,z,h')$ can be calculated using the budget constraint

$$c(y,z,h') = y + z - a'(y,z,h') - p(1-\tilde{b}'(y,z,h')h' \tag{51}$$

Where any negative value of c is replaced with $1e-9$.

(iv) **Choose** h'. Like with the choice for $\tilde{b}'$, we use a root finder over the first order condition. The first order condition for the outer problem is the envelope condition of the middle problem with respect to h', which in turn is the envelope condition of the inner problem with respect to h'. This is

$$V^{a,(2)}_{h'} = u_d(c(y,z,h'),h') + W_d(y,z,h') - p(1-\tilde{b})u_c(c(y,z,h'),h') \tag{52}$$

As above, we use a root finding algorithm to find all local maximum points, and use $V^a(y,z,h')$ to determine the global maximum. The root finding algorithm exploits that for each state value $\{y,z\}$ there are values of h' which push cash-on-hand negative and cannot be solutions.

The resulting policy function is $h'(y,z)$. At the end of this step, we can calculate $V^a(y,z)$, $a'(y,z)$, and $\tilde{b}'(y,z)$ by evaluating $V^a(y,z,h')$, $a'(y,z,h')$, ad $\tilde{b}'(y,z,h')$ at $h'(y,z)$.

5. **Interpolate** $z \to \{h, \tilde{b}, a\}$. Because we need our guesses for V, V_a, $V_{\tilde{b}}$, V_h to be in terms of the original state space $\{y,h,\tilde{b},a\}$, we interpolate for each combination of $\{y,h,a\}$ to put all policy functions and guesses onto the original grid.

6. **Update guesses**. First calculate $c(y,h,\tilde{b},a)$ as

$$c(y,h,\tilde{b},a) = y + (1+r)a + \Big(p(1-f)(1-\delta) - (1+r^b)\tilde{b}p^-\Big)h \\ - a'(y,h,\tilde{b},a) - p(1-\tilde{b}'(y,h,\tilde{b},a))h'(y,h,\tilde{b},a) \tag{53}$$

   As in the non-adjustment problem, there may be some states for which it is impossible to have positive consumption. For these states, we force consumption to $1e-9$.

   Then, we can use the envelope conditions to update guesses as follows:

$$V^a_a(y,h,\tilde{b},a) = (1+r)u_c(c(y,h,\tilde{b},a), h'(y,d,b,a)) \tag{54}$$

$$V^a_d(y,h,\tilde{b},a) = \Big((1-f)(1-\delta)p - (1+r^b)\tilde{b}p^-\Big)u_c(c(y,h,\tilde{b},a), h'(y,h,\tilde{b},a)) \tag{55}$$

$$V^a_{\tilde{b}}(y,h,\tilde{b},a) = -(1+r^b)p^- h u_c(c(y,h,\tilde{b},a), h'(y,d,\tilde{b},a)). \tag{56}$$

7. **Discrete choice**. Given solutions for both the adjustment and non-adjustment problem, calculate the adjustment probabilities and solve the discrete choice problem using equations (58) and (59). This will give updated guesses for V, V_a, $V_{\tilde{b}}$ and V_h.

   Go back to step 2, repeat until convergence.

C.2 Implications of introducing taste shocks in the value function

A common problem in models with discrete choices such as the one introduced in Section 3 is that, due to the presence of the *max* operator, there can be kinks in the value function and discontinuities in the agents' optimal policy functions for continuous variables. As a consequence, it is not possible to make use of derivatives in the solution algorithm, which creates significant complications when solving these models.[41] To overcome these

[41] In particular, this implies that the endogenous grid-point method (EGM) developed by Carroll (2006) cannot be directly applied.

problems, I follow the methodology in Iskhakov et al. (2017), Bardóczy (2022) and Beraja and Zorzi (2024), and rewrite the overall value function as:

$$V(e,h,b,a) = \max\{V^{buy}(e,h,b,a) + \sigma_\epsilon \epsilon_b, V^{stay}(e,h,b,a) + \sigma_\epsilon \epsilon_s\} \tag{57}$$

where ϵ_b and ϵ_s are independent and identically distributed taste shocks drawn from a type 1 extreme value (Gumbel) distribution with scale parameter σ_ϵ.[42] The computational value of the taste shocks is to smooth out the value function around the discrete choice, allowing the use of derivatives in the solution algorithm. In addition, the use of taste shocks allows the model to better capture the fact that, in the data, the probability of choosing to buy a new house changes smoothly: without them, the model would imply a discontinuous change in these probabilities as soon as $V^{buy}(e,h,b,a)$ exceeds $V^{stay}(e,h,b,a)$.

