



BANK FOR INTERNATIONAL SETTLEMENTS



BIS Working Papers

No 835

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

by Leonardo Gambacorta, Luigi Guiso, Paolo Emilio Mistrulli, Andrea Pozzi and Anton Tsoy

Monetary and Economic Department

December 2019

JEL classification: G21, D18, D12

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

BIS Working Papers are written by members of the Monetary and Economic Department of the Bank for International Settlements, and from time to time by other economists, and are published by the Bank. The papers are on subjects of topical interest and are technical in character. The views expressed in them are those of their authors and not necessarily the views of the BIS.

This publication is available on the BIS website (www.bis.org).

© *Bank for International Settlements 2019. All rights reserved. Brief excerpts may be reproduced or translated provided the source is stated.*

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

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

Leonardo Gambacorta* Luigi Guiso♦ Paolo Emilio Mistrulli♥

Andrea Pozzi♠ Anton Tsoy†

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, while “naïve” ones are susceptible to steering by their banks. Using data on the universe of Italian mortgages, we estimate the model and quantify the welfare implications of steering. The analysis shows that banks’ steering activity could generate distortions, with welfare effects that vary between households depending on their degree of sophistication. However, the introduction of measures to restrict the scope for banks to steer their customers would not necessarily increase household welfare, because such activities, even if potentially distortive, may also contain useful information. By contrast, a financial literacy campaign always has a beneficial effect on the welfare of naïve households, which are proportionately more exposed to the risk of taking inappropriate financial decisions.

JEL Classification: G21, D18, D12.

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

* We thank Victor Aguirregabiria, Jason Allen, Fernando Alvarez, Steffen Andersen, Judith Chevalier, Joao Cocco, Anthony Cookson, Dean Corbae, Francesco Decarolis, Mark Egan, Liran Einav, Andreas Fuster, Thomas Gehrig, Daniel Green, Jean-Francois Houde, Andrey Malenko, Claudio Michelacci, Ariel Pakes, Franco Peracchi, Maya Shaton and, in particular, two anonymous referees for useful comments and suggestions. We also thank seminar audiences at CSEF, EIEF, LSE, Tilburg, WU Vienna, Rotman, McGill, Mannheim, IDC Herzlyia, Tel Aviv University, Hebrew University, Ben Gurion University, CREST–ECODEC Conference (Paris), RBFC (Amsterdam), FCA/Brevan Howard Conference on Consumer Choice in Mortgage Market (Imperial), AEA 2017 (Chicago), 10th Swiss Conference on Financial Intermediation (Lenzerheide), 2nd CEPR Symposium in Financial Economics (London), CEPR Workshop in Household Finance (Copenhagen), Queen’s-Bank of Canada Conference on Financial Intermediation and Regulation (Kingston), Barcelona GSE Summer Forum 2017, MaCCI SummerInstitute 2017 (Romrod), 2017 NBER Summer Institute (IO), ESSFM 2017 (Gerzensee), Norges Bank Workshop on Housing and Household Finance (Oslo), EARIE 2017 (Maastricht), Tinbergen Workshop in Industrial Organization 2018 (Amsterdam), ECB Conference on Household Finance and Consumption, FIRS (Barcelona), EFA (Warsaw). The views expressed in this article are those of the authors and do not necessarily represent the views of the Bank of Italy or the Bank for International Settlements.

* Bank for International Settlement and CEPR, leonardo.gambacorta@bis.org

♦ EIEF and CEPR, guiso@tin.it

♥ Bank of Italy, paoloemilio.mistrulli@bancaditalia.it

♠ EIEF and CEPR, andrea.pozzi@eief.it

† EIEF, tsoianton.ru@gmail.com

1 Introduction

Retail financial products, such as residential mortgages, credit cards, investment products, retirement plans, etc., are often quite complex and many households lack knowledge or sophistication to decide which financial product 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 the financial intermediary provides private advice to its customer, it may explain the advantages of a complex financial product that the customer would not be confident to purchase on their own initiative.¹ It may also shroud some of the product's features to make it seem more appealing, thus potentially distorting the customer's choice. 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. Financial intermediaries will also tend to more vigorously advertise the benefits of products in which they hold a competitive advantage.

There is a substantial empirical and anecdotal evidence that steering is pervasive in financial markets. The evidence spans many countries and all markets for household financial products.² Egan et al. (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. In this case, legislators may enact new regulations with the aim of better aligning the interests of financial intermediaries with those of their customers.³

These features raise a number of questions that have 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, and what would be the welfare benefit or cost of this policy? What are the welfare consequences of specific policies, such

¹There is ample evidence that households often rely on experts' advice. For example, Hung and Yoong (2013) report that 73% of US investors rely on professional advice to conduct stock market or mutual fund transactions. In the UK 91% of intermediary mortgage sales are "with advice" (Chater et al. (2010)) and according to a broad survey of German retail investors, 80% consult financial advisors.

