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Abstract

We build a model of the mortgage market where banks attain their optimal mortgage portfolio by setting rates and steering customers. Sophisticated households know which mortgage type is best for them; naive households are susceptible to banks' steering. Using data on the universe of Italian mortgages, we estimate the model and quantify the welfare implications of steering. The average cost of the distortion is equivalent to 16% of the annual mortgage payment. A financial literacy campaign is beneficial for naive households, but hurts sophisticated ones. Since steering also conveys information about mortgages, restricting steering might result in significant welfare losses.

JEL Classification: G21, D18, D12

Keywords: steering, financial advice, mortgage market, consumer protection

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1 Introduction

Retail financial products, such as mortgages, credit cards, investment products, retirement plans, etc., are often quite complex and many households lack knowledge or sophistication to decide which one best suits their needs. This allows financial intermediaries to affect households' choices not only through pricing, but also by "steering" customers towards certain products. Steering – i.e., persuading a customer to pursue a course of action – takes many forms. For example, when providing private advice to its customer, the financial intermediary may explain the advantages of a complex financial product that the customer would not be confident to purchase on her own initiative, but may also shroud some features to make it seem more appealing, thus potentially distorting the customer's choice.[1] In extreme cases, the intermediary might resort to outright deception in promoting the product that is more to the intermediary's advantage than the customer's.

There is a substantial empirical and anecdotal evidence that steering is pervasive in financial markets.[2] Egan, Matvos, and Seru (2019) document that biased financial advice and even more reprehensible behaviors are intrinsic features of retail financial markets. The most extreme forms of steering are sometimes exposed by financial scandals leading legislators to enact new regulations that better align interests of financial intermediaries with those of their customers.[3]

These features raise a number of questions yet to be addressed in the literature. How sizable is the welfare cost of steering for consumers and do all consumers bear it to the same extent? Should steering be restricted? What are the welfare consequences of specific policies, such as a financial education campaign? What is the role played by the degree of competition between intermediaries? Crucially, households in financial markets are heterogeneous in terms

[1]There is ample evidence that households rely on experts' advice: 73% of US investors rely on professional advice to conduct stock market transactions (Hung and Yoong, 2013), 91% of intermediary mortgage sales in the UK are "with advice" (Chater, Huck, and Inderst, 2010), and according to a broad survey of German retail investors, 80% consult financial advisors.

[2]E.g., markets for mortgages (Gurun, Matvos, and Seru, 2016; Agarwal, Ambrose, and Yao, 2020; Foà, Gambacorta, Guiso, and Mistrulli, 2019), retail investments (Bergstresser, Chalmers, and Tufano, 2009; Hackethal, Haliassos, and Jappelli, 2012; Mullainathan, Noeth, and Schoar, 2012; Christoffersen, Evans, and Musto, 2013; Foerster, Linnainmaa, Melzer, and Previtero, 2017; Chalmers and Reuter, 2020; Hoechle, Ruenzi, Schaub, and Schmid, 2018), credit cards (Ru and Schoar, 2017), insurance (Anagol, Cole, and Sarkar, 2017).

[3]E.g., the Obama administration's attempt to raise fiduciary standards or tighter requirements on independent financial advice introduced by the European Mifid II directive.

of sophistication (and thus, susceptibility to steering), and answers to these questions must take into account potential redistributive effects. The goal of this paper is to quantify the impact of steering in financial markets on households' welfare while explicitly accounting for heterogeneity in sophistication among consumers.

The welfare cost of steering and the implications of different policies depend on the distribution in the population of sophisticated and unsophisticated consumers as well as on the financial intermediaries' response to these policies. To identify these objects, we take a structural approach. We build and estimate a model of households' mortgage choice in which some households are susceptible to steering. The mortgage market is an excellent setting in which to study steering in financial markets. Not only does it involve as participants a large fraction of the populations of all advanced economies, but a high degree of sophistication is required from mortgage-takers to evaluate the pros and cons of different products. Financial intermediaries provide information and advice to their customers, giving them scope to take advantage of their customers' lack of knowledge and experience.

Our data consist of administrative records on the universe of mortgages originated between 2005 and 2008 by a sample of 127 Italian banks covering 90 percent of the market. In addition to the information on loan terms, the data identifies the bank originating the mortgage, allowing us to match rich data on the balance sheet of the originator. The Italian mortgage market is well suited to the purpose of our study thanks to a number of institutional characteristics. There are only two main products available to customers – plain vanilla fixed- and adjustable-rate mortgages (henceforth, FRMs and ARMs, respectively) – and both are popular. Banks retain originated mortgages on their balance sheets. This creates an interest rate exposure, which is not completely hedged through derivatives (Esposito, Nobili, and Ropele, 2015; Cerrone, Cocozza, Curcio, and Gianfrancesco, 2017; Hoffmann, Langfield, Pierobon, and Vuillemey, 2019). Further, banks are the main providers of information and advice about mortgages to customers (Oliver Wyman, 2003). Thus, Italian banks have both the motive and the opportunity to use steering along with relative pricing of mortgages in order to manage their maturity mismatch.

Foà, Gambacorta, Guiso, and Mistrulli (2019) use data similar to ours to provide reduced form evidence of steering in the Italian mortgage market. Building on this reduced form evidence, we set up a parsimonious model of households' mortgage choices where banks can steer their customers. In our model, households pick the bank from which they take out a mortgage and decide between a FRM and an ARM. Borrowers can be "sophisticated" or "naive" in their choice of the mortgage type. Sophisticated households choose their mortgage type using the "spread rule" (Campbell and Cocco, 2003; Koijen, Van Hemert, and Van Nieuwerburgh, 2009). They compare the spread between the best available FRM and ARM rates to a household-specific cutoff which subsumes all the household heterogeneity that affects the rational choice of the mortgage type.[4] Another distinguishing feature of sophisticated households is that they are not subject to steering: their mortgage type decision cannot be influenced by banks other than through interest rate setting.

To capture the choice of naive households, we suppose that, in the absence of steering by their bank, they would choose the easy-to-grasp (but potentially more costly) FRM. This assumption is in line with extensive empirical evidence that less financially literate households are more likely to choose FRMs (see Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff, 2010; Fornero, Monticone, and Trucchi, 2011; Gathergood and Weber, 2017; Albertazzi, Fringuellotti, and Ongena, 2018).[5] Unlike sophisticated households, naive households are prone to steering by banks. Importantly, the effect of steering on naive households' welfare is ambiguous, because while it expands the naive households' choice sets (from only FRMs to both mortgage types), it also potentially distorts their choices.

A fraction of households are "unattached", meaning that they can shop around for the best rate in the market. The rest are "attached" and consider only mortgages at their primary bank. This captures different market frictions, such as search or switching costs heterogeneous across households, and gives banks a certain degree of market power over customers. In order to identify this friction, we complement our data with the Bank of Italy Survey of Households Income and Wealth data (henceforth, SHIW), which contains information on households who changed

[4]E.g., heterogeneity in risk aversion, beliefs, wealth/income ratio, real interest rate risk, prepayment option, borrowing constraints, etc. Prior literature (Campbell and Cocco, 2003; Koijen, Van Hemert, and Van Nieuwerburgh, 2009; Badarinza, Campbell, and Ramadorai, 2018) has shown that the spread rule approximates well the optimal choice of mortgage type.

[5]We experiment with different assumptions on the default behavior of naive borrowers when using the model to quantify the cost of steering.

their primary bank in the same year they took a mortgage. To provide a rich characterization of heterogeneity, we allow for correlation between household attachment and sophistication reflecting the possibility that both features may be driven by some common factors.

Since the sensitivity to FRM and ARM rates of unattached households is different depending on whether they are sophisticated or naive, we can identify the fraction of naive among unattached households as well as the distribution of the cutoffs in the spread rule among sophisticated households from the data on the banks' market shares in the mortgage market. However, to identify the fraction of naive among attached households, we need to recover banks' steering strategies and exploit the data on the mortgage type chosen, hence, relying on the supply side of the model.

On the supply side, banks vary in the target FRM/ARM composition of their mortgage portfolio and compete with each other by setting rates to attract borrowers. The target FRM/ARM ratio reflects the trade-off between returns on two products and risk, arising, for example, from the maturity mismatch. After they attract their customer base, they can also steer their naive customers towards a particular mortgage type. Thus, our model captures steering that occurs through one-on-one interactions between customers and their banks, e.g., through informative or distorted advice at the branch or targeted advertising of financial products.[6] We use the optimality conditions for rate setting and steering policies in order to recover the underlying supply parameters as well as the fraction of naive among attached households.

We estimate that a large fraction of borrowers are naive: 48% among unattached households and 62% of the attached households. These figures square with survey measures of financial sophistication of the Italian population and imply that naiveté and attachment are positively correlated: more financially sophisticated customers are also more likely to shop around for the best deal when taking a mortgage. In this respect, we obtain that banks have considerable market power: based on our estimates, only 9% of households potentially obtain mortgages outside their home bank. These parameter estimates suggest that banks can effectively use both pricing (through their substantial market power) and steering (by exploiting a significant

[6]This choice comes at little cost, as Foà, Gambacorta, Guiso, and Mistrulli (2019) document that other forms of steering that we do not model, such as, strategic rationing or public advertising campaigns, are not particularly relevant in the Italian market.

proportion of naive borrowers) in order to manage the maturity mismatch on the asset side of their balance sheet.

We quantify the welfare cost of steering to be 1,350 euros per year for the average household (about 16% of the annual mortgage payment). However, we find an implicit subsidy from naive households to sophisticated households (Gabaix and Laibson, 2006). Banks take advantage of their ability to steer naive households to adjust their mortgage portfolios, which imposes a cost on naive households (2,430 euros per year on average). At the same time, sophisticated households benefit (by 303 euros per year), because banks rely less on rates to achieve their desired mortgage mix resulting in cheaper mortgages for the average sophisticated borrower.

The welfare effects of a financial education campaign that effectively halves the fraction of naive households are similarly heterogeneous. Households on average gain 658 euros per year (8% of the annual mortgage payment). Most of the welfare gain accrues to naive households who become sophistication thanks to the campaign (2,538 euros per year). The effect on rates makes sophisticated households lose on average (306 euros per year). Therefore, even before we take into account the cost of funding these policies, it emerges that they are not necessarily Pareto improving.

Unlike reducing the relevance of financial sophistication, enhancing the competitiveness of the market by easing customer attachment to their primary bank does not have redistributive effects, but generates substantial gains for both naive and sophisticated households. This indicates that equating lower financial sophistication with higher search frictions, as it is customarily done in the literature, can mislead the evaluation of the implications of different policies.

Interestingly, we show that even though banks use steering to their advantage, restricting such practice is not necessarily a good idea. We find that the success of such policy relies crucially on which choices naive households will make when left on their own. If naive households are more inclined to choose ARMs absent steering, then there is an optimal scope of restriction that benefits households on average. At the same time, if naive households' choices are tilted towards FRMs, then restrictions on steering result in significant losses to both naive and sophisticated households. This result stems from the fact that even though steering can distort the choice of naive borrowers, it also exposes them to information on mortgage types that they would not consider and yet could be suitable for them. Sophisticated households lose in both scenarios, because in the absence of steering, banks rely more on higher rates to balance their mortgage portfolios. It follows that simply prohibiting all forms of steering is too risky of a policy.

Our policy implications are of general relevance for steering in financial markets where individual heterogeneity and the complexity of financial products give scope for steering by intermediaries. Both in the case of mortgages and of other financial products like investment and retirement products, insurance policies, credit cards, etc, consumers face a choice between simpler, more basic, often default financial products and more complex products that potentially better fit their needs. Financial intermediaries, while more knowledgable about the optimal choice, may have preferences imperfectly aligned with their customers. Our analysis centers on banks' influence on the type of mortgage that households take. Steering could, however, also occur along other dimensions, such as maturity, loan amount, pre-payment options, negative amortization, interest only payments, etc, that are less relevant in the Italian market we study. Finally, it is important to emphasize that our analysis does not apply to predatory cases of steering where financial intermediaries deliberately take advantage of less sophisticated customers by selling them dominated financial products. In particular, our implication that a ban on steering might be a risky policy would not apply in that case.

From our results and methodology, we draw two broader lessons for steering in financial markets. First, steering could lead to an implicit transfer from naive to sophisticated households, and policies that mitigate the distortionary part of steering (such as financial education campaigns) would reduce this transfer, thus benefiting naive households but hurting sophisticated ones. Our methodology can be fruitfully applied to quantify the effects of steering on different groups of households in other markets for consumer financial products. Second, there are both benefits and costs to steering by intermediaries, and the structural approach is instrumental in determining whether these costs outweigh the benefits. We caution policy makers that simply banning all forms of steering might hurt consumers, particularly the naive consumers that such regulations are designed to protect.

Related Literature This study relates to several strands of literature. First, it relates to a large literature in households finance documenting that many households make suboptimal financial decisions due to the lack of sophistication, either reflecting limited knowledge and mistakes or behavioral biases (e.g., Campbell, 2006; Campbell, Jackson, Madrian, and Tufano, 2011; Gathergood, Mahoney, Stewart, and Weber, 2019) which financial intermediaries may exploit (see Guiso and Sodini, 2013; Gomes, Haliassos, and Ramadorai, forthcoming for reviews). Our study advances this literature by providing a structural estimate of the share of unsophisticated consumers and the correlation of naiveté and mobility in an important financial market. This way, we complement existing estimates based on surveys and reduced-form evidence.[7] Further, by simultaneously allowing for these sources of heterogeneity and banks' optimal response to them, our approach allows us not only to assess the welfare impact of different policies, but also to quantify their redistributive effects in the population of borrowers.[8]

Second, we contribute to the growing literature on financial advice (Ru and Schoar, 2017; Egan, Matvos, and Seru, 2019; Robles-Garcia, 2019; Egan, 2019; Foà, Gambacorta, Guiso, and Mistrulli, 2019; Bhattacharya, Illanes, and Padi, 2019). Robles-Garcia (2019)'s study of brokers' incentives to steer borrowers in the UK mortgage market is the closest to ours in this set. With respect to her paper, we abstract from the role of brokers (in part because their role in the Italian mortgage market is limited), but introduce naiveté/sophistication as another dimension of household heterogeneity, which is particularly relevant for financial transactions where complex products are often sold along with simpler, more familiar alternatives. Thus, we are able to study the heterogeneity of the effects of different policies for naive and sophisticated as well as attached/unattached households. One of our most notable results is that these policies often have redistributive effects and the presence of naive households provides a subsidy to sophisticated households. Further, existing literature (Robles-Garcia, 2019; Egan, 2019) tends to conflate lower financial sophistication and higher search frictions. By separating these two frictions,

[7]There is a large theoretical literature on financial advice that relies on the presence of both sophisticated and naive investors (see Inderst and Ottaviani, 2012 for a review). Our estimates point to a large fraction of households with limited financial sophistication and mobility which engage in high-stakes transactions, vindicating the main tenet of this literature.

[8]The presence of the implicit subsidy from naive households to sophisticated households has been established theoretically in Gabaix and Laibson, 2006.

our analysis reveals that they can have different policy implications. For example, a financial literacy campaign (leading to fewer naive households) has a redistributive effect, unlike policies that increase market competition (resulting in fewer attached households) which tend to benefit all groups of households.

More broadly, our evidence on the role of steering ties in with the empirical literature that studies the relevance of other dimensions of the interactions between borrowers and lenders in credit markets, such as information asymmetry (Einav, Jenkins, and Levin, 2012; Crawford, Pavanini, and Schivardi, 2018), inattention and inertia (Woodward and Hall, 2012), and bargaining (Allen, Clark, and Houde, 2019). Besides the focus on credit markets, we are linked to these studies by a common methodological approach, following a growing literature that applies tools developed in Industrial Organization to the analysis of financial markets (Cassola, Hortacsu, and Kastl, 2013; Aguirregabiria, Clark, and Wang, 2016; Egan, Hortacsu, and Matvos, 2017).

The rest of the paper is organized as follows. Section 2 describes the Italian mortgage market. Section 3 describes the data. Section 4 presents the model. Section 5 discusses the identification. Section 6 reports estimation results. Section 7 presents the results of the policy experiments. Section 8 concludes.

2 Institutional Background

In this section, we argue that the simple structure of the Italian mortgage market provides a suitable environment for quantifying the effect of steering in financial markets.[9] Despite Italy's high homeownership rate, the size of the household mortgage market is smaller than in other developed countries. Total household debt amounts to 63% of disposable income, compared to 95% in the euro area and 103% in the US. Based on data from SHIW, only 12% of Italian households have a mortgage, half of the average figure for households in the euro area. Yet, mortgages became increasingly popular in the 90s and early 2000. In our sample, nearly 250,000 mortgages with a maturity of 25 to 30 years are originated on average each year.

The most common mortgage types in Italy are an ARM where the bank charges a spread

[9] Online Appendix A provides a more extensive description.

over an underlying benchmark rate (usually the 1- or 3-month Euribor); and a FRM where the interest rate stays fixed for the whole length of the mortgage. They represent over 90% of mortgages issued in our sample.[10] Unlike in other countries, both types of loans are popular. In our data, just over 30% of the mortgages issued are FRMs, but in some years, FRMs represent nearly 70% of the mortgages issued. Non-interest components of mortgages, such as origination fees, discounts, periodic expenses, and pre-payment penalties, are small compared to interest rate payments and are the same for the two types of mortgages. Thus, rates fully capture the relative costs of these two mortgages. The Italian regulation sets the maximum loan-to-value ratio at 80%, and exceeding this threshold requires banks to hold more regulatory capital. The average LTV over our sample period lies between 63% and 70%.

Italian households often rely on information and mortgage advice provided by banks, which ensures that banks have plenty of opportunity to steer less sophisticated customers. We document in Online Appendix B a fairly low level of financial sophistication of Italian households. Based on the SHIW data, we construct an index of financial literacy that demonstrates that most households have difficulty interpreting basic financial information. Further, we present evidence from a survey administered in 2007 by a major Italian bank to a sample of its customers that banks are key providers of information to their customers (see Guiso, Sapienza, and Zingales, 2018). This survey asks how often the respondent resorts to various sources of information when making a financial decision. Banks are the leading source of information for customers: over 63% of customers consult them "sometimes", "often", or "very often". This is a 20 percentage points gap with the second most popular source, the broker.[11] Friends and relatives, and media outlets, such as newspapers, magazines, TV, Internet, etc., are used to gather information by 12% and 18% of the interviewees, respectively.

Banks' play a prominent role in information provision and advising of households about mortgage choices, because they are the main mortgage originators (80% of mortgages are sold directly at the branch according to Oliver Wyman, 2005) and they have a tight relationship

[10] During our sample period, Italian banks de facto do not originate non-standard mortgages (e.g., interest only, negative amortization, balloon payment) and issue few partially adjustable mortgages.

[11] This figure overstates the importance of brokers in providing mortgage information, because it includes sources of information about investment in stocks, retirement funds, insurance, etc., where the role of brokers is more prominent, and brokers often work for a company tightly linked to some bank (Oliver Wyman, 2003).

with their customers. The SHIW data show that over 80% of the households conduct all of their financial transactions at a single bank, and for nearly 60% of them, the relationship with their main bank has been ongoing for more than 10 years. Therefore, information and advice provided by the (loan officer of the) bank that issues the mortgage is the most easily accessible expert opinion for a household.[12]

The extent of trust in banks' advice in Italy indicates that it is informative and helpful to customers. However, there is also a wealth of anecdotal evidence from the Italian media reporting cases of banks presenting non-reliable information to their customers in order to steer their financial decisions, in particular, their mortgage choices.[13] Foà, Gambacorta, Guiso, and Mistrulli (2019) provide reduced form evidence of steering in the Italian mortgage market, validating our attempt to quantify its importance and the effect of policy actions in response to it. In Online Appendix E, we replicate their key finding in our sample, discuss their robustness, and use additional data sources to provide further evidence of steering.

Finally, we describe the strength and nature of banks' incentives to steer households. First, we compute for each bank in our sample the margin on ARMs (i.e., the spread between the bank's ARM rate and the 1-month Euribor) and the margin on FRMs (i.e., the spread between the bank's FRM rate and a 25-year interest rate swap) and calculate the impact on profits from moving all customers in each period to the more profitable mortgage type. The median increase in profits across banks and periods is 7%, a figure significant enough to make it appealing for banks to influence their customers' mortgage choices.

Second, Italian banks maintain significant exposure to interest rate risk, an important component of which comes from residential mortgages, which is only partially hedged with derivatives (Esposito, Nobili, and Ropele, 2015; Cerrone, Cocozza, Curcio, and Gianfrancesco, 2017; Hoffmann, Langfield, Pierobon, and Vuillemey, 2019).[14] In imperfect credit markets, banks have

[12]In our sample period, the market for online mortgages was still in its infancy. The largest distributor of online mortgages, MutuiOnline, reports that its market share in the mortgage market was 0.9% in 2005; 1.1% in 2006 and 1.9% in 2007.

[13]The Italian ombudsman dealing with financial disputes between customers and banks (Arbitro Bancario Finanziario) reports that during our sample period, over 70% of complaints were related to mortgage issues.

[14]Unlike in the US (Fuster and Vickery, 2015), Italian banks do not rely heavily on securitization and retain on their balance sheets most of the originated mortgages, which account for an important fraction of banks' assets (as of 2015, mortgages represented 10% of banks' total assets, Ciocchetta, Cornacchia, Felici, and Loberto, 2016). In Online Appendix A, we document that our emphasis on interest rate risk is justified, because banks do not

incentives to manage the maturity structure of their assets in order to minimize the risk of a maturity mismatch (Kashyap and Stein, 1995). In particular, supply factors, such as differences across banks in their costs of long-term financing or their share of deposit financing affect bank's preferences over assets of different maturities, such as FRMs and ARMs. Banks with higher costs of long-term borrowing or a lower deposit share are less willing to increase their exposure to interest rate risk through issuing too many FRMs and would prefer to issue ARMs instead. As shown in Table 1, the relative importance of different sources of financing varies substantially across banks. For large banking groups, deposits account for as little as a third of total liabilities. Given the higher volatility of bond funding compared to deposits, they may find themselves more exposed to the risk of a maturity mismatch. Other banks are primarily funded through deposits, suggesting that they can finance their loans with fewer concerns about fluctuations in the cost of their funding sources. Further, the spread between fixed and variable rate bank bonds varies substantially between banks in our sample: it averages 28 basis points but goes up to 100 basis points for banks in the top decile of the distribution. These differences shape banks' preferences towards issuing a higher/lower share of FRMs or ARMs. Therefore, banks have strong incentives to manage maturities on the asset side through both mortgage pricing and steering of unsophisticated customers.