The assumption on the distribution of the taste shocks implies that the probability that households choose to change their housing stock as a function of their state $\{e,h,b,a\}$ is given by the multinominal logit form:

$$P(buy|e,h,b,a) = \frac{exp\left(\frac{V^{buy}(e,h,b,a)}{\sigma_\epsilon}\right)}{exp\left(\frac{V^{buy}(e,h,b,a)}{\sigma_\epsilon}\right) + exp\left(\frac{V^{stay}(e,h,b,a)}{\sigma_\epsilon}\right)} \tag{58}$$

and the value function is given by:

$$V(e,h,b,a) = \sigma_\epsilon \log\left(exp\left(\frac{V^{buy}(e,h,b,a)}{\sigma_\epsilon}\right) + exp\left(\frac{V^{stay}(e,h,b,a)}{\sigma_\epsilon}\right)\right). \tag{59}$$

[42] These are linearly additive taste shocks à la McFadden (1973).

C.3 Calibration of μ

The parameter governing the speed of mortgage repayment is calibrated to match the duration of a typical Spanish mortgage. In particular, given the maturity of a mortgage equal to T and mortgage interest rate r^b, the duration formula is given by:

$$Duration = \frac{\sum_{t=1}^{T} tPV_t}{\sum_{t=1}^{T} PV_t} = \frac{\sum_{t=1}^{T} tPV_t}{P} \tag{60}$$

where t is the time until a mortgage payment will be made and PV_t is the present value of that mortgage payment. P represents the present value of all future mortgage payments, which is the principal. Since mortgage payments M are computed such that:

$$P = \sum_{t=0}^{T} \frac{M}{(1+r^b)^t} \tag{61}$$

it follows that:

$$M = \frac{r^b P(1+r^b)^T}{(1+r^b)^T - 1}. \tag{62}$$

Applying this definition of M, it follows that equation (60) can be re-written as:

$$Duration = \sum_{t=1}^{T} \frac{t}{(t+r^b)^t} \frac{r^b(1+r^b)^T}{(1+r^b)^T - 1}. \tag{63}$$

Given the mortgage repayment structure in the model, where $M^{model} = (r^b + \mu)b$, it follows that $M_t^{model} = (r^b + \mu)(1-\mu)^{t-1}P$, where P is the principal amount of the mortgage. Accordingly, the duration in the model will be:

$$Duration^{model} = \frac{\sum_{t=1}^{T} \frac{t(r^b+\mu)(1-\mu)^{t-1}P}{(1+r^b)^t}}{P} = \frac{1+r^b}{1+\mu}. \tag{64}$$

It follows that in order for $Duration = Duration^{model}$, it has to be the case that:

$$\mu = (1+r^b)\left(\sum_{t=1}^{T} \frac{r^b t(1+r^b)^T}{((1+r^b)^T - 1)(1+r^b)^t}\right)^{-1} - r^b. \tag{65}$$

Given my targets of $T = 25$ years and $r^b = 3\%$, and quarterly calibration, it follows that $\mu = 0.015$.

C.4 Isolating the impact of MPCs in transmission through ARMs

The model described in Section 3 defines each household's i consumption function as depending on the risk-free interest rate r, the mortgage rate r^b, and a set of state variables $z = e, h, b, a, p$. We can write this function as $c^i(r, r^b, z)$.

