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Fixed Rate versus Adjustable Rate Mortgages: Evidence from Euro Area Banks*

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Abstract

Why do residential mortgages carry a fixed or an adjustable interest rate? To answer this question we study unique data from 103 banks belonging to 73 different banking groups across twelve countries in the euro area. To explain the large cross-country and time variations observed, we distinguish between household conditions that determine the local demand for credit and the characteristics of banks that supply credit. As bank funding mostly occurs at the group level, we disentangle these two sets of factors by comparing the outcome observed for the same banking group across the different countries. Local household conditions dominate. In particular we find that the share of new loans with a fixed rate is larger when: (1) the historical volatility of inflation is lower, (2) the correlation between unemployment and the short-term interest rate is higher, (3) households' financial literacy is lower, and (4) the use of local mortgages to back covered bonds and of mortgage-backed securities is more widespread.

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1 Introduction

Conventional mortgages can be classified in two main types: fixed rate mortgages and adjustable rate mortgages. Fixed rate mortgages (henceforth abbreviated as FRMs) charge a nominal interest rate that does not change during the entire life of the loan. Adjustable rate mortgages (henceforth, ARMs) charge an interest rate that is tied to a benchmark and varies over time. The volume of FRMs and ARMs extended to households in the economy depends on a broad set of factors that affect the demand by borrowers and the supply by lenders (ECB, 2009).

A striking feature of the credit market in the euro area is the very large heterogeneity across countries in the granting of FRMs versus ARMs. FRMs are dominant in Belgium, France, Germany and the Netherlands, while ARMs are prevailing in Austria, Greece, Italy, Portugal and Spain (ECB, 2009; Campbell, 2012). The time variation in the share of FRMs to total new mortgages differs across countries as well, with little variation over time in Germany and Portugal, but far more in Italy and Greece (ECB, 2009).

This observed variation across countries and over time has three major implications. First, the transmission of monetary policy is heterogeneous across countries and over time with relevant redistributive effects (Tzamourani, 2021; Pica, 2022). A prevalence of FRMs or ARMs in the economy entails a different interest rate exposure of the household sector. Being a major liability in the balance sheet of most households, mortgages likely play a key role in the transmission of monetary policy (Di Maggio et al., 2017). This is especially true in systems where ARMs are dominant because, on top of the traditional balance sheet channel and bank lending channel, also the cash-flow channel is at work, with significant macroeconomic effects (Garriga et al., 2017; Ippolito et al., 2018; Flodèn et al., 2021; Tzamourani, 2021; Cumming, 2022; Pica, 2022).[1] This means that ARMs amplify the transmission mechanism of monetary policy through mortgage interest payments. Second, the allocation of interest-rate risk between the banking sector and the real sector differs across countries and over time, with direct consequences for financial stability. For example, in a context of rising interest rates, mortgage defaults are more likely when ARMs are prevalent (Campbell and Cocco, 2003). Third, the effectiveness of macroprudential policies in containing mortgage defaults varies across countries and over time, with potential repercussions for the financial system and the real economy (Stanga et al., 2017).[2] In light of that, investigating the determinants of the prevalent type of mortgage across countries and over time is crucial in order to derive normative insights.

In this paper we exploit unique bank-level information on lending activity in the euro area to analyse what drives the granting of FRMs versus ARMs. In particular, we investigate to what degree the wide cross-country heterogeneity in the interest rate type of mortgages is caused by salient differences in the characteristics of borrowing households and/or lending banks. The distinction between what is potentially attributable to household demand versus bank supply is crucial because the policy implications may differ substantially depending on the main drivers of the mortgage choice.

[1]The cash-flow channel is the mechanism whereby conventional monetary policy actions are transmitted directly to borrowers' balance sheets via a change in the interest rate paid on outstanding (indexed) loans.

[2]Stanga et al. (2017) show that restrictive macroprudential policies are negatively associated with mortgage delinquencies in countries where FRMs are prevalent.

In general, household-specific factors include all features that make borrowers demand one or the other type of mortgage, as well as those that make a household more or less suitable to be financed at a fixed rate. Bank-specific factors include, instead, funding and liquidity conditions which may influence the ability of banks to supply FRMs.

Our empirical identification and estimation strategy rests on the availability of bank-level information on lending for a set of banks belonging to a banking group that operates in different markets and it relies on the assumption that funding of the banking group takes place at the consolidated level. Thus, the ability and willingness of a banking group to grant loans with certain features is also mainly determined at the consolidated level, particularly when the group operates in a monetary union, such as the euro area. Intuitively, this allows us to disentangle the impact of household-specific factors from that of bank-specific factors by comparing, on the one hand, the lending patterns observed for the same cross-border banking group in different economies and, on the other hand, the lending patterns observed in the same economy by different cross-border banking groups.

In practice, we decompose the variation of the share of FRMs to total new mortgages, henceforth abridged with “share of FRMs”, into “country-level household factors” and “bank factors”, by using fixed effects models and exploiting the wide-spread presence of cross-border banking groups. This approach is close in spirit to Amiti and Weinstein (2018) and Greenstone et al. (2019). Country-level household factors capture specific features of the borrowing country which are more related to loan demand, that is to the characteristics of the households in that country, whilst bank supply factors capture funding and liquidity conditions which are relevant for the lending supply by banks.

The main advantage of our approach is that we are able to jointly investigate the role played by household characteristics and bank conditions. Moreover, we are not bound to select a list of proxies for demand and supply factors, as typically done in the literature. Making such a selection is difficult as one cannot be sure that the list is exhaustive and, more importantly, that the variables under consideration truly capture only demand or only supply. On the down side, our estimated country-level household factors are not directly interpretable in economic terms, as they are likely to encompass a heterogeneous set of variables. Thus, in a second step, and similar to Ongena and Smith (2000), we adopt a two-stage approach whereby the estimated loadings on the country-level household factors are regressed on variables that are theoretically motivated.

Our main finding indicates a prominent role for country-level household factors which explain almost 72% of the total variation in the share of FRMs observed in the sample, as opposed to 19% associated with bank factors (the remaining 9% being the variation that the model is unable to explain).

In an extension of the baseline model we explore more in detail the time variation in the share of FRMs, which turns out to be strongly and negatively correlated with the term spread, that is the slope of the yield curve. In line with the main findings, the results of this exercise suggest that changes in the term spread mainly entail changes in the demand for FRMs, relatively to ARMs. Specifically, 79% of the variation in the share of FRMs driven by the term spread is ascribable to country-level household factors, although the elasticity of demand on the term spread differs across countries.

We more broadly explore the economic variables behind the cross-country differences in local household conditions, according to the two-stage procedure, as described above. The variables selected are taken from the existing literature, but we also put emphasis on a novel variable that has not been considered so far. We start from the observation that if households expect to be unemployed when interest rates are low, the ARM provides households with an insurance coverage (while the FRM does not). This simple (but at first sight somewhat counter-intuitive) observation leads us to check whether the share of FRMs is related to the correlation between the unemployment rate and the short-term interest rate. This correlation turns out to be highly significant and economically relevant in explaining the component of the share of FRMs associated to country-level household factors. Specifically, an increase in the correlation between the unemployment rate and and the short-term interest rate by one standard deviation (an increase of 0.49) leads to an increase of 14 percentage points in the average share of FRMs per country explained by household conditions.

Concerning the statistical significance of the other (more standard) economic factors underlying the country-level household factors (having controlled for bank factors), we document a role for financial literacy, whose effect turns out to be negative, in line with the notion that more educated borrowers can better understand complex financial products such as ARMs.

Households in countries where the covered bonds market is more developed are more likely to borrow at a fixed rate, given that such bank funding instruments backed by mortgages are typically issued at long maturities and at fixed rates. For a similar reason, also the volume of securitized mortgages entails a higher likelihood of households selecting a FRM. An increase in the outstanding amount of mortgage covered bonds and residential mortgage-backed securities, scaled by GDP, by one standard deviation (corresponding to 6 percentage points for both) leads to an increase of 32 and 17 percentage points, respectively, in the average share of FRMs per country explained by the demand.

Finally, high historical volatility of inflation is strongly and negatively related to the share of FRMs, consistent with the idea that the macroeconomic history of a country affects households' mortgage choices. A one standard deviation increase in the historical inflation volatility (an increase of 9 basis points) entails a decrease of 59 percentage points in the average share of FRMs per country.

We complete our study adopting a similar approach to explain prices instead of quantities, that is considering as dependent variable the spread between FRMs and ARMs interest rates, rather than the share of FRMs. Our findings indicate that also the spread between FRMs and ARMs interest rates is mainly driven by country-level household conditions.

The remainder of the paper is organized as follows. The next section reviews the existing literature and explains the contribution of our work. Section 3 discusses the identification strategy, while Section 4 describes the dataset. Section 5 presents the methodology and the results of the empirical analysis. Section 6 concludes.

2 Literature and Contribution

2.1 Demand and Supply Factors

The existing literature provides both theoretical modeling and empirical evidence on the determinants of the prevalent type of mortgage. A wide range of household factors and bank factors may drive the choice between FRMs and ARMs.

Household factors consist in all conditions affecting households' preference for one or the other type of mortgage, as well as their ability to be financed at a fixed rate. The risk profile of the lending exposure determines if a mortgage can be financed through long-term funds at a fixed rate, for example, by issuing covered bonds or mortgage-backed securities.

In general, an important role is ascribed to borrower's financial condition and level of education. In a pioneering work, Campbell and Cocco (2003) derive relevant theoretical predictions by treating mortgage choice as a problem in household risk management. In their framework, households subject to binding borrowing constraints at the time of the loan application, such as low income and low level of savings, are likely to choose the loan with the lowest interest rate. In general, this is then an adjustable rate as a fixed interest rate will include a term premium and the cost of the prepayment option.[3] Yet, an ARM exposes households to the income risk of short-term variability in the periodic payments. Thus, households with a limited income risk bearing capacity, for example in case of high loan-to-income ratio and

[3]The interest rate on an ARM is close to the short-term interest rate. The interest rate on a FRM is related, instead, to the long-term interest rate. The existence of a term premium and a cost of early repayment means that the interest rate on a FRM is not equivalent to the expectation of the future short-term interest rate. As a consequence, at inception of a loan the interest rate on an ARM and the interest rate on a FRM are not equivalent.

low financial wealth, are likely to select a FRM.

Several empirical papers have extensively investigated the role of income, savings, indebtedness and financial wealth in the choice of housing loans relying on households' income and wealth surveys (Paiella and Pozzolo, 2007; Fornero et al., 2011; Cocco, 2013; Ehrmann and Ziegelmeyer, 2017). These studies provide a general support for the predictions of Campbell and Cocco (2003).

Borrowers' education, especially the degree of financial literacy, is an important driver of mortgage choice as well (Agarwal et al., 2010; Fornero et al., 2011; Gathergood and Weber, 2017). In general, more educated borrowers have a deeper understanding of the intrinsic features of ARMs and FRMs. On the one hand, they are aware that, unconditionally, a FRM is more expensive than an ARM, due to the term premium and the cost of the prepayment option mentioned above. For this reason, they are more likely to select an ARM (Agarwal et al., 2010; Gathergood and Weber, 2017). On the other hand, they are also mindful of the potential exposure to income risk if they choose an ARM (Fornero et al., 2011).

Bank factors consist in bank funding and liquidity conditions. In general, the composition of liabilities affects, and is affected, by the type of loan a bank is more willing to offer (Kirti, 2020). Since bank liabilities have typically a short duration, banks have a preference in originating ARMs.[4] However, a few empirical studies show that low bank bond spreads, low deposit pass-through, low exposure to interest rate risk and high access to securitization make banks more prone to extend fixed rate loans (Fuster and Vickery, 2014; Foà et al., 2019; Basten et al., 2017).

[4] This holds true as long as banks can bear the exposure to interest rate risk, as documented by Hoffmann et al. (2019). Indeed, if banks were to fully hedge, they would be equally willing to supply FRMs and ARMs.

Beside these rather intuitive factors, there exist a set of macroeconomic factors that exert their effects either through demand or supply. These include current and future expected interest rates, as well as the unemployment rate and the macroeconomic history of a country.

The current spread between the interest rates on FRMs and ARMs is a leading factor of mortgage choice (Paiella and Pozzolo, 2007; Koijen et al., 2009; Fornero et al., 2011; Badarinza et al., 2018). This suggests that households behave myopically, selecting the type of loan that requires the lowest payments at the time of the loan application. However, households' expectations on the future interest rate applied on ARMs play a role as well, but only over the short horizon of one year (Koijen et al., 2009; Foà et al., 2019; Badarinza et al., 2018).

The difference between long-term and short-term interest rates is a component of the spread between FRMs and ARMs interest rates. As such, the current term spread is also a determinant of mortgage choice (Koijen et al., 2009; Basten et al., 2017; Ehrmann and Ziegelmeyer, 2017). Since in the literature on the bank lending channel the level of interest rates is recognized to be able to shift both the demand and the supply of credit, one can surmise that the term spread may act as a shifter of both the demand and the supply of FRMs, relatively to ARMs.

The historic volatility of inflation plays an important role in the choice of mortgages as well. Countries with a history of high volatility of inflation show a prevalence of ARMs (Campbell, 2012; Badarinza et al., 2018). This is because the supply of FRMs is low when inflation is volatile and prepayment penalties are low, as lenders are more exposed to inflation risk than borrowers through a FRM. In fact, if inflation rises, the real value of payments declines, hereby favoring the borrower at the expense of the lender. Conversely, if inflation declines, the real value of payments increases, but the borrower often has the option to prepay and refinance at lower rates (Campbell and Cocco, 2003; Campbell, 2012; Badarinza et al., 2018). The dominance of ARMs in countries with a history of high inflation persists even after the adoption of the euro (i.e., after the national inflation rates converged), suggesting a substantial inertia in households' behavior (Campbell, 2012).

The volatility of the unemployment rate, as a proxy for households' expected income, is an additional driver of the prevalent type of mortgage. In countries with high volatility of the unemployment rate households are more likely to select a FRM, as future income is expected to be unstable (Ehrmann and Ziegelmeyer, 2017).

Guren et al. (2020) emphasize the prominent role in mortgage choice of the monetary policy reaction function to aggregate shocks. If the central bank decreases interest rates in response to a crisis, an ARM provides households with higher insurance benefits allowing a higher degree of consumption smoothing. We are the first to test empirically this prediction including among our country demand factor a novel variable, namely the correlation between the unemployment rate and the short-term interest rate.

Table A1 in Appendix A.1 summarizes all the determinants of mortgage choice identified in the literature, as well as those analysed in this study.

2.2 Contribution

The existing literature investigates the plethora of factors driving the choice between FRMs and ARMs, mainly focusing on one specific country and without providing information on the relative importance of household and bank factors. To the best of our knowledge, the works of Ehrmann and Ziegelmeyer (2017) and Badarinza et al. (2018) are the only two papers to examine the determinants of mortgage choice across countries.

Using a new household wealth survey, the Eurosystem household finance and consumption survey, Ehrmann and Ziegelmeyer (2017) provide a deep investigation of the household-specific factors, but ignore bank-specific factors. Relying on monthly country-level information, Badarinza et al. (2018) analyse how current and future expected interest rates affect the time variation in the share of ARMs to total new mortgages. They partially investigate the cross-country variation as well, but look exclusively at the role played by the historic volatility of inflation. Both these studies are not able to investigate jointly the broad spectrum of household and bank factors driving mortgage choice, neither to disentangle their impact.

We are able to overcome these limitations by using unique granular bank-level information on a sample of intermediaries operating in twelve countries in the euro area. The structure of our dataset allows us to take a step towards identifying the role of household and bank conditions in shaping the demand and supply of FRMs, relatively to ARMs. Assessing the relative importance of household-specific factors and bank-specific factors is crucial because the policy implications may differ substantially depending on what is the actual driver. Eventually, we are the first to explore the role of households' and banks' conditions also on the relative price of FRMs and ARMs.

3 Identification

Our identification strategy builds on the idea that funding takes place at the consolidated bank level. This allows us to disentangle country-level household factors from bank factors by comparing the lending behavior of the same cross-border banking group in different countries, as well as the lending behavior in the same economy by different cross-border banking groups operating there.

Our identification strategy is supported by several facts. First, lending policies are mainly driven by bank funding and liquidity conditions. In a cross-border banking group funding is defined at the consolidated level as to minimize the cost of capital. For example, Gu et al. (2015) show that international banks raise debt through subsidiaries operating in countries with a more favorable tax system. In general, cross-country differences in terms of taxation, regulation, bureaucracy, services and infrastructure, as well as the development of capital markets play a crucial role in the way banks issue long-term funding instruments. Additionally, in a cross-border banking group funding mainly occurs at the consolidated level. Although international banks have progressively adopted a more decentralized funding model after the recent financial crisis, Gambacorta et al. (2019) show that cross-border banks' liabilities from foreign branches and subsidiaries represent, even recently, only 41% of total funds raised abroad. For similar reasons, also liquidity conditions are defined at the consolidated level. As a consequence, the ability and willingness of a cross-border banking group to grant loans with given characteristics is also mainly determined at the consolidated level. This is especially true if the group operates in a monetary union, such as the euro area, characterized by homogeneous regulations and integrated capital markets.

Second, when looking at cross-border banks, investors and regulators are mainly focused on consolidated balance sheets. For example, the "core principles for effective banking supervision" depicted by the Basel Committee on Banking Supervision pointedly refer to the assessment of consolidated balance sheet conditions, also regarding the exposure to interest rate risk (BCBS, 2012). These principles are broadly confirmed by the ECB guide to banking supervision (ECB, 2014). Additionally, the design of banks' surveys is typically aimed at gauging lending standards at the consolidated level. This is the case, for example, of the Euro Area Bank Lending Survey and the Senior Loan Officer Opinion Survey, run by the Eurosystem and by the Federal Reserve System, respectively.

Third, our identification assumption is consistent with the literature on cross-border banks as shock propagators. This literature shows that funding and liquidity shocks to the holding of a cross-border banking group affect local lending supply (Cetorelli and Goldberg, 2011, 2012; Schnabl, 2012; Célérier et al., 2020).

While it is reasonable to argue that lending policies are mainly driven by funding and liquidity conditions of the banking group, we cannot exclude that local funding or other factors may affect bank supply at the country level. For example, local subsidiaries may experience a certain degree of flexibility, which would be subsumed in our country-level household factors. However, the fact that fund-raising and liquidity conditions are prominent determinants of lending supply, as well as the fact that they are mostly defined at the consolidated level, ensures that our identification strategy is reliable.

More importantly, we cannot exclude that cross-border banks define local lending policies taking into account the household conditions that are specific to each country in which they operate. For example, it could be the case that a bank is less willing to extend ARMs in an economy characterized by high default rates (if it thinks that granting ARMs would entail even higher default rates). Our methodology includes such component of lending decisions that varies with borrowers' characteristics within the broad category of country-level household factors. In this respect, our analysis shares exactly the same advantages and limitations of studies exploiting more granular data to identify household conditions. Even in studies relying on, e.g., credit register data, factors that shape the risk-profile of households, and hence their borrowing capacity, are often subsumed by (time invariant or time varying) borrower fixed effects, which are typically meant to capture household (demand) conditions (Khwaja and Mian, 2008; Amiti and Weinstein, 2018).