3 Data

We use data from two administrative sources: the Italian Credit Register (CR) and the Survey on Loan Interest Rates (SLIR). Both datasets are maintained by the Bank of Italy. Credit Register collects information on loan exposures above the threshold of 75,000 euros originated by all Italian banks and foreign banks operating in Italy at any of their branches. It includes information on the type of loan, the loan size, the identity of the bank originating the loan and several characteristics of the borrower. We use aggregated data on the total number of fixed and adjustable rate mortgages issued in each quarter between 2005 and 2008 by each bank in each Italian province, a geographical unit roughly equivalent to a US county, which we adopt as

face significant default and renegotiation risks.

our definition of the consumer market. We focus on mortgages with maturities between 25 and 30 years. We also restrict attention to plain vanilla ARMs or FRMs. The final dataset includes information from nearly 1,000,000 mortgages.

We merge this information with data from SLIR on the average rate for the FRMs and ARMs originated in each bank-quarter-province triplet. A subset of 127 banks reports interest rate data to SLIR and are active in the mortgage market. This set includes all main banking groups active in Italy and covers more than 90 percent of the market (see Online Appendix D for additional details on sample construction). Some provinces are quite small and only a handful of mortgages were originated in a quarter. This results in missing data on the interest rate since the rate is reported only by banks that actually issued a mortgage in the province in the quarter. To alleviate this problem, we calculate interest rates for each bank-quarter as averages at the regional level, rather than at the province level.[15] This choice is unlikely to introduce significant distortions in our estimation of the supply side decisions, as most of the competitors faced by a bank are the same in all the provinces of a given region. Further, there is evidence that the rates are indeed set at the regional level: in 25% of the observations, a bank sets the exact same rate in all the provinces within a region, and conditional on observing differences in rates between provinces of the same region, the median deviation from the regional mean is 12 basis points for ARMs and 8 basis points for FRMs.

The main dataset is complemented by other ancillary sources of data. First, we merge the mortgage dataset with detailed supervisory data on bank characteristics and balance sheets. Second, we obtain information at the bank-year-province level on the share of deposits in the market held by each bank. Further, SHIW documents several characteristics of households' behavior in financial transactions. Table 1 displays summary statistics on our main data.

4 Model

Households A continuum of households of mass M_t indexed by h take up a mortgage in quarter t from one of N banks in the market. Each household has a *home bank,* which is the

[15] Regions are administrative entities formed by collections of provinces. There are 20 regions and 110 provinces in Italy (the number of provinces per region varies between 2 and 12).

Variable	*Obs.*	*Mean*	*Standard deviation*	*25th percentile*	*50th percentile*	*75th percentile*
Branch level variables						
FRM-ARM spread	13,747	0.54	0.63	0.23	0.54	0.84
FRM rate	13,747	5.47	0.62	5.17	5.58	5.91
ARM rate	13,747	4.63	0.87	3.80	4.66	5.36
FRM rate – Swap 25-yrs spread	13,747	1.16	0.47	0.99	1.16	1.32
ARM rate – Euribor 1-m spread	13,747	1.29	0.50	1.13	1.38	1.54
Number of mortgages	13,747	47.41	95.09	8	20	48
Prob. of setting the lowest ARM	13,747	0.12	0.16	0	0.06	0.20
Prob. of setting the lowest FRM	13,747	0.16	0.19	0	0.12	0.25
Share of deposit market	13,747	0.10	0.12	0.02	0.05	0.13
Share of mortgage market	13,747	0.10	0.09	0.03	0.06	0.13
Share of FRMs issued	13,747	0.37	0.34	0.03	0.27	0.67
Bank level variables						
Total assets	268	39,495	45,098	11,737	17,169	57,768
Deposits/Total assets	268	0.46	0.11	0.38	0.45	0.53
Bank bond spread	280	0.27	0.52	-0.07	0.28	0.64
Market variables						
Number of banks in the market	1,350	10.18	1.98	9	10	11

Table 1: **Summary Statistics**

Notes: The level of observation is branch-province-quarter for branch level statistics, bank-quarter for bank level variables and province-quarter for market level variables. The variables *Prob. of setting the lowest ARM* and *Prob. of setting the lowest FRM* measure the fraction of times in which a particular bank has set, respectively, the lowest adjustable and the lowest fixed rate in the market. *Share of deposit market* and *Share of mortgage market* are, respectively, the fraction of deposits and the fraction of mortgages represented by the bank in the province. *Share of FRMs issued* is the fraction of fixed rates mortgages over the total number of mortgages issued by a bank. The assets are in millions of euros.

default option for the household to do business with (e.g., a bank where it holds a primary checking account). Bank i is the home bank of household h in quarter t with probability p_{it}. A fraction $1 - \psi$ of households is *attached* to their home bank and they only choose mortgages offered by their home bank. The rest of households are *unattached* and can take a mortgage from any bank in the market. Attachment captures frictions, such as switching or search costs, that prevent households from choosing the best rate available in the market, which are common in the retail financial market (Woodward and Hall, 2012; Bhutta, Fuster, and Hizmo, 2018; Ater and Landsman, 2018), and are present in Italy as documented by Barone, Felici, and Pagnini (2011) and witnessed by the large dispersion in rates in our data (see Figure 19 in Online Appendix).

A fraction μ_a of attached households and a fraction μ_u of unattached households are *naive.* The rest of households are *sophisticated.* Given the objective of our study, this is the key dimension of household heterogeneity: naive households are susceptible to the bank's steering, whereas sophisticated households make their choices based only on their own knowledge and are immune to steering. We allow for $\mu_u \neq \mu_a$, introducing correlation between naiveté and attachment.

Naive and sophisticated households choose the bank and the mortgage type differently. It was shown empirically and theoretically (Campbell and Cocco, 2003; Koijen, Van Hemert, and Van Nieuwerburgh, 2009; Badarinza, Campbell, and Ramadorai, 2018) that the optimal choice of mortgage type is well approximated by the "spread rule:" a household should take an ARM if and only if

$$r_t^f(h) - r_t^a(h) \geq \delta(h), \tag{4.1}$$

where $r_t^f(h)$ and $r_t^a(h)$ are the lowest FRM and ARM rates, respectively, available to household h, which are the lowest market rates for unattached households and the rates in the home bank for attached households. Campbell and Cocco (2003) show that the spread rule approximates the optimal decision rule in a dynamic model that considers an extensive set of factors, such as wealth, income, real interest rate risk, prepayment option, household mobility, borrowing constraints, etc.[16] These factors enter the household's decision rule through the household-

[16]Similar optimality of the spread rule up to a first-order is also obtained in Koijen et al. (2009). In Online Appendix F, we provide a simple version of their model.

specific cutoff $\delta(h)$, which depends on household's risk aversion, exposure to various risks, beliefs about future inflation and rates, etc. Thus, all the individual heterogeneity affecting the optimal mortgage choice besides naiveté and attachment is reflected in the cutoff on FRM-ARM spread $\delta(h)$. We suppose that δ is normally distributed with mean μ_δ and variance σ_δ^2 and is independent from naiveté and attachment, and across households.

Accordingly, sophisticated households follow the spread rule (4.1) and are not affected by banks' steering. We suppose that naive households depart from the spread rule, and before steering takes place, they only consider a FRM, which is a much simpler and familiar option than an ARM.[17] It does not require the household to understand factors affecting the evolution of the benchmark EURIBOR rate and its exposure to these factors. In essence, with a FRM all the household needs to know is its fixed monthly payments. There is ample empirical evidence that indeed households with a lower degree of financial literacy are more likely to choose FRMs (Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff, 2010; Fornero, Monticone, and Trucchi, 2011; Gathergood and Weber, 2017; Albertazzi, Fringuellotti, and Ongena, 2018). In Online Appendix C, we analyze data on Italian mortgage searchers and show that borrowers with below college education are more likely to search for FRMs rather than ARMs. In Campbell and Cocco (2003)'s model that accounts for a rich set of factors of optimal mortgage choice, under various reasonable parametrizations, ARMs dominate FRMs. This result, coupled with dominance of FRMs in the US, suggests that many households must make suboptimal choices and be biased towards FRMs in their choices. Further, the FRM/ARM choice is analogous to the choice in retail investment between a more familiar and easy to understand bank deposit and more complex investment in the stock market. Under-participation in equities by less sophisticated households is well-documented (Calvet, Campbell, and Sodini, 2007), which again supports the assumption that naive households bias their choices towards simpler options (a FRM in our case).[18]

Naive unattached households become customers of the bank with the lowest FRM rate,

[17]This is consistent with the empirical evidence that households taking ARMs tend to underestimate or not fully understand the terms of the ARMs (see Bucks and Pence, 2008).

[18]Gennaioli, Shleifer, and Vishny (2015) build a theory capturing households' aversion to more complex products and how financial intermediaries can alleviate it. In Online Appendix F, we describe how this theory can be applied in our setup to justify our assumptions about the behavior of naive households.

	Unattached	Attached
Sophisticated	bank with the best fixed or adjustable rates best mortgage type given rates	home bank best mortgage type given rates
Naive	bank with the best fixed rate steered towards a mortgage type	home bank steered towards a mortgage type

Table 2: **Household Choices of the Bank and Mortgage Type**

ignoring ARM rates. Naive attached households become customers of their home bank. After they become customers of a certain bank, both unattached and attached naive households are susceptible to the bank's steering in their choice of mortgage type and they can be "convinced" to take a mortgage type different from the one that they intended to take initially (i.e., before being steered by the bank). Households' choices are summarized in Table 2.

Banks The manager of bank i maximizes in quarter t the following objective function

$$\underbrace{\left((s^a_{it}(1-x_{it})+s^f_{it}x_{it}-\lambda(x_{it}-\theta_{it})^2\right)}_{\text{net profit margin}}\times\underbrace{m_{it}}_{\text{customer base}}\times\underbrace{\bar{L}}_{\text{avg. mortgage size}}\times\underbrace{e^{-\beta r^f_{it}}}_{\text{penalty for excessive rates}},\tag{4.2}$$

where m_{it} is the mass of bank i's customers and x_{it} is the fraction of FRMs issued by bank i in quarter t. The first term in (4.2) reflects the net profit margin in basis points on one euro lent through mortgages, which is multiplied by the size of the bank's customer base m_{it} and the average mortgage size $\bar{L}$ to obtain the total profit from mortgages issued.[19] The last term $e^{-\beta r^f_{it}}, \beta > 0$, penalizes banks for offering very high FRM rates to their customers and captures in a reduced form the fact that excessive mortgage rates could turn away even attached customers to some outside option, e.g., renting.

The net profit margin represents the standard trade-off between risk and return in the port-

[19]We do not model explicitly the household's choice of the mortgage size. In Online Appendix F, we provide a model of the mortgage size choice in which the bank's profit per customer can indeed be decomposed into the product of the net profit margin and the average mortgage size.

folio optimization problem. The returns are represented by the spreads between the FRM/ARM rates and corresponding benchmarks that proxy the costs of providing a mortgage of a particular type. Specifically, s^a_{it} is the spread of the ARM rate over the one-month Euribor (r^{eurbr}_t) and s^f_{it} is the spread of the FRM rate over the 25-year swap rate (r^{swap25}_t). The one-month Euribor rate represents the cost of financing ARMs with short-term borrowing in the interbank market, and the 25-year swap rate represents the cost of financing FRMs by borrowing short-term and entering an interest rate swap contract. Figure 11 in Online Appendix documents, using data from one of the largest banks in Italy, that these are indeed relevant benchmarks.

Portfolio risk is associated with a maturity mismatch from issuing too many FRMs and is captured in a reduced form by the penalty term $\lambda(x_{it} - \theta_{it})^2$. Recent literature documents that banks maintain significant exposure to interest rate risk due to the limited use of derivative hedging or banks' relative efficiency in managing the maturity mismatch (Begenau, Piazzesi, and Schneider, 2015; Drechsler, Savov, and Schnabl, forthcoming; Rampini, Viswanathan, and Vuillemey, 2020; Gomez, Landier, Sraer, and Thesmar, forthcoming). We refer to θ_{it} as the bank's *cost-efficient fraction of FRMs*, which is the fraction of FRMs that bank i can issue without negatively affecting their net profit margins. This parameter is bank-quarter specific and represents the bank's current views on the future evolution of rates and inflation, its existing maturity mismatch, costs of long-term funding, etc. A composition x_{it} of the bank's mortgage portfolio deviating from θ_{it} leads to a reduction in the profit margin by $\lambda(x_{it} - \theta_{it})^2$ basis points, where parameter $\lambda > 0$ reflects how banks trade off portfolio risk and return. We are agnostic on the drivers of θ_{it}. Banks may want to issue more FRMs to do right by their own customers (for instance, if they think rates will go up in the future) or because of supply factors (e.g., their ability to borrow long-term at better terms). In Section 6, we use our estimates to provide evidence that the latter seems to be the case, suggesting that banks' steering may be distortive.

The timing in quarter t is as follows. First, each bank privately observes its θ_{it}, which is an i.i.d. draw across banks and quarters from a normal distribution with mean μ_θ and variance σ^2_θ truncated from below at 0 and from above at 1. All banks observe all the adjustable rate spreads of their competitors and simultaneously set spreads s^f_{it} for FRM rates over the 25-year swap rate. The assumption that ARM rates are determined outside of our model, and banks

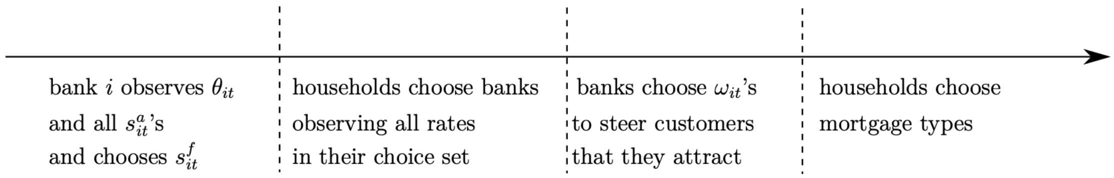


Figure 1: **Timeline**

compete only by setting spreads s^f_{it} is motivated by the common practice of rate setting in the industry.[20] Second, the customer base is determined: banks retain attached households for whom they are their home bank. In addition, the bank attracts unattached naive households if it posts the lowest fixed rate, and unattached sophisticated customers for whom one of its mortgages is the best option in the market. Third, given its customer base, each bank chooses to attempt to steer a fraction $1-\omega_{it}$ of its customers towards the ARM, where $\omega_{it} \in [0,1]$. Steering only affects a fraction $1-\omega_{it}$ of the naive customers of the bank, as sophisticated customers are not susceptible to it.

Our model captures all forms of steering hinging on the direct interaction between the customer and the bank employee, including both informative and distorted advice as well as targeted advertising in the form of leaflets that can be handed or mailed to them.[21] Such steering can both improve naive households' welfare through expansion of their choice sets and reduce it through distortions of their choices.

Equilibrium The solution concept is the perfect Bayesian equilibrium. The timeline is summarized in Figure 1.

We next derive the banks' optimality conditions that we use in estimation. Consider first a subgame, in which bank i sets spreads of ARM and FRM rates over benchmarks s^a_{it} and s^f_{it}, respectively, and attracted mass m_{it} of customers. Bank i steers a fraction $1-\omega_{it}$ of its customers to take the ARM, which affects only the choice of naive customers, while sophisticated customers ignore it and choose the mortgage type based on the spread rule. We denote by $\underline{x}_{it}$

[20] Figure 10 in Online Appendix documents that, for one of the largest banks in Italy, the ARM spread over the Euribor is held constant over long time intervals; whereas the spread of FRM rate over the swap rate adjusts at a much higher frequency. A similar pattern is obtained when we average rates over all the banks in our sample.

[21] We abstract from public ad campaigns and strategic application rejections, which are less relevant in the Italian mortgage market (see Foà, Gambacorta, Guiso, and Mistrulli (2019) and Online Appendix E).

and $\overline{x}_{it}$ respectively the minimal and maximal fractions of FRMs that can be attained through steering (by setting ω_{it} to 0 and 1, respectively). Thus, the choice of ω_{it} is equivalent to the direct choice of x_{it} to maximize (4.2) subject to $x_{it} \in [\underline{x}_{it}, \overline{x}_{it}]$. Because banks choose their steering policies after they set the rates and attract customers, bank i chooses its steering policy to maximize its net profit margins:

$$\max_{x_{it} \in [\underline{x}_{it}, \overline{x}_{it}]} s^a_{it}(1 - x_{it}) + s^f_{it} x_{it} - \lambda(x_{it} - \theta_{it})^2. \tag{4.3}$$

The optimal choice of x_{it} is given by:

$$x(\phi_{it}|\theta_{it}) = \max\left\{\min\left\{\theta_{it} + \tfrac{1}{2\lambda}\left(\phi_{it} - r^{swap25}_t + r^{eurbr}_t\right), \overline{x}_{it}\right\}, \underline{x}_{it}\right\}, \tag{4.4}$$

where we used $\phi_{it} = s^f_{it} + r^{swap25}_t - (s^a_{it} + r^{eurbr}_t)$ to substitute for s^f_{it}. The optimal steering policy is given by $\omega(\phi_{it}|\theta_{it}) = (x(\phi_{it}|\theta_{it}) - \underline{x}_{it}) / (\overline{x}_{it} - \underline{x}_{it})$. Given the optimal share of FRMs $x(\phi_{it}|\theta_{it})$, the bank's profit per customer equals

$$V(\phi_{it}|\theta_{it}) = \left(s^a_{it} + \left(\phi_{it} - r^{swap25}_t + r^{eurbr}_t\right) x(\phi_{it}|\theta_{it}) - \lambda\left(x(\phi_{it}|\theta_{it}) - \theta_{it}\right)^2\right) e^{-\beta(\phi_{it} + s^a_{it} + r^{eurbr}_t)}. \tag{4.5}$$

We now turn to optimal spread setting by banks. Given θ_{it} and the profile of ARM-Euribor spreads across banks, $\mathbf{s}_t \equiv \{s^a_{1t}, \ldots, s^a_{N_k t}\}$, bank i chooses ϕ_{it} to maximize

$$\int m_{it} V\left(\phi_{it}|\theta_{it}\right) dG_i\left(\underline{s}^f_{-it} \middle| \mathbf{s}_t\right), \tag{4.6}$$

where $G_i(\cdot|\mathbf{s}_t)$ is the distribution of $\underline{s}^f_{-it} \equiv \min_{j \neq i}\{s^f_{jt}\}$ given $\mathbf{s}_t$ and the equilibrium rate setting strategies of other banks (see Online Appendix F for a more explicit formula for (4.6)). Our model of competition among banks bears similarities to first-price auctions: the bank that posts the lowest FRM rate wins the auction and its reward is attracting unattached households.

5 Identification

Our identification strategy proceeds as follows. First, given the timing of choices (Figure 1), households choose banks before they are subject to steering. We use this fact to identify in the first stage demand parameters that govern those choices (namely, $\mu_u, \psi, \mu_\delta, \sigma_\delta$) from the data on market shares and rates posted as well as auxiliary data on household mobility across banks. Here, we crucially rely on the difference in choices of banks between naive unattached (who only pay attention to FRM rates) and sophisticated unattached households (who pay more/less attention to FRM vs ARM rates depending on their cutoff δ).

In the second stage, we use the data on banks' mortgage portfolios and rates posted together with the banks' optimality conditions for rates and steering to back out supply parameters and μ_a, which determines the extent to which banks can steer their customers. Thus, μ_a is identified from data on the mortgage portfolio composition and rates, while μ_u is identified from data on the banks' market shares and rates. By obtaining these two estimates, we can determine the correlation between naïveté and attachment.

5.1 Stage 1: Identification of Demand Parameters

We estimate parameters of the model in two steps. First, we focus on a set of parameters that we identify using households' choices on the bank where they take the mortgage. These are the fraction of unattached household (ψ); the fraction of naive among unattached households (μ_u); and the mean and variance of the cutoff for the ARM/FRM choice ($\mu_\delta, \sigma_\delta$). We refer to this subset of paramters as $\Omega^d = (\mu_u, \psi, \mu_\delta, \sigma_\delta)$. We identify demand parameters exploiting differences in the reaction of sophisticated and naive un-attached households to variation in rates. Since this amounts to estimating price elasticities, our strategy follows the classic approach of the demand estimation literature and relies only on data on rates and banks' market shares in the mortgage market.