In Section 4.2.1, I analyze a monetary policy shock that changes r by dr and, via the pass-through specified in equation (9), also changes r^b by dr^b. In this partial equilibrium environment, the change in aggregate consumption in country c can be written as:

$$dC^c = \underbrace{\int \frac{\partial c^i}{\partial r} dr di}_{\text{direct effect of } dr \text{ in } c} + \underbrace{\int \frac{\partial c^i}{\partial r^b} \frac{\partial r^b}{\partial r} dr di}_{\text{indirect effect of } dr \text{ through ARMs in country } c} . \tag{66}$$

The second term reflects the pass-through from r to r^b, which depends on the share of households with ARMs, since FRM holders are insulated from changes in r^b. In both terms, the magnitude of the consumption response depends on households' MPCs.

As a result, cross-country differences in MPCs affect both the direct and indirect responses. However, my analysis focuses on isolating how MPCs and ARM shares jointly shape transmission through the mortgage channel alone — that is, the indirect effect via r^b.

To do so, I proceed as follows. I first compute the consumption response in Spain as:

$$dC^{ES} = \left(\int \frac{\partial c^i}{\partial r} dr di \right)^{ES} + \left(\int \frac{\partial c^i}{\partial r^b} \frac{\partial r^b}{\partial r} dr di \right)^{ES} . \tag{67}$$

Then, I construct a counterfactual version of Spain, in which the economy has the ARM share and MPC level observed in country c. This change affects both the direct and indirect terms. To isolate the impact through the mortgage channel, I compute:

$$dC^c = \left(\int \frac{\partial c^i}{\partial r} dr di \right)^{ES} + \left(\int \frac{\partial c^i}{\partial r^b} \frac{\partial r^b}{\partial r} dr di \right)^{c} . \tag{68}$$

In this counterfactual, I fix the direct effect through r to be equal to that of Spain. Only the indirect effect, driven by country c's ARM share and MPC level, differs. This procedure ensures that the change in aggregate consumption arises solely from transmission through r^b, the mortgage channel.

The model-implied difference in transmission between Spain and country c, shown in the "Model" column of Table 2, is thus:

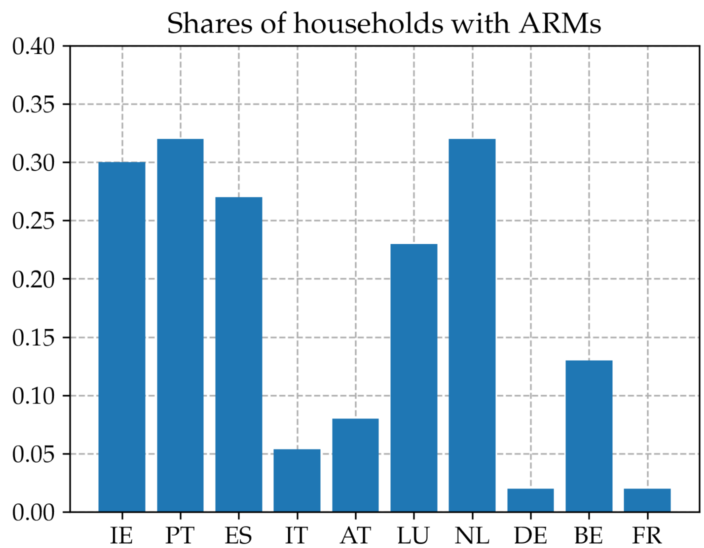
$$dC^{ES} - dC^c \tag{69}$$

where this difference reflects variation in mortgage-driven transmission only.

C.5 Results matching the fraction of households with ARMs in the population

This section replicates all results from Section 4 where, in the calibration of the model, I match the fraction of households with ARMs in the population instead of the fraction of ARMs within the total stock of mortgages. Figure C.20 shows the fraction of households with ARMs in each Euro Area economy.