²E.g., the mortgage market (Gurun et al. (2016); Agarwal et al. (forthcoming); Foà et al. (2019)); the market for retail investments (Bergstresser et al. (2009); Hackethal et al. (2012); Mullainathan et al. (2012); Christoffersen et al. (2013); Foerster et al. (2017); Chalmers and Reuter (2017); Hoechle et al. (2018)); the credit cards market (Ru and Schoar (2017)); and the insurance market (Anagol et al. (2017)).

³An example is the Obama administration's attempt to raise fiduciary standards. In Obama's words the goal of the policy was to establish "a very simple principle: you want to give financial advice, you've got to put your client's interest first." The same motivation is behind the tighter requirements on independent financial advice introduced by the European Mifid II directive.

as a financial education campaign? The goal of this paper is to quantify the impact of steering in financial markets on households' welfare.

While the presence of steering in financial markets has been documented by several studies, assessing its economic relevance is an even harder task. In fact, the welfare cost of steering and welfare implications of different policies depends on the distribution in the population of sophisticated and unsophisticated consumers as well as on the financial intermediaries' response to these policies. These two elements have yet to be investigated in the literature. Moreover, since in retail financial markets steering often occurs in private, face-to-face interactions between two parties, hard data on whether a household was steered and on the particular content of the interaction are almost impossible to come by. Therefore, our strategy of inferring the impact of steering cannot rely on such information.

To overcome these challenges, 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 appreciate the pros and cons of different products and choose the most suitable one. Financial intermediaries provide information and advice to their customers about the range of mortgage type on offer, 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 identify 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. Namely, 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 on their balance sheets the mortgages that they originate. This creates an interest rate exposure, which is not completely hedged through derivatives, such as interest rate swaps (Esposito et al. (2015); Cerrone et al. (2017); Hoffmann et al. (2019)). Thus, banks have incentives to use both relative pricing of mortgages and steering in order to manage the maturity mismatch. Further, banks (rather than brokers or other intermediaries) are the main providers of information and advice about mortgages to customers (Oliver Wyman (2003)). This means

that Italian banks have both the motive and the opportunity to steer their customers.

In a companion paper, Foà et al. (2019) use data similar to ours to provide reduced form evidence of lender’s non-price influences in the mortgage choice, which we also replicate in our sample. Building on this reduced form evidence (which we strengthen even further), we set up a parsimonious model of households’ mortgage choices where banks can steer their customers. In our model, households make two choices: they pick the bank from which they take out a mortgage and they decide between an FRM and an ARM. A fraction of households can shop around for the best rate in the market, while other households consider only mortgages at their home bank. This captures in a reduced form different market frictions, such as search or switching costs, and gives banks a certain degree of market power over their customers. In order to identify this friction, we complement our data with the Survey of Households Income and Wealth data, which contains information on households who switched their home bank in the same year that they took the mortgage.

Borrowers in our model can be “sophisticated” or “naive” in their choice of the mortgage type. It has been shown theoretically and documented empirically (Campbell and Cocco (2003); Kojien et al. (2009); Badarinza et al. (2018)) that the optimal choice of the mortgage type can be approximated by the spread rule: in order to decide which type of mortgage to take up, a household needs to compare the spread between the best available FRM and ARM rates to its household-specific cutoff. In our model, sophisticated households follow the spread rule. Importantly, all the heterogeneity among households that affects the rational choice of the mortgage type (e.g., risk aversion or beliefs about stochastic processes for inflation, income, and rates) is summarized in this household-specific cutoff on the FRM-ARM spread.

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 et al. (2010); Fornero et al. (2011); Gathergood and Weber (2017); Albertazzi et al. (2018)), and can be microfounded by the “money doctors” model by Gennaioli et al. (2015). Unlike the sophisticated households, naive households are prone to steering by banks. Importantly, the effect of steering on naive households’ welfare is ambiguous, because on the one hand, it expands the naive households’ choice sets (from only FRMs to both mortgage types), but on the other hand, it also potentially distorts their choices. Given that the sensitivity to FRM and ARM rates of sophisticated and naive households is different, we can identify the fraction of

naive as well as the distribution of the optimal cutoffs on the FRM-ARM spread among sophisticated households from the data on the banks' market shares in the mortgage market.

On the supply side, banks vary in the target fixed/adjustable composition of their mortgage portfolio and compete with each other by setting rates to attract borrowers. After they attract their customer base, they can also use non-pricing channels to steer customers towards a particular type of mortgage, naive customers being more susceptible to such steering. Thus, our model captures steering that occurs through one-on-one interactions between customers and their banks, e.g., through (informative or distorted) financial advice at the branch or the targeted advertising of financial products (as in Ru and Schoar (2017)). This choice comes at little cost, as Foà et al. (2019) document that other forms of steering that we do not explicitly model (e.g., strategic rationing or public advertising campaigns) are not particularly relevant in the Italian market. We use the optimality conditions for rate setting and steering policies in order to recover the underlying supply parameters.