For every quarter $t = 1, \ldots, T$ and province $j = 1, \ldots, J$, our data include: the set of banks actively issuing mortgages in the province, $i = 1, \ldots, N_j^d$;[22] the number of mortgages issued

[22] To avoid dealing with banks intermittently active in a market, we retain in our sample only banks issuing at least 2% of the mortgages in the market.

by every bank, $\mathbf{M}_{jt}^d = (M_{1jt}^d, \ldots, M_{N_j^d jt}^d)$; FRM rates posted by banks, $\mathbf{r}_{jt}^d = (r_{1jt}^f, \ldots, r_{N_j^d jt}^f)$; ARM-Euribor spreads of banks, $\mathbf{s}_{jt}^d = (s_{1jt}^a, \ldots, s_{N_j^d jt}^a)$; banks' shares in the province depositor market, $\mathbf{p}_{jt}^d = (p_{1jt}^d, \ldots, p_{N_j^d jt}^d)$. Superscript d signifies that variables are aggregated at the provincial level. Let $\underline{r}_{jt}^f \equiv \min_{i=1,\ldots,N_j^d} r_{ijt}^f$ and $\underline{s}_{jt}^a \equiv \min_{i=1,\ldots,N_j^d} s_{ijt}^a$. For $i = 1, \ldots, N_j^d$, the probability that a randomly drawn household takes a mortgage at bank i is given by

$$\begin{aligned}\ell_{ijt} =&(1-\psi)p_{ijt} + \psi\mu_u 1\{r_{ijt}^f = \underline{r}_{jt}^f\} + \psi(1-\mu_u)1\{s_{ijt}^a = \underline{s}_{jt}^a\}\Phi\left(\frac{\underline{r}_{jt}^f - \underline{s}_{jt}^a - r_t^{eurbr} - \mu_\delta}{\sigma_\delta}\right) \\ &+ \psi(1-\mu_u)1\{r_{ijt}^f = \underline{r}_{jt}^f\}\left(1 - \Phi\left(\frac{\underline{r}_{jt}^f - \underline{s}_{jt}^a - r_t^{eurbr} - \mu_\delta}{\sigma_\delta}\right)\right),\end{aligned} \tag{5.1}$$

where 1 is the indicator function and Φ is the cdf of the standard normal distribution. A household is attached and i is its home bank with probability $(1-\psi)p_{ijt}$. Since the identity of a household's home bank is not observed in our data, we use the bank's share in the province depositor market p_{ijt}^d as a proxy for p_{ijt}. A household is un-attached and naive with probability $\psi\mu_u$, and it takes a mortgage from bank i only if $r_{ijt}^f = \underline{r}_{jt}^f$. A household is un-attached and sophisticated with probability $\psi(1-\mu_u)$, and it takes a mortgage from bank i if and only if bank i offers the best mortgage for the household. The log-likelihood of the realization of issued mortgages, $\mathbf{M}_{jt}^d, j = 1, \ldots, J, t = 1 \ldots T$, equals up to a constant

$$L\left(\mathbf{M}_{jt}^d \middle| \Omega^d, \mathbf{r}_{jt}^d, \mathbf{s}_{jt}^d, \mathbf{p}_{jt}^d\right) = \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{N_j^d} M_{ijt}^d \ln \ell_{ijt}. \tag{5.2}$$

We complement our main data with microdata from the 2006 wave of SHIW that asks respondents to report whether they took a mortgage in the year and the length of the relationship with their main bank. Given that 80% of Italian households do business with only one bank and the mortgage is one of the most important financial decisions for households, we assume that new mortgage takers with short relationships with their main bank ("less than 2 years") changed bank when taking the mortgage. This auxiliary information on the number of households that take mortgages outside of their home bank helps the identification of ψ, because being unattached is a necessary condition to do that.[23] The likelihood that a household in province j

[23] SHIW has another wave in 2008, yet, the question on the length of the relationship with the main bank is not asked there. This may be significant, because in early 2007 the Bersani law voided or reduced refinanc-

and quarter t takes a mortgage outside its home bank is

$$\begin{aligned}\ell_{jt}^{SHIW} =&\psi\mu_u(1-p_{jt}^F)+\psi(1-\mu_u)\Phi\left(\frac{1}{\sigma_\delta}(\underline{r}_{jt}^f-\underline{s}_{jt}^a-r_t^{eurbr}-\mu_\delta)\right)(1-p_{jt}^A)+\\ &\psi(1-\mu_u)\left(1-\Phi\left(\frac{1}{\sigma_\delta}(\underline{r}_{jt}^f-\underline{s}_{jt}^a-r_t^{eurbr}-\mu_\delta)\right)\right)(1-p_{jt}^A),\end{aligned} \tag{5.3}$$

where p_{jt}^F and p_{jt}^A are the probabilities that the bank posting the lowest fixed rate and the lowest adjustable rate, respectively, is the home bank for a household. The SHIW data are at a yearly rather than quarterly frequency. Thus, for each province, we average the quarterly likelihood in (5.3) weighted by the total number of mortgages originated in the province-quarter to obtain the average yearly likelihood of observing a certain number of households taking mortgages outside their home bank ℓ_{j2006}^{SHIW}.

For $j=1,\ldots,J$, let M_{j2006} be the number of new mortgages issued in province j (according to the 2006 SHIW wave), and let S_{j2006} be the number of households that took their mortgage from a new bank. The log-likelihood of the realization $\mathbf{M}_{2006}^{SHIW}=(S_{j2006},M_{j2006},j=1,\ldots J)$ equals up to a constant to

$$L\left(\mathbf{M}_{2006}^{SHIW}\middle|\Omega^d,\mathbf{r}_{jt}^d,\mathbf{s}_{jt}^d,\mathbf{p}_{jt}^d\right)=\sum_{j=1}^{J}\left(S_{j2006}\ln\ell_{j2006}^{SHIW}+(M_{j2006}-S_{j2006})\ln(1-\ell_{j2006}^{SHIW})\right). \tag{5.4}$$

Given that SHIW is administered to a sample of about 8000 households selected to ensure the representativeness of the Italian population, we use weights provided by SHIW to project statistics calculated from the survey to the overall Italian population. Thus, (5.2) and (5.4) are on the same scale, and the aggregate likelihood equals

$$\mathcal{L}=L\left(\mathbf{M}_{jt}^d\middle|\Omega^d,\mathbf{r}_{jt}^d,\mathbf{s}_{jt}^d,\mathbf{p}_{jt}^d\right)+L\left(\mathbf{M}_{2006}^{SHIW}\middle|\Omega^1,\mathbf{r}_{jt}^d,\mathbf{s}_{jt}^d,\mathbf{p}_{jt}^d\right).$$

We maximize $\mathcal{L}$ over $\mu,\psi,\mu_\delta,\sigma_\delta$ to find estimates $\hat{\Omega}^d=(\hat{\mu},\hat{\psi},\hat{\mu}_\delta,\hat{\sigma}_\delta)$.

ing/prepayment fees, potentially increasing borrowers' willingness to shop for better mortgage rates. In Online Appendix G, we analyze this issue in depth and show that the reform did not have an immediate substantial effect on several auxiliary measures of household mobility. We argue that the reform had a slow start, and thus, should not have had a significant impact on customers' choices during our sample period.

Intuition The main source of identification of the fraction of un-attached households is SHIW data documenting directly the number of people taking mortgages outside their home bank. The fraction of naive unattached households is identified by exploiting differences in the elasticity of banks' market shares to the event that a bank posts the best fixed or the best adjustable rate in the market. This can be most clearly seen if we fix δ to be the same for all households. In this case, if for example $\underline{r}_{jt}^{f} - \left(\underline{s}_{jt}^{a} + r_{t}^{eurbr}\right) > \delta$, then all sophisticated un-attached households take the mortgage from the bank with the lowest ARM rate. If bank i posts the lowest fixed but not the lowest adjustable mortgage rate, then its market share increases by $\psi\mu_u$, because it attracts naive un-attached households. Instead, if bank i posts the lowest adjustable but not the lowest fixed mortgage rate, then its market share increases by $\psi(1-\mu_u)$, because it attracts sophisticated un-attached households. This way we can recover μ_u from the variation in market shares of the banks when the lowest adjustable and fixed rates are occasionally posted by different banks. In Table 1, we show that in our data there is substantial variation in the identity of the bank offering the best rates: The top decile for the fraction of times a bank offers the lowest rate is 0.36 for ARMs and 0.44 for FRMs.

Table 1 documents that in our data, the FRM-ARM spread varies enough that the fraction of sophisticated households who prefer FRMs to ARMs differs across time and markets. This variation allows us to identify the distribution of δ. The standard deviation of the FRM-ARM spread is 0.63 with an interquartile range of over 50 basis points.

So far, we only used the data on market shares and prices. These data identify the fraction of naive only among un-attached households, as their naiveté/sophistication is reflected in which bank they take their mortgage from. However, these data alone do not identify the fraction of naive among attached households, for which we need to exploit the data on the type of mortgage chosen and recover the steering strategy of the bank. Thus, we estimate μ_a together with supply parameters, which we do next.

5.2 Stage 2: Identification of Supply Parameters and μ_a

We now turn to the estimation of the cost of deviating from the cost-efficient fraction of FRMs issued (λ); the penalty for setting extreme rates for FRMs (β) and the cost-efficient fraction of FRMs to be issued for each bank-quarter pair (θs). The identification of these parameters exploits data on the type of mortgage chosen by the household (ARM vs FRM) and on the rates set by the banks for each type of mortgage. The same variables are also used to estimate the prevalence of naive households among attached customers (μ_a).

Denote $\Omega^s \equiv \{\lambda, \beta, \mu_a\}$. For every quarter $t = 1, \ldots, T$ and region $k = 1, \ldots, K$, our data include the set of banks actively issuing FRMs in the region, $i = 1, \ldots, N_k^s$;[24] the distribution of households taking mortgages at each bank, $\mathbf{M}_{kt}^s = (M_{1kt}^s, \ldots, M_{N_k^s kt}^s)$; the fraction of FRMs in the total number of mortgages issued by each bank, $\mathbf{x}_{kt} = (x_{1kt}, \ldots, x_{N_k^s kt})$; the FRM-ARM spreads posted by banks, $\boldsymbol{\phi}_{kt} = (\phi_{1kt}, \ldots, \phi_{N_k^s kt})$; the ARM-Euribor spreads of banks, $\mathbf{s}_{kt}^s = (s_{1kt}^a, \ldots, s_{N_k^s kt}^a)$; banks' shares in the regional depositor market, $\mathbf{p}_{kt}^s = (p_{1kt}^s, \ldots, p_{N_k^s kt}^s)$. Superscript s signifies that variables are aggregated at the regional level. The estimation procedure is as follows.

Step 1: For a given guess of Ω^s, we obtain estimates of the cost-efficient fraction of FRMs issued for each bank, which we denote by $\hat{\theta}(\Omega^s, \mathbf{x}_{kt}, \boldsymbol{\phi}_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s)$, by picking the θ_{ikt} that minimizes the discrepancy between the fraction of FRMs issued by a bank observed in the data and the fraction predicted by the model

$$\left(x_{ikt} - \max\left\{\min\left\{\theta_{ikt} + \tfrac{1}{2\lambda}\left(\phi_{it} - r_t^{swap25} + r_t^{eurbr}\right), \overline{x}_{ikt}\right\}, \underline{x}_{ikt}\right\}\right)^2. \tag{5.5}$$

When the observed fraction lies below the lowest ($x_{ikt} < \underline{x}_{ikt}$) or above the highest ($x_{ikt} > \overline{x}_{ikt}$) fraction achievable by the bank according to the model, there is a range of $\hat{\theta}_{ikt}$ that minimizes expression (5.5). To obtain an estimate of θ for those cases, we estimate the parameters μ_θ and σ_θ of the distribution of θ by maximizing the likelihood of the observed fraction of FRMs issued (see Online Appendix F for the likelihood function). Then, we use the estimated distribution of θs to impute $\hat{\theta}_{ikt} = \mathbb{E}[\theta | \theta \leq \underline{x}_{ikt} - (\phi_{it} - r_t^{swap25} + r_t^{eurbr})/(2\lambda)]$ when the bank-specific lower bound is hit and $\hat{\theta}_{ikt} = \mathbb{E}[\theta | \theta \geq \overline{x}_{ikt} - (\phi_{it} - r_t^{swap25} + r_t^{eurbr})/(2\lambda)]$ for observations at the upper bound.

Step 2: Conditional on $\theta_{ikt}, \boldsymbol{\phi}_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s$ and parameters Ω^s, we can compute the predicted

[24] Since we need variation in the FRM-ARM spread, we only consider banks that are regularly active in issuing FRMs and hold a market share of at least 1% in the FRM segment in the market.

share of FRMs from equation (4.4), which we denote by $\hat{x}(\theta_{ikt}|\Omega^s, \boldsymbol{\phi}_{kt}, \mathbf{s}^s_{kt}, \mathbf{p}^s_{kt})$. We then compute the predicted FRM-ARM spread, $\hat{\phi}(\theta_{ikt}|\Omega^s, \mathbf{s}^s_{kt}, \mathbf{p}^s_{kt})$, from maximizing equation (4.6). In order to do so, we need an estimate of the distribution of the minimum of $N^s_k - 1$ FRM rates for each region, $\hat{G}_k(\cdot)$. Following the auction literature (Athey and Haile, 2007), we use the observed rates to obtain the kernel density estimator for the regional distribution of FRM rates and an estimate of the first-order statistic of this distribution for each region k.[25]

Step 3: Define $\hat{\theta}_{ikt}(\Omega^s) \equiv \hat{\theta}(\Omega^s, \mathbf{x}_{kt}, \boldsymbol{\phi}_{kt}, \mathbf{s}^s_{kt}, \mathbf{p}^s_{kt})$, $\hat{x}_{ikt}(\theta_{ikt}, \Omega^s) \equiv \hat{x}(\theta_{ikt}|\Omega^s, \boldsymbol{\phi}_{kt}, \mathbf{s}^s_{kt}, \mathbf{p}^s_{kt})$, and $\hat{\phi}_{ikt}(\theta_{ikt}, \Omega^s) \equiv \hat{\phi}(\theta_{ikt}|\Omega^s, \mathbf{s}^s_{kt}, \mathbf{p}^s_{kt})$. We find estimates $\hat{\Omega}^s = (\hat{\lambda}, \hat{\beta}, \hat{\mu}_a)$ that minimize the discrepancies between the fractions of FRMs issued and spreads set by banks as predicted by our model and observed in the data:

$$\frac{1}{\mathrm{Var}(x_{ikt})} \sum_{i,k,t} \left(\hat{x}_{ikt}(\hat{\theta}_{ikt}(\Omega^s), \Omega^s) - x_{ikt} \right)^2 + \frac{1}{\mathrm{Var}(\phi_{ikt})} \sum_{i,k,t} \left(\hat{\phi}_{ikt}(\hat{\theta}_{ikt}(\Omega^s), \Omega^s) - \phi_{ikt} \right)^2 ,$$

We adjust the objective function so that the importance of matching a particular moment is inversely proportional to its volatility.

Intuition Recall that β captures in reduced form decreasing demand for mortgages with respect to rates, thus, it is largerly determined by the level of rates.

Parameter λ captures how banks trade off the risk and return of their mortgage portfolios. If λ were close to zero, banks would set rates and steer customers to maximize returns, which given large estimates of μ_a and μ_u would imply mortgage portfolios close to the corners (100% FRMs or 100% ARMs). Hence, the identification of λ is given by the shape of the portfolio of mortgages originated from the banks in our sample (especially the amount of mass in the tails). The fact that in our data most banks have a balanced portfolio of mortgages naturally leads to an estimate of λ away from 0, indicating a non-trivial trade-off between risk and return in mortgage portfolios. The identification of μ_a, instead, is obtained using the variation in the

[25] The banks' value function involves such a distribution conditional on the entire vector of ARM-Euribor spreads posted in the market, i.e., $G_{ik}(\cdot|\mathbf{s}^s_{kt})$. This requirement is data intensive because it implies estimating a different function for each combination of adjustable rates posted by banks active in the market. We exploit the fact that, as shown in Figure 10 in Online Appendix, the ARM-Euribor spreads are fairly persistent and proxy the conditional distribution with the unconditional one.

FRM shares in banks' mortgage portfolios.

Whereas λ was inferred by the shape of the distribution of the optimal porfolio of mortgages issued, the estimate of μ_a is informed by the location of this distribution. Given the estimate of the distribution of δ and rates set by each bank, we can predict the fraction of FRMs issued if all its attached customers were sophisticated. Then, μ_a is identified by the extent to which this prediction deviates from the actual share of FRMs issued by banks.

Finally, we identify the unobserved cost-efficient fraction of FRMs for each bank-market-quarter exploiting the fact that the model can map the realized fraction of FRMs issued by a bank in a quarter into the underlying value of θ. Assuming that customers preferences over the type of mortgage, conditional on the characteristics of the contract, do not change significantly during our sample span ensures that the variation in the realized fraction of FRMs issued reflects swings in the preferences of banks and not in those of the customers.[26]

6 Estimation Results

Demand Estimates Several facts emerge from demand estimates (Table 3). First, there is a limited fraction of unattached households (8.8%). This resonates with the extreme inertia in the deposit market (Bhutta, Fuster, and Hizmo, 2018; Ater and Landsman, 2018) and suggests substantial search and switching frictions in the Italian mortgage market, which are further witnessed by the significant within-market dispersion in mortgage rates across banks (see Figure 9 in Online Appendix). Second, the average fraction of naive households is large (60.5%), which is consistent with the survey-based measures of sophistication of Italian households presented in Online Appendix B. This evidence points to a very low level of basic financial knowledge by Italian households, providing ample opportunity for banks to steer customers.

Third, attachment is positively correlated with naiveté. 61.7% of the attached households are estimated to be naive; whereas the fraction of naive unattached households is 47.8%. This suggests that sophisticated borrowers are (i) more likely to be aware of potential gains from shopping around, and thus, more likely to search; (ii) more likely to secure a loan in a bank

[26] We provide evidence supporting the stationarity of customers preferences for the mortgage type in Online Appendix H.

	Demand					*Supply*	
Parameter	μ_u	μ_a	ψ	μ_δ	σ_δ	λ	β
Estimate	0.478 (0.006)	0.617 (0.024)	0.088 (0.001)	−0.683 (0.077)	0.894 (0.047)	3.192 (0.994)	0.519 (0.028)

Table 3: **Estimates of the Parameters**

Notes: Standard errors estimated from 200 bootstrap replications are in parentheses.

where they have not been customers before, due to the positive correlation between sophistication and other characteristics that impact credit rating positively. In Online Appendix I, we use data from a survey of customers of a large Italian bank to construct proxies of attachment and naiveté, and confirm strong positive correlation between these two characteristics.

The main implication of these estimates is that banks have enough scope to use both pricing and steering in order to manage the maturity risk of their mortgage portfolios. Significant market power allows them to use relative pricing in order to discourage sophisticated customers from taking a certain mortgage type without losing them to a competitor. In addition, they can steer a significant share of naive customers in order to affect the maturity of mortgages at origination, and hence, reduce the exposure to interest rate risk. This result complements recent findings that banks use their market power over depositors in order to manage the maturity of their liabilities (Drechsler, Savov, and Schnabl, forthcoming) by showing that banks also have scope to do so on the asset side.

Further, the estimate of the distribution of the optimal spread cut-off δ for sophisticated households indicates that ARMs are on average a better option in the market. This result is in line with Campbell and Cocco, 2003's finding that when choosing a mortgage optimally, ARMs tend to dominate FRMs. At the same time, Figure 12 in Online Appendix shows that the estimated distribution of δ has substantial overlap with the empirical distribution of the FRM-ARM spread in our data. This indicates that sophisticated households following the spread rule choose both types of mortgages.

Supply Estimates The key object estimated on the supply side is the distribution of time-varying and bank-specific cost-efficient fractions of FRMs, θs, displayed in Figure 2. It is fairly

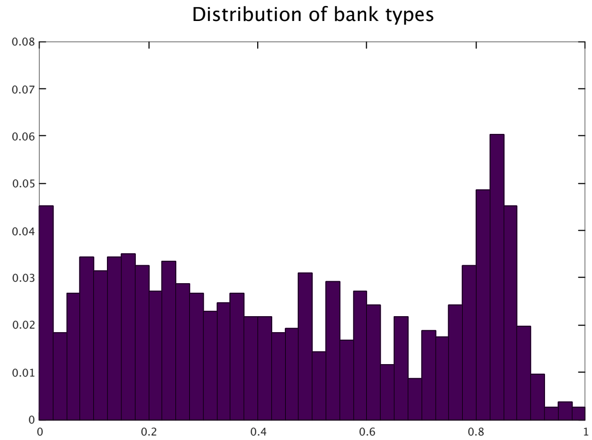


Figure 2: **Histogram of Estimated θs**

dispersed, with a slight concentration of mass around 0.1 and 0.8, likely due to the fact that some banks in certain quarters specialize in issuing a particular mortgage type.

The parameter θ is the key determinant of a bank's rate setting and steering policies. Our interpretation is that it reflects the bank's risk of maturity mistmatch and it should be affected by the bank's structure of liabilities and costs of financing. Hence, bank's efforts to issue a fraction of FRMs close to its θ can be read as intent to steer customers toward the product the bank prefers to sell. Such interpretation is consistent with the reduced form evidence in Foà, Gambacorta, Guiso, and Mistrulli (2019).

Here, we exploit our estimates of the bank θs to provide additional evidence consistent with steering. We regress θs on the bank bond spread, which is the difference between the rate of long- and short-term bonds issued by the bank.[27] We focus on this measure, because it varies often and it is outside the control of the bank (as banks are mostly price takers in the bond market).

In Table 4, we show that controlling for time and bank fixed effects, a higher level of bond spread is associated with a lower cost-effective fraction of FRMs issued.[28] Banks in our sample

[27] Since supply factors listed in the balance sheets vary only at the bank and not at the branch level, we average all the θs belonging to branches of the same bank in a given quarter weighting them by the total number of mortgages issued to obtain θ_{it}, the average cost-efficient share of mortgages for bank i in quarter t.

[28] While we focus in this exercise on funding costs as determinants of banks' preferences towards a particular mix of FRMs/ARMs, these preferences can also be affected by other determinants. For instance, it is consistent with our model that θ partially reflects banks' reputation concerns. Banks may prefer to avoid too extreme steering for fear of customer backslash. In this case, our estimated θ would reflect the net effect on the preferred FRM

Variables	*All sample*	*Deposit/ Liabilities < 75 pctile*	*Deposit/ Liabilities < 50 pctile*	*Deposit/ Liabilities < 25 pctile*
Bank bond spread	-0.051^{*} (0.026)	-0.068^{**} (0.030)	-0.074^{**} (0.034)	-0.108^{*} (0.058)
Observations	762	521	386	202
R-squared	0.72	0.71	0.70	0.67

Table 4: **Correlation between θ and Supply Factors**

Notes: An observation is a bank-quarter pair. All the specifications include a full set of year-quarter fixed effects and bank fixed effects. Standard errors (in parenthesis) are clustered at the bank level. Significance level: ***=1 percent, **=5 percent, *=10 percent.

significantly differ in their reliance on external funding and this could impact the extent to which the cost of financing influences their goals in terms of how many FRMs to issue. Therefore, we repeat the exercise, focusing on subsamples with different deposits-to-liabilities ratios. It consistently emerges that when it is more costly for a bank to finance itself through fixed rate bonds, it will be less keen on issuing FRMs, because it finds it expensive to match them with fixed rate liabilities. As our model predicts, such banks would steer their customers towards ARMs.

Finally, to interpret the estimate of λ in Table 3, we take the net profit margin in equation (4.2) as a point of reference. For the median bank in our data, the loss due to the deviation from the cost-efficient fraction of FRMs issued represents 1.8% of its margin per euro lent. The distribution of such costs has a fat right tail: banks with large deviations from their cost-efficient share of FRMs suffer significant reductions in their margins.