Figure C.20: Shares of households with ARMs across Euro Area countries



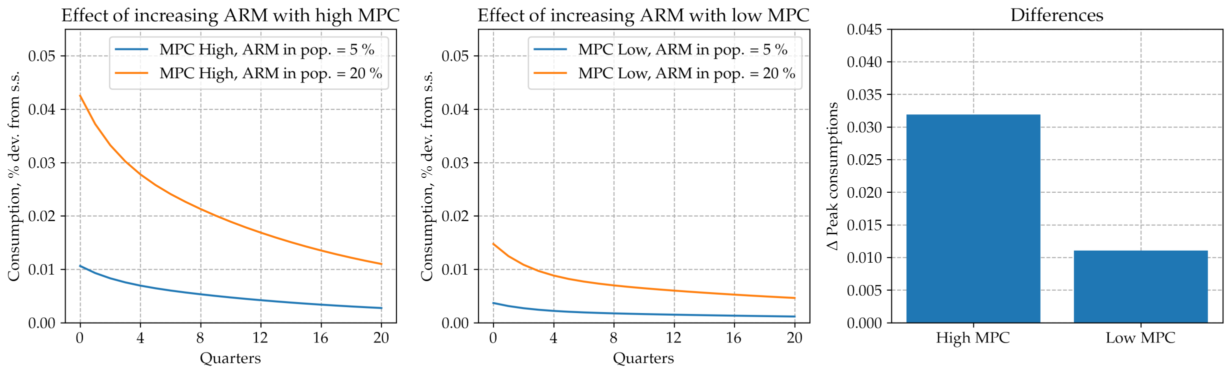
Notes: Each bar represents, for each Euro Area country, the fraction of households with ARMs in the population. Countries are ranked by the strength of monetary policy transmission, from Ireland (strongest) to France (weakest), in line with the estimates from equation (1) shown in figure 2.

Figure C.21 replicates the exercise in Section 4.1.2, showing that the model keeps predicting a positive interaction between ARMs and MPCs also when using this alternative definition of the share of ARMs.

Table C.3 replicates the exercise in Section C.6, showing that the model keeps predicting a positive interaction between ARMs and MPCs when considering a complete monetary policy shock also under this alternative definition of the share of ARMs. In particular, the percentage increase in the peak response of consumption increases by 5% in the low MPC economy and by 15% in the high MPC economy.

Finally, Table C.4 replicates the results in Section 4.2.1. Relative to the analysis in Section 4.2.1, where I implement counterfactual exercises adjusting the share of ARMs

Figure C.21: Interaction between ARMs and MPCs after a mortgage rate shock, alternative ARM share



Notes: The left and middle panels show the consumption response, in percentage deviations from its steady-state value, to a mortgage rate shock in the high and low MPC economies, respectively. The blue line shows the response when the share of households with ARMs in the economy is 5%, while the orange line shows the response when the share is 20%. The right panel displays the difference in the peak response of consumption when the share of households with ARMs increases from 5% to 20%. The mortgage rate shock is calibrated to lead to a 100 basis points reduction in r^b on impact, and it follows an AR(1) process with persistence 0.75.

Table C.3: Interaction between ARMs and MPCs after a complete monetary policy shock, alternative ARM share

	Low MPC	High MPC	Δ MPC
Low ARM	0.213%	0.217%	0.004%
High ARM	0.224%	0.249%	0.025%
Δ ARM	0.011%	0.032%	0.036%

Notes: High MPC refers to the reference Spanish economy, while *Low MPC* refers to the counterfactual economy with MPC half that of Spain. *Low ARM* and *High ARM* refer to shares of households with ARMs of 5% and 20%, respectively. Each entry represents the peak consumption response after a monetary policy shock. The entries in the Δ *MPC* column and Δ *ARM* row show the differences in peak consumption. The shock is calibrated to lead to a reduction in r of 100 basis points on impact and it follows an AR(1) process with a persistence of 0.75.