We estimate the fraction of naive borrowers at 48%, which squares with survey measures of financial sophistication of the Italian population. Further, we obtain that banks have a significant market power: at 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 proportion of naive borrowers) in order to manage the maturity mismatch on the asset side.

The welfare cost of steering is 661 euros per year for the average household (about 11% of the annual mortgage payment). However, this varies markedly between households. While the cost is positive for naive households (1,705 euros on average), sophisticated households can benefit (by 295 euros on average). Because banks can adjust their mortgage portfolios by steering the choices of naive households, they rely less on rates to achieve their desired mortgage mix. At the estimated parameters, this results in cheaper mortgages for the average sophisticated borrower. In essence, we quantify the size of an implicit subsidy from naive households to sophisticated households.⁴ It follows that a policy that forces banks to steer customers towards their best choice would benefit naive households but hurt sophisticated ones.

We find that the welfare effects of a financial education campaign that effectively halves the fraction of naive households are also heterogeneous. Households on average

⁴The presence of this implicit subsidy has been established theoretically (Gabaix and Laibson (2006)).

gain 304 euros per year (5.2% of the annual mortgage payment). Most of the welfare gain accrues to households who were naive but gain in sophistication thanks to the campaign (1,845 euros per year). However, because banks react to the policy by adjusting the rates, sophisticated households stand to lose on average (314 euros per year). Therefore, these policies are not necessarily Pareto improving, even when the costs of funding them are not taken into account. On the other hand, we show that restricting steering by banks results in a welfare loss for both naive and sophisticated borrowers. On average, this policy entails a welfare loss as great as 998 euros per year. The amount for the naive households is particularly large (1,444 euros per year), because banks often steer customers to a more beneficial mortgage type and the gain from this then exceeds the distortion costs. Because of the effect on rates, the loss is also significant for the sophisticated (590 euros per year). In sum, simply prohibiting all forms of steering imposes costs on both naive and sophisticated households.

Although our implications are obtained using data from the Italian mortgage market, they are relevant more generally for steering in financial markets where the complexity of financial products gives scope for steering by intermediaries. Our results have two broader implications for steering in financial markets. First, there are both benefits and costs to steering by intermediaries, and the structural approach is instrumental in determining whether these costs outweigh the benefits. In particular, simply banning all forms of steering might hurt consumers (as occurs in our case), particularly the naive consumers that such regulations are designed to protect. Second, the effect of different policies that restrict steering will vary across naive and sophisticated households. 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 financial markets.

This study relates to several strands of literature. First, we contribute to the household finance literature on various forms of steering (Ru and Schoar, 2017; Egan et al., 2019; Robles-Garcia, 2019; Egan, 2019; Foà et al., 2019) by explicitly modeling steering by banks and quantifying its welfare consequences and the implications of several policies that can be adopted to deal with it. Second, 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 et al., 2012; Crawford et al., 2018), inattention and inertia (Woodward and Hall (2012);

Andersen et al. (2017)), and bargaining (Allen et al., 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 et al. (2013); Aguirregabiria et al. (2016); Egan et al. (2017)). Further, we relate to the literature on financial advice games that rely on the presence of both sophisticated and naive investors (Ottaviani and Squintani (2006); Kartik et al. (2007)).⁵ Our estimates point to a large fraction of households with limited financial sophistication which engage in high-stakes transactions, vindicating the tenet of these models.

The rest of the paper is organized as follows. Section 2 describes institutional features of the Italian mortgage markets. Section 3 describes the data and provides reduced form evidence of steering. Section 4 presents the model. Section 5 discusses the identification of the model. Section 6 reports estimation results and provides further evidence of steering. Section 7 presents the results of the policy experiments. Section 8 concludes.

2 Institutional Background

The functioning of the mortgage market is greatly affected by a number of institutional characteristics (Campbell (2013)). In this section, we describe the Italian mortgage market to illustrate that its simple structure provides a suitable environment for the empirical study of steering in financial markets and to highlight the differences between the Italian mortgage market and other markets (most notably the US). Online Appendix A.1 provides a more extensive description of salient characteristics of the Italian market.

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 the Survey of Households Income and Wealth (henceforth, SHIW) – a comprehensive survey administered every two years by the Bank of Italy to a representative sample of Italian households – only 12% of Italian households have a mortgage, half the average figure for households in the euro area. Yet, reliance on mortgages to finance a purchase of a house has become increasingly popular in the 90s and early 2000. In our sample, nearly 250,000 mortgages with maturity 25 to 30 years are originated on average each year.

⁵A rich literature provides the theoretical underpinnings on how advice affects unsophisticated households’ financial choices when brokers and/or intermediaries have a conflict of interest. See Inderst and Ottaviani, 2012 for a review.