7 Policy Experiments

In this section, we quantify the impact of steering on households' welfare and assess the welfare effect of different policies restricting banks' ability to distort households' choices through

share due to balance sheet motives and that dictated by reputation concerns. Similarly, we can assume that our estimated θs are also net of other monetary costs of steering (e.g., incentives to loan officers).

steering. We use our estimates to simulate a population of customers equal to the number of mortgages issued in our data and compute banks' responses to various policies. We calculate the consumer surplus induced by counterfactual exercises on the sample of simulated households (see Online Appendix F for details). In doing so, we suppose that the distribution of the optimal cutoff δ is the same for naive and sophisticated households. We also assume that banks steer their customers to different products minimizing the welfare loss caused by steering.[29] This assumption captures in reduced form potential benefits to banks from customer satisfaction with the product sold, e.g., due to customer loyalty or increased trust, which in turn, allows banks to sell other financial products to their customers more easily.

7.1 Quantifying the Cost of Steering

We first quantify the welfare cost of steering. To do so, we consider the effect of forcing banks to recommend to their customers the best mortgage type for them. This means that banks make naive households follow the spread rule and have to rely solely on pricing to manage their mortgage portfolios.[30] In this exercise, every household takes the "right" mortgage and the average welfare gain is large: 1,350 euros per capita per year (see Table 5). This is equivalent to 16% of the total amount (principal and interest) a household would have to repay in a year for a 125,000 euros mortgage at the average FRM rate in our data (5.6%).[31] Interestingly, not all households gain. While naive households benefit the most, gaining 2,430 euros per year each, sophisticated households lose 303 euros per year.[32] Further, attached households gain on average 1,549 per year, while unattached households lose 703 euros per year.

Whereas the effect for naive households comes mostly from them making better choices, the losses for sophisticated households are due to the change of FRM rates by banks. When banks can opportunistically steer their customers, they have incentives to lower FRM rates, as this

[29]In our model, banks are indifferent between which households get a mortgage of a particular type as long as the mortgage portfolio composition stays the same, which however matters for welfare computation.

[30]Note that the considerations weighed in the previous section about the behavior of the naive households in the absence of steering do not impact the results of this counterfactual and of those in the following sections. Therefore, we do not need to specify a value for α to perform the calculations.

[31]This total amount paid in a year equals 8,616 euros and is computed using the mortgage calculator http://www.mutuionline.it/guide-mutui/calcolo-rata-mutuo.asp.

[32]The gain for naive households from picking the optimal type of mortgage is comparable to the figures reported in Campbell and Cocco (2003).

	Undistorted Advice	Financial Literacy Campaign	Increased competition
All	1,350	658	578
Sophisticated	-303	stay sophisticated: -306	361
Naive	2,430	stay naive: 38 turn sophisticated: 2,538	720
Attached	1,549	731	stay attached: 290 turn unattached: 3,766
Unattached	-703	-99	stay unattached: 67

Table 5: **Welfare Effect of Undistorted Advice, Financial Literacy, and Competition**

Notes: The table reports the policy effect on consumer welfare as changes in the certainty equivalent in euros per household per year. Positive numbers correspond to gains; negative to losses. Reported gains/losses are averaged over 100 simulations of the population of 527,504 households.

allows them to attract unattached households. Doing so is relatively cheap, as banks have the option of steering their naive clients to ARMs. This is no longer an option when banks are obliged to provide undistorted advice to their clients. In this case, setting a low FRM rate exposes the bank to the risk of attracting too many customers who will end up with FRMs. To prevent this, banks with low θs set FRM rates sufficiently high to avoid attracting unattached households. This effectively reduces the competition among banks for unattached households, and as a result, there are fewer low FRM rates in the market. In fact, replacing steering with undistorted advice, increases the average FRM rate on mortgages taken by unattached households from 3,86% to 4,25%. Because of that, unattached households suffer an average loss of 703 euros per year. The gain of attached households is explained by the strong positive correlation between naiveté and attachment, and large gains from the policy to the former group.

7.2 Redistributive Effect of Financial Literacy Campaign

Arguably, removing distortionary steering is not easy to implement in practice. A more practical policy is a financial literacy campaign aimed at increasing knowledge of the basic factors that should be taken into account when choosing the type of mortgage. We next assess the impact of a campaign that halves the share of naive households in the population.[33] An average household experiences a gain of 658 euros per year, which is 8% of the average mortgage payment. The large share of the welfare gains accrue to households who were naive and become sophisticated due to the financial literacy campaign: they gain on average 2,538 euros per year (or 30% of the average mortgage payment). At the same time, naive households who remain naive gain merely 38 euros per year and sophisticated households lose on average 306 euros per year (see Table 5).The nature of these losses and gains is similar to that of undistorted advice. Naive households who become sophisticated gain because of their ability to choose the proper mortgage type.

The effect of the policy on rates is complex, as it affects the whole distribution of rates. Since banks' ability to steer naive customers is curtailed, they compete less agressively for unattached households. As a result, the average FRM rate paid by unattached households increases from 3.86% to 4.18%. At the same time, because banks have to rely more on rates rather than steering in attaining the optimal mortgage portfolio, banks that are more keen on issuing FRMs will lower their FRM rates after the policy change. At our estimates, this results in a decrease of the average FRM rate paid from 5.05% to 4.82%. Because sophisticated households are more likely to be unattached, they lose from the policy change, while the naive households who remain naive experience a slight gain.

To summarize, enabling better choices of mortgage type either through enforcing undistorted advice by banks or improving financial literacy of households brings large benefits to naive households that are directly affected by the policy, but might lead to losses to other groups of households due to reduced competitiveness in the mortgage market. Therefore, the presence of distortionary steering leads to a subsidy from naive to sophisticated households, and the financial literacy campaign reduces this subsidy, and hence, has a redistributive effect.

[33]Whereas a financial literacy intervention has a very similar flavor to a policy forcing banks to provide undistorted advice, these policies are not exactly identical. When receiving undistorted advice, naive customers will pick the "right" mortgage for them, but they will still be served by a bank chosen on the basis of the mortgage type they were seeking before being advised. A financial literacy campaign affects also the search stage of our model: households shop for the bank best suited to offer the mortgage type which is best for them.

7.3 Mortgage Market Competition

A novelty of our analysis is that we explicitly consider the role of financial sophistication of the borrowers and distinguish it from market frictions represented by ψ. It is interesting to contrast the effect of financial literacy to that of increased competition due, for instance, to the advent of rate comparison web sites or more active brokerage services (Robles-Garcia, 2019). To simulate a toughening of the competitive environment, we double the fraction of unattached households from 8.8% to 17.6%.[34]

We observe an average gain of 578 euros per year per capita (7% of the average mortgage payment). As we see in Table 5, both naive and sophisticated households gain with the former group gaining the most (720 euros per year) due to the fact that naive households are more likely to be unattached, and hence, more likely to be directly affected by the policy. However, the gain of sophisticated households is also substantial (361 euros per year). The increase in competition reduces the average FRM rate on a mortgage taken from 5.05% to 4.81%, fueling the welfare gains we observe. Naturally, attached households who become unattached gain the most from this decline in rates (3,766 euros per year). Yet, both attached households and unattached households who remain unattached also gain on average 290 and 67 euros per year, respectively.

This exercise stresses that acting on the competitiveness of the market has different welfare consequences from reducing distortions induced by intermediation through steering. While the former tends to benefit (to a different extent) all groups of households, the latter has winners and losers. This insight is relevant because the literature routinely uses measures of market frictions (such as search costs) as a proxy for the level of financial sophistication. Our empirical results confirm that the search friction and naivete are indeed closely related. However, our results indicate that conflating the effect of financial education of the borrowers with that of market characteristics affecting competitiveness ignores the redistributive dimension of the policy. This insight is especially relevant when considering the markets for complex financial products.

[34] Given that naiveté and attachment are correlated, we keep the fraction of naive households in the population constant by converting a fraction $\psi/(1-\psi)$ of attached households into unattached without changing their sophistication.

	All	Sophisticated	Naive	Unattached	Attached
Max Gains	813	171	1,335	1	893
Max Losses	4,436	939	6,720	4,090	4,470

Table 6: **Maximal Average Gains and Losses from Restricting Steering to Different Groups of Households**

7.4 Restricting Steering

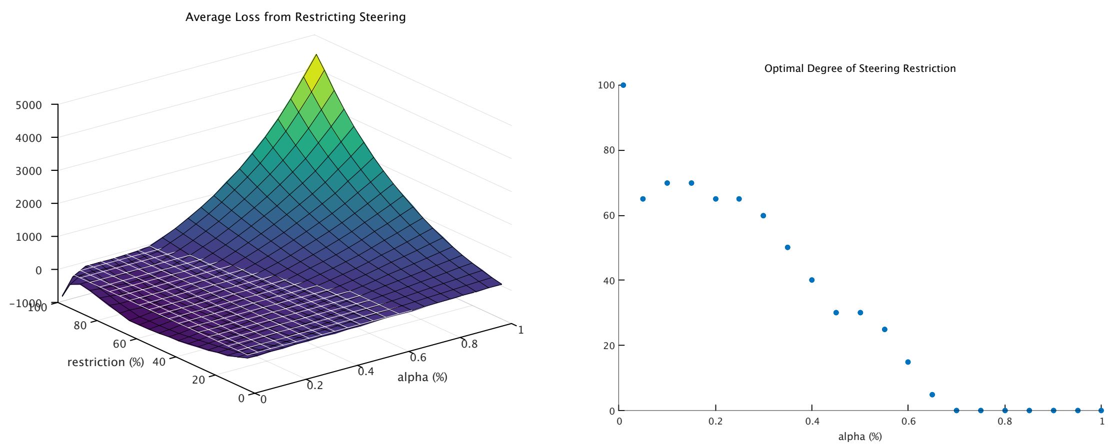
Finally, we investigate the effect of reducing banks' ability to steer their customers. This exercise captures policies, such as increased regulators' oversight, advent of online banking, tightening of fiduciary standards, etc., which effectively limit the scope for distorted advice and shrouding in direct one-on-one interactions between bank employees and clients. We consider an array of policies curbing steering with the different degree of restrictions on steering ranging from 0% (no restrictions) to 100% (complete ban of steering).

The effect of restricting steering depends on mortgage choices of naive households in the absence of steering.[35] We assume that in the absence of banks' steering, a fraction α of naive households chooses a FRM and the remaining $1-\alpha$ fraction chooses ARM. These choices arise from either intrinsic preferences of households or are affected by advice obtained from other sources, such as media, friends, family, etc.[36]

Figure 3 reports the average losses in euros per household per year for each $\alpha \in [0, 1]$ and degree of steering restriction. Several findings emerge from our analysis. First, we find that significant gains from the policy are possible only if naive households are more likely to choose ARMs in the absence of steering. The maximal average gain of 813 euros per year is attained when all naive households choose ARMs and steering is completely banned. In comparison, when 60% of naive households choose ARMs ($\alpha = 40\%$), a complete steering ban results in an average loss of 142 euros per year, and the optimal steering restriction of 40% results in an

[35] As in the baseline model, sophisticated borrowers continue following the spread rule and naive borrowers, who are steered by the bank, follow the suggestion given to them by the bank.

[36] Because naive households consult other information sources *after* they have chosen the bank, this counterfactual exercise does not require re-estimation of the model for each scenario. We use estimates in Section 6 for all scenarios.



(a) (b)

Figure 3: **Average Loss from Restricting Steering and Optimal Restriction**

Notes: Panel (a) reports the policy effect on consumer welfare as changes in the certainty equivalent in euros per household per year for the average household. Panel (b) depicts the optimal level of restriction to banks' stering ability (i.e. the level of restriction that maximizes welfare) for each probability α that naive households choose FRMs absent steering. Reported gains/losses are averaged over 100 simulations of a population of 527,504 households. The degree at which steering is restricted varies from 5% (i.e., banks are still able to steer 95% of their customers) to 100% (i.e., banks are unable to steer any of their customers). The probability α that naive households choose a FRM varies from 0% to 100%. The vertical axis measures welfare losses: positive numbers indicate that the reform reduced the certainty equivalent, negative numbers that it raised it. Lighter colors correspond to larger losses; darker colors correspond to smaller losses (or larger gains, if the loss is negative). The white transparent grid indicates the level at which the policy has no impact on welfare (i.e., losses are equal to zero).

average gain of 187 euros per year.

Second, large losses from the policy occur when naive households are more likely to choose FRMs in the absence of steering. Importantly, as can be seen from Figure 3a, the potential welfare losses from the steering restriction are generally much more significant in size than the potential gains. These losses are more severe when the scope of steering restrictions is larger. For example, the maximal average loss from steering ban of 4,436 euros per year occurs when all naive households choose FRMs in the absence of steering. The loss equals to 2,353 euros per year when $\alpha = 80\%$. However, losses are substantial even when the bias towards FRMs is less extreme. For example, when 60% of naive households choose FRMs ($\alpha = 60\%$), a complete steering ban results in an average loss of 1,003 euros per year, while a 50% restriction of steering leads to an average loss of 212 euros per year.

The losses of naive households arise because the information value of steering outweighs the costs of distortion, despite steering being provided in the banks' self interest. Specifically, while naive households are occasionally steered to a suboptimal choice, banks also inform them about an alternative, potentially more beneficial product, which they did not consider at first. Further, banks try to minimize the distortionary effect of their steering by encouraging to switch to an alternative product households to whom this is beneficial or least costly. This advantage of steering is not present, when naive households choose their mortgage randomly.

Third, there are potentially significant redistributive consequences from restricting steering. Figures (4a) and (4b) decompose the aggregate welfare effect into the effect on sophisticated and naive households. For naive households, the general pattern commented for aggregate effects still holds: strong preferences for FRMs and stricter regulation of steering combine to give the policy a negative welfare effect. Instead, strong preference for ARMs contribute to the policy raising naive households' welfare. The number of parameter combinations for which the welfare effect is positive is larger for naive households than for the average household, but it is still true that potential welfare losses are much more significant in size than potential gains.

The results for sophisticated households are much less nuanced: they incur welfare losses from the enactment of a policy restricting steering for nearly any combination of the parameters governing the strength of the policy and the preferences of naive households. These large losses

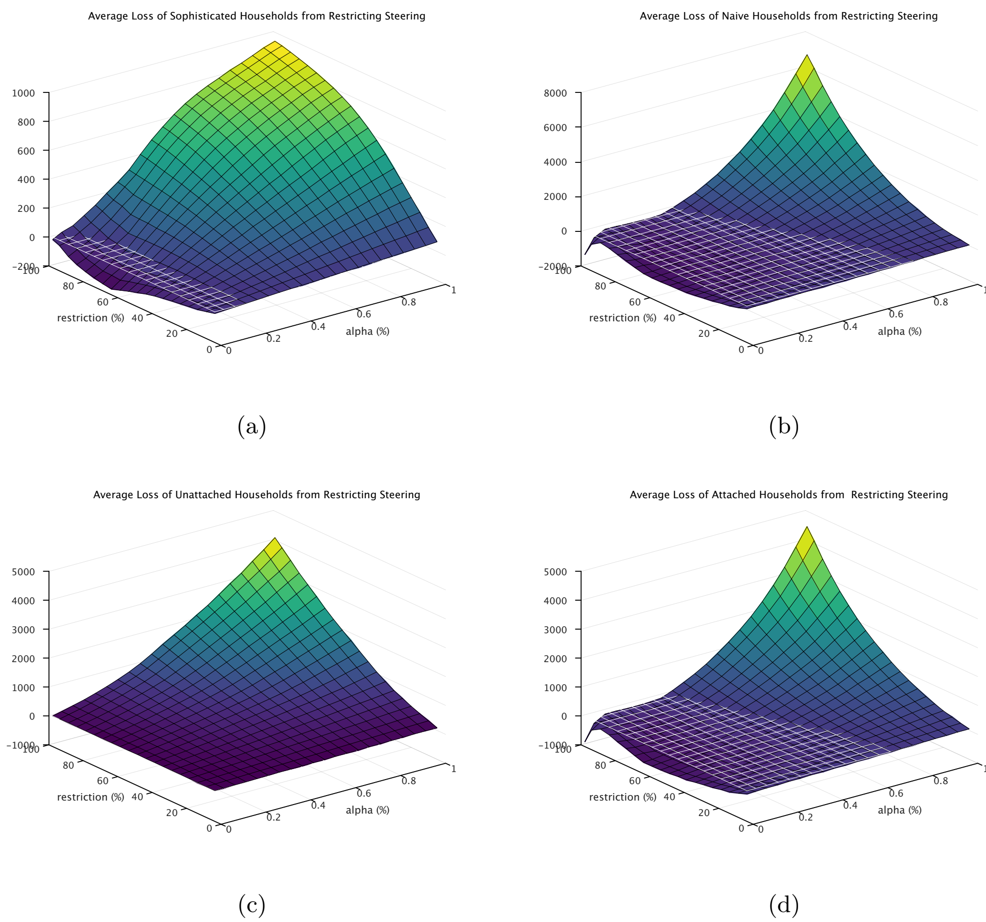


Figure 4: **Average Loss from Restricting Steering to Different Groups of Households**

Notes: Panels (a)-(d) report the policy effect on consumer welfare as changes in the certainty equivalent in euros per household per year for subgroups of the population. Reported gains/losses are averaged over 100 simulations of a population of 527,504 households. The degree at which steering is restricted varies from 5% (i.e., banks are still able to steer 95% of their customers) to 100% (i.e., banks are unable to steer any of their customers). The probability α that naive households choose a FRM varies from 0% to 100%. The vertical axis measures welfare losses: positive numbers indicate that the reform reduced the certainty equivalent, negative numbers that it raised it. Lighter colors correspond to larger losses; darker colors correspond to smaller losses (or larger gains, if the loss is negative). The white transparent grid indicates the level at which the policy has no impact on welfare (i.e., losses are equal to zero).

are explained by the change in pricing of mortgages. When banks are restricted in their ability to steer their customers, they are more cautious to post low FRM rates that can attract many customers creating costly imbalances in their mortgage portfolios. This results in an increase in the lowest FRM market rates in response to the policy. This fact explains the welfare losses of unattached households under any combination of parameters (Figure 4c).

Our results indicate that restricting steering, while potentially beneficial in some circumstances, can also lead to large welfare losses. The losses are substantial, when naive households' choices are tilted to FRMs and steering is severely restricted. In Online Appendix C, we analyze online searchers for mortgages from the leading Italian mortgage comparison website, MutuiOnline.it. Web searches for mortgages are more likely to reflect the true preferences of the households, since they are usually performed before any interaction with -and, therefore, any influence of- the bank has occurred. We find support for the assumption that less sophisticated households tend to direct their searches more towards FRM absent banks' advice. This result is also consistent with a literature that documents that less financially sophisticated households are more likely to take up FRMs (Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff, 2010; Fornero, Monticone, and Trucchi, 2011; Gathergood and Weber, 2017; Albertazzi, Fringuellotti, and Ongena, 2018). Thus, our evidence suggests that the scenario in which restrictions to steering cause welfare losses (that is, large values for α) is plausible, if not even probable.

To summarize, restrictions to steering can generate both welfare gains or losses for borrowers. We believe it is particularly important to warn about the latter because of three main reasons. First, according to our calculations, the circumstances in which the policy has a negative welfare effect are associated with much more severe consequences than the gains materializing when the policy is welfare improving. Second, our analysis of online mortgage searches suggests that circumstances in which large losses occur are likely to arise. Third, steering restrictions have significant redistributive effects with sophisticated households much more likely to lose from the policy. Therefore, we stress that the outcome of restricting steering is uncertain, which is particularly important given that there are other policies that have unambiguously positive effects on borrowers' welfare. One alternative is the financial literacy campaign which increases average welfare of the agents no matter the value of the parameter α (although it does have redistributive effects).[37]

8 Conclusion

In this paper, we pursue two objectives. First, we quantify the costs of steering in financial markets. We estimate that a large fraction of borrowers lack sophistication to make independent financial decisions and an even larger fraction of borrowers are attached to their home banks. From a practical standpoint, these findings imply that there is ample scope for intermediaries to steer their customers' choices. Consistently, we estimate that the cost of the distortion is significant and amounts to 19% of the annual mortgage payment for the average household.

Second, we assess the consequences of different policies to address it. A set of counterfactual exercises leads us to conclude that the gains from forcing intermediaries to only steer customers to their optimal choices or from educating borrowers are sizable. Importantly, they are also unequally distributed both in size and sign: While the naive borrowers gain, the sophisticated ones lose. This exposes financial education campaigns and policies that remove the distortion to non-trivial political economy implementation problems. We also find that restricting steering may not be recommendable. In fact, steering has an informational value and can be beneficial to customers even when it is not done with their best interests in mind. As a result, restricting steering and leaving unsophisticated households on their own can hurt their welfare.

[37] As we stressed in the introduction, our results do not apply to cases of predatory steering in which financial intermediaries steer their customers to an a priori inferior financial products.

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Online Appendix (Not for Publication)

"The Cost of Steering in Financial Markets:
Evidence from the Mortgage Market"

Luigi Guiso, Andrea Pozzi, Anton Tsoy, Leonardo Gambacorta, Paolo Mistrulli

A Characteristics of the Italian Mortgage Market

In Section 2, we discuss several features of the Italian mortgage market which shape our modeling and identification strategy. Here, we provide additional details on each of them.

Adjustable and fixed rate mortgages in Italy Our data include only plain vanilla adjustable and fixed rate mortgages. As can be seen in Figure 1, these types represent the majority of mortgages issued in Italy. In the years of our sample, other types of mortgages had a negligible market share. In the period 2006-2015, the combined market share of fixed and adjustable mortgages was on average close to 85%. Another feature emerging from the picture is that both adjustable and fixed rate mortgages are popular. They each represent no less than 20% of the mortgages issued every year.

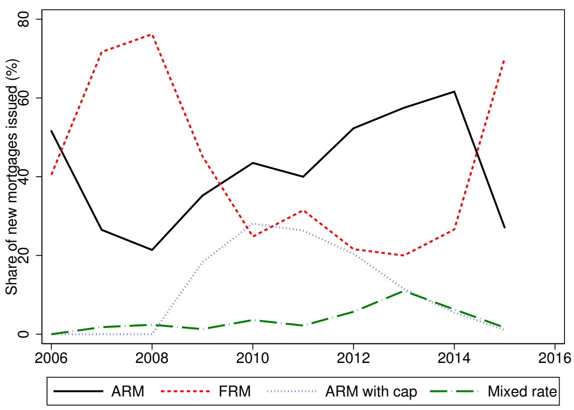


Figure 1: **Market Share by Type of Mortgage**

Notes: The figure reports the market shares of the main types of mortgages offered by Italian banks. The source is the mortgage comparison website MutuiOnline.it.