4 Data

This paper uses the Individual Monetary and Financial Institution Interest Rates (IMIR) dataset held by the Bank of Italy. This dataset includes monthly bank-level information on a representative sample of 103 monetary and financial institutions (MFIs),[5] which we will henceforth simply call "banks", acting in twelve countries in

[5] According to the European Central Bank monetary and financial institutions are resident credit institutions as defined in European Union law, and other resident financial institutions whose busi-

the euro area. In particular our panel includes banks operating in Austria, Belgium, France, Germany, Greece, Italy, Latvia, Luxembourg, Portugal, Slovenia, Spain and the Netherlands. Data cover the period that goes from July 2007 to December 2015.

The available information encompasses the amount granted and the weighted average interest rate applied to adjustable rate and fixed rate mortgage contracts. ARMs are identified as loans to households for house purchase with a floating rate and and interest fixation period of up to one year, whereas FRMs are identified as mortgages with an interest fixation period of over one year. For FRMs we also have information on the volume and price of loans with a fixation period over 10 years. While the typical length of a FRM may vary across countries, loans with an interest fixation period of over 10 years represent, on average, half of FRMs extended in a given country in our sample. This ensures a certain comparability of FRMs across different jurisdiction. We caveat, though, that we do not have information on prepayment penalties and other specific contract terms.

Overall, we have 103 banks associated to 73 banking groups. The latter include 5 cross-border banking groups with 19 affiliated banks out of the 103 in total. Detailed information on the composition of banks in our dataset is exposed in Table 1. While the supervisory of our data is per se a guarantee of representativeness, we note that new mortgages extended by banks in our sample correspond, on average, to 34.2% of total mortgage origination in each country and each month.

Figure 1 shows the average share of FRMs, the average spread between FRMs and ARMs interest rates, and the term spread computed as the difference between

ness is to receive deposits and/or close substitutes for deposits from entities other than MFIs and, for their own account (at least in economic terms), to grant credits and/or make investment in securities.

the 10-year Interest Rate Swap rate and the 3-month Overnight Index Swap rate at the semi-annual level. Looking at the average share of FRMs, we find a substantial cross-country heterogeneity. We can divide countries in two main groups. France, Germany and the Netherlands exhibit a large proportion of FRMs over the entire time period of our analysis. All the other countries exhibit more time variation and for most of them the average share looks negatively related to the average spread. Looking at the spread between FRMs and ARMs interest rates, some differences are observable as well, although for this metric the heterogeneity seems contained. The time patterns of the average spread largely reflect those of the slope of the term structure as measured by the term spread.

Figure 2 displays the evolution of the share for domestic and foreign banks within countries, for the two representative group of economies. The heterogeneity across banks within (these groups of) countries is non negligible, but still much smaller than what is observable across such (groups of) countries. In both groups of economies foreign banks behave consistently with the domestic banks of the country in which they operate. This evidence suggests that country-level household factors may play a major role than bank factors.

Table 2 reports basic statistics for the share of FRMs and the spread between FRMs and ARMs interest rates for each country in our data set.

5 Empirical Analysis

5.1 Baseline Model

Our methodology relies on the approach proposed by Amiti and Weinstein (2018), although applied to our unique dataset, and exploits cross-border banking groups to decompose the share of FRMs into country-level household factors and bank factors.[6] More specifically, we estimate the following type of regression:

$$share(b, c, t) = \alpha(c, t) + \beta(h(b), t) + \varepsilon(b, c, t) \tag{1}$$

In equation 1 the share of FRMs extended by a given bank b operating in a given country c at time t is regressed on a set of different fixed effects. The terms $\alpha(c, t)$ represent month-country fixed effects. They capture all observable and unobservable time varying and time invariant characteristics of country c and, as such, they are meant to capture the household conditions prevailing in that economy. Obviously, no other country specific controls can be added to the specification, as these would be subsumed in the month-country fixed effects. This means that the inclusion of month-country fixed effects in equation 1 is equivalent to the use of an arbitrarily large set of country macroeconomic controls, which is why we argue that we are effectively capturing country-level household factors. Nonetheless, their limitation in this context is related to the inability to control for borrower conditions that are specific to individual intermediaries. As most of our analysis focuses on cross-border banks, and since these are typically large banks operating on a national scale and

[6] Greenstone et al. (2019) adopt a similar methodology, but they decompose the variation of their dependent variable using time invariant rather than time varying fixed effects.

with a diversified set of borrowers, we consider our approach appropriate. The terms $\beta(h(b), t)$ represent month-banking group fixed effects, $h(b)$ denoting the holding of bank b. They consist in all observable and unobservable time varying and time invariant characteristics of banking group h and, as such, they are aimed at capturing bank conditions. In light of the fact that lending policies are usually defined at the consolidated level taking into account the financing conditions of the entire group, we argue that this set of fixed effects reasonably accounts for bank supply factors.[7]

By construction, equation 1 can only be estimated in the subsample of observations pertaining to cross-border banking groups. In this sample, equation 1 provides the upper limit of the R^2 that is achievable by regressing the share of FRMs on any set of variables capturing (time varying) characteristics of the borrowing country c and (time varying) characteristics of the lender h. Ideally, we would control for supply factors at the bank level, as we cannot exclude the possibility that some of these intermediaries experience some degree of autonomy (Houston et al., 1997). We investigate whether this is the case by estimating alternative specifications to model 1 where we can say something about the role of bank-specific factors defined at the individual bank level. Of course this comes at some cost, as it requires to abandon the use of time varying fixed effects. We evaluate the size of costs associated with this approximation. Eventually, in order to exploit the information available in the entire sample, we also explore simpler specifications where the set of controls is less fine that what is implied

[7]Cross-border banks may sort themselves in countries that share similar characteristics. Even within a country, they may specialize in lending to households that demand a certain type of mortgage. If this is the case, our banking-group fixed effects may capture demand rather than supply factors. Nevertheless, the set of cross-border banks that we exploit in our regression analysis includes big universal banks which operate in countries that show a significant difference in the prevalent type of mortgage. Such big players are likely to operate on a national scale without specializing in a specific type of mortgage.

in model 1.

5.2 Baseline Results

Models 1-3 of Table 3 report three specifications in which the share of FRMs is regressed on, respectively, month-country fixed effects, month-banking group fixed effects and both of these sets of fixed effects jointly. The latter is exactly the model specified in equation 1. Month-country fixed effects explain a significant fraction of the variation in the share (84%), suggesting a prominent role of country-level household factors. When considered alone, month-banking group fixed effects also explain some of the variation in the dependent variable (32%), but significantly less than month-country fixed effects. If taken together these two sets of fixed effects can explain 91% of total variation in the share. By decomposing the R^2 of model 3 according to the Shorrocks-Shapely approach, we find that the component of R^2 related to month-country fixed effects (72%) is considerably higher than the component related to month-banking group fixed effects (19%), confirming that country-level household conditions play a prominent role.[8]

When saturating the previous specification by including also bank (time invariant) fixed effects, as in model 4, we are able to explain almost the entire variation in the dependent variable. Even if we interpret these dummies as (time invariant) supply

[8]In the fixed-effect decomposition of model 3 we have 688 month-country dummies versus 480 month-banking group dummies. Although the number of the former is 28% larger than the number of the latter, the two sets of fixed effects are quite balanced. As will we show in the next section, results remain virtually unchanged when we re-estimate the model on a subsample of 1085 observations covering countries and time periods for which we have information on a set of macroeconomic characteristics of the country (model 3 of Table A2). The econometric specification of this subsample encompasses 360 month-country dummies and 393 month-banking group dummies. Although, in this case, the set of month-banking group fixed effects is somewhat larger than the set of month-country fixed effects, we still find that country-level household conditions have a much higher explanatory power than bank factors. This means that our results are not driven by the relative size of the two sets of fixed effects included in the model.

factors at the bank level, we would still conclude that overall bank conditions explain only a minor portion of the total variation in the share of FRMs.

To limit concerns that month-country fixed-effects capture to some extent bank factors that are specific to each country where the banking group operates, in model 5, we focus on a subset of banking groups whose holding company plays a more prominent role in driving the supply of FRMs versus ARMs. If we rely on heteroscedasticity robust standard errors, the estimates of model 2 reveal that about half of the coefficients of the month-banking group dummies are statistically significant and these observations pertain to three banking groups. Intuitively, these are exactly the banking groups where credit decisions are more centralized. We, thus, re-estimate model 3 on the subset of these three banking groups. Results are virtually unchanged compared to model 3.

One may be concerned whether the specific sample over which we are able to conduct our exercise, which is given by all observations (bank-month pairs) pertaining to cross-border banking groups, is representative enough. As shown in Table 3, this sample comprises 1644 observations, corresponding to about one fourth of the overall sample. On average, each cross-border banking group accounts for 13.2% of new mortgages extended in the countries where it operates and 50.5% of total originations covered by our sample in those countries.[9] Therefore, cross-border banking groups in our sample encompass a set of large and representative institutions.

[9]The average volume of new mortgages extended by a banking group (either cross-border or not) in a country in a month is EUR 255 mln in our sample, while the standard deviation is EUR 414 mln. By comparison, the average volume of new mortgages originated in a country in a month is EUR 5156 mln, with a standard deviation of EUR 5451 mln. If we focus the attention on the cross-border banking groups where the baseline model of equation 1 is estimated, the average volume of new mortgages originated by those banking groups in a country in a month is EUR 387 mln, whereas the standard deviation is EUR 452 mln.

A second concern is whether the lending activity of cross-border banking groups in foreign countries is large enough to ensure a meaningful analysis. It could be the case that those banking groups originate only a small volume of loans outside of their borders, implying a volatile share of FRMs extended in foreign countries. Since month-banking group fixed effects are equally weighted, this may contribute to the limited explanatory power of month-banking group dummies. However, new mortgages extended by cross-border banking groups in non-home countries represent, on average, 44.4% of their total originations, hereby corroborating our methodological approach. While this figure is reassuring, to help further softening any concern, we check that our findings are not driven by any specific banking group (which, e.g., may conduct only a marginal mortgage business in foreign countries). To this end, we replicate the estimation of the baseline model of equation 1 by excluding each of the 5 cross-border banking groups in our sample one at the time. This robustness test is presented in Table A6 of Appendix A.5. Irrespective of which cross-border banking group is excluded from the sample, the estimates are virtually unchanged compared to those of model 4 in Table 3. We conclude that our baseline results are not by driven the lending behavior one specific institution.

Lastly, since cross-border banking groups encompass a rather homogeneous set of lenders, typically the largest players in the industry, our analysis may underestimate the relevance of bank-specific factors as a determinant of mortgage choice. For instance, it could be the case that large banks can more easily access financial markets to buy protection against interest rate risk or to raise long-term funds at fixed rate via covered bonds. If this is the case, focusing only on cross-border banking groups may lead to neglect part of the role played by lender conditions. To tackle this issue we conduct an exercise that requires a departure from our identification setup. In particular, we consider time invariant country fixed effects and banking group fixed effects to capture household-specific and bank-specific factors, respectively. In this way we are able to estimate similar regressions to those in Table 3, but run on the entire sample of banking groups, which is likely to be more heterogeneous than the subset of cross-border banking groups. This robustness exercise, illustrated in Appendix A.5, corroborates our conclusions drawn on the subsample of cross-border banking groups, emphasizing the role played by country-level household factors.

5.3 Two-Stage Model

Regressions reported in previous tables provide a useful breakdown of the contribution of country-level household factors and bank factors in explaining the share of FRMs. This breakdown is powerful, as it relies on reasonable identifying assumptions. However, its main limitation is that it consists in a mere statistical decomposition, which prevents from providing a meaningful economic interpretation. In particular, as discussed earlier, our results suggest that country-level household factors play a prominent role, but these may include a rather heterogeneous set of borrower-specific characteristics. The normative conclusions may be quite different depending on what is the actual driver.

A natural way to investigate which country-level household factors are more relevant would be to estimate a modified version of equation 1 where the time varying country fixed effects are replaced by a set of variables capturing different country demand conditions. The results of this exercise, presented in Appendix A.3, reveal that our selection of variables largely explains month-country fixed effects and that real disposable income and macroeconomic conditions play a prominent role in explaining the share of FRMs. While this represents a simple approach to shed some light on the determinants of the wide cross-country heterogeneity in the share of FRMs, it suffers from a major flaw. Our sample is characterized by significant differences in the number of banks operating in each country. Over-represented countries in the sample may drive the results and, hence, prevent from identifying the real mechanisms behind the observed heterogeneity in the prevalent type of mortgage across countries.

We, thus, consider a different approach. To ensure that we draw conclusions by giving an equal weight to the observations pertaining to each country, we adopt a two-stage model, as in Ongena and Smith (2000). In particular, we regress the estimated coefficients of the month-country fixed effects in the full specification of equation 1 on a set of explanatory variables.[10] Unfortunately, 147 out of 393 month-country dummies in model 3 of Table 3 are omitted because of collinearity. As a consequence, performing the second stage regression with only 246 dependent variables would prevent us to get reliable results. To circumvent this issue, we estimate a similar regression to the one of equation 1, in which we substitute month-banking group fixed effects with quarter-banking group fixed effects. In this way, we are able to estimate 344 out of 393 month-country dummies and to perform the second stage regression accordingly. To be more specific, our two-stage regression looks as follows:

[10] To perform the second stage regression we only need that the estimated coefficients of the month-county fixed effects are unbiased. We argue that this condition is satisfied as the time varying country fixed effects and banking group fixed effects included in the first stage regression span all the possible factors determining the dependent variable.

$$share(b,c,t) = \alpha(c,t) + \beta(h(b),t) + \varepsilon(b,c,t)$$

$$\hat{\alpha}(c,t) = \boldsymbol{x'(c,t)\gamma} + \upsilon(c,t) \tag{2}$$

The terms $\beta(h(b),t)$ represent quarter-banking group fixed effects, while $\boldsymbol{x'(c,t)}$ denotes the vector of explanatory variables capturing country-level household conditions. These variables include a set of metrics suggested by the literature (those described in Section 2) plus a novel variable. In particular, we consider the following variables: financial literacy, indebtedness, gross disposable income per capita, historical volatility of inflation, correlation between unemployment and the short-term interest rate, outstanding amount of mortgage covered bonds to gross domestic product (GDP) and outstanding amount of residential mortgage-backed securities (RMBS) to GDP.

Our measure of *Financial Literacy* is obtained from the S&P Global FinLit Survey performed in 2014 (Klapper et al., 2015). The survey is based on interviews with more than 150000 adults in over 140 countries. It provides information on the degree of knowledge of four basic concepts in finance: risk diversification, inflation, numeracy and interest compounding. Financial literacy is measured as the percentage of 3 out of 4 answers correctly given by adults interviewed in each country. Table 5 and Figure A1 in Appendix A.2 show that the level of financial education increases as we move from southern countries to northern countries.

To measure households' *Indebtedness* we use the ratio of total outstanding debt as percentage of gross disposable income provided by the OECD on a quarterly frequency. Table 5 and Figure A1 in Appendix A.2 display important differences in the level of households' indebtedness across countries. We consider the indebtedness ratio as a suitable proxy for households' income risk bearing capacity over the duration of the mortgage.

As a measure of *Real Disposable Income Per Capita* we use the gross disposable income (adjusted for social transfers in kind) of households (and non-profit institutions serving households) expressed in purchasing power standard (PPS) per inhabitant, obtained from Eurostat on an annual basis. Table 5 and Figure A1 in Appendix A.2 show a marked heterogeneity in households' real disposable income across countries over our sample period.

It is recognized in the literature that the unemployment rate plays a role in the mortgage choice (Ehrmann and Ziegelmeyer, 2017). A related aspect which has not been emphasized so far is that borrowers choosing between FRMs and ARMs should care not only about the expected evolution in labor market conditions, but also about how unemployment will correlate with the level of interest rates (Statman, 1982). Risk-averse households expecting to be unemployed in a context of low interest rates tend to prefer, ceteris paribus, an ARM, as this implies a higher degree of consumption smoothing (mortgage installments decrease when income goes down and vice versa). Guren et al. (2020) provide a theoretical support for this argument. Usually a crisis unfolds because of a aggregate shock to the demand, leading to a drop in income and inflation. In such situation, interest rates may decline due to the monetary policy reaction of the central bank. Guren et al. (2020) show that, if the central bank reduces interest rates in response to a aggregate shock, households should select an ARM rather than a FRM. If, instead, interest rates increase during a downturn, for example because of a aggregate shock to the supply, households should prefer a FRM.

In light of that, the correlation between interest rates and unemployment depends on different factors including the slope of the Phillips curve and the monetary policy rule adopted. A full discussion of these aspects is outside the scope of this paper. Here we limit ourselves to highlight that, whenever such correlation is negative, the mortgage contract providing more protection against income fluctuations is, somewhat counterintuitively, the ARM and the insurance motive attached to it is stronger the smaller the correlation. We postulate that households make their expectations looking at the past. Then, to capture this effect we introduce a novel variable, namely the correlation between unemployment and the short-term interest rate.

We calculate *ρ(Unemployment, Short-term IR)* as the realized correlation between the unemployment rate and a short-term interest rate,[11] relying on a rolling window approach with a window of 7 years. We opt for a window of 7 years for two reasons: First, we assume that households make long-term expectations;[12] second, we make sure that, at the beginning of our sample period in 2007, we measure the correlation between these two variables after the introduction of the euro.[13] Table 5 and Figure A2 in Appendix A.2 show that the correlation between unemployment and the short-term interest rate is negative in most countries over our sample period. This suggests that in periods of economic growth unemployment is low and the short-term

[11] Data on short-term interest rates are retrieved from the OECD. For euro area countries the 3-month European Interbank Offer Rate is used from the date the country joined the euro. For the other countries the short-term interest rate is either the 3-month interbank offer rate or the yield on short-term Treasury bills, Certificates of Deposits or similar instruments with a maturity of three months.

[12] Usually long-term expectations have an horizon of at least five years (ECB, 2016, 2017).

[13] In this way we ensure that households expectations are made taking into account that monetary policy is defined by the ECB for the entire euro area. This clearly implies that we estimate the correlation between unemployment and short term interest rate having the same short-term interest rate for all countries (with the only exception of Greece, Latvia and Slovenia before their access to the euro area respectively in 2001, 2014 and 2007).

interest rate is high as a result of a tight monetary policy aimed at containing inflation. Conversely, in bad times, such as the recent double-dip European recession, unemployment is high and the short-term interest rate is low due to an expansionary monetary policy. However, there are some exceptions. For example, Germany exhibits a positive correlation from the end of 2010 on-wards. That is because the unemployment rate in Germany started to decrease in 2009, revealing a substantial improvement in economic fundamentals.[14]

We include as an indicator of the macroeconomic history of a country the volatility of the inflation rate over a period of 30 years prior to the introduction of the euro. We calculate *Historical Inflation Volatility* as the realized standard deviation of the monthly month-on-month inflation rate during the period 1970-1999 expressed in basis points.[15] While a metric for the historical volatility of inflation constructed using a rolling window approach may allow to capture adaptive expectations on inflation across generations of households, our variable has a different interpretation. Before 1999, inflation rates in Europe where characterized by a strong variability and heterogeneity across countries. As soon as the Euro was adopted (in 1999 for most cuountries), national inflation rates sharply converged and became less volatile due to the common monetary policy set by the European Central Bank. As in Campbell (2012), we estimate our measure on a pre-euro period in order to emphasize differences across countries. This metric is aimed at capturing the stickiness in households' mortgage choice given the macroeconomic history of their country prior to the birth

[14]This reflects, in turn, a flight-to-quality episode in the context of a monetary union. When economic conditions worsen due, e.g., to a global financial crisis, policy rates drop by the same extent for every economy in the monetary union, but flight to quality makes unemployment increase more more in peripheral countries.