The two most common types of contracts available in Italy are ARM where the bank charges a spread over an underlying benchmark rate (usually the 1- or 3-month Euribor); and FRM where an interest rate is agreed upon when the contract is signed and a fixed amount is repaid in each installment for the whole length of the mortgage. Together, these products represent over 90% of the mortgages issued in our sample.⁶ 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 in the sample FRMs represent nearly 70% of the mortgages issued. The presence of only two mortgage types eases the identification of steering by banks. Importantly, 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, FRM vs ARM 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%.

We next argue that Italian banks have both opportunities and incentives to steer mortgage-takers to a particular product.

Banks’ opportunities to steer customers Steering by banks can take many forms: advice, advertisement, shrouding, etc. Two conditions necessary for any form of steering to be possible are that: i) some households lack the sophistication to make an informed decision about the mortgage choice based only on rates, and ii) households often turn to banks for financial information and advice.

In Online Appendix A.2, we document that the level of financial sophistication of Italian households is fairly low. Specifically, based on the SHIW data we construct an index of financial literacy that demonstrates that most households have difficulty reading and analyzing basic financial information. To document that banks are key providers of information to their customers, we present evidence from a survey administered by a major Italian bank to a sample of 1,686 of its customers in the summer of 2007.⁷ One of the questions in the survey asks how often the respondent resorts to various sources of information when making a financial decision. Banks emerge as the leading source of information for customers: over 63% of customers consult them “sometimes”, “often”, or

⁶During our sample period, Italian banks de facto do not originate non-standard mortgages, e.g., interest only, negative amortization, balloon payment. They issue very few partially adjustable mortgages. Accordingly, teaser rates are not common.

⁷More details on the survey can be found in Guiso et al. (2018).

“very often”. This is a 20 percentage points gap with the second most popular source, the broker.⁸ 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.

The main factor leading to banks’ prominent role in both information provision and advising of households about mortgage choices is the way mortgages are sold in Italy. First, banks are the main originators of mortgages: 80% of mortgages are sold directly to customers at the local branch (Oliver Wyman (2005)).⁹ Second, the Italian retail banking system is characterized by a tight relationship between a customer and its home bank. Data from the SHIW 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, the information and the advice provided by the (loan officer of the) bank that issues the mortgage is the most easily accessible expert opinion for a household. Since the mortgage application takes place on the premises of the bank’s branch, bank’s employees have the chance to steer their customers towards a particular mortgage type.¹⁰ In Section 3, we provide further anecdotal and empirical evidence that steering is pervasive in the Italian mortgage market.

Banks’ incentives to steer customers We have argued that banks have scope to strategically steer households to one type of mortgage or another. To give a sense of the strength of banks’ incentives to do so, we compute for each bank in our sample the margin on ARMs (i.e., the spread between the ARM rate set by the bank and the 1-month Euribor) and the margin on FRMs (given by the spread between the FRM rate and 25 years interest rate swap) and calculate the rough impact on profits from being able to move in each period all the customers to the type of mortgage that is more profitable

⁸This 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 than for mortgages. Moreover, households could refer to as “broker” to the employee of the bank that manages their investment, and brokers often work for a company tightly linked to some bank (see Oliver Wyman (2003)).

⁹The prominence of banks as financial advisors is not unique to Italy but characterizes all countries where banks play a relevant role in originating and selling mortgages. For instance, Financial Services Authority (2009) points out that in the UK “mortgage advice – where a recommendation is made to take out a particular mortgage – is a significant feature of the current market,” and 70% of the UK mortgage sales are advised.

¹⁰In our sample period, the market for online mortgages was still in its infancy. In a 2009 report, MutuiOnline, by far the larger distributor of online mortgages reports that its market share in the mortgage market was 0.9% in 2005; 1.1% in 2006 and 1.9% in 2007. Therefore, the large majority of our household must have physically visited a bank branch to apply for a mortgage.

for the bank. The median (across banks and periods) increase in profits is 7%, a figure significant enough to make it appealing for banks to try and influence their customers' mortgage choice.

In reality, banks usually issue a balanced portfolio of mortgages, which could be attained through both pricing and non-price channels. Thus, we next describe what factors determine these decisions. Banks issue loans of different maturities on the asset side of the balance sheet and borrow at different maturities on the liability side. In the Modigliani-Miller world, the structure of liabilities should not affect the structure of assets. However, because of credit market imperfections, supply factors (i.e., differences across banks in costs of long-term financing or the share of deposit financing) should affect bank's preferences over assets of different maturities, such as FRMs and ARMs (Kashyap and Stein (1995)). Thus, banks with higher costs of long-term borrowing or lower share of deposits would be less willing to increase their exposure to the interest rate risk through issuing too many FRMs, and if possible, would prefer to issue ARMs instead. Several features of Italian banks make such preferences of banks relevant.