Exposure to interest rate risk The US mortgage market is dominated by mortgage banks, which off-load mortgages from their balance sheets shortly after origination. Banks issuing mortgages in Europe

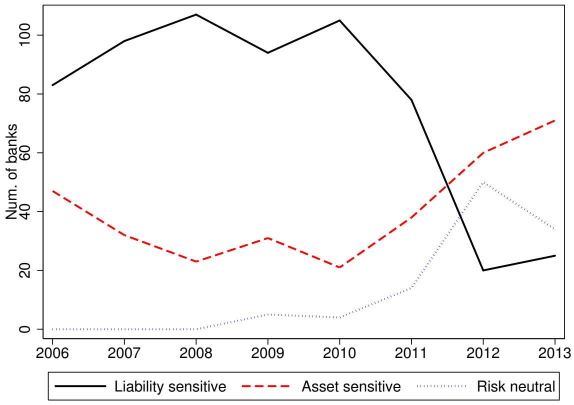


Figure 2: **Exposure of Italian Banks to Interest Rate Risk**

Notes: The figure displays the time series for the number of Italian banks that are "Liability sensitive" (lose value in case interest rates go down); "Asset sensitive" (lose value if interest rates go up) and "Risk neutral" (value of the bank unaffected by changes in interest rate). Banks have been categorized by Table 5 in Cerrone et al. (2017) according to the Bank of Italy's duration gap approach.

are instead portfolio lenders: they fund loans with deposits and bond issuance and they keep mortgages on their balance sheets. In particular, Italian banks not only retain a large chunk of mortgages on their balance sheets, but also carry a substantial fraction of the associated interest rate risk as they appear not to hedge perfectly their position with derivatives. This distinction is important because it implies that Italian banks have the incentive to steer customers towards ARM or FRM to manage their exposure to interest rate risk.

In Figure 2, we plot the time series for the number of banks in the Italian system exposed to interest rate risk. The figure is based on the evidence provided in Cerrone et al. (2017) which implement a duration gap approach on data from the balance sheets of a representative sample of 130 Italian commercial banks. They offset assets and liabilities – on and off balance sheets – at each maturity to obtain a net position and assess the effect on the value of the bank of a 200 basis points parallel shift of the yield curve. Banks losing value in case of interest rate increase are defined "Asset sensitive"; banks losing value in case of an interest rate decrease are categorized as "Liability sensitive"; those hedged against interest rate risk are "Risk neutral". The picture shows that every bank in the sample analyzed by Cerrone et al. (2017) was exposed to interest risk for the full span of the time period that we analyze. In terms of the size of the exposure to interest rate, they report that over the period 2006-2013 the loss of value due to a 200 basis point parallel shift upward in the yield curve was 10.37% of the regulatory capital for "Asset sensitive" banks; whereas the average "Liability sensitive" bank would lose 6.62% of its regulatory capital from an equally sized downward shift. Hence, the exposure to interest rate risk, while below the 20% threshold set by Basel Committee on Bank Supervision, was significant throughout the period. Therefore, banks tend to have an overall mismatch between maturity of their assets and liabilities, which is not offset with the use of derivatives. Thus, they have incentives to skew their mortgage portfolios to mitigate this problem.

Other types of risk Our discussion of the bank incentives to influence mortgages choice centered on interest rate risk. This is because in the Italian setting this appears to be a more prominent source of risk taken by banks when issuing mortgages compared to credit and pre-payment risks. Like in many other European countries, mortgages are full recourse in Italy: households cannot walk away if the value of the property falls short of the outstanding mortgage. Hence, the incidence of mortgage defaults is rather limited: the fraction of mortgages with late repayment or default is typically below 1% and surges only marginally to 1.5% during the 2009 financial crises. This also reflects banks' tight screening policies with high rejection rates of risky loan applicants. Based on SHIW data, on average 13% of the households have had a rejected loan application in 2004; the figure rises to 27% in 2008. For this reason we do not include in our analysis the risk of default and also abstract from sophisticated pricing policies conditioning the mortgage rate offered on individual characteristics. In fact, banks submit applications to severe screening to minimize the default risk but then tend to ignore differences in accepted borrowers riskiness setting flat rates, with the exception of a recent attention to loan size or LTV (Liberati and Vacca (2016)).

Most Italian mortgages are held until maturity and it is relatively uncommon that households renegotiate the terms of the mortgage or transfer it to another bank. For most of the time span in our analysis, both prepayment and renegotiation were burdened by unregulated fees in the order of at least 3% of the remaining debt (Brunetti et al. (2020)). A reform enacted in April 2007 (the "Bersani law") removed prepayment penalty fees for all new mortgages and capped them at a mandated level for existing ones. The reform bill also removed additional cost of renegotiation such as notary fees. Still, the effect of these changes on renegotiation has been modest (Bajo and Barbi (2018); Beltratti et al. (2017)). Based on Bank of Italy data, the share of refinanced mortgages is close to zero up until 2007 and consistently below 1% after. Refinanced mortgages represent between 10% and 15% of newly issued mortgages between 2005 and 2008; the same figure is between 40% and 50% for the US in the same period.

Pricing of mortgages Whereas Italian banks thoroughly screen mortgage applicants, the interest rate is set with much less sophistication. Income and other personal characteristics are not priced and until recently even loan to value did not significantly affect the interest rate charged. Further, the negotiation over rates with banks rarely impacts significantly the interest rate that the household pays.

	% borrowing at posted rate	Discount (bps) 25th pctile	50th pctile	75th pctile
Mortgages issued in the same quarter	56	16	38	76
Allen et al. (2019)	25	50	75	95

Table 1: **Mortgage Pricing**

Notes: The table reports statistics on the fraction of households taking a mortgage at an interest rate lower than the modal rate emerging in a particular bank branch in a particular quarter for a particular type of mortgage. Conditional on the rate the household obtains being lower than the modal rate, we report descriptive statistics on the size of the gap. The last row reports comparable statistics for the Canadian market from Allen et al. (2019).

To gauge the extent to which paid rates differ from posted rates in our sample, we rely on the microdata on 40% of all the mortgages issued between 2005 and 2008 which carry information on the rate set for each loan. We identify the modal interest rate paid by households for a branch-quarter-mortgage type combination as the posted rate for the type of mortgage in that market in that period. We then attribute to bargaining and pricing of individual characteristics the dispersion of the rates away from the modal rate and quantify it. This approach is prone to overstate the importance of bargaining, because the frequency of the data is quarterly. Hence, some of the changes in the rate paid by households are due to changes in the price set by the bank within the quarter.

Table 1 shows the results of this exercise. Over 50% of the mortgages of the same type issued by branches of the same bank in the same quarter and province are taken at the same interest rate, which points to both limited bargaining over rates and to little sophistication in the formulation of the price. For households taking mortgages at rates below the modal interest rate, we compute the size of the discount whose quartiles are 16, 38 and 76 basis points. These figures, especially the first two quartiles, are substantially lower than those reported by Allen et al. (2019) for the Canadian market where negotiation on mortgage rates is customary.

B Evidence of Limited Sophistication

In this appendix, we present evidence on the limited sophistication of Italian households using measures of the financial literacy. This evidence points to the prevalence of unsophisticated households, which provides the scope for banks to steer their customers; and reflects differences in the behavior of financially literate and illiterate households, which is broadly consistent with some of our modeling assumptions.

The evidence relies on the 2006 wave of SHIW. Half of the interviewees in 2006 (3,992 households) were administered a section of the questionnaire meant to elicit financial literacy using a set of standard questions in the literature (Van Rooij et al. (2011); OECD (2016)). The section consists of six questions testing the ability to recognize the balance of a checking account statement, to compare the returns of two mutual funds, to understand the difference between real and nominal interest, the concept of compound interest, the wealth consequence of stock prices fluctuations, and the properties of fixed and adjustable rates. For each question, four options are offered: one of them is correct, two incorrect, and a fourth option allows the interviewee to profess his cluelessness about the topic.[38]

We construct a summary index of sophistication by counting the number of correct answers given by an individual. The index ranges from zero (least financially literate households) to six (most sophisticated). In Figure 3, we show the distribution of this sophistication index among the whole sample and for the subset of those who have a mortgage outstanding (information about mortgages and other forms of debt is collected in another section of SHIW). Only 3% of the households interviewed answers correctly all the questions, 18% do not get a single one right, and 42% do not do better than two correct answers out of six. Compared to the distribution of the index for the whole sample, mortgage holders show higher sophistication (80% of them answer at least two questions correctly), yet, still less than 10% of them answered all questions correctly.

Figure 4 uses the second indicator of sophistication that provides information on people's ability to understand the properties of FRMs and ARMs. It shows the distribution of the answers to the question: "*Which of the following mortgage types allows you to know since the very beginning the maximum amount that you will paying annually and for how many years before you extinguish the mortgage?*" The answers offered are: 1) Adjustable rate mortgage; 2) Fixed rate mortgage; 3) Adjustable rate mortgage with constant annual payment; and 4) I do not know. Only 50% of the interviewees provide the right answer. Even among mortgage holders, nearly one third of the interviewees are either clueless or provide a wrong answer.

Further, we provide support to our assumption that unsophisticated borrowers tend to opt for fixed rate mortgages by exploiting a question meant to elicit people's ability to understand the link between interest rates and inflation. Specifically, they are asked: *"Suppose you have 1000 Euros in an account*

[38]The questionnaire of the 2006 wave of SHIW is available (in Italian) at `https://www.bancaditalia.it/statistiche/tematiche/indagini-famiglie-imprese/bilanci-famiglie/documentazione/documenti/2006/Quest_it2006.pdf`.

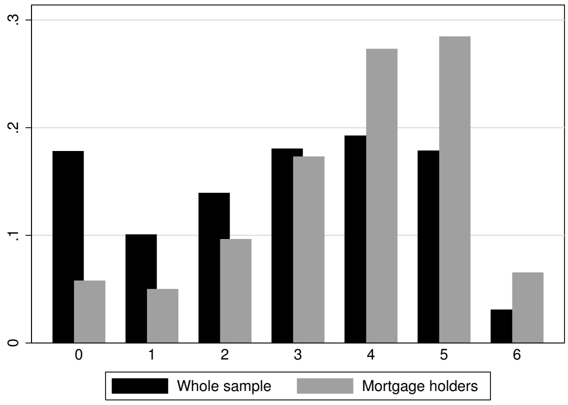


Figure 3: **Distribution of the Sophistication Index**

Notes: The Summary Sophistication Index is constructed as the number of correct answers to the six financial literacy questions contained in the 2006 wave of SHIW. The whole sample includes all the SHIW interviewees in 2006 who were administered the financial literacy section of the questionnaire. The mortgage holders sample consists of all the households who answered the financial literacy questions and also reported elsewhere in the survey to have an outstanding mortgage.

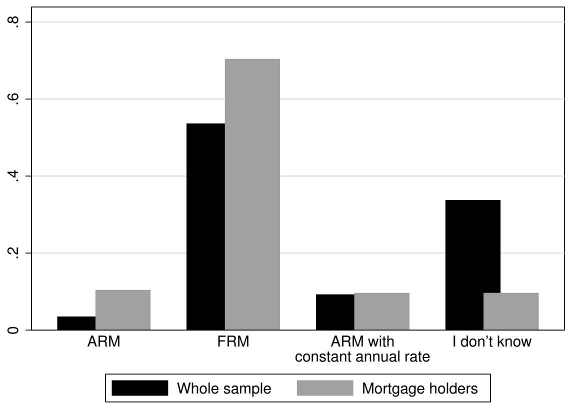


Figure 4: **Understanding of Mortgage Characteristics**

Notes: The figure shows the distribution of the answers to the following question *"Which of the following mortgage types allows you to know since the very beginning the maximum amount that you will paying annually and for how many years before you extinguish the mortgage?"* Answers: 1) Adjustable rate mortgage; 2) Fixed rate mortgage; 3) Adjustable rate mortgage with constant annual payment; and 4) I do not know. The whole sample includes all the SHIW interviewees in 2006 who were administered the financial literacy section of the questionnaire; the mortgage holders sample consists of all the households who answered the financial literacy questions and also reported elsewhere in the survey to have an outstanding mortgage.

	Sophisticated	Naive	Clueless
Adjustable rate	0.63	0.53	0.5
Fixed rate	0.37	0.47	0.5

Table 2: **Mortgage type and borrower sophistication**

that yields a 1% interest and carries no cost (e.g management fees). If inflation is going to be 2% do you think that in one year time you could be able to buy the same goods that you could by today spending your 1000 euros?" The answers are: 1) Yes, I would be able; 2) No, I could only buy a lower amount; 3) No, I could buy a higher amount; 4) I do not know. We define *Sophisticated* all those who provide the correct answer (answer 2); *Naive* those who provide either of the wrong answers (answer 1 or 3); and *Clueless* those who cannot answer (answer 4). We tabulate the type of mortgage that households in these different groups:

Note that SHIW reports the mortgage chosen by the household (i.e., picked after the bank provided advice) and not what it wanted to obtain before advice was provided (which is what our modeling assumption refers to). Nevertheless, there is a clear pattern that sees the choice of FRM more likely among the unsophisticated and even more so among the clueless.

C Household Choices absent Steering

The evidence above relies on mortgages mostly originated from banks. This means that the borrower already had some interaction with employees of the bank and the resulting mortgage choice could have been slanted by steering and does not reflect only the borrower's preferences.

To address this problem and further enrich the evidence, we obtained a novel data set on Internet searches for mortgage deals provided by the leading Italian mortgage comparison website, MutuiOnline.it. The website only registers data on queries that result in the filing of an online application and our data consists of all such queries. The information collected includes both basic demographics of the potential borrower (city of residence, occupation, age, gender) and information on the characteristics of the type of contract the potential borrower was researching: the queried bank, the amount requested, the value of the house used as collateral, the type of mortgage and whether the applicant was looking for a new mortgage or to refinance. We observe the outcome of the search: the interest rate and the monthly instalment offered by the bank queried for the desired contract characteristics. Given that we know the province where the individual making the query lives, we can complement the demographic information with weighted province-level averages of demographic variables. Most notably, we include variables measuring the province-level share of individuals with education level below high school, that of those who attended high school, and that of those who at least attended college. We take the province average of educational attainment as a proxy of financial sophistication of a potential borrower, with the least educated agents being more likely to be naive.

The sample we were able to obtain refers to the universe of searches on the website in two different years: 2007 and 2014. The 2007 data fit right in the middle of the sample span we used for our main analysis. However, the market for online mortgages was still in its infancy then and the sample of borrowers looking for a mortgage online may be selected. The 2014 sample refers to a later period than the one our estimates are based on, but it has the advantage that by then searching for mortgages online had become a much more common activity. This is witnessed by the sheer number of searches on the platform that rises from 32,486 in 2007 to 51,561 in 2014. Accordingly, we pool data from the two years, thus, increasing the size and representativeness of the sample. Importantly, the availability of searches at two points in time allows us to exploit the panel dimension introducing province fixed effects when studying the effect of education on mortgage type preference. This way we take care of time invariant heterogeneity across provinces that may confound the analysis. Because we observe the universe of searches in two instances seven years apart, the amount of within-province variation in educational attainment is substantial.[39] Hence, we can obtain precise estimates of the effect of education on the borrower preference for the type of mortgage.

Before showing the results of these estimates, we note that the average share of FRMs on the MutuiOnline platform in the two years follows the same time pattern as that of the total originated mortgages. Notably, the share of FRMs filed by consumers on MutuiOnline exceeds that chosen in the total population in both years: it is 13 percentage points higher in 2007 and 5 percentage points higher in 2014 (the population shares of FRMs in these years are 67% and 35%, respectively). This pattern is fully consistent with our assumption that absent steering, naive households tend to prefer FRMs, while banks steer them towards ARMs.

To further test this implication, we estimate a linear probability model where the dependent variable is a dummy taking value 1 if the individual searched for an FRM, and 0 otherwise. As before, we restrict the analysis to either pure ARMs or FRMs – which constitute over 95% of the searches in the data –and consider only newly issued mortgages, dropping searches for refinancing. As explanatory variables, we use

[39]For the share of households with attainment below high school, the within province variation is 2/3 of the variation across provinces. The same is true for the share of households with college education, whereas for the share of households with a high school diploma the within province variation is over 3/4 of the cross province variation.

	Dependent variable FRM=1
Below high school education	0.204 0.055
High school education	0.275 0.072
Maturity	−0.007 0.000
Amount requested	−0.007 0.000
Household size	−0.004 0.016
Age	−0.003 0.000
Income	0.002 0.002
Single bank account	0.020 0.033
Individual occupation controls	Yes
Province fixed effects.	Yes
Year fixed effects.	Yes
Bank fixed effects.	Yes

Table 3:

Notes: The dependent variable is a dummy for whether the individual searched for an FRM. The sample includes the universe of searches for new mortgages on MutuiOnline.it in 2007 and 2014. The variables on educational attainment are province level shares and the excluded group is that with education above high school diploma. The specification includes fixed effects for the year of the search, the occupation of the individual making the query, the bank whose offering are queried and the province where the individual lives.

indicators of the level of education in the province where the individual lives excluding for comparison the share of the most sophisticated (those with college education); maturity and size of the mortgage; age, income, and household size of the individual making the search as well as whether she has relationships with a single bank. We include a dummy to control for the year in which the search was carried as well as controls for individual occupation, province and bank fixed effects. The latter capture systematic differences across banks in the interest rate spread between FRM and ARM.

Table 3 reports estimation results. First, compared to those with a college degree, the less sophisticated individuals tend to direct their searches more towards FRMs. Differences are economically significant: in a province with all borrowers having below college education the fraction of people voluntarily looking for a fixed rate mortgage would be more than 20 percentage points higher than in a province with all borrowers having a college degree. Second, we find no significant difference between searches of households with just high school education attainment and those below high school. This suggests that acquiring financial sophistication may require a substantial investment in general education, and accordingly, that the share of unsophisticated borrowers in the population may be quite large. This evidence lends support to our structural estimates of a significant share of naive borrowers in population.

To summarize, we find evidence that supports our assumption that less sophisticated borrowers are more inclined to choose FRMs when acting on their own.

D Sample Construction

As we explained in the main text, whereas we have information on the universe of mortgages issued in Italy, the interest rate of the loan is only available if the bank issuing the mortgage is among the 175 regularly surveyed by the Bank of Italy for information on rates of the loans they issued. Therefore, we exclude from our analysis banks that do not participate in the survey, which represent a small fraction of the market.

The aggregation of the level of observation at the region level for the estimation of the supply introduces another constraints. National and regional banks set identical (or nearly identical) rates across provinces in the same region and do not pose any problem when we construct regional rates for ARMs and FRMs. However, there is a number of banks that are active in more geographically limited areas (provincial banks). For these banks it would be problematic to extrapolate provincial rates to the regional level. Therefore, for the estimation of supply, we retain only banks that issue mortgages in at least 40% of the provinces belonging to the region where the bank is located.

Finally, some restrictions are imposed by the need for information on the amount of the deposits (in Euros) held by each bank in a given market. Such data are missing for some bank-quarter-province triplet and we exclude from the sample banks for which less than one year of data on the amount of deposits is available. For banks with less severe missing data problems, we extrapolate the amount of deposits for a given bank in a given province in a given year using a linear regression to fill the gaps between available observations. When the time series ends without resuming later on, we impute for all the missing province-year the last amount of deposits recorded in the data. We remove from the sample three small provinces where either a bank missing deposit data issues more than 15% of the mortgages or the market share held in the mortgage market by banks with missing data on the amount of deposits exceeded 30%.

E Reduced Form Evidence of Steering

Foà et al. (2019) use data similar to ours to provide reduced form evidence that banks slant customers' mortgage choices. Since establishing the presence of steering is a natural prerequisite for our goal to quantify its welfare implications, below we introduce the main findings by Foà et al. (2019) and show that they hold in our sample. We refer the reader to their paper for further details.

Foà et al. (2019) propose a test of the presence of a non-price channel through which banks influence customers' mortgage choices. The basic idea is that if households are savvy, then the relative price of different financial products should be a sufficient statistic for their choice. However, if some households lack sophistication and the intermediary is able to steer their behavior to its own advantage, for given prices households' choices could also be affected by characteristics of the bank (arguably, unobservable to the borrower) that affect the incentives of the bank to steer its customers towards a certain product. In this case, the direction of the effect should be consistent with the bank's interest. Importantly, this methodology does not rely on a particular mechanism through which the customers were steered towards a certain product. Steering can be simply inferred from mortgage choices, relative prices, and balance sheet shocks to the bank originating the mortgage.

In Table 4, we use our data to replicate the main result in Foà et al. (2019). The choice between ARM and FRM is systematically correlated not only with the relative costs of two mortgage types (the Long Term Financial Premium or LTFP), but also with time varying characteristics of the bank that originates mortgages. We estimate a linear probability model where an indicator variable, which takes value 1 if the household chooses an FRM, is regressed on the Long Term Financial Premium (computed as the difference between the FRM rate and a moving average of ARM rates), household characteristics and the Bank Bond Spread, which measures the relative cost for the bank of securing funds at a fixed rate.[40] We also include bank fixed effects to capture time-invariant unobserved heterogeneity across banks and systematic sorting. Region-quarter fixed effects capture aggregate market effects.

As expected, the Long Term Financial Premium negatively affects the probability that the household picks an FRM. However, the negative and significant coefficient on the Bank Bond Spread implies that households borrowing from a given bank are less likely to choose an FRM in a given quarter if in that quarter the bank faces a higher cost of raising fixed-rate funding compared to households borrowing from

[40] The Bank Bond Spread is the difference between the rates of the fixed and adjustable rate bonds issued by the bank. We calculate it as a weighted average over all the bond maturities issued by the bank and consider only newly issued bonds to non-financial residents in Italy. See https://www.bancaditalia.it/pubblicazioni/moneta-banche/2010-moneta/index.html for further details on the construction and the sample of banks reporting it.