[15]Because of a lack in the available data, the historical volatility of inflation is computed over the period 1991-1999 for Latvia and 1980-1999 for Slovenia.

of the eurozone.

In Table 5 and Figure A1 in Appendix A.2 we see that the periphery economies of the euro area have experienced a substantial higher inflation volatility than central countries in the past. High variability of inflation is typically related to a high share of ARMs, because FRMs become very expensive when inflation is volatile. Countries with a history of high inflation volatility before 1999 still exhibit a prevalence of ARMs even after the introduction of the euro. Following Campbell (2012) and Badarinza et al. (2018), we interpret this fact as evidence of a sticky demand, meaning that households tend to select the type of mortgage they are more familiar with.

We label the variables listed so far as pure demand factors, as they relate to specific characteristics affecting households' preference for FRMs vis-à-vis ARMs. We take into account also two additional variables, namely *Outstanding Covered Bonds to GDP* and *Outstanding RMBS to GDP*. The size of the covered bond market and the RMBS market of a country results from the interaction of two main forces. On the one hand, investors' demand for covered bonds and RMBS, and, hence, the ability of lenders to fund mortgages using these instruments. On the other hand, the extent to which local mortgages are suitable to back covered bonds or asset-backed securities based on, e.g., the credit quality of borrowers and the dynamics of the housing market. The former force represents funding conditions that affect the supply of FRMs. The latter, instead, represents demand conditions that affect the ability of households to be financed at a fixed rate.[16] Our identification strategy builds on cross-border banking groups, which are typically large and have access to global financial markets.

[16]For example, covered bonds regulations in most European countries specify that only mortgages having a loan-to-value below a certain threshold are eligible to be used as collateral for covered bonds (ECBC Covered Bond Comparative Database; ECB, 2008; ECBC, 2016).

This means that a cross-border banking group can fund FRMs originated in a certain country by issuing covered bonds purchased by investors elsewhere.[17] While we cannot exclude that mortgages, covered bonds and RMBS are jointly issued locally to meet investors' demand for these securities in a given country, our time varying banking group fixed effects should capture to a large extent the reliance of cross-border banking groups on these funding instruments. Hence, conditional on bank financing conditions and demand factors affecting households preferences for one type of mortgage, the covered bonds to GDP ratio and the RMBS to GDP ratio should capture the extent to which mortgages originated in a country are suitable to back covered bonds or RMBS.

We retrieve annual data on outstanding covered bonds from the European Covered Bond Council (ECBC). Our variable is the average over the last four years of the outstanding amount of mortgage covered bonds issued in a given country as percentage of GDP. Table 5 and Figure A2 in Appendix A.2 show that mortgage covered bonds are particularly popular in Portugal and Spain. As for residential mortgage-backed securities, we get quarterly data from the Securities Industries and Financial Markets Association (SIFMA). Our variable is the average over the last four quarters of the outstanding amount of RMBS by country of collateral scaled by GDP. Table 5 and Figure A2 in Appendix A.2 show that RMBS are common in the Netherlands and Portugal. Table 4 summarizes all the explanatory variables that we use to model country-specific factors, whilst Table 5 reports basic statistics. Both the summary statistics and the time series plots Appendix A.2, reveal that all the time varying

[17] Indeed, legislations on issuance of covered bonds in most European countries allow to include mortgages originated abroad in the covered pool (ECBC Covered Bond Comparative Database; ECB, 2008; ECBC, 2016).

country demand variables, except for *ρ(Unemployment, Short-term IR)*, exhibit a much stronger variation in the cross section than in the time series.

5.4 Two-Stage Results

We now present the results of the two-stage model of equation 2. Model 1 of Table 6 reports the estimates of the first stage regression where we include month-country fixed effects and quarter-banking group fixed effects. In this specification we drop observations where the explanatory variables used in the second stage are missing. The R^2 is close to that of model 3 of Table 3.

In models 2-3, the coefficients of month-country fixed effects estimated by running model 1 are regressed over the set of explanatory variables capturing demand conditions. In order to make sure that our regressors are predetermined, we include lagged values for those variables that are available on a lower frequency than monthly.[18] To have a reliable basis for inference, both in model 2 and in model 3, we rely on standard errors clustered by country and quarter.[19] Given the different nature of the two groups of variables that we take into account, we first consider those capturing pure demand only and then integrate with the other country-level institutional factors. Model 2 shows the results for the specification including pure demand factors only. We find a negative and significant coefficient for Historical Inflation Volatility, which confirms our prior. Our result is consistent with that of Campbell (2012) and Badarinza et al. (2018), showing that households' are more likely to select the type of

[18] These are all the explanatory variables except for ρ(Unemployment, Short-term IR).

[19] This conservative two-way clustering has been selected according to the procedure suggested by Petersen (2009), Cameron et al. (2011), and Cameron and Miller (2015). To tackle the issue that we may have few clusters, we adopt a small-sample correction for both standard errors and test statistics, as suggested by Cameron et al. (2011), and Cameron and Miller (2015).

loan they are more familiar with based on the macroeconomic history of their country. As expected, the sign of the coefficients for Financial Literacy, Indebtedness and ρ(Unemployment, Short-term IR) are, respectively, negative, positive and positive, but neither of the three is statistically significant.

Model 3 extends the preceding including the whole set of regressors. Historical Inflation Volatility maintains its sign and significance. The coefficient of Financial Literacy turns out to be negative and statistically significant. This is consistent with the idea that financially educated households are more willing to select an ARM, as they are able to understand that, unconditionally, an ARM is cheaper than a FRM. Statistically significant is also the coefficient of ρ(Unemployment, Short-term IR). The positive sign corroborates our view that the smaller such correlation, the stronger the insurance protection provided by an ARM. This suggests that households make expectations on what would be the macroeconomic environment in which a labor shock may occur. In particular, households that expect to be unemployed in a context of low interest rates are more willing to select an ARM, while households that envisage to be unemployed in a context of high interest rates, are more prone to choose a FRM. This result confirms the theoretical prediction of Guren et al. (2020). The coefficients of Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP are both positive and significant, suggesting that, in countries where the characteristics of borrowers ease the issuance of covered bonds and asset-backed securities, FRMs are relatively more appealing.

To obtain relevant normative insights, we do not limit ourselves to merely identifying the country-level household factors that play a role in mortgage choice, but we also provide an economic assessment of their magnitude. Table 7 reports the magnitude effects of the seven variables included in model 3 of Table 6. Focusing the attention on those that are statistically significant, we find that the Historical Inflation Volatility exhibits the strongest effect. One standard deviation increase leads to a decrease of 59 percentage points in the average share of FRMs per country cleaned of variation due to bank-specific factors. Sizable is also the effect of Financial Literacy. A rise of one standard deviation corresponds to a drop of 42 percentage points in the average share of FRMs per country ascribable to country-level household factors. Moreover, a one standard deviation increase in Outstanding Covered Bonds to GDP and in Outstanding RMBS to GDP determines a rise, respectively, of 32 and 17 percentage points in the dependent variable. Finally, a one standard deviation increase in ρ(Unemployment, Short-term IR) leads to a rise of 14 percentage points in the average share of FRMs per country left unexplained by bank-specific factors.

To ensure the soundness of our results, we perform a battery of robustness tests that challenge the design of our two-stage model. Appendix A.6 provides a comprehensive summary of those tests. Given the large magnitude effects identified for some of the explanatory variables in Table 6, as a first step, we check if our findings are driven by outliers. While some of the macro variables used in the second stage of equation 2 exhibit extreme values (e.g., the historical inflation volatility for Latvia and Slovenia), model 3 of Table 6 is effectively estimated on a subsample of six countries at the core of the euro area (Austria, Belgium, France, Germany, Italy and Spain), due to the inclusion of quarter-banking group fixed effects and to the lack of data on some variables for specific country-month pairs. Despite this reassuring fact, we still may want to dig into the drivers of our results and shed some light on the role played by outliers. To this end, we re-estimate the two-stage model of equation 2 by excluding each of the six countries one at the time. Results are reported in Table A9. We find that excluding Germany, France, Spain or Belgium does not have a major impact on our results, meaning that the estimates are to a large extent similar to those of model 3 of Table 6. Instead, Italy and Austria seem to be critical for our results, but not because they exhibit outliers. The reason lies in the fact that these two countries differ from the others along two dimensions: i) they are both characterized by a marked variability in the share of FRMs over time, especially Italy, and ii) Austria shows the strongest prevalence of ARMs throughout the sample.

Next, we test if our results are robust to the inclusion of different metrics capturing country-level household factors. We show that our findings remain virtually unchanged i) if we replace ρ(Unemployment, Short-term IR) with the correlation between the number hours worked per capita and the short term interest rate to use an alternative metric for employment conditions (Table A11), and ii) if we include the house price to income ratio in the set of regressors to capture housing affordability (Table A10). In addition, our main takeaways (in particular with respect to the role of the historical inflation volatility and the size of the covered bonds and the RMBS markets) are confirmed i) when we replace Historical Inflation Volatility with a rolling-based metric to capture adaptive expectations on inflation (Table A12), and ii) when we use the ratio of public debt to GDP to capture investors' demand for securities such as RMBS (Table A13).

Finally, our results are confirmed even when we use sampling weights based on the relative size of the mortgage market in each country to further ensure that we estimate the two-stage model by equally weighting each country (Table A14).

5.5 Time Variation

Some useful indications can be obtained by exploring more closely the variation across time in the share of FRMs. As noted in Figure 1, for those countries in which the share of FRMs changes over time, the variability seems to be related to the spread between FRMs and ARMs interest rates. Since the term spread is a component of the spread between the interest rate applied on fixed rate and adjustable rate loans, the time variation in the share is related to the term spread as well. We aim to investigate whether the sensitivity of the share of FRMs to the term spread is mainly driven by household-specific or bank-specific factors. To this end we estimate the following type of regression:

$$\begin{aligned} share(b,c,t) =& \alpha(c) + \alpha(c) \times tspread(t) \\ &+ \beta(h(b)) + \beta(h(b)) \times tspread(t) + \varepsilon(b,c,t) \end{aligned} \tag{3}$$

The terms $\alpha(c)$ represent country fixed effects, $\beta(h(b))$ denotes banking group fixed effects and $tspread(t)$ is the term spread at time t.

In this model, country fixed effects and banking group fixed effects capture the average level of the share for each country and each banking group. Their interactions with the term spread capture, instead, the sensitivity (slope) of each country and each banking group to changes in the term spread. This regression allows us to model the time variation in the share of FRMs using the term spread and assuming that the relation between these two is linear. As before, to disentangle shifts in household conditions from shifts in bank conditions, we focus the attention on cross-border banking groups.

It is important to stress that, differently from other studies, we regress the share of FRMs on the term spread rather than the spread between FRMs and ARMs interest rates, as we want to draw causal inference. While the former can be considered to a large extent exogenous, the latter is inherently endogenous. Indeed, the spread between FRMs and ARMs interest rates is simultaneously determined with the quantities of FRMs and ARMs extended in equilibrium.

In estimating this model we use the term spread computed at the European level as the difference between the 10-year Interest Rate Swap rate and the 3-month Overnight Index Swap rate. We adopt this measure for the slope of the yield curve rather than the term spread for each country obtained on the basis of the respective government bonds. The reason is that, especially for those country that were more affected by the sovereign debt crisis, the interest rate charged on FRMs is more closely related to the 10-year Interest Rate Swap rate rather than the yield on 10-year government bonds. This can be explained by the fact that, during most of the time period under analysis, sovereign default risk in several countries was sensibly higher than credit risk associated with local mortgages.

Table 8 reports six different specifications. Model 1 includes country fixed effects only, while model 4 includes both country fixed effects and their interaction with the term spread. Country fixed effects explain alone 58% of the variation in the share of

FRMs. When we add the interaction of country fixed effects with the term spread the coefficient of determination rises to 66%. This value is quite far from the 84% achieved in our baseline model with month-country fixed effects. However, while in the baseline model we allow country fixed effects to vary in a discretionary way over time, in model 4 we constrain the share of fixed rate mortgages to evolve linearly with the term spread. Of course, since the share is bounded between 0 and 100, it is likely that this relation is not linear. In fact, if we add an additional interaction term with the term spread squared, we experience an increase in the R^2 (71%). So, we conclude that the term spread is able to explain the time variation in the share of FRMs and that the relation between these two is not perfectly linear. A similar argument applies also to the two specifications with banking group fixed effects, namely model 2 and model 5.

Consistently with the evidence in Figure 1, we find that most of the coefficients of the interaction terms in model 4 are negative and significant. However, the sensitivity of the share of FRMs to the term spread differs significantly across countries. In particular, Belgium, Greece, Italy, Luxembourg and Slovenia are those countries where the share of FRMs is more reactive to changes in the term spread.

We have already pointed out that changes in the term spread can shift both the demand and the supply. On the one hand, an increase in the term spread, driven by an increase in inflation risk, may lead banks to decrease the supply of fixed rate loans, by making them relatively more expensive than adjustable rate ones. On the other hand, a rise in the spread between FRMs and ARMs interest rates due to an increase in the term spread may induce households to reduce their demand for fixed rate loans, which could signal either some form of myopic behavior (households choose ARMs when the term spread is high because they tend to give too much importance to the first installments), as well as the presence of financial constraints (matched with expectations of an increase in income). To assess whether (country-level) household-specific or bank-specific conditions are more sensitive to changes in the slope of the yield curve, we include a specification in which we interact both country fixed effects and banking group fixed effects with the term spread. Relying on the Shorrocks-Shapely decomposition, we are able to detect the contribution of each interaction to the R^2. Model 6 shows that the fraction of R^2 ascribable to the interaction between country fixed effects and the term spread is much higher than the fraction attributable to the other interaction. Thus, we conclude that changes in the slope of the yield curve shifts mainly country-level household demand.

5.6 Additional Analyses

The quantity of FRMs and ARMs, as well as their interest rates, are simultaneously determined on the market by the interaction between demand and supply. No bank should be able to individually set the share of FRMs granted neither the price of FRMs and ARMs. If this is the case, the variation in the spread between FRMs and ARMs interest rates should be explained by the same factors driving the share of FRMs. We explore this possibility by performing the same set of reduced-form regressions exposed in Section 5.1 through Section 5.5 using this time as dependent variable the spread between FRMs and ARMs interest rates, henceforth abridged simply with "spread". The results presented in Appendix A.4 reveal that all our findings are confirmed when we look at prices rather than quantities, but they are somewhat weaker.

Finally, the econometric analyses presented so far are performed using linear regressions. Our main dependent variable, the share of FRMs, is a percentage bounded between 0 and 100. Using a linear model in this setting leads to inconsistent estimates. For this reason, we perform a battery of robustness tests by replicating all our econometric specifications by using Tobit regression models. As documented in Appendix A.7, all our results are virtually unchanged.

6 Conclusions

Using granular bank level information from 103 banks belonging to 73 banking groups across twelve countries in the euro area, we provide a comprehensive analysis of the determinants of mortgage choice in the euro area. In particular, by exploiting cross-border banking groups, we investigate to what degree the wide cross-country heterogeneity in the share of fixed rate mortgages to total new mortgages is driven by differences in household-specific or bank-specific conditions.

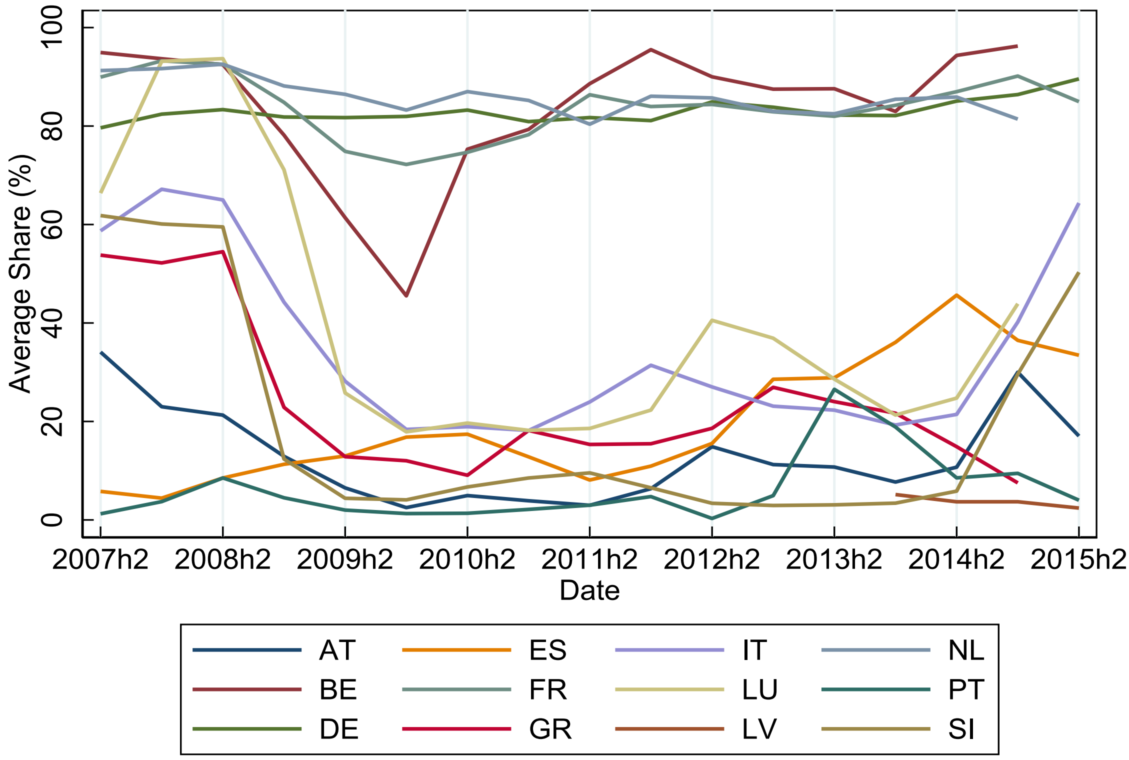
Country-level household factors seem to have a prominent role in driving the prevalence of mortgages extended at a fixed rate. Factors such as the historical volatility of inflation rates, the correlation between unemployment and the short-term interest rate, households' financial literacy, and the volume of outstanding mortgage covered bonds and mortgage-backed securities exhibit a high correlation with the estimated household-specific component of the share of fixed rate mortgages relative to adjustable rate ones.

A predominant role for country-level household factors is documented also when focusing on the sensitivity of the share of fixed rate mortgages to the slope of the yield curve, as well as when analyzing lending conditions, that is the spread between the interest rate on fixed rate mortgages and that on adjustable rate mortgages.