First, unlike in the US (Fuster and Vickery (2015)), in Italy banks retain on their balance sheets most of the mortgages that they originate, hence, bearing all associated risks. Italian banks do not heavily rely on securitization: between 2000 and 2006 only 5% of the outstanding mortgages were securitized. Thus, mortgages account for an important fraction of banks' assets: as of 2015, loans to households for purchase of a house represented 10% of banks total assets (Ciocchetta et al. (2016)).

Second, Hoffmann et al. (2019) show that European banks maintain significant exposure to the interest rate risk, an important component of which comes from residential mortgages, and that banks only partially hedge this exposure with derivatives. Esposito et al. (2015) and Cerrone et al. (2017) provide further evidence of non-trivial exposure to the interest rate risk and imperfect derivative hedging by Italian banks.^{11,12}

Third, the relative importance of different sources of financing varies substantially across banks. As shown in Table 1, for some banks deposits account for as little as a third of total liabilities. These are typically large banking groups that are more keen on issuing bonds and therefore (given the higher volatility of bond funding compared to deposits funding) are more exposed to the risk of maturity mismatch between items on their balance sheets. Other banks are primarily funded through deposits suggesting that

¹¹Incomplete derivative hedging of the interest rate risk is not unique to the European banks, and is also common in the US (see Begenau et al. (2015); Gomez et al. (2016); Rampini et al. (2016)).

¹²In Online Appendix A.1, we document that our emphasis on interest rate risk is justified since banks do not face significant default and renegotiation risks.

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 fixed or adjustable rate mortgages.

To summarize, the Italian mortgage market is characterized by the prevalence of plain vanilla FRM and ARM mortgages with long maturities. Banks originate and distribute mortgages and enjoy tight and long lasting relationships with their customers. Households rely on information and advice about mortgages provided by banks, which ensures that banks have plenty of opportunity to steer less sophisticated customers towards a certain mortgage type. Banks' incentives to steer come from their need to manage the asset side of their balance sheets (which, under imperfect credit markets, is affected by their liability structure). In order to manage maturity on the asset side, banks can resort to appropriately pricing FRM and ARM, but also to steering unsophisticated customers to a certain type of mortgage. Given that unlike pricing, the advice is costless, banks should use both instruments in forming the portfolio of mortgages. In Section 3, after introducing the data used in our analysis, we present the evidence that banks do indeed use both relative pricing and steering to affect households' mortgage choices.

3 Data and Evidence of Steering

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

<i>Variable</i>	<i>Obs.</i>	<i>Mean</i>	<i>Standard deviation</i>	<i>25th percentile</i>	<i>50th percentile</i>	<i>75th percentile</i>
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 FRM 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.

We merge this information with data from SLIR on the average rate for the FRM and ARM mortgages 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.¹³ Some provinces are quite small and only a handful of mortgages are 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 one.¹⁴ 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 banks 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.

3.2 Evidence of Steering

We next present the evidence that banks actively influence their customers' decision through both price and non-price channels (i.e., steering). First, we discuss some descriptive and anecdotal evidence, and then, present formal reduced form evidence based on our data.

Anecdotal evidence As we argued in Section 2, many Italian households lack financial sophistication and rely on banks as their main information source. There is a wealth of anecdotal evidence from the Italian media reporting cases where banks have been accused of or convicted for having presented non-reliable information to their customers in order

¹³Additional details on sample construction are relegated to Online Appendix A.3.

¹⁴Regions 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).

to lead them to a particular investment choice.¹⁵ A recent and telling example is the allegation that six banks steered their unsophisticated clients towards buying the subordinated bonds and stocks of the banks, selling them as “safe” at a time when sellers knew their bank was in distress.¹⁶ A report by the Italian Securities and Exchange Commission (Grasso et al. (2010)) documents the wide presence of banks’ biased investment advice by showing that banks systematically diverted retail customers towards bonds issued by the bank, even when a dominant alternative (e.g., a government bond of same maturity, higher yield, higher liquidity and lower riskiness) was available in the market.¹⁷ On the mortgage market one source of anecdotal evidence of banks exercising questionable influence on the financial choices of their customers is represented by customers’ complaints and lawsuits alleging unscrupulous practices by Italian mortgage originators. Data obtained from the Arbitro Bancario Finanziario, the Italian ombudsman dealing with financial disputes between customers and banks, show that during our sample period, over 70% of the complaints are related to mortgage issues.

Two additional pieces of evidence of steering in the form of distorted advice in the mortgage market have recently appeared in the press. The first is a court ruling against Barclays Bank for advising customers to take ARM mortgages with a complex indexation to the Swiss Franc between 2006 and 2010.¹⁸ The second is even more interesting as it speaks directly to the way we model biased advice. In a series of articles between 2015 and 2016, *Il Sole 24 Ore*, the main Italian financial newspaper, reported that some banks were pushing households applying for a mortgage towards FRMs on the basis of their belief that the European Central Bank would not start raising rates at least until 2020.¹⁹

The anecdotal evidence above speaks about the presence of the distortionary component of steering. However, there is also an informational component of steering. Banks often explain to their customers the specifics of different financial products, which the cus-

¹⁵Needless to say, there is also plenty of anecdotal evidence of distorted advice in other countries. In the US, for instance, the Consumer Financial Protection Bureau devotes a whole section of its web page to consumers complaints narratives describing thousands of cases of self serving recommendations by financial institutions (<https://www.consumerfinance.gov/consumer-tools/everyone-has-a-story/>).