	(1)	(2)
	Dependent variable	Dependent variable
	FRM=1	FRM=1
Long Term Financial Premium	-0.0583^{***}	-0.0590^{***}
	(0.0129)	(0.0127)
Mortgage size (log)	-0.0818^{***}	-0.0826^{***}
	(0.0109)	(0.0112)
Joint mortgage	0.0270^{***}	0.0274^{***}
	(0.0045)	(0.0046)
Italian	0.0411^{***}	0.0393^{***}
	(0.0071)	(0.0070)
Cohabitation	-0.0029	-0.0035^{*}
	(0.0020)	(0.0020)
Age	-0.0008^{***}	-0.0009^{***}
	(0.0002)	(0.0002)
Female	0.0109^{***}	0.0102^{***}
	(0.0015)	(0.0014)
Bank bond spread	-0.0831^{***}	-0.0825^{***}
	(0.0164)	(0.0163)
Bank f.e.	Yes	Yes
Year×Region f.e.	Yes	No
Year×Province f.e.	No	Yes
Observations	631,993	631,993
R-squared	0.3681	0.3721

Table 4: **The Effect of Lenders' Characteristics on Mortgage Choices**

Notes: Each observation is a new mortgage contract between a household and a bank. The dependent variable is an indicator taking value 1 if the household chose an FRM. Long Term Financial Premium defined as in Foà et al. (2019) is the difference between the FRM rate and the expected ARM rate based on borrowers' actual ARM rate and one year moving average of the one month interbank rate. The Bank Bond Spread is the average (across maturities) of the difference between the rates of fixed and adjustable rate bonds issued by the bank. Standard errors are in parentheses and are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

the same bank in a quarter where the bank faces a lower costs of borrowing at fixed rate.[41] The sign of the coefficient is consistent with the story that banks use steering (along with rate setting) in order to manage maturity of assets (in this case, issued mortgages) to that of their liabilities. The finding is confirmed in column (2) when we control for aggregate trends at a finer level of geography (a province). Thus, we establish that banks do steer customers' choices through tools other than price.

Foà et al. (2019) strengthen their analysis by 1) extending the evidence to other supply shocks; 2) documenting stronger responses to supply shocks among less sophisticated households; 3) showing stronger effects of supply shocks when banks face price adjustment costs; 4) estimating the model on a subsample of households taking multiple mortgages so that they can include household fixed effects in the specification to control for any source of time-invariant household unobserved heterogeneity. Below, we report additional results from Foà et al. (2019), which show the robustness of their findings and pinpoint more precisely the channel through which the steering occurs.

Banks can steer their customers by using advice (i.e., providing selected information in one-on-one interaction), advertising (selecting the pool of applicants through messages to the general public) or rationing (systematically denying loan requests not aligned with their needs). Foà et al. (2019) claim that in the Italian data the first mechanism is prevalent. They reason that both advertising and rationing would generate sorting of customers across banks and provide evidence (reported in our Table 5) that there is no dynamic sorting of households, i.e., the characteristics of the customer pool of a bank does not correlate with the bank bond spread which is the balance sheet variable affecting the convenience for the bank of selling ARM vs FRM.[42]

Sorting may not only occur on observable but also on unboservable characteristics. Therefore, Foà et al. (2019) deepen their analysis to rule out sorting on unobservables. First, they use data from mortgage-takers included in SHIW to assess whether we observe sorting based on risk aversion, the most critical unobserved variable affecting the mortgage choice. In SHIW, households reporting that they took a mortgage provide an identifier of the bank extending the loan and also answer questions allowing to elicit their risk aversion. The first two columns of Table 6 report the results of an ordered logit run by Foà et al. (2019), where the dependent variable is a categorical index corresponding to the investment strategy that best describes the household attitude: high return with high risk; good return with fair

[41] Our empirical strategy requires within bank variability in the spread between the rate on their fixed and adjustable rate bonds. Such variation can arise from several sources. For instance, since corporate bonds are often privately placed rather than publicly issued on the open market, idiosyncratic shocks to the risk absorption capacity of institutional investors that a particular bank can reach will affect its spread between fixed and adjustable bonds, even at quarterly frequency.

[42] Static sorting is not a plausible explanation of the correlations presented in Table 4 since it would be taken care of by the bank fixed effects.

Explanatory variables	Mortgage size (log)	Italian	Cohabitation	Age	Female
Bank bond spread	0.0005 (0.0040)	−0.0079 (0.0025)	0.0034 (0.0056)	−0.1227 (0.0774)	−0.0020 (0.0013)
Bank f.e.	yes	yes	yes	yes	yes
Region-time f.e.	yes	yes	yes	yes	yes
F-test joint significance (p-value)	0.6901	0.2414	0.4817	0.4556	0.4250

Table 5: **Dynamic sorting on observables**

Source: Table 6 in Foà et al. (2019). In the original tables, the coefficients for *Deposit ratio* and *Securitization activity* (other two potential shifters of the maturity mismatch) are also reported: neither is significant. The test of joint significance of bank characteristics row reports the p-value of an F-test testing the null that the coefficients on *Bank Bond Spread*, *Deposit ratio* and *Securitization activity* are jointly equal to 0.

capital protection; fair return with good capital protection; low return with no risk. It emerges that there is no correlation between the balance sheets of a bank and the degree of risk aversion of the customers taking a mortgage there in a particular period. The last two columns of Table 6 show instead a different exercise which Foà et al. (2019) use to rule out that rationing is used as a steering tool. They obtained extra data from the Italian Credit Registry that include the fraction of rejected mortgage applications for each bank-quarter and use it to show that banks do not respond to fluctuations in their cost of long term funding by adjusting their rejection rate, even in periods where the bank does not adjust pricing.[43]

A final exercise performed in Foà et al. (2019) to address the issue of selection on unobservables is to replicate the baseline specification on the subsample of households who take more than one mortgage during the sample period considered. These estimates are based on a smaller sample (13.7% of the households take two mortgages; 1.7% take three) but allow Foà et al. (2019) to include households fixed effects in the specification, absorbing all the unobserved time-invariant household characteristics. The results are robust to the introduction of the household fixed effects (see Table 7) and the fixed effects are not correlated with the supply factors of the bank.

[43] The price inaction dummy D_{ib} is defined as equal to 1 if the change in the FRM-ARM spread was within one-third of its bank-specific standard deviation. See Foà et al., 2019 for more details.

Explanatory variables	Dependent variable is individual risk aversion (1) Baseline	(2) adding bank and time fixed effects	Dependent variable is bank rejection rate (3) baseline	(4) with interaction terms
Bank bond spread	0.0243 (0.0692)	−0.0413 (0.797)	−0.1594 (0.1472)	−0.1759 (0.1525)
D_{ib} (price inaction dummy)				0.0520 (0.5758)
Bank bond spread*D_{ib}				0.0673 (0.2288)
Bank fixed effects (BFE)	no	yes	yes	yes
Time fixed effects (TFE)	no	yes	yes	yes
F-test on joint significance of bank-specific characteristics (P-value)	0.9269	0.3723	0.5364	0.9217
Estimator	ML-Ordered logit	ML-Ordered logit	OLS	OLS
Observations	3,023	3,023	3,023	3,023
Pseudo\Adjusted R-squared	0.0010	0.0596	0.461	0.460

Table 6: **Sorting on unobservables and rationing**

Source: Table 9 in Foà et al. (2019). In the original tables, the coefficients for *Deposit ratio* and *Securitization activity* (other two potential shifters of the maturity mismatch) and their interactions with the price inaction dummy (for the specification in column (4)) are also reported. The test of joint significance of bank characteristics row reports the p-value of an F-test testing the null that the coefficients on *Bank Bond Spread*, *Deposit ratio* and *Securitization activity* are jointly equal to 0.

	Dependent variable is a dummy=1 if a FRM is chosen		Dep. variable: borrowers' fixed effects
	(1)	(2)	(3)
	Baseline model	With borrowers' fixed effects	Test for correlation of BOFE on supply factors
Long Term Financial Premium	-0.0519^{***} (0.0052)	-0.0528^{***} (0.0103)	
Bank bond spread	-0.0569^{***} (0.0097)	-0.0635^{***} (0.0087)	0.0096 (0.0083)
Bank Fixed effects (BFE)	yes	yes	yes
Region-Time fixed effects	yes	yes	yes
Borrowers' characteristics	yes	yes	no
Borrowers' fixed effects (BOFE)	yes	yes	no
Other controls	yes	yes	no
Test of joint significance of BOFE (p-value)	.	0.000	.
Test of joint significance of bank characteristics (p-value)	0.000	0.000	0.677
Observations	253,763	253,763	253,763
Adjusted R-squared	0.332	0.342	0.142

Table 7: **Households with multiple mortgages**

Source: Table 10 in Foà et al. (2019). In the original tables, the coefficients for *Deposit ratio* and *Securitization activity* (other two potential shifters of the maturity mismatch) are also reported. The test of joint significance of BOFE row reports the p-value of an F-test testing the null that all the borrowers fixed effects are jointly equal to 0. The test of joint significance of bank characteristics row reports the p-value of an F-test testing the null that the coefficients on *Bank Bond Spread*, *Deposit ratio* and *Securitization activity* are jointly equal to 0.

E.1 Additional Evidence of Steering

We complement the evidence in Foà et al. (2019) with two additional pieces of evidence that steering is driven by banks' incentives to manage maturity mismatch and it is potentially associated with distortions. First, if the significance of the Bank Bond Spread in Table 4 indicates that banks are steering their customers' decisions to manage their maturity mismatch, then banks with larger maturity mismatch should have higher incentives to steer and, therefore, banks balance sheets should be even more significant in explaining households mortgage decisions. To test this prediction, we obtained from the Bank of Italy Supervisory Reports detailed data on maturity buckets (in months) for all banks' assets and liabilities. We have then computed each bank's duration mismatch as the difference between the average maturity of assets and that of liabilities for the bank, which is the standard measure of exposure to interest rate risk (see, e.g., Drechsler et al. (forthcoming)).[44] Overall, the measure captures the real costs each bank in our sample would incur in case of an increase in interest rates. In order to limit endogeneity problems, we use the maturity mismatch in 2003, the last year before the start of our sample span.

We divide banks into two groups: those with a low duration mismatch (below median) and those with a high duration mismatch (above median). We then repeat for each group the baseline regression whose results we reported in Table 8. The Bank Bond Spread affects negatively the probability that a household chooses an FRM both in banks with an above and a below median maturity mismatch. However, for banks with a higher maturity transformation cost the coefficient is almost twice as large. A one-tailed test rejects at 10% the null of equality of the two coefficients against the alternative of a larger effect for banks with above the median mismatch.

Second, in order to show that banks' steering sometimes distorts household choices, we exploit data on customers' complaints on mortgage contracts raised to the Arbitro Bancario Finanziario (henceforth, ABF). Specifically, we construct an indicator of the distortionary steering as follows. We use the estimates from the model in Table 4 and generate predicted values excluding supply factors from the specification. These predicted values identify what the undistorted choice of a household (with certain characteristics and facing a certain Long Term Financial Premium) should be. We compare it to the actual mortgage choice of that household and count as an instance of distortion cases where the predicted and the actual choice do not coincide. We confront this measure of alleged distortion obtained through our methodology with data on actual complaints of wrongdoing in mortgage contracts filed by customers to the ABF.[45] In

[44] For assets and liabilities that are not fixed rate, we substitute the average time to adjust interest rates for the average maturity. The duration mismatch is also corrected for the use of derivatives.

[45] We exploit data on the complaints to the ABF from 2011 to 2015. This time span is later than our sample period, because it normally takes time for the household to realize potential misconduct and to file the complaint. Cases referring to mortgages issued in the 2005-2008 period could have reached the ABF only years later.

	(1)	(2)
	Dependent variable	*Dependent variable*
	FRM=1	*FRM=1*
	Banks with below median duration mismatch	Banks with above median duration mismatch
Long Term Financial Premium	-0.0551^{***} (0.0146)	-0.0607^{***} (0.0095)
Bank Bond Spread	-0.0575^{***} (0.0198)	-0.1008^{***} (0.0180)
Bank f.e.	Yes	Yes
Year×Region f.e.	Yes	No
Borrowers' characteristics	Yes	Yes
Observations	291,138	340,855
R-squared	0.3300	0.4295

Table 8: **Effect of Lender Characteristics, by severity of maturity mismatch**

Notes: The table reports results from the specification in column (1) of Table 4 for two separate subsamples. In column (1), we consider only mortgages originated by banks whose duration mismatch was below the median in the quarter. In column (2), we consider only mortgages originated by banks whose duration mismatch was above the median in the quarter. The duration mismatch is calculated based on data from the Bank of Italy Supervisory Report that details all assets and liabilities for each bank by "buckets" of maturity (in months). The *borrowers' characteristics* included in the specifications for both columns are the same as in Table 4: (log of) mortgage size, dummy for mortgages jointly taken by two individuals, dummy for mortgages given to Italian households, dummy for mortgages given to cohabitants, age of the mortgage taker and a gender dummy.

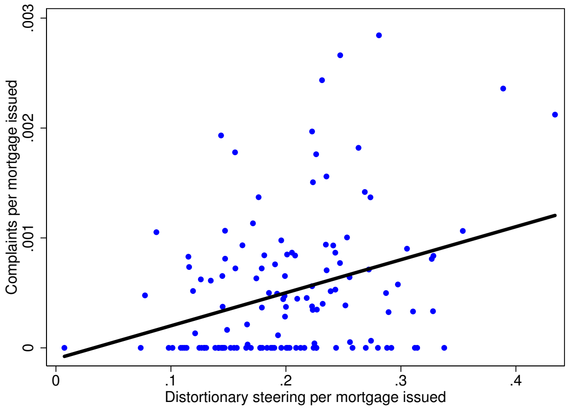


Figure 5: **Distortionary Steering is behind Borrowers' Complaints**

Notes: The figure plots on the horizontal axis the number of instances of distortionary steering inferred based on our methodology, for each bank scaled by the number of mortgages issued by the bank. On the vertical axis we have the number of actual complaints about mortgages received by the Arbitro Bancario Finanziario for each bank, also scaled by the total number mortgages issued by the bank.

Figure 5, each dot represents a bank. For each bank, we plot the share of ABF complaints against the constructed indicator of distortionary steering, both scaled by the number of mortgages issued by the bank. There is a positive and significant correlation between the incidence of distortion obtained through our methodology and a more factual measure based on lawsuits that customers are bringing against their banks.

F Omitted Analytical Details

F.1 Optimality of the Spread Rule

We present a simple version of Koijen et al. (2009) thatshows that the spread rule is optimal when households have mean-variance utility function. By the same argument, the spread rule is also optimal in the CARA-normal model. Households have several dimensions of heterogeneity: the size of their mortgage L, the degree of risk aversion γ, the future (stochastic) real income y, and their beliefs about the distribution of shocks. Each household believes that the mean and the volatility of real interest rate shock ε are ν_ε and σ_ε^2, respectively; that the mean and the volatility of inflation shock π are ν_π and σ_π^2, respectively; and that the correlation between y and ε, and y and π are $\sigma_{y\varepsilon}$ and $\sigma_{y\pi}$, respectively. For ease of notation, we omit indexing these characteristics by h, although the reader should keep in mind that they do vary across households.

Households take a mortgage of size L whose principal and interest are fully repaid after Δ quarters without intermediate payments. Thus, if r_t^{eurbr} is the 1-month Euribor benchmark rate at date t, then $r_{t+\Delta}^{eurbr} = r_t^{eurbr} + \pi + \varepsilon$ is the 1-month Euribor at date $t+\Delta$, where π and ε are inflation and real interest rate shocks at time $t+\Delta$. Let r_{it}^f be the FRM rate and s_{it}^a be the spread between the ARM and the 1-month Euribor benchmark rate set by bank i on mortgages issued at date t. Then, for a customer of bank i the payment at date $t+\Delta$ is equal to $(1+r_{it}^f)L$ when it takes the FRM, and to $(1+r_{it}^a+\pi+\varepsilon)L$ when it takes the ARM , where $r_{it}^a = s_{it}^a + r_t^{eurbr}$. Adjusted for inflation, the payments are $(1+r_{it}^f-\pi)L$ and $(1+r_{it}^a+\varepsilon)L$, respectively.

Sophisticated households have mean-variance utility function with degree of risk aversion γ, that is, their utility from the stochastic future wealth W equals $\mathbb{E}[W] - \gamma\mathbb{V}[W]$. Given this setting, it is optimal for households to follow the *spread rule* in choosing the mortgage type. Let $r_t^f(h)$ and $r_t^a(h)$ be the lowest FRM and ARM rates, respectively, available to household h. If the household is unattached to the home bank, then its choice set contains all rates in the market and $r_t^f(h) = \min_{i\in\{1,\dots,N\}} r_{it}^f$ and $r_t^a(h) = \min_{i\in\{1,\dots,N\}} r_{it}^a$. If the household is attached to the home bank, then its choice set contains only the rates set by its home bank, and $r_t^f(h)$ and $r_t^a(h)$ equal to r_{it}^f and r_{it}^a in the home bank i of the household. The sophisticated household prefers an ARM if and only if

$$\begin{aligned}\mathbb{E}\left[y-(1+r_t^a(h)+\varepsilon)L\right] - \gamma\mathbb{V}\left[y-(1+r_t^a(h)+\varepsilon)L\right]&\\ \geq \mathbb{E}\left[y-(1+r_t^f(h)-\pi)L\right] - \gamma\mathbb{V}\left[y-(1+r_t^f(h)-\pi)L\right].&\end{aligned} \tag{F.1}$$

Simplifying,

$$r_t^f(h) - r_t^a(h) \geq \nu_\pi + \nu_\varepsilon + \gamma L(\sigma_\varepsilon^2 - \sigma_\pi^2) - 2\gamma(\sigma_{y\varepsilon} + \sigma_{y\pi}), \tag{F.2}$$

which gives us the spread rule (4.1) with

$$\delta(h) \equiv \nu_\varepsilon + \nu_\pi + \gamma L(\sigma_\varepsilon^2 - \sigma_\pi^2) - 2\gamma(\sigma_{y\varepsilon} + \sigma_{y\pi}). \tag{F.3}$$

ARM is preferred when the household believes that inflation is more volatile compared to real interest rates, expects lower nominal interest rates, or when the household income tends to co-move with the nominal interest rates (e.g., because the European Central Bank tends to lower interest rates during the crisis). The effect of risk aversion and mortgage size depends on the household's beliefs about the volatility of different shocks. If the households believes that inflation is less volatile than real interest rates, then lower risk aversion and smaller mortgage size make the ARM more attractive. However, if the households believes that inflation is more volatile than real interest rates, then higher risk aversion and larger mortgage size make the FRM more attractive. Because sophisticated households are able to make the optimal mortgage choice based on mortgage rates and their knowledge of two products, steering by the bank that issues the mortgage does not affect them.

F.2 The Adjusted Spread Rule in the CRRA Model

In this section, we provide a model of the mortgage size choice in which the bank's profit per customer can be decomposed into the product of the net profit margin and the average mortgage size justifying the form of the profit function in (4.2). To do so, it is sufficient to show that the distribution of the mortgage type choices is independent of the distribution of the mortgage size.

We suppose that each household has current wealth W_0 and its future wealth equals $W_0(1+y)$, where y is the wealth shock. Households are heterogeneous in W_0 and y. We suppose that each households spends a fraction α of its current wealth on the downpayment and takes a mortgage at the LTV l. Thus, the mortgage size $L = \xi W_0$, where $\xi \equiv \frac{\alpha l}{1-l}$.

The naive households' choices of the mortgage type are shaped by the banks' steering policies, hence, their mortgage type choice is indeed independent of the mortgage size choice. Sophisticated households choose the mortgage type optimally. We suppose that sophisticated households have CRRA utility function with (heterogeneous) degree of risk aversion γ, that is, the household's utility from the stochastic future wealth W equals $U(W) \equiv W^{1-\gamma}/(1-\gamma)$. Household's beliefs about the distribution of shocks are as in the previous section. Then, the households expected utility from taking FRM equals

$$\mathbb{E}\left[U\left(W_0(1+y) - (1+r_t^f(h) - \pi)\xi W_0\right)\right] = W_0^{1-\gamma}\mathbb{E}\left[U\left(1+y-(1+r_t^f(h)-\pi)\xi\right)\right]$$

and its expected utility from taking ARM equals

$$\mathbb{E}\left[U\left(W_0(1+y) - (1+r_t^f(h) - \pi)\xi W_0\right)\right] = W_0^{1-\gamma}\mathbb{E}\left[U\left(1+y-(1+r_t^a(h)+\varepsilon)\xi\right)\right].$$

Thus, the household prefers ARM if and only if

$$\mathbb{E}\left[U\left(1+y-(1+r_t^f(h)-\pi)\xi\right)\right] \geq \mathbb{E}\left[U\left(1+y-(1+r_t^a(h)+\varepsilon)\xi\right)\right],$$

Note that the current wealth does not enter into this decision rule. Thus, if ξ is constant across households, the mortgage choice by sophisticated households is indeed independent of the mortgage sizes that they choose.