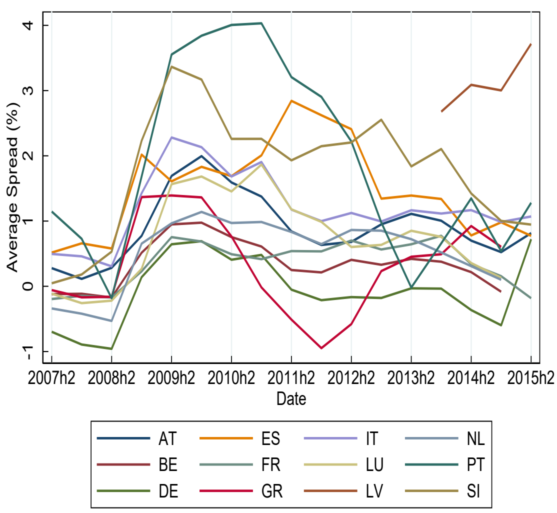
By showing the relevance of country-level household factors, a policy implication of our analysis is that it would not make sense to try to influence the share of fixed rate mortgages by pressing banks to take on more duration risk. This would be ineffective and, presumably, not even be desirable. Indeed, the heterogeneity in the share of fixed rate mortgages across economies seems to reflect an optimal allocation of interest rate risk, given the asynchronous business cycles and the expectations that monetary policy will operate in a way that stabilizes disposable income net of housing costs.

Figure 1: **Share of FRMs and spread between FRMs ands ARM interest rates.** The figure shows the average share of FRMs by country (a), the average spread between FRMs and ARMs interest rates by country (b-left), and term spread computed as the difference between the 10-year Interest Rate Swap rate and the 3-month Overnight Index Swap rate (b-right) at the semi-annual level.

(a) Average share of FRMs



(b) Average spread of FRMs-ARMs interest rates (left) and term spread (right)



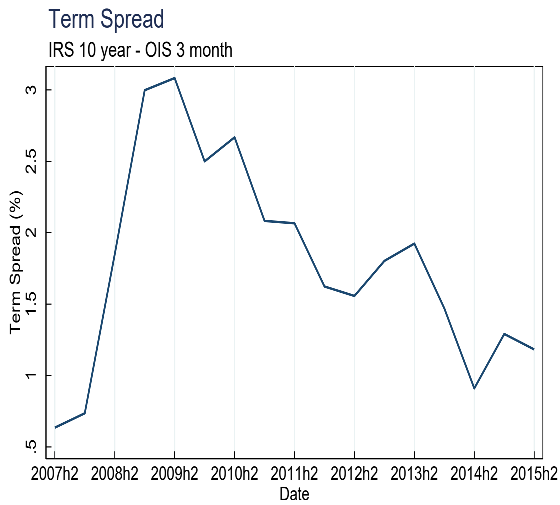
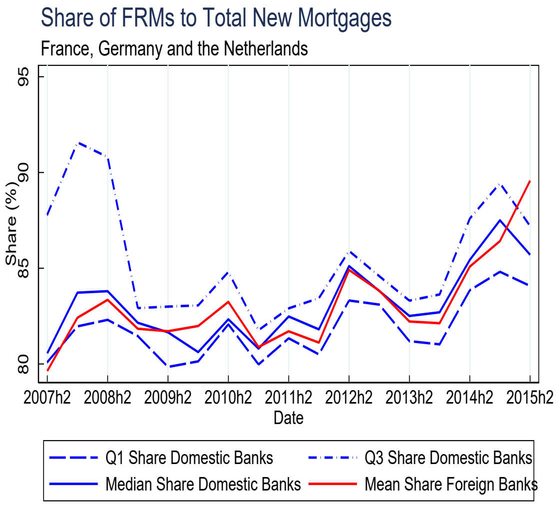


Figure 2: **Share of FRMs for groups of countries**. The figure shows different statistics (first quartile, median, second quartile and average) for the share of FRMs of domestic banks and foreign banks for two groups of countries at the semi-annual level. The first group (left) includes France, Germany and the Netherlands. The second group (right) includes Austria, Belgium, Greece, Italy, Latvia, Luxembourg, Portugal, Slovenia and Spain. Domestic banks are banks with a domestic bank holding. Foreign banks are banks with a foreign bank holding. Q1 and Q3 stand for first quartile and third quartile, respectively.

Share of FRMs 1st group (left) and share of FRMs 2nd group (right)



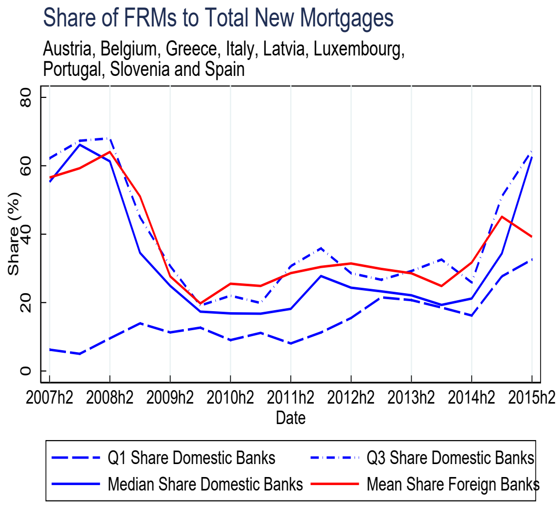


Table 1: **Overview of Banks and Banking Groups, by Country** The table reports summary statistics on the distribution of the 103 banks belonging to 73 banking groups in our sample by country. The first two columns distinguish between banks with a domestic top holder and banks with a foreign top holder. The third column reports the distribution across countries of the 19 banks affiliated to a cross-border banking group. The last two columns splits the 73 banking groups into those that operate only in one country (domestic) and those that operate in multiple countries (cross-border).

Country	Banks with a domestic top holder	Banks with a foreign top holder	Banks belonging to a cross-border banking group	Domestic banking groups	Cross-border banking groups
Germany	35	1	5	26	1
Italy	16	2	3	12	1
France	13	0	4	2	3
Spain	10	1	1	9	0
Austria	3	1	1	3	0
Slovenia	2	2	2	2	0
Belgium	3	1	1	3	0
Greece	4	0	0	4	0
The Netherlands	0	3	0	3	0
Portugal	3	0	0	3	0
Luxembourg	0	2	2	0	0
Latvia	1	0	0	1	0
Total	93	10	19	68	5

Table 2: **Overview of the Share of FRMs and the Spread between FRMs and ARMs interest rates, by Country** The table reports summary statistics on i) the share of FRMs and ii) the spread between the interest rates charged on FRMs and ARMs by country. Statics are calculated starting from our dataset at the bank-month level.

		Share of FRMs (%)				**Spread FRMs - ARMs interest rates (%)**			
Country	N	Average	Median	Minimum	Maximum	Average	Median	Minimum	Maximum
Austria	223	12.66	7.74	0.09	74.30	0.90	0.84	-0.54	3.49
Belgium	377	84.17	91.48	21.10	99.99	0.34	0.35	-1.04	1.70
France	812	84.37	93.14	6.25	100.00	0.44	0.38	-4.75	3.47
Germany	2565	82.78	85.93	14.95	99.96	-0.09	-0.04	-3.34	2.67
Greece	261	26.73	17.05	0.26	88.71	0.34	0.50	-2.08	3.39
Italy	1614	33.77	25.90	0.17	98.15	1.21	1.15	-1.12	3.43
Latvia	24	3.74	3.28	1.85	7.57	3.12	3.05	2.45	4.09
Luxembourg	161	36.39	28.50	1.58	97.95	0.86	0.77	-0.42	2.49
Portugal	183	4.50	1.99	0.05	39.93	1.94	1.83	-1.75	6.08
Slovenia	254	16.78	4.86	0.09	94.10	1.85	1.91	-0.33	4.13
Spain	605	19.10	8.37	0.09	90.84	1.49	0.93	-1.57	7.47
The Netherlands	248	86.30	86.01	71.43	98.47	0.50	0.72	-1.14	1.70
Sample	7327	57.44	71.26	0.05	100.00	0.62	0.55	-4.75	7.47

Table 3: **Baseline model**. The table reports the R^2 of various fixed effects decompositions of the share of FRMs. The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs. The estimation method is OLS. Specification (3) reports the results of the baseline model of equation 1. Specification (5) is estimated on the subsample of three banking groups whose month-banking group dummies are largely statistically significant in model (2). Standard errors are not adjusted. A Shorrocks-Shapely decomposition of the R^2 is reported for model (3) and model (5). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Month-country FE	YES	-	YES	YES	YES
Month-banking group FE	-	YES	YES	YES	YES
Bank FE	-	-	-	YES	-
N	1644	1644	1644	1644	839
R^2	0.843	0.319	0.908	0.973	0.906
Adjusted R^2	0.731	0.038	0.746	0.924	0.168
R^2 month-country FE			0.716		0.689
R^2 month-banking group FE			0.191		0.217
F-test statistic	7.493***	1.137**	5.616***	19.897***	1.230
degrees of freedom	(688,956)	(480,1164)	(1046,598)	(1057,587)	(743, 95)

Table 4: **Description of Country Demand Variables**

Variable	Description
Financial Literacy	Percentage of 3 out of 4 answers correct given by adults interviewed in each country, as results from the S&P Global FinLit Survey (Klapper et al., 2015).
Indebtedness	Ratio of total outstanding debt as a percentage of gross disposable income provided by the OECD on a quarterly frequency. Data are missing for Latvia and Luxembourg, and partially available for Greece, Italy and the Netherlands.
Real Disposable Income Per Capita	Gross disposable income (adjusted for social transfers in kind) of households (and non-profit institutions serving households) expressed in purchasing power standard (PPS in thousands) per inhabitant, obtained from Eurostat on an annual basis. Data are missing for Luxembourg.
Historical Inflation Volatility	Realized standard deviation of the monthly month-on-month inflation rate during the period 1970-1999. Because of a lack in the available data, Historical Inflation Volatility is computed over the period 1991-1999 for Latvia and 1980-1999 for Slovenia. Monthly data on the inflation rate are retrieved from the OECD.
ρ(Unemployment, Short-term IR)	Realized correlation between the unemployment rate and the short-term interest rate, calculated on a rolling window approach with a window of 7 years. Monthly data on unemployment rates and short-term interest rates are retrieved from the ECB and the OECD, respectively.
Outstanding Covered Bonds to GDP	Average over the last four years of the amount outstanding of mortgage covered bonds as a percentage of GDP. Annual data on outstanding covered bonds are retrieved from the European Covered Bond Council (ECBC). Data are missing for Slovenia.
Outstanding RMBS to GDP	Average over the last four quarters of the amount outstanding of RMBS as a percentage of GDP. Quarterly data on outstanding residential mortgage-backed securities are retrieved from the Securities Industries and Financial Markets Association (SIFMA). Data are missing for Latvia, Luxembourg and Slovenia and not available for all other countries in 2007.

Table 5: **Overview of Country Demand Variables, by Country**

	Financial literacy (%)		**Indebtedness (%)**		**Real disposable income per capita (PPS in thousands)**		**Historical inflation volatility (b.p.)**		**Correlation unemployment short-term interest rate**		**Outstanding covered bonds bonds to GDP (%)**		**Outstanding RMBS to GDP (%)**	
	Avg.	Std. Dev.	Avg.	Std. Dev.	Avg.	Std. Dev.	Avg.	Std. Dev.	Avg.	Std. Dev.	Avg.	Std. Dev.	Avg.	Std. Dev.
Austria	53.00	-	85.73	1.70	24.75	1.07	44.68	-	-0.63	0.13	3.40	1.96	0.66	0.10
Belgium	55.00	-	91.73	7.53	22.62	1.14	38.38	-	-0.64	0.15	0.50	0.81	14.00	4.58
France	52.00	-	98.36	3.77	23.10	1.07	39.73	-	-0.89	0.09	6.71	2.77	0.88	0.49
Germany	66.00	-	89.45	3.05	25.26	1.86	32.39	-	0.04	0.59	8.39	0.83	0.63	0.17
Greece	45.00	-	104.29	3.26	17.00	1.87	152.30	-	-0.69	0.19	4.91	3.70	3.08	0.56
Italy	37.00	-	83.37	0.78	20.93	0.36	57.32	-	-0.70	0.24	2.74	2.88	6.17	1.77
Latvia	48.00	-	-	-	12.37	0.55	1015.10	-	0.10	0.22	0.02	0.03	-	-
Luxembourg	53.00	-	-	-	-	-	40.46	-	-0.36	0.16	0.13	0.14	-	-
Portugal	26.00	-	134.46	4.59	16.34	0.42	146.49	-	-0.47	0.36	12.28	7.22	17.56	3.14
Slovenia	44.00	-	52.70	2.22	16.01	0.47	859.02	-	-0.40	0.50	-	-	-	-
Spain	49.00	-	132.03	8.35	18.22	0.40	70.06	-	-0.66	0.26	28.92	5.56	13.64	2.41
The Netherlands	66.00	-	263.55	3.53	22.87	0.32	44.36	-	-0.70	0.09	5.41	3.10	35.85	8.30
Sample	49.50	11.15	109.97	50.93	20.53	3.7	211.69	342.87	-0.54	0.39	7.18	8.68	10.09	11.35

Table 6: **Two-stage model.** The table reports (i) the R^2 of the first stage regression of equation 5.3 in model (1), and (iii) the coefficients and standard errors (in parentheses) of the second stage regression of equation 2 in models (2)-(3). The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs in model (1), and the estimated coefficients of month-country fixed effects obtained from the first specification in models (2)-(3). Country variables include Financial Literacy, Indebtedness, Real Disposable Income Per Capita, Historical Inflation Volatility, ρ(Unemployment, Short-term IR), Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP. All country variables except ρ(Unemployment, Short-term IR) are lagged of one period. The estimation method is OLS. Standard errors are not adjusted for model (1), and two-way clustered by country and quarter in models (2)-(3). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	1ST STAGE	***2ND STAGE***	
	(1)	(2)	(3)
Financial Literacy		-2.693	-5.386**
		(2.26)	(1.72)
Indebtedness		1.558	0.206
		(0.99)	(0.78)
Real Disposable Income Per Capita		0.137	1.979
		(4.26)	(3.65)
Historical Inflation Volatility		-3.847**	-6.482***
		(1.48)	(0.87)
ρ (Unemployment, Short-term IR)		33.128	28.726**
		(18.53)	(9.79)
Outstanding Covered Bonds to GDP			5.754***
			(0.80)
Outstanding RMBS to GDP			2.756***
			(0.50)
Quarter-banking group FE	YES		
Month-country FE	YES		
Two-way cluster	-	*country, quarter*	*country, quarter*
N	1085	344	344
R^2	0.847	0.337	0.503
Adjusted R^2	0.733	0.327	0.492
F-test statistic regressors pure demand			50.57***
degrees of freedom			(5,5)
F-test statistic regressors institutional factors			26.83***
degrees of freedom			(2,5)
F-test statistic fixed effects	7.437***		
degrees of freedom	(464,621)		

Table 7: **Magnitude effects.** The table reports the magnitude effects of the explanatory variables capturing demand conditions in model (4) of Table 6. In the third column the magnitude effect is computed as the product between the estimated coefficient and the standard deviation of the corresponding explanatory variable in the subsample where the model is estimated. In the last column the magnitude effect is computed as the product between the estimated coefficient and the interquartile range of the corresponding explanatory variable in the subsample where the model is estimated.

Variable	**Coefficients**	**Standard deviation**	**Magnitude effect (sd)**	**Interquartile range**	**Magnitude effect (ir)**
Financial Literacy	-5.386**	7.837	-42.213	3.000	-16.159
Indebtedness	0.206	11.097	2.291	12.870	2.657
Real Disposable Income Per Capita	1.979	2.216	4.386	3.260	6.453
Historical Inflation Volatility	-6.482***	9.064	-58.758	6.305	-40.872
ρ (Unemployment, Short-term IR)	28.726**	0.491	14.111	0.439	12.608
Outstanding Covered Bonds to GDP	5.754***	5.535	31.854	7.246	41.699
Outstanding RMBS to GDP	2.756***	6.330	17.445	9.652	26.603

Table 8: **Time variation**. The table reports the results of the analysis investigating the sensitivity of the share of FRMs to the term spread. The term spread is calculated as the difference between the 10-year Interest Rate Swap rate and the 3-month Overnight Index Swap rate. The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs. The estimation method is OLS. Specification (6) reports the results of the model of equation 3. Standard errors are not adjusted. A Shorrocks-Shapely decomposition of the R^2 is reported for model (6). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Austria x term spread				-9.124**		-9.643
				(3.73)		(5.87)
Belgium x term spread				-24.195***		-36.813***
				(2.47)		(4.47)
Germany x term spread				-2.031*		-9.536**
				(1.10)		(4.83)
Spain x term spread				-2.260		-11.414*
				(3.91)		(6.00)
France x term spread				-7.693***		-23.565***
				(1.24)		(4.17)
Italy x term spread				-8.795***		-16.524***
				(1.42)		(4.43)
Luxembourg x term spread				-14.020***		-18.195***
				(2.05)		(2.46)
Slovenia x term spread				-27.161***		-46.651***
				(2.32)		(4.87)
Country FE	YES	-	YES	YES	-	YES
Banking group FE	-	YES	YES	-	YES	YES
Banking group FE x term spread	-	-	-	-	YES	YES
N	1644	1644	1644	1644	1644	1644
R^2	0.580	0.1458	0.6199	0.657	0.206	0.709
Adjusted R^2	0.578	0.1437	0.6173	0.654	0.201	0.705
R^2 country FE						0.303
R^2 country FE x term spread						0.279
R^2 banking group FE						0.054
R^2 banking group FE x term spread						0.073
F-test statistic	322.089***	69.927***	241.939***	207.597***	46.976***	171.713***
degrees of freedom	(7,1636)	(4,1639)	(11,1632)	(15,1628)	(9,1634)	(23,1620)

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A Appendix

A.1 Literature Review

In this section we present Table A1 which provides a detailed overview of all the determinants of the mortgage choice identified in the literature, along with those investigated in this study.

A.2 Country Variables

In this section we summarize all the variables that we use to capture country-specific factors that may affect the prevalent type of mortgage (FRM or ARM) in the economy. Figure A1 reports values for Indebtedness, Real Disposable Income Per Capita, Financial Literacy and Historical Inflation Volatility by country. Figure A2 reports values for ρ (Unemployment, Short-term IR), Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP by country. Finally, Figure A3 reports values for Rolling Inflation Volatility, House Price to Income and Public Debt to GDP by country.