¹⁶Four of the six banks (Banca dell’ Etruria, Banca delle Marche, Cassa di Risparmio di Ferrara, Cassa di Risparmio di Chieti) were resolved in November 2015, the other two (Veneto Banca and Popolare di Vicenza) were liquidated in June 2017. The financial scandal involved so many households and caused such large losses that it turned into a political case. Parliament set up a committee to investigate it.

¹⁷See Guiso and Viviano (2015) for formal evidence of this practice.

¹⁸See http://www.repubblica.it/economia/2017/01/13/news/barclays_condannamutuo_franchi_svizzeri-155899009/.

¹⁹See <http://www.ilsole24ore.com/art/finanza-e-mercati/2015-12-11/mutui-banche-spingono-fisso-ma-e-davvero-soluzione-migliore-113932.shtml?uuid=ACS09IrB>.

tomers would not be confident to purchase on their own, and banks may only do so when it suits them. This steering is informative as it expands the set of options of the households. The fact that, as shown in Section 2, banks' information and advice are largely trusted in Italy means that the informational component is also present and significant.

Reduced form evidence Next, we turn to more systematic reduced form evidence. 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 2, 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.²⁰ We also include bank fixed effects to capture time-invariant unobserved

²⁰The 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

	(1)	(2)
	<i>FRM=1</i>	<i>FRM=1</i>
Long Term Financial Premium	−0.0583*** (0.0129)	−0.0590*** (0.0127)
Mortgage size (log)	−0.0818*** (0.0109)	−0.0826*** (0.0112)
Joint mortgage	0.0270*** (0.0045)	0.0274*** (0.0046)
Italian	0.0411*** (0.0071)	0.0393*** (0.0070)
Cohabitation	−0.0029 (0.0020)	−0.0035* (0.0020)
Age	−0.0008*** (0.0002)	−0.0009*** (0.0002)
Female	0.0109*** (0.0015)	0.0102*** (0.0014)
Bank bond spread	−0.0831*** (0.0164)	−0.0825*** (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 2: **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.

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 the same bank in a quarter where the bank faces a lower costs of borrowing at fixed rate.²¹ 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 this interpretation 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. It is beyond the scope of this paper to provide exhaustive descriptive evidence that steering plays a role in financial transactions. There is a growing body of work showing that this is the case (Egan (2019); Foerster et al. (2017); Ru and Schoar (2017)), which validates our attempt to quantify its importance and to study policy actions in response to it. Since the results in Foà et al. (2019) have been obtained in our same institutional context and are particularly apt to support the premise of our study, for the reader's convenience we report the bulk of their analysis in Online Appendix A.4.

Further, 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 2 indicates that banks are steering their customers' decisions to manage

and the sample of banks reporting it.

²¹Our 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.

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. (2017)).²² 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 3. 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.

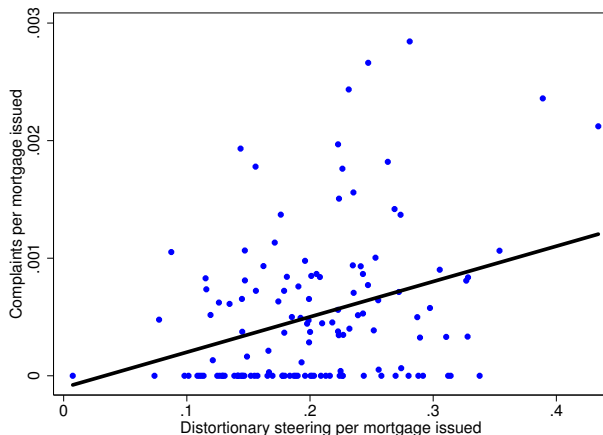


Figure 1: **Distortory Steering is behind Borrowers' Complaints**

Notes: The figure plots on the horizontal axis the number of instances of distortory 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.

²²For 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.

	(1)	(2)
	<i>Dependent variable</i>	<i>Dependent variable</i>
	<i>FRM=1</i>	<i>FRM=1</i>
	Banks with	Banks with
	below median duration mismatch	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 3: Effect of Lender Characteristics, by severity of maturity mismatch

Notes: The table reports results from the specification in column (1) of Table 2 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 2: (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.

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 2 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.²³ In Figure 1, 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.

4 Model

In this section, we capture key aspects of the Italian mortgage market in a model of households' mortgage choice and banks' choice of rates and steering policies. As discussed in Section 3, banks set rates at the regional level, while households choose the bank at the level of province. For simplicity of notation, we present the model for a single market where the definition of the region and the province coincide.