Table C.4: ARM and MPC contributions to overall transmission

	Difference			Contribution		
	Data	Model	% Explained	ARM	MPC	Interaction
AT	0.236	0.089	38%	28%	21%	51%
BE	0.314	0.075	24%	35%	31%	34%
DE	0.295	0.094	32%	69%	2%	29%
FR	0.350	0.096	27%	46%	4%	50%
IE	-0.728	-0.103	16%	11%	80%	9%
IT	0.172	0.086	50%	58%	8%	33%
LU	0.284	0.058	20%	12%	75%	13%
NL	0.287	0.044	15%	−20%	142%	−22%
PT	-0.239	-0.037	15%	50%	42%	8%
Averages	0.311	0.084	27%	32%	45%	23%

Notes: For each country, the table shows the difference in percentage points in the peak consumption response to a monetary policy shock relative to Spain. This difference is presented both in the data (second column) and in the model (third column). The fourth column shows the fraction of this difference captured by the model. The last three columns report the fraction of the model-implied differences between each country and Spain that are attributable to differences in ARMs, MPCs, and their interaction. The last row presents the average values of the column variables across countries.

within the total mortgage stock, I here implement counterfactual exercises adjusting the share of households in the population with ARMs. The main message from Table 2 is preserved. In particular, 27% of the empirical differences in transmission across Euro Area countries are captured by the model, lower than the 46% figure of the baseline results, but still large enough to conclude that transmission differentials through ARMs are an important source of overall transmission heterogeneity across Euro Area countries. In addition, with an individual contribution of 45% (slightly lower than 57% in the baseline results), MPCs keep playing a crucial role to capture transmission differentials through ARMs across Euro Area economies.

Table C.5: Interaction between ARMs and MPCs with changes in both r and r^b

	Low MPC	High MPC	Δ MPC
Low ARM	0.214%	0.237%	0.023%
High ARM	0.226%	0.330%	0.104%
Δ ARM	0.012%	0.093%	0.116%

Notes: High MPC refers to the reference Spanish economy, while *Low MPC* refers to the counterfactual economy with MPC half that of Spain. *Low ARM* and *High ARM* refer to ARM shares of 20% and 80%, respectively. Each entry reports the peak consumption response to a monetary policy shock. The entries in the Δ rows show differences in peak responses. The shock leads to a 100 basis point reduction in r on impact and follows an AR(1) process with a persistence of 0.75, as in Section 4.2.

C.6 The interaction between ARMs and MPCs with changes in both r and r^b

This appendix presents a robustness exercise to verify that the interaction between ARMs and MPCs remains relevant when both the short-term interest rate r and the mortgage rate r^b respond to a monetary policy shock.

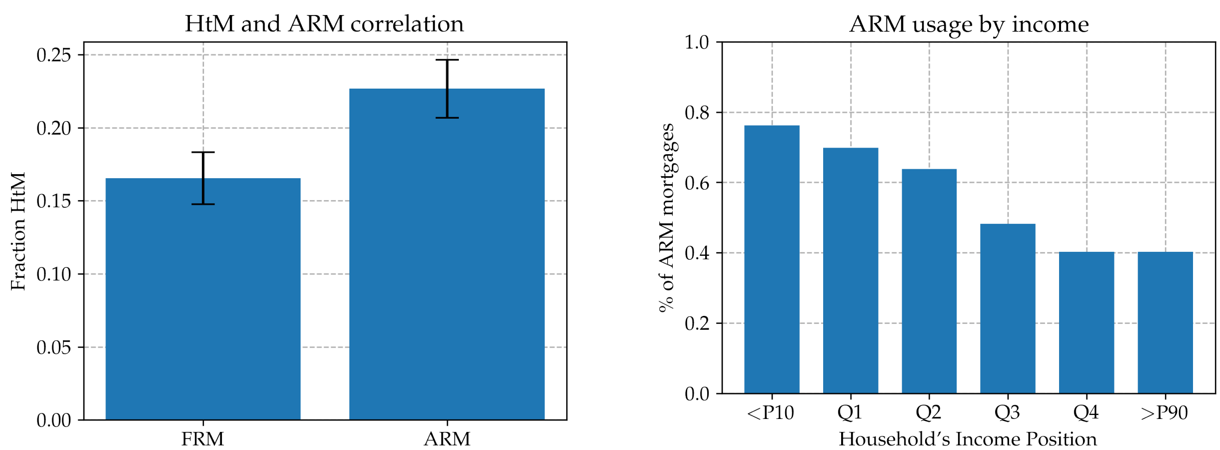
Table C.5 reports the peak consumption responses across four scenarios that vary both the ARM share (20% vs. 80%) and the level of household MPCs. The *High MPC* economy corresponds to the Spanish baseline, while the *Low MPC* economy has an MPC level half that of Spain. As in earlier sections, *Low ARM* and *High ARM* refer to ARM shares of 20% and 80%, respectively.