A.3 Advanced Model

In this section we present an extension of our baseline model of equation 1 in Section 5.1 where we directly model country-specific factors by replacing month-country fixed effects with a set of meaningful variables. In particular, we consider the same variables used in the two-stage model of Section 5.3: financial literacy, indebtedness, gross disposable income per capita, historical volatility of inflation, correlation be-

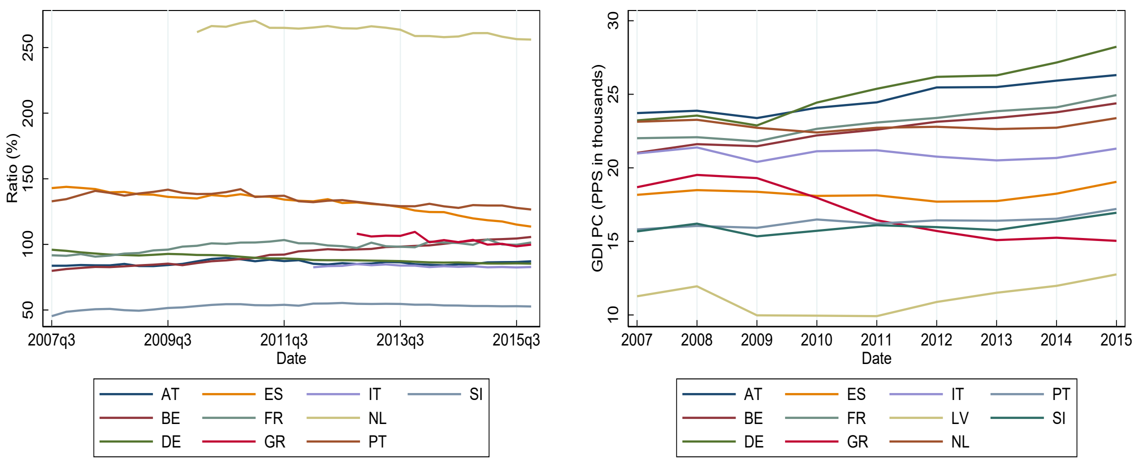
Table A1: **Determinants of the Share of FRMs and/or the Probability of a FRM Choice Identified in the Literature.** The table provides an overview of the literature analyzing the various factors driving the share of FRMs or the probability of a FRM choice. ↑ and ↓ denote a positive and a negative effect, respectively. ***,** and * stand for statistical significance at 1%, 5% and 10%. 0 denotes a variable included in the specification which is not significant. Papers are indicated by numbers from 1 to 14 as follows: [1] Paiella and Pozzolo (2007), [2] Koijen et al. (2009), [3] Agarwal et al. (2010), [4] Fornero et al. (2011), [5] Campbell (2012), [6] Fuster and Vickery (2014), [7] Foà et al. (2015), [8] Badarinza et al. (2017), [9] Basten et al. (2017), [10] Ehrmann and Ziegelmeyer (2017), [11] Gathergood and Weber (2017), [12] Campbell and Cocco (2003), [13] Kirti (2017), [14] Guren et al. (2018). Statistical significance is not reported for the variables investigated by Agarwal et al. (2010) and Campbell (2012), as well as for the historical inflation volatility analysed by Badarinza et al. (2018), as they do not perform a regression analysis. The variables reported for Badarinza et al. (2017) refer to the analysis on 3-year (left) and 1-year (right) expectations of the future ARM rate.

		Empirical papers							
	Paper	[1]	[2]		[3]	[4]	[5]	[6]	[7]
	Country	IT	US		US	IT	EU, US, CA	US	IT
	Sample Years	1995-2004	1985-2006		2005-2007	2005-2008		1996-2009	2004-2010
	Variable of interest	Pr(FRM)	Pr(FRM)	Share FRM	Pr(FRM)	Pr(FRM)	Share FRM	Pr(FRM)	Pr(FRM)
Borrower Variables	Age	$\uparrow^{**}$				0			
	Gender	0				0			
	Married	0							
	Children	$\uparrow^{**}$							
	Income	0							
	N. income recipients	0				0			
	Nondurable expenditures	$\downarrow^{**}$							
	Financial wealth	0				0			
	Education	0				0			
	Financial literacy				$\downarrow$	$\uparrow^{**}$			
	Type of employment	0				0			
	Mobility	0							
	Risk aversion					0			
	Volaility of labor income								
	Other debt								
	Credit score		$\uparrow^{***}$						
Loan Variables	Duration								
	Mortgage to income					$\uparrow^{***}$			
	House price	$\downarrow^{***}$							
	House price to income	$\uparrow^{***}$							
	Debt service to income								
	Loan to value		$\downarrow^{***}$						
	Loan balance		$\uparrow^{***}$						
Bank Variables	Deposits to total liabilities								$\uparrow^{***}$
	Deposits to total assets								
	Equity to total assets								
	Floating rate liabilities								
	Bond spread								$\downarrow^{*}$
	Exposure to interest rate risk								
	Derivatives usage								
	Size								
	Competition	$\downarrow^{**}$							
Macroeconomic and Institutional Variables	Securitisation							$\uparrow^{***}$	$\uparrow^{***}$
	Covered bonds								
	Spread FRM-ARM interest rates	$\downarrow^{***}$		$\downarrow^{***}$		$\downarrow^{***}$			
	FRM rate minus expected ARM rate		$\downarrow^{***}$	$\downarrow^{***}$					$\downarrow^{***}$
	ARM interest rate	$\downarrow^{**}$							
	Long-term interest rate	0	$\uparrow^{***}$	$\downarrow^{***}$					
	Term spread		$\downarrow^{***}$	0					
	Inflation rate								
	Inflation rate volatility								
	Historical inflation volatility						$\downarrow$		
	Unemployment rate								
	Unemployment rate volatility								
	GDP growth					$\uparrow^{*}$			
	GDP growth volatility								
	Correlation aggregate shocks short-term interest rate								

		Empirical papers				Theoretical papers			This paper	
	Paper	[8]	[9]	[10]	[11]	[12]	[13]	[14]	This paper	
	Country	EU, US, AU	CH	Euro Area	UK				Euro Area	
	Sample Years	1990-2013	2010-2013	<1980-2010	2013				2007-2015	
	Variable of interest	Share FRM	Pr(FRM)	Pr(FRM)	Pr(FRM)	Share/Pr(FRM)			Our variable	Share FRM
Borrower Variables	Age		$\downarrow^{***}$							
	Gender									
	Married									
	Children									
	Income			$\downarrow^{***}$		$\uparrow$			Real disposable income per capita	0
	N. income recipients									
	Nondurable expenditures									
	Financial wealth		$\uparrow^{***}$			$\uparrow$				
	Education									
	Financial literacy				$\downarrow^{***}$				Financial literacy	$\downarrow^{**}$
	Type of employment									
	Mobility					$\downarrow$				
	Risk aversion				0	$\uparrow$				
	Volaility of labor income					$\uparrow$				
	Other debt		$\downarrow^{**}$							
	Credit score									
Loan Variables	Duration			$\downarrow^{***}$						
	Mortgage to income				0	$\uparrow$			Indebtedbeness	0
	House price									
	House price to income									
	Debt service to income		0	$\downarrow^{***}$						
	Loan to value		$\downarrow^{**}$		$\downarrow^{**}$					
	Loan balance									
Bank Variables	Deposits to total liabilities									
	Deposits to total assets		$\downarrow^{**}$							
	Equity to total assets		$\downarrow^{*}$							
	Floating rate liabilities						$\downarrow$			
	Bond spread									
	Exposure to interest rate risk		$\downarrow^{***}$							
	Derivatives usage		0							
	Size		$\uparrow^{***}$							
	Competition									
Macroeconomic and Institutional Variables	Securitisation								Outstanding RMBS to GDP	$\uparrow^{***}$
	Covered bonds								Outstanding covered bonds to GDP	$\uparrow^{***}$
	Spread FRM-ARM interest rates	$\downarrow^{***}/0$								
	FRM rate minus expected ARM rate	$0/\downarrow^{***}$								
	ARM interest rate									
	Long-term interest rate			0		$\downarrow$				
	Term spread		$\downarrow^{***}$	$\downarrow^{***}$		$\downarrow$			Term spread	$\downarrow^{*,**,***}$
	Inflation rate			$\uparrow^{**}$						
	Inflation rate volatility			0						
	Historical inflation volatility	$\downarrow$							Historical inflation volatility	$\downarrow^{***}$
	Unemployment rate			0						
	Unemployment rate volatility			$\uparrow^{**}$						
	GDP growth			$\downarrow^{***}$						
	GDP growth volatility			0						
	Correlation aggregate shocks short-term interest rate							$\uparrow$	Correlation unemployment short-term interest rate	$\uparrow^{**}$

Figure A1: **Country variables.** The figure shows the time series of Indebtedness, Real Disposable Income Per Capita, Financial Literacy and Historical Inflation Volatility by country. Indebtedness is the ratio of total outstanding debt as a percentage of gross disposable income provided by the OECD on a quarterly frequency. Data are missing for Latvia and Luxembourg, and partially available for Greece, Italy and the Netherlands. Real Disposable Income Per Capita is the gross disposable income (adjusted for social transfers in kind) of households (and non-profit institutions serving households) expressed in purchasing power standard (PPS) per inhabitant, obtained from Eurostat on an annual basis. Data are missing for Luxembourg. Financial Literacy is measured as the percentage of 3 out of 4 answers correct given by adults interviewed in each country, as results from the S&P Global FinLit Survey (Klapper et al., 2015). Historical Inflation Volatility is the realized standard deviation of the monthly month-on-month inflation rate during the period 1970-1999. Because of a lack in the available data, Historical Inflation Volatility is computed over the period 1991-1999 for Latvia and 1980-1999 for Slovenia.

(a) Indebtedness (left) and Real Disposable Income Per Capita (right)



(b) Financial Literacy (left) and Historical Inflation Volatility (right)

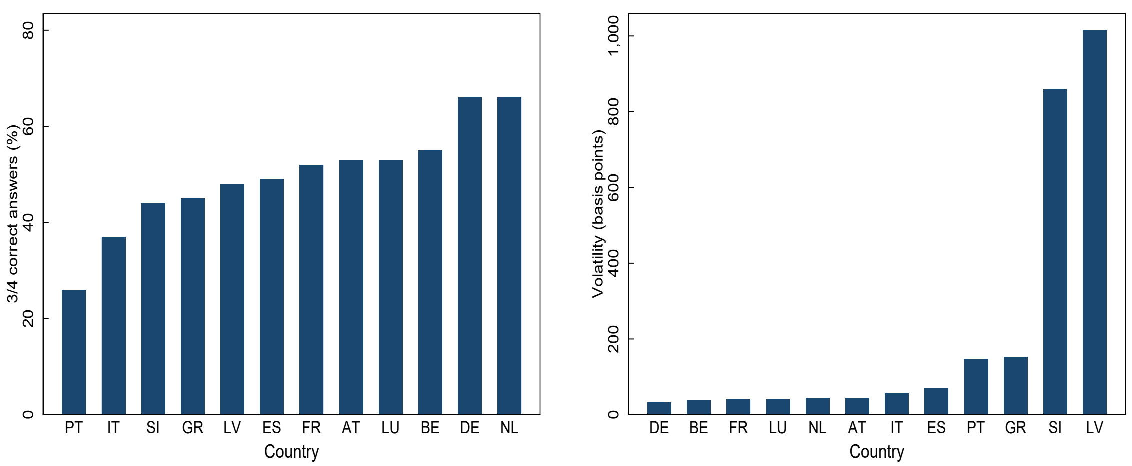
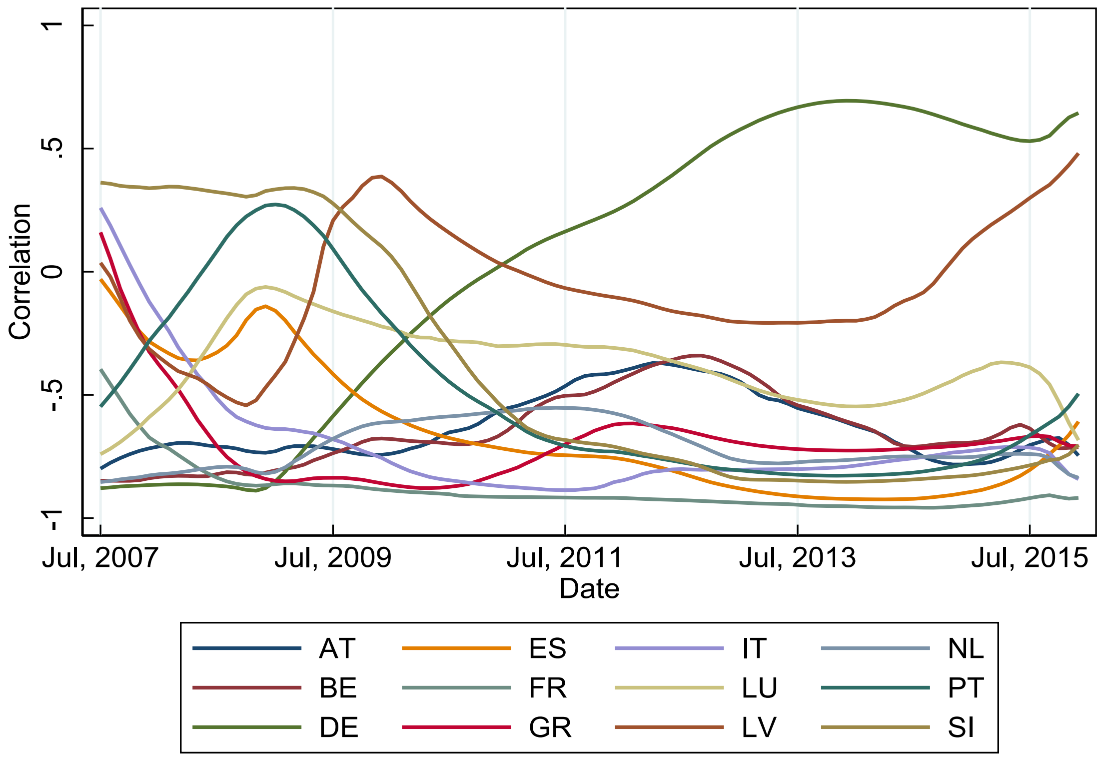


Figure A2: **Country variables.** The figure shows the time series of ρ(Unemployment, Short-term IR), Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP by country. ρ(Unemployment, Short-term IR) is the realized correlation between the unemployment rate and the short-term interest rate, calculated on a rolling window approach with a window of 7 years. Outstanding Covered Bonds to GDP is the average over the last four years of the amount outstanding of mortgage covered bonds as a percentage of GDP. Data are missing for Slovenia. Outstanding RMBS to GDP is the average over the last four quarters of the amount outstanding of RMBS as a percentage of GDP. Data are missing for Latvia, Luxembourg and Slovenia and not available for all other countries in 2007.

(a) ρ(Unemployment, Short-term IR)



(b) Outstanding Covered Bonds to GDP (left) Outstanding RMBS to GDP (right)

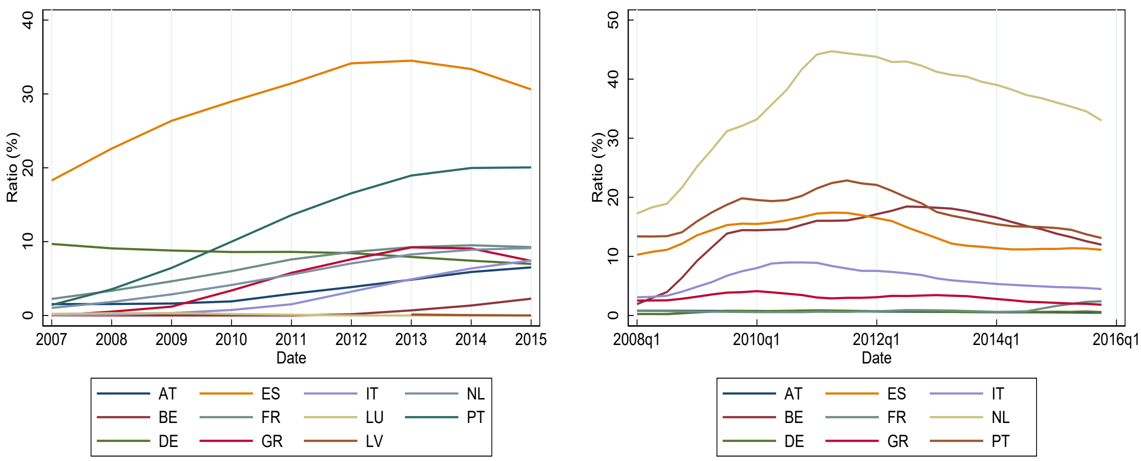
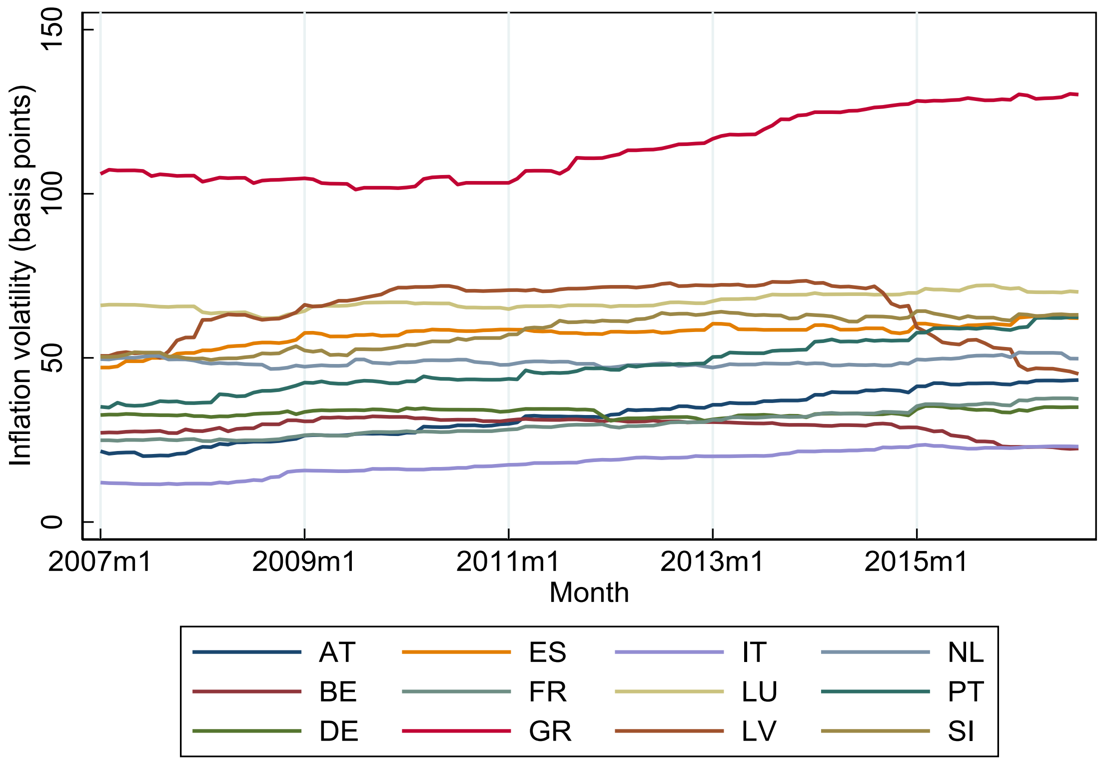
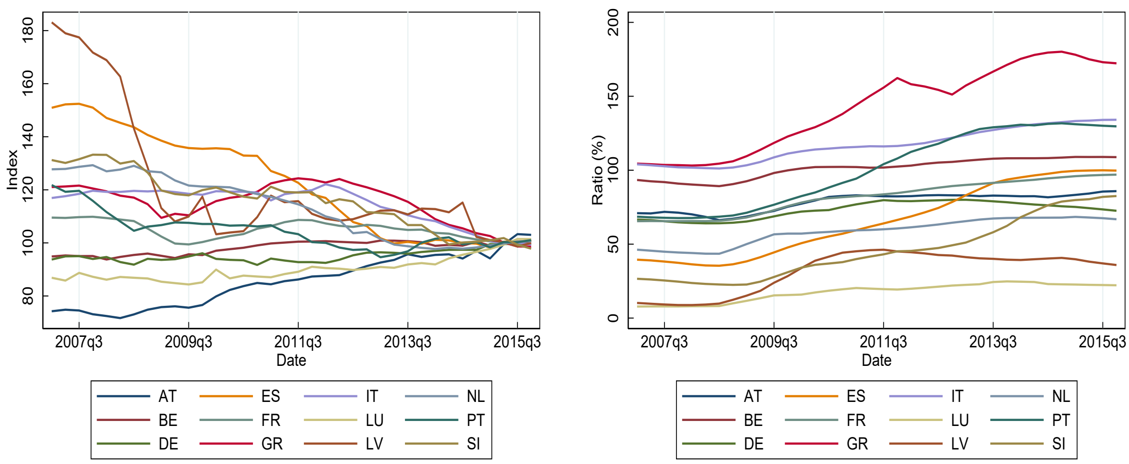


Figure A3: **Country variables.** The figure shows the time series of Rolling Inflation Volatility, House Price to Income and Public Debt to GDP by country. Rolling Inflation Volatility is the realized standard deviation of the monthly month-on-month inflation rate calculated on a rolling window approach with a window of 7 years. House Price to Income is the index of nominal house prices divided by nominal disposable income per head with base period 2015. Public Debt to GDP is the average over the last four quarters of the amount of public debt as a percentage of GDP.