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. The timeline is as follows. First, in the beginning of quarter t , banks simultaneously set rates. Second, each household h chooses the bank from which it takes the mortgage. We say that the household becomes a *customer* of this bank. Third, banks steer some of their customers towards one type of mortgage or the other. Forth, households choose the mortgage type.

We next describe households' and banks' choices in details.

²³We 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.

4.1 Households

Households are heterogenous in several dimensions. First, a fraction μ of households is *naive* and a fraction $1 - \mu$ is *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 hence, are immune to steering.

Second, each household enters the quarter with a *home bank*, which one can think of as the default option for the household to do business with (e.g., the bank where the household holds its primary checking account). The probability that bank i is the home bank of household h in quarter t is p_{it} . A fraction $1 - \psi$ of households is *attached* to their home bank in the sense that they only choose between adjustable and fixed rate mortgages offered by their home bank. A fraction ψ of households is *un-attached* in the sense that they can take a mortgage at any bank in the market. The attached/un-attached status of a household captures in a reduced form different market frictions, such as switching or search costs, that prevent households from choosing the best rate available in the market.

Further, households differ in several other dimensions: the size of their mortgage H , the degree of risk aversion γ , the future (stochastic) income y , and their beliefs about the volatility 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, and that the mean and the volatility of inflation shock π are ν_π and σ_π^2 , respectively. For the ease of notation, we omit indexing these characteristics by h , although the reader should keep in mind that they do vary across households. Our data does not allow us to separately identify the distribution of γ , H , ν_ε , σ_ε^2 , ν_π , and σ_π^2 . However, we can identify the parameters of the distribution of

$$\delta \equiv \nu_\varepsilon + \nu_\pi + H\gamma(\sigma_\varepsilon^2 - \sigma_\pi^2). \quad (4.1)$$

As we show below, δ represents the optimal cut-off on the rate spread for sophisticated households’ choices between ARM and FRM. We assume that δ is normally distributed with mean μ_δ and variance σ_δ^2 and that all household’s characteristics are independent from each other and across households.

Mortgage choice The choice of the bank and the mortgage type differs between naive and sophisticated households.

It has been shown both empirically and theoretically in Campbell and Cocco (2003); Kojien et al. (2009); Badarinza et al. (2018) that the spread between the FRM and ARM

rates is the most important determinant of the rational mortgage choice. Intuitively, rational households face the trade-off between interest rate and inflation risk embedded in the ARM/FRM decision. By taking an ARM, the household hedges against inflation risk, as interest payments adjust with inflation, but is exposed to the interest rate risk. The reverse is true, when it takes an FRM.

Accordingly, sophisticated households in our model recognize this trade-off and follow the spread rule derived in (4.3) below. It is important to note that all the individual heterogeneity that affects mortgage choice besides naivete and attachment enters the decision rule of sophisticated households through the household-specific optimal cutoff on the FRM-ARM spread (δ). This includes risk aversion, beliefs about drift and volatility of inflation and interest rates, but also any other household-specific factor not explicitly mentioned in our model of consumer behavior.

Below, we present a simple version of Kojien et al. (2009) that illustrates how sophisticated households make their mortgage choice. Households take a mortgage 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 $(1 + s_{it}^a + r_{t+\Delta}^{eurbr})H$ when she takes the ARM and to $(1 + r_{it}^f)H$ when she takes the FRM.

Sophisticated households have mean-variance utility function with the 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 $s_t^a(h)$ be the lowest FRM rate and the lowest ARM-Euribor spreads, respectively, available to household h . If the household is un-attached 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 $s_t^a(h) = \min_{i \in \{1, \dots, N\}} s_{it}^a$. If the household is attached to the home bank, then its choice set contains only rates set by its home bank, and $r_t^f(h)$ and $s_t^a(h)$ equal to r_{it}^f and s_{it}^a in the home bank i of the household. The sophisticated household prefers an ARM if and only if

$$\begin{aligned} \mathbb{E} \left[y - (1 + s_t^a(h) + r_{t+\Delta}^{eurbr} - \pi)H \right] - \gamma\mathbb{V} \left[y - (1 + s_t^a(h) + r_{t+\Delta}^{eurbr} - \pi)H \right] \\ \geq \mathbb{E} \left[y - (1 + r_t^f(h) - \pi)H \right] - \gamma\mathbb{V} \left[y - (1 + r_t^f(h) - \pi)H \right], \quad (4.2) \end{aligned}$$

	Un-attached (frac. ψ)	Attached (frac. $1 - \psi$)
Sophisticated (frac. μ)	bank with the best fixed or adjustable rates best mortgage type given rates	home bank best mortgage type given rates
Naive (frac. $1 - \mu$)	bank with the best fixed rate steered to certain mortgage type	home bank steered to certain mortgage type

Table 4: **Household Choices of the Bank and Mortgage Type**

Recalling (4.1), we can rewrite (4.2) as

$$r_t^f(h) - (s_t^a(h) + r_t^{eurbr}) \geq \delta. \quad (4.3)$$

The spread rule implies that the households chooses ARM if and only if the spread they face (the left-hand side of (4.3)) is above the cut-off δ . Thus, ARM is preferred whenever the household has low risk aversion, takes a relatively small mortgage, believes that inflation is more volatile compared to real interest rates, expects lower nominal interest rates. 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.