The results confirm the amplification pattern identified in Section 4.1.2. Increasing the ARM share from 20% to 80% raises peak consumption by only 0.012% in the low-MPC economy but by 0.093% in the high-MPC economy. These findings reinforce the importance of the ARM–MPC interaction for transmission strength, even when both r and r^b adjust in response to policy shocks.

C.7 Results with MPC-ARM correlation

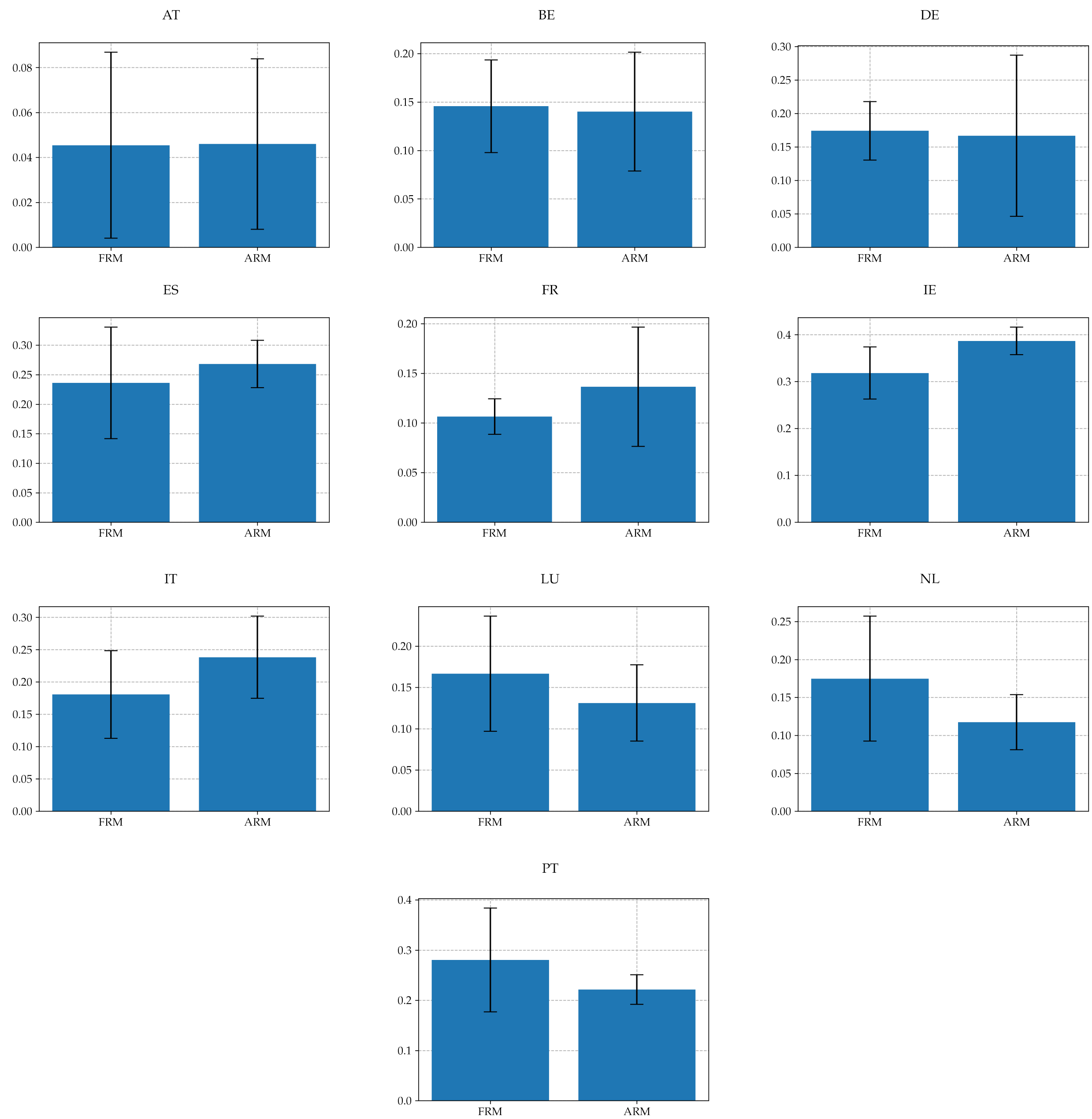
Figure C.22 shows that, in the data, ARMs tend to be more widespread across lower-income households in the Euro Area, implying that a larger fraction of households with ARMs is HtM relative to households that choose to have fixed-rate mortgages (FRMs). This appendix presents the counterfactual results generated by introducing this correlation into the model. In particular, this is achieved by calibrating a different fraction of ARM households for each income level, so that the ratio of HtM households with FRMs (HtM^{FRM}) to those with ARMs (HtM^{ARM}) in the model matches the empirical ratio observed in the HFCS for each country in the sample. Figure C.23 shows the fraction of HtM households among households with ARMs and FRMs in the HFCS for individual Euro Area countries, which I use to calibrate the different shares of ARMs across income levels in the model. Importantly, the correlations are not always in the same direction.