(a) Rolling Inflation Volatility



(b) House Price to Income (left) Public Debt to GDP (right)



tween unemployment and the short-term interest rate, outstanding amount of mortgage covered bonds to gross domestic product (GDP) and outstanding amount of residential mortgage-backed securities (RMBS) to GDP.

Table A2 displays the estimates of this model. As in Table 6, we include lagged values for those variables that are available on a lower frequency than monthly to ensure that our regressors are predetermined. Model 1 shows the results for the specification including pure demand factors only. We find a negative and significant coefficient for Real Disposable Income Per Capita in line with Ehrmann and Ziegelmeyer (2017). They interpret this finding with the view that households with higher income are more prone to select an adjustable rate loan, as they can comfortably face the income risk related to the uncertain stream of payments of an ARM. At the same time, and unlike what will be documented for Historical Inflation Volatility and ρ(Unemployment, Short-term IR), this finding is not robust to alternative specifications and should be considered with caution. The coefficient of the Historical Inflation Volatility is also negative and significant, consistent with the idea that households' are more likely to select the type of loan they are more used to based on the macroeconomic history of their country prior to join the eurozone (Campbell, 2012; Badarinza et al., 2018).

In model 2 we extend the previous specification by adding the two additional country-level household factors: Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP. The sign and statistical significance of the pure demand regressors remains unchanged if compared to model 1, with the exception of ρ(Unemployment, Short-term IR). The coefficient of ρ(Unemployment, Short-term IR) turns out to be positive and statistically significant, in line with the argument that households expecting to be unemployed in an environment of low interest rates are more likely to select an ARM (Guren et al., 2020). The coefficients of the two additional variables are positive, but they result not to be statistically significant.

In this type of exercise, we effectively control for bank-specific conditions, but we cannot be entirely sure to capture at all country-level household factors. We have relied on an exhaustive survey of existing papers in order to select a complete set of explanatory variables and we have actually enhanced it by introducing an additional (and novel) variable, i.e., ρ(Unemployment, Short-term IR). Nonetheless, we are aware that additional or alternative measures could be relevant in this setup. In order to assess whether our selection is reliable and comprehensive enough, we compare the quality of the fit obtained with the specification in model 2 with that obtained by replacing the explanatory variables with month-country fixed effects, but run on the sample used in model 2.[20] As shown in model 3, the latter amounts to 85% and represents the upper bound that can be reachable by including any arbitrarily large set of country-specific variables. The R^2 obtained by simply using our selection of seven regressors results to be quite close (79%).

A.4 Spread Analysis

In this section we present the analysis performed on the difference between the interest rate applied to newly originated FRMs to the interest rate applied to newly issued ARMs, henceforth abridged "spread". In particular, we replicate all the econometric

[20]Model 3 of Table A2 is equivalent to model 3 of Table 3, with the only difference that, in the former, the regression is run over a smaller sample to make it comparable to model 2 of Table A2. This is necessary because some of the regressors in model 2 of Table A2 are not available over some time periods.

Table A2: **Advanced model.** The table reports (i) the coefficients and standard errors (in parentheses) of two regressions of the share of FRMs on a set of country variables and month-banking group fixed effects in models (1)-(2), and (ii) the R^2 of the baseline model of equation 1 run on the same sample of the second specification in model (3). The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs. Country variables include Financial Literacy, Indebtedness, Real Disposable Income Per Capita, Historical Inflation Volatility, ρ(Unemployment, Short-term IR), Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP. Standard errors are two-way clustered by country and quarter in models (1)-(2), and not adjusted in model (3). The estimation method is OLS. The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Financial Literacy	-0.509	-1.689	
	(1.84)	(1.47)	
Indebtedness	0.835	0.602	
	(0.48)	(0.55)	
Real Disposable Income Per Capita	-14.422***	-12.366**	
	(3.18)	(4.80)	
Historical Inflation Volatility	-5.221***	-5.799***	
	(1.14)	(0.68)	
ρ (Unemployment, Short-term IR)	20.473	24.170**	
	(11.23)	(8.18)	
Outstanding Covered Bonds to GDP		1.430	
		(1.31)	
Outstanding RMBS to GDP		0.319	
		(0.88)	
Month-banking group FE	YES	YES	YES
Month-country FE	-	-	YES
Two-way cluster	*country, quarter*	*country, quarter*	-
N	1085	1085	1085
R^2	0.785	0.789	0.852
Adjusted R^2	0.677	0.682	0.666
F-test statistic regressors	275.76***	-	
degrees of freedom	(5,5)	-	
F-test statistic regressors pure demand		185.98***	
degrees of freedom		(5,5)	
F-test statistic regressors institutional factors		1.829	
degrees of freedom		(2,5)	
F-test statistic fixed effects			4.572***
degrees of freedom			(606,479)

analyses presented in Section 5.1 through Section 5.5 by substituting the share of FRMs with the spread.

Models 1-3 of Table A3 display three specifications in which the spread is regressed on, respectively, month-country fixed effects, month-banking group fixed effects and both sets of fixed effects jointly. Month-country fixed effects alone explain 60% of the variation in the spread, suggesting that, also in this case, country-level household factors play a major role. Month-banking group fixed effects explain only 38% of the variation in the dependent variable, but the difference between the R^2 of model 1 and model 2 is smaller compared to what seen for the share of FRMs in Table 3. When taken together the two sets of fixed effects can explain 73% of the total variation in the spread. We conclude that also variation in the spread is mainly driven by household-specific conditions, although here our model is somewhat less capable of describing the data. The supply plays a role as well and it seems to be slightly more relevant in explaining the spread than the share of FRMs.

The following step is to model month-country fixed effects with the selection of regressors that we used in Section 5.3. We expect that these explanatory variables have an effect also on the spread, but the relation should be of opposite sign with respect to the one observed in the analysis on the share of FRMs. To avoid possible distortions related to heterogeneous coverage of the dataset across countries (in terms of number of intermediaries) we focus on the two-stage approach of Section 5.3 only. Model 1 of Table A4 consists in the regression with month-country fixed effects and year-banking group fixed effects. We report the results of this specification including year-banking group fixed effects, instead of quarter-banking group fixed effects, because the results are not exactly the same under the two models. In light of that, we consider the specification with year-banking group fixed effects more reliable, as it allows us to perform the second stage regression having 381 out of 393 estimated coefficients of month-country fixed effects. As shown in model 4 of Table A4, three factors turn out to be significant both with the expected sign: Real Disposable Income per Capita, ρ(Unemployment, Short-term IR) and the Outstanding RMBS to GDP. In general, the coefficients of all the explanatory variables are very little and sensibly lower than those displayed in Table 6. The weak effects of our regressors are hardly surprising though. In fact, as highlighted before, the cross-country variation in the spread is much lower than the variation in the share of FRMs across countries.

We extend our analysis looking at the time variation in the spread. Model 6 of Table A5 includes country fixed effects, banking group fixed effects, as well as their interaction with the term spread. The R^2 of this specification (58%) is relatively high but fifteen percentage points lower than the coefficient of determination of our baseline model with month-country fixed effects and month-banking group fixed effects (73%). As before, this suggests that the term spread is able to capture the time variation in the spread, but the relation with the dependent variable might be nonlinear. In Figure 1 we observe that the evolution of the spread over time is directly related to the evolution of the term spread. The positive and significant coefficients of the interactions between country fixed effects and the term spread confirm this evidence. As for the share of FRMs, in Belgium, Greece, Italy, Luxembourg and Slovenia the spread is more sensitive to changes in the term spread. The Shorrocks-Shapley decomposition of the R^2 of model 6 eventually corroborates that the term spread is mainly able to shift (country-level) household-specific conditions, although the effect it exerts on the bank-specific conditions is slightly higher than what is detected in Table 8.

Table A3: **Baseline model, spread.** The table reports the R^2 of various fixed effects decompositions of the spread between FRMs and ARMs interest rates. The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the spread between FRMs and ARMs interest rates. The estimation method is OLS. Standard errors are not adjusted. A Shorrocks-Shapely decomposition of the R^2 is reported for model (3). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Month-country FE	YES	-	YES	YES
Month-banking group FE	-	YES	YES	YES
Bank FE	-	-	-	YES
N	1642	1642	1642	1642
R^2	0.605	0.378	0.729	0.873
Adjusted R^2	0.322	0.124	0.256	0.646
$R^2 month-countryFE$			0.478	
$R^2 month-bankinggroupFE$			0.251	
F-test statistic	2.139***	1.486***	1.540***	3.842***
degrees of freedom	(686,956)	(478,1164)	(1044,598)	(1055,587)

A.5 Robustness: Baseline Model

In this section we present three robustness tests for the baseline model of Section 5.1.

First, we test if our findings are driven by one specific banking group. To this end, we replicate the estimation of the baseline model of equation 1 by excluding each of the 5 cross-border banking groups in our sample one at the time. Table A6 reports the results of this exercise. Irrespective of which banking group we exclude from the sample, the R-squared and Shorrocks-Shapely decomposition deliver very

Table A4: **Two stage regression analysis, spread.** The table reports (i) the R^2 of the first stage regression of the spread between FRMs and ARMs interest rates on month-country fixed effects and year-banking group fixed effects in model (1), (ii) the coefficients and standard errors (in parenthesis) of a regressions of the spread between FRMs and ARMs interest rates on a set of country variables and year-banking group fixed effects in model (2), and (iii) the coefficients and standard errors (in parentheses) of the second stage regression of the estimated coefficients of month-country fixed effects obtained from the first specification on the set of country variables in models (3)-(4). The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the spread between FRMs and ARMs interest rates in models (1)-(2), and the estimated coefficients of month-country fixed effects obtained from the first specification in models (3)-(4). Country variables include Financial Literacy, Indebtedness, Real Disposable Income Per Capita, Historical Inflation Volatility, ρ(Unemployment, Short-term IR), Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP. All country variables except ρ(Unemployment, Short-term IR) are lagged of one period. The estimation method is OLS. Standard errors are not adjusted for model (1), and two-way clustered by country and quarter in models (2)-(4). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	1ST STAGE		***2ND TAGE***	
	(1)	(2)	(3)	(4)
Financial Literacy		-0.044	0.041	0.014
		(0.03)	(0.04)	(0.02)
Indebtedness		-0.006	-0.010	-0.007
		(0.01)	(0.02)	(0.01)
Real Disposable Income Per Capita		-0.007	-0.098	-0.175*
		(0.11)	(0.05)	(0.07)
Historical Inflation Volatility		0.008	0.042	0.015
		(0.02)	(0.03)	(0.01)
ρ (Unemployment, Short-term IR)		0.012	-0.411	-0.183***
		(0.25)	(0.26)	(0.04)
Outstanding Covered Bonds to GDP		0.045***		0.020
		(0.01)		(0.03)
Outstanding RMBS to GDP		-0.011		-0.039***
		(0.01)		(0.01)
Year-banking group FE	YES	YES		
Month-country FE	YES	-		
Two-way cluster	-	*country, quarter*	*country, quarter*	*country, quarter*
N	1085	1085	381	381
R^2	0.616	0.534	0.249	0.348
Adjusted R^2	0.380	0.517	0.239	0.336
F-test statistic regressors		-	-	-
degrees of freedom		-	-	-
F-test statistic regressors pure demand		45.27***		188.69***
degrees of freedom		(5,5)		(4,5)
F-test statistic regressors institutional factors		8.26**		65.21***
degrees of freedom		(2,5)		(2,5)
F-test statistic fixed effects	2.614			
degrees of freedom	(413,672)			

Table A5: **Time variation, spread.** The table reports the results of the analysis investigating the sensitivity of the spread between FRMs and ARMs interest rates to the term spread. The term spread is calculated as the difference between the 10-year Interest Rate Swap rate and the 3-month Overnight Index Swap rate. The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the spread between FRMs and ARMs interest rates. The estimation method is OLS. Standard errors are not adjusted. A Shorrocks-Shapely decomposition of the R^2 is reported for model (6). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Austria x term spread				0.288*		0.206
				(0.16)		(0.25)
Belgium x term spread				0.454***		0.183
				(0.10)		(0.19)
Germany x term spread				0.308***		0.282
				(0.05)		(0.20)
Spain x term spread				0.353**		0.332
				(0.17)		(0.25)
France x term spread				0.319***		0.174
				(0.05)		(0.18)
Italy x term spread				0.605***		0.486***
				(0.06)		(0.19)
Luxembourg x term spread				0.644***		0.519***
				(0.09)		(0.11)
Slovenia x term spread				1.082***		1.132***
				(0.10)		(0.21)
Country FE	YES	-	YES	YES	-	YES
Banking group FE	-	YES	YES	-	YES	YES
Banking group FE x term spread	-	-	-	-	YES	YES
N	1644	1644	1644	1644	1644	1644
R^2	0.377	0.198	0.456	0.496	0.294	0.581
Adjusted R^2	0.375	0.196	0.452	0.491	0.290	0.575
R^2 country FE						0.171
R^2 country FE x term spread						0.220
R^2 banking group FE						0.076
R^2 banking group FE x term spread						0.114
F-test statistic	141.490***	101.288***	124.139***	106.504***	75.335***	97.653***
degrees of freedom	(7,1634)	(4,1637)	(11,1630)	(15,1626)	(9,1632)	(23,1618)

similar estimates to those of Table 3. We conclude that our results are not driven by the lending behavior one specific institution.

Second, we test if country-level household factors play a bigger role in explaining the share of FRMs compared to bank-level factors even when we consider the full set of banks in our sample, which is likely characterized by larger heterogeneities than the subset of cross-border banking groups. To this end, we estimate a similar model to that of equation 1, but including time invariant rather than time varying fixed effects.

We start with the specification shown in model 1 of Table A7 including only time dummies, which turn out to explain only a negligible portion of the total variation in the dependent variable (3%). Broadly speaking, this suggests that, in our sample, the cross section is a much more important dimension than the time series. Interestingly, by simply plugging country fixed effects, the R^2 raises to a surprising 70%. Model 3 displays instead the equation where the share of FRMs is regressed just on the set of banking group fixed effects. Despite the fact that these largely coincide with country fixed effects, as most banking groups operate only in one country, and despite they are significantly more granular,[21] the coefficient of determination not only does not change, but actually slightly diminishes (69%) with respect to model 2. In other words, if bank-specific factors played a more critical role than country-specific factors in driving the share of FRM, we would expect a significantly higher R^2 in model 3 than in model 2, which is however not the case. When we combine country dummies and bank dummies, as in model 4, we are able to explain almost 78% of the variation in the share. Using a Shorrocks-Shapely decomposition of the R^2, we find that country

[21] The dataset includes 73 banking groups as opposed to only 12 countries.

fixed effects exhibit a higher explanatory power than banking group fixed effects. The same applies in the two corresponding specifications also including month fixed effects, although, by construction, the R^2 raises somewhat. These considerations corroborate our conclusions drawn on the subsample of cross-border banking groups, emphasizing the role played by country-level household factors.

As a further exercise, Table A8 shows the results of regressions including time invariant fixed effects run on the subsample of cross-border banking groups. Again, the role of time dummies is rather limited. Country fixed effects capture a sizable part of the variation in the share of FRMs, while banking group fixed effects have a much smaller explanatory power, as in Table 3.

Table A6: **Baseline Model excluding One Banking Group**. The table reports the R^2 of various fixed effects decompositions of the share of FRMs. The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. Each column reports the estimates of the baseline model of equation 1 where we exclude each of the five cross-banking banking groups in the sample one at the time. The dependent variable is the share of FRMs. The estimation method is OLS. A Shorrocks-Shapely decomposition of the R^2 is reported for model (3) and model (5). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Month-country FE	YES	YES	YES	YES	YES
Month-banking group FE	YES	YES	YES	YES	YES
Bank FE	-	-	-	-	-
N	1137	1560	1346	1185	1348
R^2	0.907	0.903	0.907	0.948	0.890
Adjusted R^2	0.510	0.747	0.739	0.871	0.694
$R^2 month - countryFE$	0.719	0.735	0.692	0.759	0.733
$R^2 month - bankinggroupFE$	0.188	0.168	0.215	0.189	0.157
F-test statistic	2.28***	5.78***	5.39***	12.44***	4.54***
degrees of freedom	(921, 215)	(961, 598)	(867, 478)	(701, 483)	(864, 483)

Table A7: **Fixed effects decomposition with time invariant fixed effects.** The table reports the R^2 of various fixed effects decompositions of the share of FRMs. The sample includes all banks and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs. The estimation method is OLS. Standard errors are not adjusted. A Shorrocks-Shapely decomposition of the R^2 is reported for models (4)-(7). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Month FE	YES	-	-	-	YES	YES	YES
Country FE	-	YES	-	YES	YES	-	YES
Banking group FE	-	-	YES	YES	-	YES	YES
N	7327	7327	7327	7327	7327	7327	7327
R^2	0.026	0.697	0.687	0.779	0.735	0.724	0.818
Adjusted R^2	0.012	0.696	0.684	0.776	0.730	0.717	0.813
R^2 month FE							0.034
R^2 country FE				0.394			0.397
R^2 banking group FE				0.385			0.387
F-test statistic	1.879***	1528.181***	221.414***	323.015***	178.15***	108.512***	178.425***
degrees of freedom	(102,7225)	(12,7315)	(73,7254)	(80,7247)	(113,7214)	(174,7153)	(181,7146)

Table A8: **Fixed effects decomposition with time invariant fixed effects on the subsample of cross-border banking groups** The table reports the R^2 of various fixed effects decompositions of the share of FRMs. The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs. The estimation method is OLS. Standard errors are not adjusted. The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Month FE	YES	-	-	-	YES	YES	YES
Country FE	-	YES	-	YES	YES	-	YES
Banking group FE	-	-	YES	YES	-	YES	YES
N	1644	1644	1644	1644	1644	1644	1644
R^2	0.080	0.580	0.146	0.620	0.669	0.223	0.708
Adjusted R^2	0.019	0.578	0.144	0.617	0.646	0.170	0.687
F-test statistic	1.319**	322.089***	69.927***	241.939***	28.712***	4.194***	33.198***
degrees of freedom	(102,1542)	(8,1636)	(5,1639)	(12,1632)	(109,1535)	(106,1538)	(113,1531)

A.6 Robustness: Two-Stage Model

In this section we present a battery of robustness tests to examine if the results of the two-stage model discussed in Section 5.4 are confirmed when we consider different subsets of countries, we use different metrics to capture country-level household factors or we enhance the weighing scheme for observations pertaining to each country.