We next show that this rule can be simplified to yield an adjusted spread rule. First, the normalized (by $W_0^{1-\gamma}$) expected utility from taking FRM equals

$$\begin{aligned}
&\mathbb{E}\left[U\left(1+y-(1+r_t^f(h)-\pi)\xi\right)\right]\\
=&\frac{\mathbb{E}\left(1+y-(1+r_t^f(h)-\pi)\xi\right)^{1-\gamma}}{1-\gamma}\\
\approx&U\left(1+\nu_y-\xi\right)+\frac{\mathbb{E}\left[y-\nu_y-(r_t^f(h)-\pi)\xi\right]}{\left(1+\nu_y-\xi\right)^{\gamma}}-\frac{\gamma\mathbb{E}\left[(y-\nu_y-(r_t^f(h)-\pi)\xi)^2\right]}{2\left(1+\nu_y-\xi\right)^{\gamma+1}}\\
=&U\left(1+\nu_y-\xi\right)-\frac{(r_t^f(h)-\nu_\pi)\xi}{\left(1+\nu_y-\xi\right)^{\gamma}}-\frac{\gamma\mathbb{E}\left[(y-\nu_y)^2-2(y-\nu_y)(r_t^f(h)-\pi)\xi+(r_t^f(h)-\pi)^2\xi^2\right]}{2\left(1+\nu_y-\xi\right)^{\gamma+1}}\\
=&U\left(1+\nu_y-\xi\right)-\frac{(r_t^f(h)-\nu_\pi)\xi}{\left(1+\nu_y-\xi\right)^{\gamma}}-\frac{\gamma\left[\sigma_y^2+2\sigma_{y\pi}\xi+\sigma_\pi^2\xi^2+(r_t^f(h)-\nu_\pi)^2\xi^2\right]}{2\left(1+\nu_y-\xi\right)^{\gamma+1}},
\end{aligned}$$

where we used second-order approximation in the third line. Similarly, the normalized (by $W_0^{1-\gamma}$) expected utility from taking ARM equals

$$\begin{aligned}
&\mathbb{E}\left[U\left(1+y-(1+r_t^a(h)+\varepsilon)\xi\right)\right]\\
=&\frac{\mathbb{E}\left(1+y-(1+r_t^a(h)+\varepsilon)\xi\right)^{1-\gamma}}{1-\gamma}\\
\approx&U\left(1+\nu_y-\xi\right)+\frac{\mathbb{E}\left[y-\nu_y-(r_t^a(h)+\varepsilon)\xi\right]}{\left(1+\nu_y-\xi\right)^{\gamma}}-\frac{\gamma\mathbb{E}\left[(y-\nu_y-(r_t^a(h)+\varepsilon)\xi)^2\right]}{2\left(1+\nu_y-\xi\right)^{\gamma+1}}\\
=&U\left(1+\nu_y-\xi\right)-\frac{(r_t^a(h)+\nu_\varepsilon)\xi}{\left(1+\nu_y-\xi\right)^{\gamma}}-\frac{\gamma\mathbb{E}\left[(y-\nu_y)^2-2(y-\nu_y)(r_t^a(h)+\varepsilon)\xi+(r_t^a(h)+\varepsilon)^2\xi^2\right]}{2\left(1+\nu_y-\xi\right)^{\gamma+1}}\\
=&U\left(1+\nu_y-\xi\right)-\frac{(r_t^a(h)+\nu_\varepsilon)\xi}{\left(1+\nu_y-\xi\right)^{\gamma}}-\frac{\gamma\left[\sigma_y^2-2\sigma_{y\varepsilon}\xi+\sigma_\varepsilon^2\xi^2+(r_t^a(h)+\nu_\varepsilon)^2\xi^2\right]}{2\left(1+\nu_y-\xi\right)^{\gamma+1}}.
\end{aligned}$$

Thus, the sophisticated household prefers an ARM if and only if

$$r_t^f(h)-r_t^a(h)\geq\nu_\varepsilon+\nu_\pi+\frac{(\sigma_\varepsilon^2-\sigma_\pi^2)\xi-2\left(\sigma_{y\pi}+\sigma_{y\varepsilon}\right)}{2(1+\nu_y-\xi)/\gamma+\xi\left(\nu_\varepsilon-\nu_\pi\right)+\xi\left(r_t^a(h)+r_t^f(h)\right)}.$$

Thus, the spread rule (4.1) should be adjusted to account for the fact that the level of rates (quantity $r_t^a(h)+r_t^f(h)$) also matters for the optimal mortgage choice of the household with CRRA utility function. Observe that the spread rule is a good approximation whenever ξ is close to zero (e.g., when the downpayment consistitutes a small fraction of the household's wealth) or the risk aversion γ is low.

F.3 Microfoundation for Naive Households' Behavior

Next, we use the "money doctors" framework introduced in Gennaioli et al. (2015) to microfound the behavior of naive households. Suppose that naive households are uncertain about $\nu_\pi, \sigma_\pi^2, \nu_\varepsilon$, and σ_ε^2, and have some full-support beliefs F about their joint distribution. Conditional on $\nu_\pi, \sigma_\pi^2, \nu_\varepsilon$, and σ_ε^2, the utility of naive households from taking FRM is the same as of sophisticated households and is given by $\mathbb{E}[y-(1+r_t^f(h)-\pi)H]-\gamma\mathbb{V}[y-(1+r_t^f(h)-\pi)H]$.[46] However, conditional on $\nu_\pi, \sigma_\pi^2, \nu_\varepsilon$, and σ_ε^2, their utility from ARM is given by

$$\mathbb{E}\left[y-(1+s_t^a(h)+r_{t+\Delta}^{eurbr}-\pi)H\right]-a\gamma\mathbb{V}\left[y-(1+s_t^a(h)+r_{t+\Delta}^{eurbr}-\pi)H\right].$$

The difference from sophisticated households is that the variance is multiplied by the factor $a \geq 1$ reflecting the anxiety of naive households of taking ARMs, which is a less familiar option. We suppose that a is sufficiently large so that naive households only consider FRMs when they choose the bank. Thus, if a naive household is unattached, it becomes a customer of the bank with the lowest FRM rate in the market.

As in Gennaioli et al. (2015), banks act as money doctors and alleviate the anxiety of their customers by lowering a to 1. In addition, we suppose that banks provide to their customers signals about $\nu_\pi, \sigma_\pi^2, \nu_\varepsilon$, and σ_ε^2 (that can differ across households), which naive households believe to be undistorted and perfectly informative. Thus, if the bank's signal is such that $\sigma_\varepsilon^2-\sigma_\pi^2$ and/or $\nu_\pi+\nu_\varepsilon$ is sufficiently low, the bank can effectively steer the naive household from FRM towards ARM when they provide the advice. Thus, we obtain the type of choices by naive households that we described in the main text.

F.4 Optimal Spread Setting

We derive an explicit formula for (4.6) that we use in the estimation. We distinguish two cases depending on whether bank i has the lowest ARM-Euribor spread on the market ($s_{it}^a < \underline{s}_{-it}^a$) or not ($s_{it}^a > \underline{s}_{-it}^a$).[47] We use super-index a for the former case and super-index A for the latter. After banks post FRM-ARM

[46] Thus, their unconditional utility equals

$$\mathbb{E}_{v_\pi,\nu_\varepsilon,\sigma_\pi^2,\sigma_\varepsilon^2}\left[\mathbb{E}[y-(1+r_t^f(h)-\pi)H]-\gamma\mathbb{V}[y-(1+r_t^f(h)-\pi)H]\right],$$

where the outside expectation is with respect to household's beliefs about $\nu_\pi, \sigma_\pi^2, \nu_\varepsilon$, and σ_ε^2.

[47] We abstract from ties as they are not observed in our data.

spreads, bank i has either the lowest FRM rate ($s^f_{it} < \underline{s}^f_{-it}$) or not ($s^f_{it} > \underline{s}^f_{-it}$). We use super-index f for the former case and super-index F for the latter.

When $s^a_{it} > \underline{s}^a_{-it}$, we can rewrite the expected profit as

$$m^{AF}_{it} V^{AF}(\phi_{it}|\theta_{it}) G\left(s^f_{it}\middle|\mathbf{s}_t\right) + m^{Af}_{it} V^{Af}(\phi_{it}|\theta_{it}) \left(1 - G\left(s^f_{it}\middle|\mathbf{s}_t\right)\right), \tag{F.4}$$

and similarly, when $s^a_{it} < \underline{s}^a_{-it}$, we can rewrite the expected profit as

$$m^{aF}_{it} V^{aF}(\phi_{it}|\theta_{it}) G\left(s^f_{it}\middle|\mathbf{s}_t\right) + m^{af}_{it} V^{af}(\phi_{it}|\theta_{it}) \left(1 - G\left(s^f_{it}\middle|\mathbf{s}_t\right)\right). \tag{F.5}$$

Then ϕ_{it} is determined by maximizing either ($F.4$) or ($F.5$) depending on whether $s^a_{it} > \underline{s}^a_{-it}$ or $s^a_{it} < \underline{s}^a_{-it}$, respectively. To complete the characterization of the optimal rate setting, we determine functions $m_{it}, \underline{x}_{it}$, and $\overline{x}_{it}$ for different cases. Let

$$\kappa(\phi) \equiv 1 - \Phi\left(\tfrac{\phi - \mu_\delta}{\sigma_\delta}\right),$$

and $\phi_t \equiv \underline{s}^f_t + r^{swap25}_t - (\underline{s}^a_t + r^{eurbr}_t)$ be the spread between best FRM and ARM rates in the market. The following cases are possible:

1. Bank i does not have the lowest ARM-Euribor spread in the market ($s^a_{it} > \underline{s}^a_{-it}$)

   (a) If $s^f_{it} > \underline{s}^f_{-it}$, then bank i keeps only attached households initially assigned to it. The mass of them is $m^{AF}_{it} = (1-\psi)p_{it}$. Among bank i's customers, there is a fraction $1-\mu_a$ of sophisticated, and among sophisticated, a fraction $\kappa(\phi_{it})$ chooses the FRM. Thus, $\underline{x}^{AF}_{it} = (1-\mu_a)\kappa(\phi_{it})$ and $\overline{x}^{AF}_{it} = (1-\mu_a)\kappa(\phi_{it}) + \mu_a$.

   (b) If $s^f_{it} < \underline{s}^f_{-it}$, then bank i, in addition to its attached customers, attracts all naive unattached households and sophisticated unattached households that prefer to take FRM in the market. The mass of the former is $\psi\mu_u$, the mass of the latter is $\psi(1-\mu_u)\kappa(\phi_t)$. Thus, the total mass of bank i's customers equals

   $$m^{Af}_{it} = (1-\psi)p_{it} + \psi\mu_u + \psi(1-\mu_u)\kappa(\phi_t)$$

   Sophisticated attached households take FRM with probability $\kappa(\phi_t)$, while all sophisticated unattached households that bank i attracts take FRM. Thus,

   $$\underline{x}^{Af}_{it} = \frac{(1-\psi)p_{it}(1-\mu_a)\kappa(\phi_{it}) + \psi(1-\mu_u)\kappa(\phi_t)}{(1-\psi)p_{it} + \psi\mu_u + \psi(1-\mu_u)\kappa(\phi_t)}.$$

The fraction of naive households is given by

$$\mu_{it}^{Af} = \frac{(1-\psi)p_{it}\mu_a + \psi\mu_u}{(1-\psi)p_{it} + \psi(1-\mu_u)\kappa(\phi_t) + \psi\mu_u}$$

and so,

$$\overline{x}_{it}^{Af} = \underline{x}_{it}^{Af} + \frac{(1-\psi)p_{it}\mu_a + \psi\mu_u}{(1-\psi)p_{it} + \psi\mu_u + \psi(1-\mu_u)\kappa(\phi_t)}.$$

2. Bank i has the lowest ARM-Euribor spread ($s_{it}^a < \underline{s}_{-it}^a$).

   (a) If $s_{it}^f > \underline{s}_{-it}^f$, then bank i, in addition to its attached customers, attracts all sophisticated unattached households who prefer to take ARM in the market. They constitute a fraction $1-\kappa(\phi_t)$ of sophisticated unattached households. Then, the total mass of bank i's customers is

   $$m_{it}^{aF} = (1-\psi)p_{it} + (1-\mu_u)\psi(1-\kappa(\phi_t))$$

   Among those, there is a fraction

   $$\mu_{it}^{aF} = \frac{\mu_a(1-\psi)p_{it}}{(1-\psi)p_{it} + (1-\mu_u)\psi(1-\kappa(\phi_t))}$$

   of naive households. Further,

   $$\underline{x}_{it}^{aF} = \frac{(1-\mu_a)(1-\psi)p_{it}\kappa(\phi_{it})}{(1-\psi)p_{it} + (1-\mu_u)\psi(1-\kappa(\phi_t))},$$
   $$\overline{x}_{it}^{aF} = \frac{(1-\mu_a)(1-\psi)p_{it}\kappa(\phi_{it}) + \mu_a(1-\psi)p_{it}}{(1-\psi)p_{it} + (1-\mu_u)\psi(1-\kappa(\phi_t))}$$

   (b) If $s_{it}^f < \underline{s}_{-it}^f$, then bank i in addition to its attached customers attracts all unattached households. Thus, the total mass of bank i's customers is $m_{it}^{af} = (1-\psi)p_{it} + \psi$; and $\underline{x}_{it}^{af} = ((1-\psi)(1-\mu_a) + \psi(1-\mu_u))\,\kappa(\phi_{it})$ and $\overline{x}_{it}^{af} = ((1-\psi)(1-\mu_a) + \psi(1-\mu_u))\,\kappa(\phi_{it}) + ((1-\psi)\mu_a + \psi\mu_u)\,.$

F.5 Likelihood Function for Distribution of θs

The likelihood for distribution of θs is given by

$$\sum_{t,k}\Bigg[\sum_{x_{ikt}\in(\underline{x}_{ikt},\overline{x}_{ikt})}\ln\left(\frac{1}{\sigma_\theta}\phi\left(\frac{x_{ikt}-\frac{1}{2\lambda}(\phi_{it}-r_t^{swap25}+r_t^{eurbr})-\mu_\theta}{\sigma_\theta}\right)\right)-N_k^s\ln\left(\Phi\left(\frac{1-\mu_\theta}{\sigma_\theta}\right)-\Phi\left(\frac{-\mu_\theta}{\sigma_\theta}\right)\right)$$
$$+\sum_{x_{ikt}\leq\underline{x}_{ikt}}\ln\left(\Phi\left(\frac{\underline{x}_{ikt}-\frac{1}{2\lambda}(\phi_{it}-r_t^{swap25}+r_t^{eurbr})-\mu_\theta}{\sigma_\theta}\right)-\Phi\left(\frac{-\mu_\theta}{\sigma_\theta}\right)\right)$$
$$+\sum_{x_{ikt}\geq\overline{x}_{ikt}}\ln\left(\Phi\left(\frac{1-\mu_\theta}{\sigma_\theta}\right)-\Phi\left(\frac{\overline{x}_{ikt}-\frac{1}{2\lambda}(\phi_{it}-r_t^{swap25}+r_t^{eurbr})-\mu_\theta}{\sigma_\theta}\right)\right)\Bigg].$$

We maximize it over μ_θ and σ_θ to obtain estimates of these parameters.

F.6 Computing Changes in Certainty Equivalent

Sophisticated households' welfare is evaluated according to their mean-variance utility function. Following Kahneman et al. (1997), naive households' welfare is evaluated according to their "experienced" utility function, which is the same as the mean-variance utility function of sophisticated households. Our welfare measure is the average yearly per capita change in the certainty equivalent mortgage payment due to the policy intervention. This measure reflects the variation in yearly mortgage payment for the average household due to the policy. The certainty equivalent of an FRM with rate $r_t^f(h)$ equals

$$CE\left(r_t^f(h)\right)=\mathbb{E}[y]-\gamma\mathbb{V}[y]-H\left(1+r_t^f(h)-\nu_\pi+\gamma H\sigma_\pi^2\right). \tag{F.6}$$

The certainty equivalent of an ARM with ARM-EURIBOR spread $s_t^a(h)$ equals

$$CE\left(s_t^a(h)\right)=\mathbb{E}[y]-\gamma\mathbb{V}[y]-H\left(1+s_t^a(h)+r_t^{eurbr}+\nu_\varepsilon+\gamma H\sigma_\varepsilon^2\right). \tag{F.7}$$

We set the mortgage size H to the median mortgage size in our sample (125,000 euros) and compute the change in the certainty equivalent for every household as follows. If the household switches from ARM with $s_t^a(h)$ to ARM with $\tilde{s}_t^a(h)$, or from FRM with $r_t^f(h)$ to FRM with $\tilde{r}_t^f(h)$, then the change in the certainty equivalent equals $H\left(s_t^a(h)-\tilde{s}_t^a(h)\right)$ and $H\left(r_t^f(h)-\tilde{r}_t^f(h)\right)$, respectively. If the household switches from ARM with $s_t^a(h)$ to FRM with $\tilde{r}_t^f(h)$ or from FRM with $r_t^f(h)$ to ARM with $\tilde{s}_t^a(h)$, then the change in the certainty equivalent equals $H\left(s_t^a(h)+r_t^{eurbr}+\delta-\tilde{r}_t^f(h)\right)$ and $H\left(r_t^f(h)-\tilde{s}_t^a(h)-r_t^{eurbr}-\delta\right)$, respectively.

G Frictions in the Italian mortgage market

On January 31st, 2007 the Italian government issued Legislative Decree n.7, which came to be known as *Bersani law* named after the minister who drafted it. The decree included provisions meant to liberalize several sectors of the economy. For instances, it prohibited surcharges on purchases of credit for prepaid mobile phones and voided penalty fees for changes of telecom provider. Most relevant for our study, it also banned prepayment and renegotiation fees for newly issued mortgages (and drastically reduced them for existing ones).

The chief moment driving identification of ψ, the parameter picking up the degree of frictions in the mortgage market, is computed using data from the 2006 wave of SHIW. This raises a potential concern to the extent that we believe that the Bersani law altered the ability of borrowers to shop around for mortgages and their expectations on their chances to be able to renegotiate their contracts with a bank other than the one that originated it.

It is important to notice that the effects of the Bersani law can threaten our demand estimates but not our supply parameters. The estimate of bank's cost efficient fraction of FRMs, θ_{ikt}, is the residual that makes the first-order condition for steering hold for each bank-market-quarter. This means that, if there is a change in banks' preferences over mortgage types due to the Bersani reform, it will be picked up by our estimates of θ_{ikt}'s, as we allow them to vary across banks and quarters. Therefore, any potential impact of the Bersani reform on the supply side would be fully accounted for in our model (banks choose their spread conditional on the realized θ_{ikt}).

The Bersani reform had the full force of law immediately after it had been issued. Therefore, the reform had the potential to influence mortgage transactions in the second half of our sample. However, we show below that according to several auxiliary measures of household mobility the reform did not have an immediate substantial impact on the mortgage market. If there were obstacles in the initial implementation of the reform, as press reports suggest, the option of refinancing would be less salient and would not affect much the decisions of households at the stage of mortgage origination in our sample span.

In the paper, we identify households able to take a mortgage outside their home bank (*"switchers")* as those who declare they have obtained a mortgage in the year and whose relationship with their main bank started recently (less than two years before the survey was administered). The fraction of switchers is then given by the ratio between the number of such households over the total number of mortgage-takers, computed using the sampling weights provided by SHIW. The survey is administered to a representative sample of Italian households every two years. The two questions that we use to define switchers are present in the waves collected in 1995, 1998, 2000, 2002, 2004, 2006, 2010 and 2012. In 2008, the question asking whether the household had taken a mortgage is present but the one about the length of the relationship with the main bank is not. This is the reason why we only used 2006 SHIW data in our estimation procedure.

In order to check if there was a spike in switchers caused by Bersani reform, we impute the fraction of switchers in 2008 indirectly using SHIW2008 and SHIW2010 as follows. We consider a subsample of households who are interviewed both in the 2008 and in the 2010 wave of SHIW. Households reporting in 2010 that the relationship with their main bank was between two and four years old, would have had a relationship shorter than 2 years in 2008. This way we can impute the desired length of relationship with the main bank for a subsample of surveyed households in 2008, and compute the fraction of switchers in year 2008. To compare the procedure relying on current SHIW data with those exploiting imputation, we repeat the imputation procedure even for years where we have the information on the length of the relationship available in the survey. In Figure 6, we present both the fraction of switchers constructed using the original SHIW (red dots) and the fraction of switchers obtained using the imputation from the subsequent SHIW (blue dots).

The figure delivers several insights. First, both actual and imputed fractions of switchers stay on average around 8-9% in years before 2012, which is in line with our structural estimate 8.8% of the fraction of unattached households.

Second, the variation in the fraction of switchers is larger for the imputed series than the actual series, which is explained by the fact that the imputed series is based on a smaller subsample of households who are present in two consecutive waves of SHIW. We cannot say that the imputed series is systematically biased in one direction relative to the actual series, which is the reason why we decided not to use the imputed fraction of switchers in 2008 in our estimation.

Third, the imputed fraction of switchers in 2008 is around 5%, which points that there was no significant jump in the fraction of switchers right after Bersani reform was introduced. In fact, even if we were to assume that in 2008 the imputed fraction underestimates the true figure by 10 percentage points (which is the largest observed gap between the actual and the imputed series), this would put the actual fraction of switcher in 2008 at about 15 percent. This is higher than the 11% from the 2006 SHIW but it hardly suggests that we would be completely off using it to inform our estimation procedure. Further, in years 2010 and 2012 –when arguably the awareness of the Bersani reform is higher than right after the announcement – the actual fraction of switchers does not spike considerably either and is below 14%.

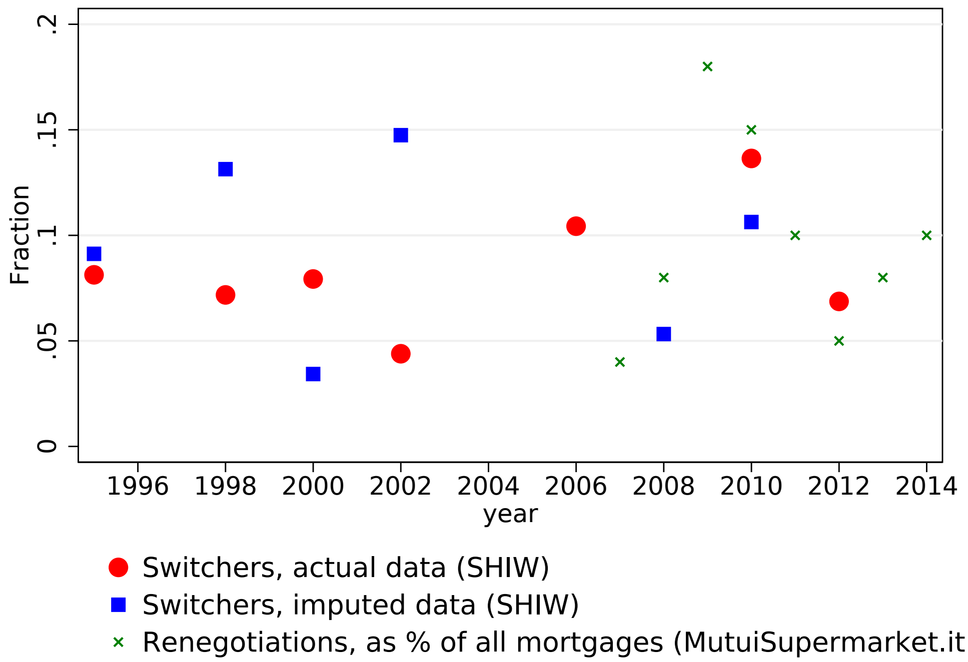


Figure 6: **Fraction of Borrowers Switching Bank**

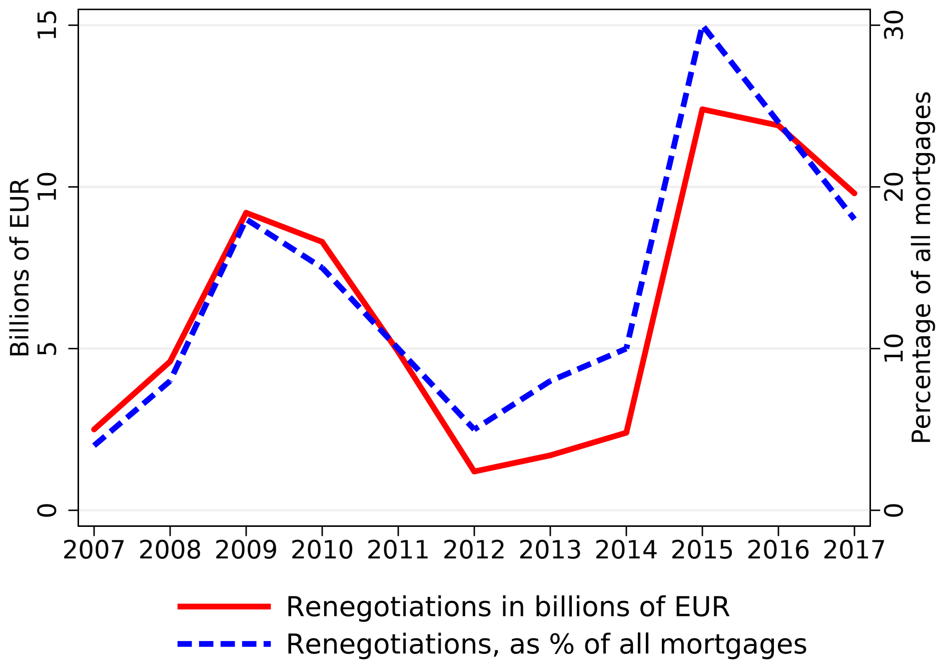


Figure 7: **Trend in Mortgage Renegotiations**

To confirm the conclusion that the Bersani reform is unlikely to have changed dramatically the fraction of unattached households during our sample period, we also look at the evidence on mortgage renegotiations during this period. We find indications that the effect of Bersani law on the mortgage market materialized with a significant lag. Some anecdotal evidence is provided, for instance, in an article published by *Il Sole 24 Ore* on the 10 years anniversary of the reform.[48] In this article, it is recounted how in the Spring of 2007 and, in part, even in the following year "*mortgage-takers trying to switch bank at no cost lamented issues in obtaining the enforcing of the new rules*" and how "*.. the very first surge* [in renegotiations]*... was only in 2009 and subsequent years*". The same article contains data on renegotiations based on elaboration by MutuiSupermarket.it, a mortgage comparison website. We use them to create the plot in Figure 7.