Figure C.22: Correlation between HtM and ARM in the Euro Area



Notes: The source of the data is the HFCS. The left panel shows the share of HtM agents among households that have fixed-rate mortgages (FRM) and adjustable-rate mortgages (ARM). The vertical lines represent 95% confidence intervals. The right panel shows the average fraction of mortgages that have an adjustable-rate for households across the income distribution (*P* stands for "percentile", *Q* stands for "quartile").

Figure C.23: Correlation between HtM and ARM in the individual Euro Area countries



Notes: The source of the data is the HFCS. The chart shows the share of HtM agents among households that have fixed-rate mortgages (FRM) and adjustable-rate mortgages (ARM). The vertical lines represent 95% confidence intervals.

Table C.6 shows the counterfactual results of this analysis. The results mirror closely the ones in Table 2, suggesting that accounting for the HtM-ARM correlation does not change the main message from Section 4.2.1, and the average fraction of empirical differences captured by the model moves from 46% to 47% only. This is mainly the consequence of the fact that introducing the correlation does not help the model better capture differences in transmission between Spain and all other Euro Area economies. In particular, economies such as Germany or the Netherlands, which are characterized by having FRM households being more constrained than ARM households, have smaller transmission through the mortgage channel in this analysis, which implies that the model captures a larger fraction of the empirical difference in the response of consumption between these economies and Spain. Nonetheless, Portugal is also characterized by having FRM households being more constrained than ARM households, which pushes the model to predict stronger transmission through mortgages in Spain than in Portugal, decreasing the ability of the model to capture the overall transmission differential (since the response of consumption in Portugal is larger than the one of Spain in the data).

Table C.6: ARM and MPC contributions to overall transmission

	Difference			Contribution		
	Data	Model	% Explained	ARM	MPC	Interaction
AT	0.236	0.150	64%	4%	72%	24%
BE	0.314	0.142	45%	16%	45%	34%
DE	0.295	0.153	52%	51%	9%	40%
FR	0.350	0.165	46%	26%	8%	66%
IE	-0.728	-0.228	36%	1%	97%	2%
IT	0.172	0.105	62%	18%	60%	22%
LU	0.284	0.126	44%	3%	89%	8%
NL	0.287	0.127	44%	−0%	101%	−1%
PT	-0.239	-0.072	30%	45%	39%	16%
Averages	0.311	0.141	47%	18%	58%	24%

Notes: For each country, the table shows the difference in percentage points in the peak consumption response to a monetary policy shock relative to Spain. This difference is presented both in the data (second column) and in the model (third column). The fourth column shows the fraction of this difference captured by the model. The last three columns report the fraction of the model-implied differences between each country and Spain that are attributable to differences in ARMs, MPCs, and their interaction. The last row presents the average values of the column variables across countries.