The estimates reported in Section 5.4 reveal a strong impact of five of the seven country-level variables, i.e., Historical Inflation Volatility, Outstanding Covered Bonds to GDP, Outstanding RMBS to GDP, Financial Literacy and ρ*(Unemployment, Short-term IR)*. Some of these variables exhibit large outliers. For example, it is the case of Latvia and Slovenia for the historical inflation volatility, or Germany for the correlation between unemployment and the short-term interest rate after the global financial crisis. Thus, a natural question to ask is whether our results are driven or largely influenced by these outliers.

A reassuring fact is that the two-stage model of Table 6 is effectively estimated on a subset of six countries, Austria, Belgium, France, Germany, Italy and Spain, due to the inclusion of quarter-banking group fixed effects and the lack of data on some variables for specific country-month pairs. This subsample includes countries at the core of the eurozone, which do not exhibit extreme values (except for ρ*(Unemployment, Short-term IR)* in the case of Germany) and are anyway hard to consider outliers from an economic viewpoint.

We, nonetheless, test the drivers behind our findings in a formal way. To this end, we follow a similar approach to that adopted for cross-border banking groups in the robustness test of Section A.5 and re-estimate the two-stage model of Table 6 by excluding each of the six countries listed above one at the time. The results of this robustness exercise are presented in Table A9. The first evidence to note is that excluding Germany, France, Spain or Belgium does not have a major impact on our results, meaning that the estimates and the main takeaways are to a large extent similar to those of Table 6. At the same time, Italy and Austria seem to be critical for our results. While these two countries do not exhibit large outlier values in any of the seven variables used to capture country-level household factors, they differ from the other countries for two main reasons: i) they are both characterized, especially Italy, by a marked variability in the share of FRMs which relates to the time varying component of some country variables and ii) Austria is the country showing the strongest prevalence of ARMs throughout the sample (see Figure 1).

We, next, explore potentially alternative specifications of our two-stage regression exploring other metrics to model country-demand households' factors. First, our list of variables includes Indebtedness, which measures the size of households liability compared to their income and, hence, is aimed at capturing the ability of households to meet the future schedule of mortgage payments. Since mortgages represent the most prominent liability in the balance sheet of most households, this metric accounts to a large extent for housing affordability, which has recently been highlighted as a driver of the mortgage choice (Furlong et al., 2019). However, we may want to test explicitly if housing affordability affects the prevalent type of mortgage in our sample. We, thus, re-estimate the two-stage model of Table 6 by adding the house price to income ratio among the set of explanatory variables. This metric equals the nominal house prices divided by nominal disposable income per head with base period 2015, as retrieved by the OECD, and has a quarterly frequency (see Figure A3 for the dynamics across countries and over time). For this reason, it is included with a lag of one quarter in the second stage regression. Table A10 reports the results of this exercise. The coefficient of House Price to Income is negative but not statistically significant. This suggests that, conditional on bank factors and other country factors, housing affordability does not explain the share of FRMs. The coefficients of all the other variables, instead, remain almost unchanged compared to Table 6.

Second, to construct ρ*(Unemployment, Short-term IR)* we use data on the national unemployment rates produced by Eurostat and obtained from the European Central Bank Statistical Data Warehouse. While Eurostat ensures that this metric conforms to the International Labour Organisation (ILO) guidelines and uses harmonised criteria, we may still wonder if it is fully consistent across jurisdictions. We, thus, consider an alternative and perhaps more homogeneous variable to capture employment conditions across countries, namely the number of hours worked per capita. Hence, we re-estimate the two-stage model of Table 6 by replacing ρ*(Unemployment, Short-term IR)* with the correlation between the number of hours worked per capital and the short-term interest rate. Information on the number of hours worked and on the population of a country at the yearly frequency is obtained from Eurostat. Similar to ρ*(Unemployment, Short-term IR)*, we calculate this correlation using a rolling window approach with a window of 7 years. We expect the coefficient of ρ*(Hours Worked, Short-term IR)* to be positive, in line with the idea that, whenever the short-term interest rate is low when the number of hours worked per capita is low, households have a preference for ARMs. Table A11 presents the results. Consistent with our prior, the coefficient of ρ*(Hours Worked, Short-term IR)* is positive and statistically significant. In addition, the coefficients of the other six variables are very similar to those of Table 6.

Third, as we note in Section 5.3, the historical inflation volatility may have different interpretations depending on how, and especially over which time frame, it is calculated. In principle, the past variability of the inflation rate can be used to measure adaptive expectations on inflation across generations of households. In our setup, we use the historical inflation volatility calculated over a 30-year period (1970-1999) prior to the introduction of the euro, similar to Campbell (2012). As discussed in Section 5.3, this metric is aimed at capturing the stickiness in households' preference for FRMs versus ARMs given the macroeconomic history of their country prior to joining the eurozone. Our modeling framework includes another variable capturing adaptive expectations on future macro conditions, i.e. the correlation between unemployment and the short-term interest rate, which is to some extent related to the past history of inflation. We, nonetheless, may want to test explicitly if expectations on future inflation matter for the mortgage choice.

Therefore, we extend our two-stage model to include a measure for adaptive expectations on inflation variability calculated as the realized standard deviation of the monthly month-on-month inflation rate on a rolling window approach with a window of 7 years. Similar to ρ*(Unemployment, Short-term IR)*, we start the rolling window in 2000 to make sure that, at the beginning of our sample period in 2007, we measure the volatility of the inflation rate since monetary policy in the euro area is set by the ECB. Results are summarized in Table A12. As expected, the coefficient of the Rolling Inflation Volatility is negative and statistically significant, whereas the coefficient of the Historical Volatility of Inflation is negative but loses its statistical significance compared to Table 6. This is not surprising as the two variables are collinear, exhibiting a correlation of 0.7 in the six countries where the model is estimated (Austria, Belgium, France, Germany, Italy, and Spain). While the values of the Rolling Inflation Volatility are somewhat lower than those of the 1970-1999 inflation volatility, the ranking of countries based on the former is similar to that of the latter at any point in time. As for the other regressors, we have similar estimates for Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP. Financial Literacy and ρ*(Unemployment, Short-term IR)* become insignificant, whereas Real Disposable Income Per Capita turns positive and significant.

In the last of this set of exercises exploring different country variables, we focus on the Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP. One concern is that these variables are to some extent endogenous, given that the volume of FRMs in the economy may impact investors' demand for these securities. In the two-stage model of equation 2 we control for a large set of demand conditions shaping households' preference for FRMs versus ARMs (such as income, indebtedness, financial literacy, familiarity with a specific type of mortgage and adaptive expectations on unemployment). This set of controls should limits concerns about the endogeneity of our variables for corporate bonds and RMBS. Nevertheless, we can also consider an alternative and more exogenous approach to capture the size of the covered bond market and the RMBS market, e.g., by using a metric for the scarcity or excess of long-term securities. Public debt to GDP ratio represents a possible candidate, but it can explain only one of the two variables as its correlation with the Outstanding Covered Bonds to GDP is negative (-0.4) and that with the Outstanding RMBS to GDP is positive (0.5). That might be explained by institutional differences between covered bonds and RMBS. Unlike RMBS, when covered bonds are issued, the mortgages in the covered pool are retained in the balance sheet of the bank. This means that, while the issuance of RMBS allows a full risk transfer to investors and, hence, a capital relief for the lender, the issuance of covered bonds allows only a reduction of the duration gap between mortgages and their source of funding. Countries with a high public debt to GDP ratio are considered more risky than countries with a low ratio. Therefore, it is reasonable to think that, everything else being equal, the issuance of covered bonds is more likely in countries with a low public debt to GDP ratio.

We thus, re-estimate the two-stage model of Table 6 by replacing the ratio of outstanding RMBS to GDP with the ratio of public debt to GDP, while keeping our variable for covered bonds. Similar to Outstanding RMBS to GDP, we use the average of the public debt to GDP ratio over the last four quarters using a rolling window approach and we include this variable lagged of one quarter. Table A13 reports the results of this analysis. Similar to the coefficient of Outstanding RMBS to GDP in Table 6, the coefficient of Public Debt to GDP is positive and statistically significant. This confirms that the size of the local RMBS market is positively related to the share of FRMs. The coefficients of Historical Inflation Volatility and Outstanding Covered Bonds to GDP maintain the same sign and significance of Table 6. Financial Literacy and ρ*(Unemployment, Short-term IR)* lose their statistical significance, being partially subsumed by Public Debt to GPD. Indebtedness, instead, turns slightly significant.

As a last exercise, we perform a test aimed at further ensuring that we weight each country equally when exploring the drivers behind cross-country differences in the share of FRMs. As discussed in section 5.3, we consider a two-stage model exactly to achieve this goal. Since the number of month-country dummies slightly differs across countries when we estimate this two-stage regression, a more conservative approach would be to directly weight each observation. We, thus, re-estimate the two-stage model of Table 6 by using sampling weights based on the relative size of the mortgage market in each country. The estimates reported in Table A14 are almost unchanged compared to those of Table 6.

A.7 Robustness: Tobit

In this section we discuss a series of robustness tests aimed at testing if the analyses presented in Section 5.1 through Section 5.5 are confirmed when we use a nonlinear estimation method to account for the fact that the share of FRMs is bounded between 0 and 100.

In particular, we consider a censored Tobit model of the form:

$$y^* = \boldsymbol{x}\boldsymbol{\beta} + \varepsilon \tag{4}$$

Table A9: **Two-Stage Model excluding One Country.** The table reports the coefficients and standard errors (in parentheses) of the second stage regression of equation 2 where we exclude each of the six countries where the model is estimated (Germany, France, Italy, Spain, Belgium and Austria) one at the time. The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the estimated coefficients of month-country fixed effects obtained from the first stage regression of equation 2. Country variables include Financial Literacy, Indebtedness, Real Disposable Income Per Capita, Historical Inflation Volatility, ρ(Unemployment, Short-term IR), Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP. All country variables except ρ(Unemployment, Short-term IR) are lagged of one period. The estimation method is OLS. Standard errors are two-way clustered by country and quarter. The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	2ND STAGE					
	Excluding Germany (1)	Excluding France (2)	Excluding Italy (3)	Excluding Spain (4)	Excluding Belgium (5)	Excluding Austria (6)
Financial Literacy	-5.226***	-10.716***	0.821	-5.445**	-4.613**	-0.469
	(0.31)	(1.93)	(1.15)	(1.88)	(1.45)	(1.59)
Indebtedness	1.411	1.907*	1.812**	1.372	-0.843*	-0.230
	(0.83)	(0.87)	(0.54)	(1.68)	(0.32)	(0.65)
Real Disposable Income Per Capita	5.718	0.630	-5.413*	2.047	-5.795	13.214
	(3.15)	(3.17)	(1.96)	(2.14)	(3.48)	(7.20)
Historical Inflation Volatility	-4.154***	-11.777***	-5.184***	-5.115*	-5.170**	-0.622
	(0.88)	(1.03)	(0.65)	(2.36)	(1.60)	(2.07)
ρ (Unemployment, Short-term IR)	21.054	25.982***	-2.195	45.692**	37.634*	-14.605
	(29.30)	(3.99)	(9.18)	(11.46)	(17.23)	(12.98)
Outstanding Covered Bonds to GDP	2.653	7.454***	1.295	5.348	7.463**	2.298
	(1.86)	(0.57)	(1.24)	(3.12)	(1.91)	(1.39)
Outstanding RMBS to GDP	2.516***	1.130	0.901	3.009	-3.753	1.919**
	(0.51)	(0.69)	(0.46)	(1.50)	(8.09)	(0.52)
Two-way cluster	country, quarter					
N	249	253	286	325	257	288
R^2	0.533	0.585	0.666	0.619	0.596	0.410
Adjusted R^2	0.520	0.573	0.658	0.611	0.584	0.396
F-test statistic regressors pure demand	3175907.1***	9155.68***	19702.08***	6380.94***	5151.72***	345.58***
degrees of freedom	(5, 4)	(4, 4)	(5, 4)	(4, 4)	(5, 4)	(5, 4)
F-test statistic regressors institutional factors	12.63**	97.21***	2.81	6.28*	10.67**	6.93*
degrees of freedom	(2, 4)	(2, 4)	(2, 4)	(2, 4)	(2, 4)	(2, 4)

Table A10: **Two-Stage Model with House Price to Income.** The table reports (i) the R^2 of the first stage regression of equation 2 in model (1) and (ii) the coefficients and standard errors (in parentheses) of a modified version of the second stage regression of equation 2 where we include the house price to income ratio in model (2). The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs in model (1), and the estimated coefficients of month-country fixed effects obtained from the first specification in model (2). Country variables include Financial Literacy, Indebtedness, House Price to Income, Real Disposable Income Per Capita, Historical Inflation Volatility, ρ(Unemployment, Short-term IR), Outstanding Covered Bonds to GDP and Public Debt to GDP. The estimation method is OLS. Standard errors are not adjusted for model (1), and two-way clustered by country and quarter in model (2). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	1ST STAGE (1)	***2ND STAGE*** (2)
Financial Literacy		-6.543**
		(1.68)
Indebtedness		0.960
		(1.16)
House Price to Income		-0.621
		(0.50)
Real Disposable Income Per Capita		1.868
		(2.65)
Historical Inflation Volatility		-7.157***
		(0.79)
ρ (Unemployment, Short-term IR)		26.258*
		(10.57)
Outstanding Covered Bonds to GDP		4.991**
		(1.66)
Outstanding RMBS to GDP		3.256***
		(0.41)
Quarter-banking group FE	YES	
Month-country FE	YES	
Two-way cluster	-	country, quarter
N	1085	344
R^2	0.847	0.517
Adjusted R^2	0.733	0.505
F-test statistic regressors		-
degrees of freedom		-
F-test statistic regressors pure demand		123.21***
degrees of freedom		(5, 5)
F-test statistic regressors institutional factors		32.25***
degrees of freedom		(2, 5)
F-test statistic fixed effects	7.437***	
degrees of freedom	(463,621)	

Table A11: **Two-Stage Model with Correlation between the Number of Hours Worked and the Short-term Interest Rate.** The table reports (i) the R^2 of the first stage regression of equation 2 in model (1) and (ii) the coefficients and standard errors (in parentheses) of the second stage regression of equation 2 in model (2). The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs in model (1), and the estimated coefficients of month-country fixed effects obtained from the first specification in model (2). Country variables include Financial Literacy, Indebtedness, Real Disposable Income Per Capita, Historical Inflation Volatility, ρ(Hours Worked, Short-term IR), Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP. The estimation method is OLS. Standard errors are not adjusted for model (1), and two-way clustered by country and quarter in model (2). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	1ST STAGE (1)	***2ND STAGE*** (2)
Financial Literacy		-4.420**
		(1.43)
Indebtedness		-0.049
		(0.79)
Real Disposable Income Per Capita		3.796
		(4.35)
Historical Inflation Volatility		-5.766***
		(0.88)
ρ (Hours Worked, Short-term IR)		-17.108**
		(6.11)
Outstanding Covered Bonds to GDP		5.765***
		(1.09)
Outstanding RMBS to GDP		3.387***
		(0.65)
Quarter-banking group FE	YES	
Month-country FE	YES	
Two-way cluster	-	country, quarter
N	1085	344
R^2	0.847	0.477
Adjusted R^2	0.733	0.466
F-test statistic regressors		-
degrees of freedom		-
F-test statistic regressors pure demand		23.70***
degrees of freedom		(5, 5)
F-test statistic regressors institutional factors		15.27
degrees of freedom		(2, 5)
F-test statistic fixed effects	7.437***	
degrees of freedom	(463,621)	

Table A12: **Two-Stage Model adding Rolling Volatility of Inflation.** The table reports (i) the R^2 of the first stage regression of equation 2 in model (1) and (ii) the coefficients and standard errors (in parentheses) of a modified version of the second stage regression of equation 2 including a rolling volatility of inflation in model (2). The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs in model (1), and the estimated coefficients of month-country fixed effects obtained from the first specification in model (2). Country variables include Financial Literacy, Indebtedness, Real Disposable Income Per Capita, Historical Inflation Volatility, Rolling Inflation Volatility (calculated as the realized standard deviation of the monthly month-on-month inflation rate relying on a rolling window approach of 7 years starting in 2000), ρ(Unemployment, Short-term IR), Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP. The estimation method is OLS. Standard errors are not adjusted for model (1), and two-way clustered by country and quarter in model (2). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	1ST STAGE (1)	***2ND STAGE*** (2)
Financial Literacy		0.277
		(2.01)
Indebtedness		0.496
		(0.37)
Real Disposable Income Per Capita		9.874***
		(1.91)
Historical Inflation Volatility		-1.623
		(1.65)
Rolling Inflation Volatility		-4.507***
		(1.11)
ρ (Unemployment, Short-term IR)		-7.531
		(7.31)
Outstanding Covered Bonds to GDP		6.614***
		(0.95)
Outstanding RMBS to GDP		3.776***
		(0.46)
Quarter-banking group FE	YES	
Month-country FE	YES	
Two-way cluster	-	country, quarter
N	1085	344
R^2	0.847	0.591
Adjusted R^2	0.733	0.582
F-test statistic regressors		-
degrees of freedom		-
F-test statistic regressors pure demand		1709.72***
degrees of freedom		(4,5)
F-test statistic regressors institutional factors		100.29***
degrees of freedom		(2,5)
F-test statistic fixed effects	7.437***	
degrees of freedom	(463,621)	

Table A13: **Two-Stage Model replacing RMBS to GDP with Public Debt to GDP.** The table reports (i) the R^2 of the first stage regression of equation 2 in model (1) and (ii) the coefficients and standard errors (in parentheses) of a modified version of the second stage regression of equation 2 where the outstanding RMBS to GDP ratio is replaced with the public debt to GDP ratio in model (2). The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs in model (1), and the estimated coefficients of month-country fixed effects obtained from the first specification in model (2). Country variables include Financial Literacy, Indebtedness, Real Disposable Income Per Capita, Historical Inflation Volatility, ρ(Unemployment, Short-term IR), Outstanding Covered Bonds to GDP and Public Debt to GDP (calculated using a rolling window approach with a window of one year). The estimation method is OLS. Standard errors are not adjusted for model (1), and two-way clustered by country and quarter in model (2). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	1ST STAGE (1)	***2ND STAGE*** (2)
Financial Literacy		0.131
		(0.68)
Indebtedness		1.207*
		(0.59)
Real Disposable Income Per Capita		-0.194
		(3.50)
Historical Inflation Volatility		-3.129***
		(0.40)
ρ (Unemployment, Short-term IR)		13.863
		(7.56)
Outstanding Covered Bonds to GDP		2.486***
		(0.23)
Public Debt to GDP		1.047***
		(0.23)
Quarter-banking group FE	YES	
Month-country FE	YES	
Two-way cluster	-	country, quarter
N	1187	380
R^2	0.854	0.482
Adjusted R^2	0.743	0.473
F-test statistic regressors		-
degrees of freedom		-
F-test statistic regressors pure demand		173.44***
degrees of freedom		(4, 5)
F-test statistic regressors institutional factors		246.04***
degrees of freedom		(2, 5)
F-test statistic fixed effects	7.708***	
degrees of freedom	(511, 675)	