The plot features two measures of the relevance of renegotiations in the Italian mortgage market since the Bersani reform. Both in terms of amount of money lent (left axis) and fraction of new mortgages issued (right axis) renegotiations in 2007 and 2008 were at levels not comparable to those reached in

[48]"Mutui, la surroga compie 10 anni. Conviene ancora cambiare?", published on June 22, 2017.

the years since 2009. The explosion in renegotiations, which has in part created the perception that the Bersani reform had a seismic shift in the Italian mortgage market, materializes only in 2009 and 2010 and, after a drop due to a sharp rise in spreads, from 2015 on. In short, we have reason to believe that the Bersani reform would not have significantly affected transactions in our sample span. This evidence is not necessarily inconsistent with the findings in the Beltratti et al. (2017). Their estimates are based on two cross sections of mortgage-takers: one in 2005, well before the reform, and one in 2009 when, as we have shown, the take up in renegotiations had already ramped up. The fact that they document that there was some effect on pricing in 2009 does not conflict with our claim that the reform had a slow start. The fraction of renegotiated mortgages computed by MutuiSupermarket.it is depicted in Figure 7 with green crosses. This series tracks pretty closely our other two measures of household mobility, hence, validating them. It also indicates that in 2007 and 2008 (years in our sample), the Bersani reform did not lead to a significant increase in renegotiations: Renegotiated mortgages constitute merely 5% of total mortgages issued. This points again to limited mobility of households across banks during our sample period. Even when households have a very low cost option to renegotiate their mortgages, not many ended up using this option. This is consistent with Andersen et al. (2020)who document long delays in mortgage refinancing and, more generally, with the pervasive finding in studies of household financial decision-making that individuals respond slowly to changing financial incentives.[49]

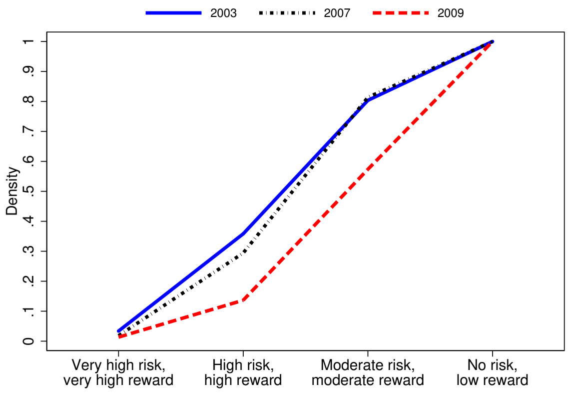
To summarize, we argued above that our model is flexible enough to incorporate the effect of Bersani reform on the supply side, while additional evidence indicates that its effect on the demand side was limited during our sample period.

H Stationarity of Households Characteristics

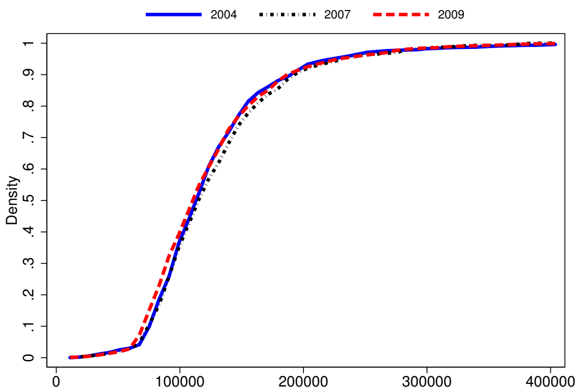
Here, we show that the distribution of risk aversion and mortgage size experienced negligible changes in the period that we analyze. Figure 8 plots the cumulative distribution of a proxy of risk aversion and of the mortgage size for the beginning and the end of the time span covered by our data. Since they represent the main elements determining the optimal spread cutoff, this evidence should reassure on the stationarity of the distribution of δ which underlies our identification of the supply side estimation.

Figure 8a plots the cumulative distribution of the answer to a question meant to elicit risk aversion. The data come from a survey conducted by a major Italian bank on its retail customers. The question we are focusing on asks respondents about the investment strategy that best identifies their approach. The

[49] See for example Choi et al. (2002), and Madrian and Shea (2001) on retirement savings plans and Anagol et al. (2018) and Calvet et al. (2009) on portfolio rebalancing.



(a) Distribution of Risk Aversion



(b) Distribution of Mortgage Size

Figure 8: **Cumulative Distribution of Households Characteristics**

Notes: The top panel plots the cumulative distribution of the responses to a question asking a sample of retail investors of a major Italian banking group to indicate the investment strategy that best characterizes their behavior. The bottom panel plots the cumulative distribution of granted mortgage size using a random sample of Credit Registry microdata representing 40% of the mortgages originated in Italy between 2004 and 2010.

four options offered span a profile consistent with high risk tolerance (households pursuing "very high reward" and willing to be exposed to "very high risk" to achieve it) to extreme risk aversion (households content to obtain "low reward" as long as it entails "no risk" at all). The survey counts several waves and is a repeated cross section. The distribution of answers in 2003 (before the beginning of our sample) and 2007 (the next to last year we consider) is nearly identical. The risk aversion of Italian investors seems instead profoundly affected by the explosion of the financial crisis which dates to the second semester of 2009 in Italy. The investors surveyed in 2009 report a much more risk averse attitude than measured before. This evidence motivates the choice to limit our analysis to the years prior to the financial crisis in Italy.

Figure 8b depicts the distribution of the real mortgages size (in 2004 euros) exploiting microdata on a random subsample covering 40% of the mortgages issued between 2004 and 2009. Conditional on the mortgage being issued, the distribution of mortgage size does not change through our sample. Interestingly, this variable does not seem to be affected even by the intervention of the financial crisis: the distribution in 2009 is nearly identical to the 2004 and 2007 ones.

I Correlation between attachment and naivete

Our estimation strategy for the correlation between naivete and attachment relies on the restrictions implied by the model and does not require external data to proxy these measures. This give us the opportunity to validate our findings using survey data that contain proxies for naivete and attachment. For this purpose, we turn to a survey administered by a major Italian bank to a representative sample of 1,686 of its customers in the summer of 2007.[50] The survey records detailed demographic information and includes several questions on customers preferences and attitudes towards investment management and usage of financial services. We use the survey to construct two different proxies for lack of attachment and six different proxies for sophistication.

- Proxies for lack of attachment

    1. Dummy variable for whether the customer is considering product and services offered by banks other than the one running the survey. This indicator signals that the customer is willing to entertain the idea of shopping around for financial services.

[50] We entertained the idea of using these proxies directly in the estimation. Our main concern was that these measures come from the clientele of a single bank, though large. Hence, our preferred strategy was to rely on the main data from the Credit Registry for the identification of the parameters of the model and to resort to this survey only to provide a sanity check of our findings.

2. Dummy variable for whether the customer had a bank account with banks other than the one running the survey. This indicator identifies customers who have a relationship with multiple banks and, therefore, a clear opportunity to move around them looking for the best conditions.

- Proxies for sophistication

  1. Dummy for whether the customer has ever invested in stocks. We assume that those who have familiarity with the mechanics of the stock market will have a level of financial literacy higher than those who stuck to more simple financial assets (bonds, saving accounts,...).
  2. Age of first investment in stocks (only for the subsample of those who ever did). The assumption is that more sophisticated customers will have entered the stock market earlier.
  3. Correct answer to a financial literacy question. The survey includes a question meant to measure customers' understanding of the working of financial instruments. The question asks the interviewee whether it is optimal to purchased asset yielding a fixed interest rate if one expects interest rates to rise. We construct a dummy identifying as sophisticated those who answer correctly.
  4. Frequency at which the customer checks his/her investments. The survey asks to report the frequency at which the customer checks the status of his/her investment. The possible answers range from "I have no investment" to "I check my investments daily". We assume that subject controlling their investments more frequently display a higher degree of sophistication. In particular, we construct an indicator that signals as sophisticated all the customers reporting that they check their investment at a frequency higher than the median (i.e. at least once per month).
  5. Frequency at which the customer adjusts his/her investments. This proxies is akin to the previous one but relies on the frequencies at which customers actually reallocate their investment portfolio. Interviewees that re-optimize more frequently can be thought of as more sophisticated. We consider as sophisticated all the customers reporting that they reallocate their investment at a frequency higher than the median (i.e. about once per year).
  6. Time spent collecting financial information. The survey asks each interviewee how much time do they spend gathering information useful to make investment decisions. The answers can range from "No time at all" to "Over 7 hours per week". We define as sophisticated the

	Considers other banks	Has other bank accounts
Has ever held stocks	0.057***	0.136***
Age of first stock investment	-0.003**	-0.004**
Correct answer to finlit question	0.033**	0.027
Frequency of investments check	0.052***	0.096***
Frequency of investment reallocation	0.042**	0.037
Time spent gathering information	0.11***	0.11***

subjects that report spending more time gathering financial information than the median person in the sample (i.e. more than 30 minutes per week).

We estimate correlations between these two set of proxies conditional on a series of demographic controls: geographical area of residence, wealth, age, gender, education, employment status and household size. The table below reports in each cell the result of a different regression where the proxy for lack of attachment listed in the column header is the dependent variable run on the proxy for naivete listed in the row, accounting for all the controls just mentioned.

This simple set of regressions delivers a positive correlation between sophistication and lack of attachment which confirms the finding of our structural estimation that more naive customers are more likely to be attached to their home bank.

J Additional Figures and Tables

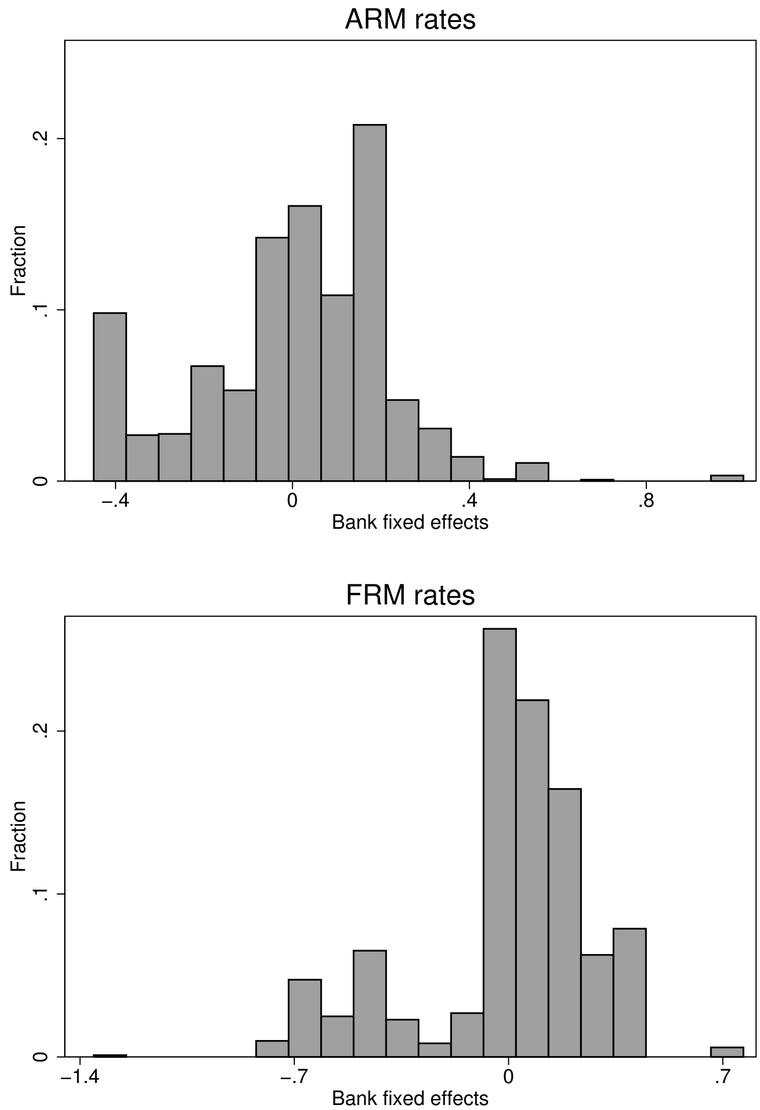


Figure 9: **Dispersion of Rates**

Notes: The figures display the bank fixed effects (in rate percentage points) estimated from regressing adjustable rates (top figure) and fixed rates (bottom figure) on bank, province and quarter dummies.

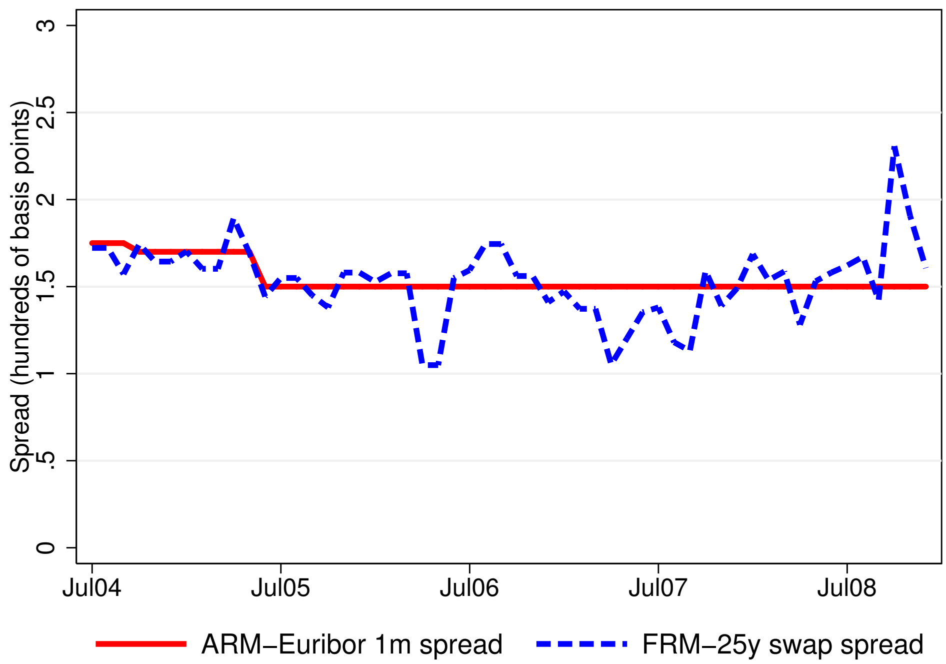


Figure 10: **Rate Spreads on a 25-year Mortgage Set by a Major Italian Bank**

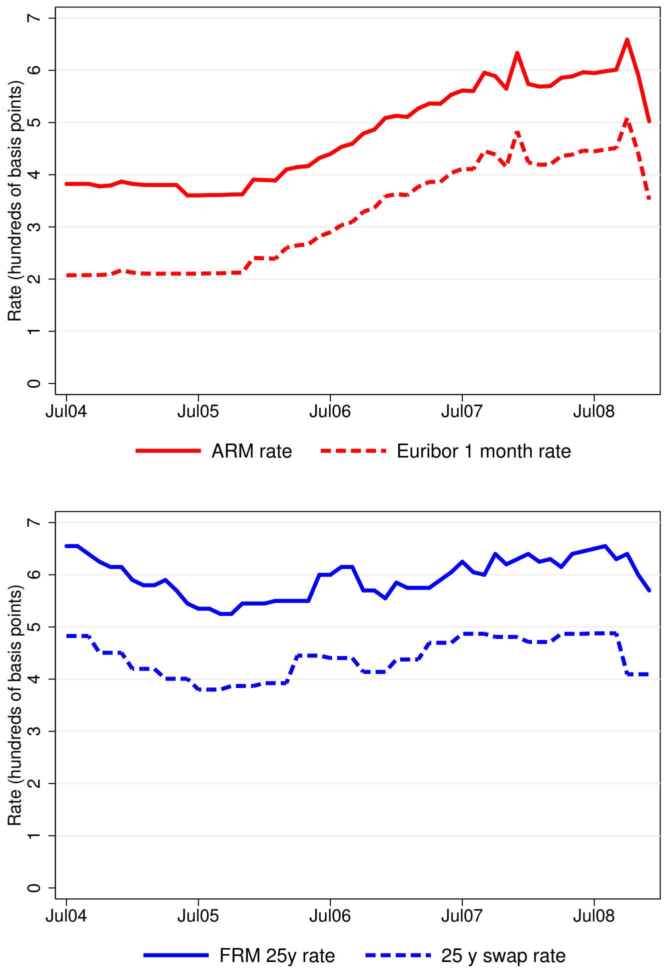


Figure 11: **Benchmark Rates for adjustable and fixed rate mortgages**

Notes: The figure portrays the evolution of adjustable and fixed rates posted by a large bank during the sample span we analyze. We compare them with the rate of the instrument we assume banks use as benchmark for the pricing of their mortgages. In the top panel, we display the ARM rate posted by the bank and the Euribor 1 month rate; in the bottom panel, the rate on a 25 years FRM is porttrayed alongside the rate of a 25 years interest rate swap.

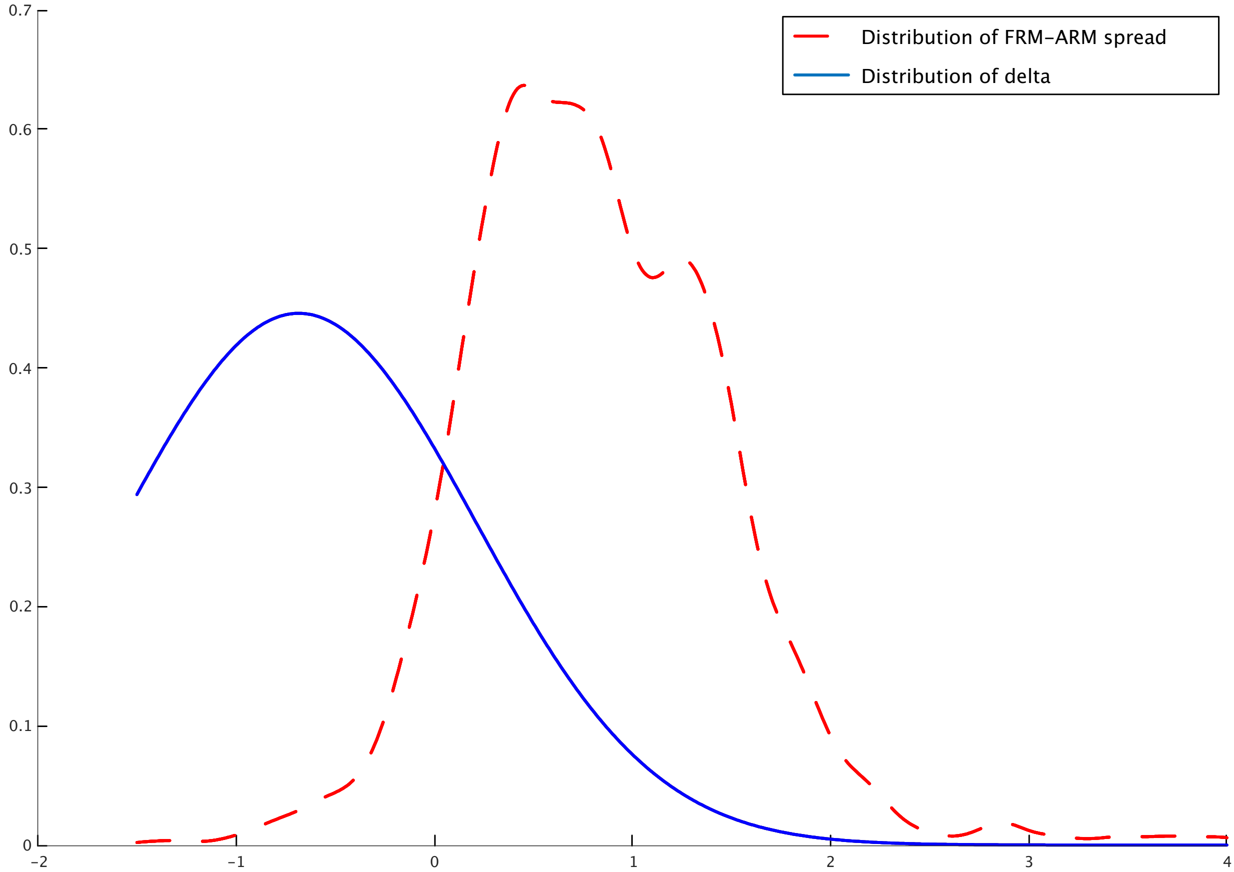


Figure 12: **Estimated Distribution of δ and Kernel Density of ϕ_{it}**