Table A14: **Two-Stage Model with Weighted by the Relative Size of the Mortgage Market.** The table reports (i) the R^2 of the first stage regression of equation 2 in model (1) and (ii) the coefficients and standard errors (in parentheses) of the second stage regression of equation 2 in models (2), where each observation is weighted according to the relative size of the country's mortgage market. The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs in model (1), and the estimated coefficients of month-country fixed effects obtained from the first specification in model (2). Country variables include Financial Literacy, Indebtedness, Real Disposable Income Per Capita, Historical Inflation Volatility, ρ(Unemployment, Short-term IR), Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP. Sampling weights are equal to the inverse of the aggregate volume of new mortgages originated in the current month one of the six countries where the model is estimated (Austria, Belgium, France, Germany, Italy and Spain) as a percentage of the total volume on new mortgages originated in these countries. Standard errors are not adjusted for model (1), and two-way clustered by country and quarter in model (2). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	1ST STAGE (1)	***2ND STAGE*** (2)
Financial Literacy		-7.743***
		(1.62)
Indebtedness		0.876
		(1.20)
Real Disposable Income Per Capita		3.938
		(2.07)
Historical Inflation Volatility		-7.631***
		(1.26)
ρ (Unemployment, Short-term IR)		35.583***
		(6.26)
Outstanding Covered Bonds to GDP		6.137***
		(1.49)
Outstanding RMBS to GDP		2.790**
		(0.99)
Quarter-banking group FE	YES	
Month-country FE	YES	
Two-way cluster	-	country, quarter
N	1085	344
R^2	0.949	0.538
Adjusted R^2	0.912	0.528
F-test statistic regressors		-
degrees of freedom		-
F-test statistic regressors pure demand		33.83***
degrees of freedom		(5, 5)
F-test statistic regressors institutional factors		8.52**
degrees of freedom		(2, 5)
F-test statistic fixed effects	7.44***	
degrees of freedom	(463,621)	

$$
y = \left\{ \begin{array}{ccc} 0 & \text{if} & y^* < 0 \\ y^* & \text{if} & 0 \leq y^* \leq 100 \\ 100 & \text{if} & y^* > 100 \end{array} \right\}
$$

Recall that most of our findings are drawn by comparing the coefficients of determination of different specifications. Unfortunately, Tobit models do not provide such measure. Alternative metrics known as pseudo-R^2 cannot be considered as meaningful as the coefficient of determination of linear models. Moreover, in the specifications where we model the demand relying on a set of explanatory variables, we control for bank supply conditions including month-banking group fixed effects. It is well known that nonlinear models with fixed effects suffer from the so called "incidental parameters problem" (Neyman and Scott, 1948; Lancaster, 2000). This implies that the maximum likelihood estimator (MLE) is inconsistent. Greene (2004a,b) shows that, for the specific case of Tobit models with fixed effects, the slope coefficients are slightly affected by the incidental parameters problem. However, the bias can be sizable for the disturbance variance, with clear implications also on the estimation of the marginal effects. Therefore, either using linear or nonlinear models, we have to deal with relevant issues that can produce unreliable results. In light of the fact that our sample includes only four observations where the share of FRMs is exactly equal to one of the two bounds,[22] we believe that the issue related to linear regression models is less severe and, hence, we rely on them to derive our main results. Nonetheless, we perform a set of Tobit robustness checks in order to test whether our findings are robust to nonlinear specifications.

[22] In these four observations the value of the share is equal to the upper bound 100.

We start by replicating Table 3 using a censored regression model with lower bound 0 and upper bound 100. We calculate the pseudo R^2 according to the methodology suggested in Wooldridge (2010). In particular, we computed it as the square of the correlation coefficient between the dependent variable and the estimate of $\mathbb{E}[y|x]$. Table A15 shows that, as before, month-country fixed effects explain a larger fraction of the variation in the dependent variable than month-banking group fixed effects. We extend our analysis also including Tobit models with lower bound 1 and upper bound 99, in order to check whether our findings are affected by a more restrictive censoring. Results are virtually unchanged.

Tables A16-A17 replicate Table A7. In both tables the pattern of the R^2 across the different specifications is equal to the one displayed in Table A7. This confirms the prominent role of country demand factors, even when considering the whole sample of banks. However, in this setting we are not able to perform a decomposition of the R^2 to get additional insights.

Table A18 shows the estimates of the censored regression models including country specific explanatory variables and month-banking group fixed effects. For each regressor we report the marginal effect of the censored variable $\mathbb{E}[y|x]$ at the sample means. Differently from Table A2, we cluster standard errors only by country, as the statistical software that we use does not allow to implement two-way clustering in the Tobit model that we employ. We consider this a minor limitation, as we detected a higher serial correlation than cross correlation in our data set. In the specifications with the full set of country variables, we find, as before, a negative and statistically significant coefficient for Real Disposable Income Per Capita and Historical Inflation Volatility, as well as a positive and statistically significant coefficient for ρ(Unemployment, Short-term IR).

As in the previous section, we improve our analysis making sure that we equally weight each country when explaining the cross-country heterogeneity in the share of FRMs. To this aim, we rely on a two-stage approach. In the first stage we perform a censored regression including month-country fixed effects and quarter-banking group fixed effects. In the second stage we regress the estimated coefficients of the month-country fixed effects, which correspond to the marginal effects of the latent variable y^*, on our set of explanatory variables. While in the first stage we use a Tobit model, in the second stage we employ a linear regression, as the dependent variable is not constrained between 0 and 100. Model 4 of Tables A19-A20 shows, as in Table 6, a negative and significant coefficient for Financial Literacy and Historical Inflation Volatility, as well as a positive and significant coefficient for ρ(Unemployment, Short-term IR), Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP.

Finally, in Table A21 we investigate the time variation in the share of FRMs using censored regression models. As in Table 8, we find that the sensitivity of the share of FRMs to the term spread is quite heterogeneous across countries. Moreover, the term spread captures an important fraction of the time variation in the dependent variable.

The Tobit robustness checks exposed above highlight that the results obtained using linear regression models are indeed robust to nonlinear specifications.

Table A15: **Baseline model, Tobit.** The table reports the pseudo R^2 of various fixed effects decompositions of the share of FRMs. The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs. The estimation method is Tobit with lower bound 0 and upper bound 100 in model (1)-(4), and lower bound 1 and upper bound 99 in models (5)-(8). Standard errors are not adjusted. The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Month-country FE	YES	-	YES	YES	YES	-	YES	YES
Month-banking group FE	-	YES	YES	YES	-	YES	YES	YES
Bank FE	-	-	-	YES	-	-	-	YES
N	1644	1644	1644	1644	1644	1644	1644	1644
Pseudo R^2	0.843	0.318	0.908	0.977	0.842	0.318	0.908	0.978
LR test statistic	3047.719***	630.833***	3914.214***	5927.208***	-	631.552***	-	-
degrees of freedom	687	479	1045	1052	-	479	-	-
lower bound	0	0	0	0	1	1	1	1
upper bound	100	100	100	100	99	99	99	99
left censored obs	0	0	0	0	9	9	9	9
right censored obs	0	0	0	0	8	8	8	8

Table A16: **Fixed effects decomposition with time invariant fixed effects, Tobit.** The table reports the pseudo R^2 of various fixed effects decompositions of the share of FRMs. The sample includes all banks and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs. The estimation method is Tobit with lower bound 0 and upper bound 100. Standard errors are not adjusted. The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Month FE	YES	-	-	-	YES	YES	YES
Country FE	-	YES	-	YES	YES	-	YES
Banking group FE	-	-	YES	YES	-	YES	YES
N	7327	7327	7327	7327	7327	7327	7327
Pseudo R^2	0.026	0.696	0.686	0.778	0.740	0.730	0.825
LR test statistic	191.219***	8740.390***	8515.165***	11051.019***	9714.870***	9436.297***	12483.017***
degrees of freedom	101	11	72	79	112	173	180
lower bound	0	0	0	0	0	0	0
upper bound	100	100	100	100	100	100	100
left censored obs	0	0	0	0	0	0	0
right censored obs	4	4	4	4	4	4	4

Table A17: **Fixed effects decomposition with time invariant fixed effects, Tobit.** The table reports the pseudo R^2 of various fixed effects decompositions of the share of FRMs. The sample includes all banks and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs. The estimation method is Tobit with lower bound 1 and upper bound 99. Standard errors are not adjusted. The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Month FE	YES	-	-	-	YES	YES	YES
Country FE	-	YES	-	YES	YES	-	YES
Banking group FE	-	-	YES	YES	-	YES	YES
N	7327	7327	7327	7327	7327	7327	7327
Pseudo R^2	0.025	0.697	0.687	0.779	0.741	0.732	0.827
LR test statistic	207.054***	8544.702***	8603.544***	10992.751***	9532.775***	9566.057***	12463.168***
degrees of freedom	101	11	72	79	112	173	180
lower bound	1	1	1	1	1	1	1
upper bound	99	99	99	99	99	99	99
left censored obs	187	187	187	187	187	187	187
right censored obs	214	214	214	214	214	214	214

Table A18: **Advanced model, Tobit.** The table reports (i) the marginal effects of the censored variable $\mathbb{E}[y|x]$ at the sample means and standard errors (in parentheses) of various regressions of the share of FRMs on a set of country variables and month-banking group fixed effects in models (1)-(2)-(4)-(5), and (ii) the pseudo R^2 of the baseline model of equation 1 run on the same sample of models (2)-(5) in the specifications (3)-(6). The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs. Country variables include Financial Literacy, Indebtedness, Real Disposable Income Per Capita, Historical Inflation Volatility, ρ(Unemployment, Short-term IR), Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP. All country variables except ρ(Unemployment, Short-term IR) are lagged of one period. Standard errors are one-way clustered by country in models (1)-(2)-(4)-(5), and not adjusted in models (3)-(6). The estimation method is Tobit with lower bound 0 and upper bound 100 in models (1)-(3), and lower bound 1 and upper bound 99 in models (4)-(6). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Financial Literacy	-0.502	-1.666		-0.516	-1.677	
	(1.64)	(1.12)		(1.66)	(1.10)	
Indebtedness	0.823*	0.593		0.820*	0.588	
	(0.45)	(0.51)		(0.46)	(0.52)	
Real Disposable Income Per Capita	-14.215***	-12.199***		-14.217***	-12.220***	
	(3.14)	(4.31)		(3.22)	(4.33)	
Historical Inflation Volatility	-5.146***	-5.720***		-5.164***	-5.737***	
	(1.04)	(0.57)		(1.05)	(0.56)	
ρ (Unemployment, Short-term IR)	20.180*	23.842***		19.999*	23.665***	
	(10.56)	(7.35)		(10.64)	(7.39)	
Outstanding Covered Bonds to GDP		1.411			1.416	
		(1.20)			(1.18)	
Outstanding RMBS to GDP		0.314			0.309	
		(0.70)			(0.69)	
Month-banking group FE	YES	YES	YES	YES	YES	YES
Month-country FE	-	-	YES	-	-	YES
One-way cluster	*country*	*country*	-	*country*	*country*	-
N	1085	1085	1085	1085	1085	1085
Pseudo R^2	0.787	0.791	0.852	0.787	0.790	0.852
LR test statistic			2075.750***			-
degrees of freedom			605			-
F-test statistic regressors	6263.96***	441.79***		3.9e+06***	435.72***	
degrees of freedom	(5,721)	(5,719)		(5,721)	(5,719)	
F-test statistic regressors pure demand		433.93***			435.72***	
degrees of freedom		(5,719)			(5,719)	
F-test statistic regressors institutional factors		2.16			2.20	
degrees of freedom		(2,719)			(2,719)	
lower bound	0	0	0	1	1	1
upper bound	100	100	100	99	99	99
left censored obs	0	0	0	3	3	3
right censored obs	0	0	0	6	6	6

Table A19: **Two-stage model, Tobit.** The table reports (i) the pseudo R^2 of the first stage Tobit regression of equation 5.3 in model (1), (ii) the marginal effects of the censored variable $\mathbb{E}[y|x]$ at the sample means and standard errors (in parenthesis) of a Tobit regressions of the share of FRMs on a set of country variables and quarter-banking group fixed effects in model (2), and (iii) the coefficients and standard errors (in parentheses) of the second stage regression of equation 2 in models (3)-(4). The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs in models (1)-(2), and the estimated coefficients of month-country fixed effects obtained from the first specification in models (3)-(4). Country variables include Financial Literacy, Indebtedness, Real Disposable Income Per Capita, Historical Inflation Volatility, ρ(Unemployment, Short-term IR), Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP. All country variables except ρ(Unemployment, Short-term IR) are lagged of one period. The estimation method is Tobit with lower bound 0 and upper bound 100 in models (1)-(2), and OLS in models (3)-(4). Standard errors are not adjusted for model (1), one-way clustered by country in model (2), and two-way clustered by country and quarter in models (3)-(4). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	1ST STAGE			***2ND TAGE***	
	(1)	(2)		(3)	(4)
Financial Literacy		-1.608		-2.693	-5.386**
		(1.08)		(2.26)	(1.72)
Indebtedness		0.576		1.558	0.206
		(0.51)		(0.99)	(0.78)
Real Disposable Income Per Capita		-12.222***		0.137	1.979
		(3.93)		(4.26)	(3.65)
Historical Inflation Volatility		-5.682***		-3.847**	-6.482***
		(0.60)		(1.48)	(0.87)
ρ (Unemployment, Short-term IR)		23.390***		33.128	28.726**
		(7.20)		(18.53)	(9.79)
Outstanding Covered Bonds to GDP		1.414			5.754***
		(1.16)			(0.80)
Outstanding RMBS to GDP		0.309			2.756***
		(0.67)			(0.50)
Quarter-banking group FE	YES	YES			
Month-country FE	YES	-			
Clustering	-	*country*		*country, quarter*	*country, quarter*
N	1085	1085	N	344	344
Pseudo R^2	0.847	0.780	R^2	0.337	0.503
LR test statistic	2038.38***		Adjusted R^2	0.327	0.492
degrees of freedom	463				
F-test statistic regressors		510.36		-	-
degrees of freedom		(5,959)		-	-
F-test statistic regressors pure demand		493.94***			50.57***
degrees of freedom		(5, 959)			(5,5)
F-test statistic regressors institutional factors		2.36*			26.83***
degrees of freedom		(2, 959)			(2,5)
lower bound	0	0			
upper bound	100	100			
left censored obs	0	0			
right censored obs	0	0			

Table A20: **Two-stage model, Tobit.** The table reports (i) the pseudo R^2 of the first stage Tobit regression of equation 5.3 in model (1), (ii) the marginal effects of the censored variable $\mathbb{E}\left[y\,|x\right]$ at the sample means and standard errors (in parenthesis) of a Tobit regressions of the share of FRMs on a set of country variables and quarter-banking group fixed effects in model (2), and (iii) the coefficients and standard errors (in parentheses) of the second stage regression of equation 2 in models (3)-(4). The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs in models (1)-(2), and the estimated coefficients of month-country fixed effects obtained from the first specification in models (3)-(4). Country variables include Financial Literacy, Indebtedness, Real Disposable Income Per Capita, Historical Inflation Volatility, ρ(Unemployment, Short-term IR), Outstanding Covered Bonds to GDP and Outstanding RMBS to GDP. All country variables except ρ(Unemployment, Short-term IR) are lagged of one period. The estimation method is Tobit with lower bound 1 and upper bound 99 in models (1)-(2), and OLS in models (3)-(4). Standard errors are not adjusted for model (1), one-way clustered by country in model (2), and two-way clustered by country and quarter in models (3)-(4). The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	1ST STAGE			***2ND TAGE***	
	(1)	(2)		(3)	(4)
Financial Literacy		-1.599		-2.904	-5.744**
		(1.05)		(2.33)	(1.73)
Indebtedness		0.572		1.506	0.087
		(0.51)		(1.03)	(0.79)
Real Disposable Income Per Capita		-12.291***		0.339	2.248
		(3.96)		(4.31)	(3.70)
Historical Inflation Volatility		-5.690***		-4.079**	-6.857***
		(0.59)		(1.53)	(0.88)
ρ (Unemployment, Short-term IR)		23.163***		33.141	28.596**
		(7.20)		(19.26)	(10.05)
Outstanding Covered Bonds to GDP		1.406			6.052***
		(1.13)			(0.84)
Outstanding RMBS to GDP		0.295			2.882***
		(0.65)			(0.51)
Quarter-banking group FE	YES	YES			
Month-country FE	YES	-			
Clustering	-	*country*		*country, quarter*	*country, quarter*
N	1085	1085	N	344	344
Pseudo R^2	0.847	0.780	R^2	0.337	0.509
LR test statistic	-		Adjusted R^2	0.327	0.499
degrees of freedom	-				
F-test statistic regressors		535.80***		-	-
degrees of freedom		(5,959)		-	-
F-test statistic regressors pure demand		511.37***			51.48***
degrees of freedom		(5, 959)			(5, 5)
F-test statistic regressors institutional factors		2.41*			27.46***
degrees of freedom		(2, 959)			(2, 5)
lower bound	1	1			
upper bound	99	99			
left censored obs	3	3			
right censored obs	6	6			

Table A21: **Time variation, Tobit.** The table reports the results of the analysis investigating the sensitivity of the share of FRMs to the term spread. The term spread is calculated as the difference between the 10-year Interest Rate Swap rate and the 3-month Overnight Index Swap rate. The sample includes cross-border banking groups only and the unit of observation is at the bank-country-month level. The dependent variable is the share of FRMs. The estimation method is Tobit with lower bound 0 and upper bound 100 in models (1)-(3), and lower bound 1 and upper bound 99 in models (4)-(6). The displayed coefficients represent the marginal effects of the censored variable $\mathbb{E}[y\,|x]$ at the sample means. Standard errors are not adjusted. The $*$, $**$, and $***$ marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Austria x term spread	-6.009***		0.249	-6.221***		-0.392
	(2.30)		(3.53)	(2.21)		(3.52)
Belgium x term spread	-21.005***		-24.816***	-20.683***		-24.485***
	(2.19)		(2.49)	(2.18)		(2.49)
Germany x term spread	-1.556*		0.252	-1.519*		0.256
	(0.84)		(1.19)	(0.82)		(1.16)
Spain x term spread	-1.755		-1.272	-2.199		-1.733
	(2.96)		(3.31)	(2.86)		(3.25)
France x term spread	-6.736***		-12.875***	-6.757***		-12.948***
	(1.08)		(1.73)	(1.07)		(1.73)
Italy x term spread	-8.706***		-6.58***	-8.687***		-6.536***
	(1.40)		(1.44)	(1.41)		(1.45)
Luxembourg x term spread	-13.716***		-7.159***	-13.663***		-6.96**
	(2.01)		(2.76)	(2.02)		(2.73)
Slovenia x term spread	-23.464***		-30.941***	-23.157***		-30.493***
	(2.02)		(2.44)	(2.00)		(2.43)
Country FE	YES	-	YES	YES	-	YES
Banking group FE	-	YES	YES	-	YES	YES
Banking group FE x term spread	-	YES	YES	-	YES	YES
N	1644	1644	1644	1644	1644	1644
Pseudo R^2	0.662	0.204	0.715	0.663	0.204	0.716
LR test statistic	1757.598***	378.309***	2030.115***	1752.183***	374.900***	2020.307***
degrees of freedom	15	9	23	15	9	23
lower bound	0	0	0	1	1	1
upper bound	100	100	100	99	99	99
left censored obs	0	0	0	9	9	9
right censored obs	0	0	0	8	8	8

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