The behavior of naive households departs from the spread rule. By the analogy with the “money doctors” framework of Gennaioli et al. (2015), before steering takes place naive households prefer FRM, which is a more familiar option with a pre-fixed installment plan, to a more complex option, ARM. Hence, naive un-attached households always become customers of the bank with the lowest FRM rate, ignoring ARM rates. Naive attached households become customers of their home bank. However, after they become customers of some bank, both un-attached and attached naive households are susceptible to bank’s steering in their choice of mortgage type. Thus, naive households 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 4.

Discussion of assumptions Our assumption that naive households purchase FRMs in the absence of bank’s steering can be microfounded using the “money doctors” model by Gennaioli et al. (2015). Below, we outline the similarities between our setup and theirs. The formal treatment is in Appendix A.5. In Gennaioli et al. (2015), households choose between two investment opportunities: the bank deposit, which is a more familiar option,

and the stock market, which is a more rewarding, but more complex option that requires certain sophistication and skill. Investors experience “anxiety” when investing in a more complex product, and might choose to stay out of the market, which is consistent with well-documented under-participation in the stock market by less sophisticated households (Calvet et al. (2007)). Financial intermediaries act as “money doctors” by providing information about more rewarding options and reducing the investors’ anxiety.

We draw a parallel between the household’s decision about the mortgage type and the retail investor’s portfolio decision. FRM is conceptually similar to a bank deposit and represents a more familiar and easy to understand option.²⁴ ARM is similar to the stock market investment in that it is more complex and requires sophistication in order to acquire and process information about future rates and associated risks.²⁵ Similar to Gennaioli et al. (2015), naive households suffer anxiety when taking the ARM on their own and therefore prefer taking FRMs. However, banks can alleviate the households’ anxiety and convince them to take ARM. Unlike in Gennaioli et al. (2015), in our model intermediaries can steer naive customers into taking ARMs, even when FRM is better for them.

As we mentioned, the attached/un-attached status captures different market frictions that prevent households from taking a mortgage at the best market terms. These frictions are a general feature of the retail financial sector (Woodward and Hall (2012); Deuffhard (2016); Ater and Landsman (2018)), and are present in Italy as documented by prior literature (Barone et al. (2011)) and witnessed by the large dispersion in rates observed in our data (see Figure 9 in Appendix A.9). However, our data is not rich enough to pinpoint the precise nature of these frictions. Therefore, the model is agnostic on the source of this phenomenon and instead includes a generic friction which binds for a fraction $1 - \psi$ of the households. One could interpret it as a switching cost, in which case, the home bank would be the bank where the household has its primary checking account, and for a fraction $1 - \psi$ of households the cost of switching bank is prohibitively high.²⁶

²⁴Indeed, FRM is essentially the reverse of the bank deposit. In the mortgage contract, the household pays a fixed interest rate to the bank on the loan, while in the deposit contract, it receives a fixed interest rate on the amount deposited from the bank.

²⁵This 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)). Appendix A.2 reports the results of surveys on financial literacy of Italian households indicating that there is a significant fraction of mortgage takers failing to answer basic questions measuring their financial literacy, and that households with outstanding FRMs are those less financially literate.

²⁶Italian banks require that in order to get a mortgage, a customer must have an account with them. Households that wish to take a mortgage from a bank different from the bank where they hold their primary checking accounts have to incur switching costs (both financial and opportunity costs of time) of

Alternatively, the attached/un-attached status could reflect search frictions. In this case, the home bank is the bank from which the household starts its search and the search costs are so high for a fraction $1 - \psi$ of households that they do not search past their first inquiry, whereas a fraction ψ of households screens all rates in the market and finds the best available.

4.2 Banks

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

$$\underbrace{\left(s_{it}^a (1 - x_{it}) + s_{it}^f x_{it} - \lambda (x_{it} - \theta_{it})^2 \right)}_{\text{net profit margin}} \times \underbrace{m_{it}}_{\text{customer base}} \times \underbrace{e^{-\beta r_{it}^f}}_{\text{penalty for excessive rates}}, \quad (4.4)$$

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 (4.4) reflects the net profit margin in basis points on one euro lent through mortgages. This margin is multiplied by the size of the bank's customer base m_{it} to obtain the total profit from all mortgages issued. The last term $e^{-\beta r_{it}^f}$, $\beta > 0$, penalizes banks for offering very high fixed 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 increases with the average spread of rates over benchmarks. We denote by s_{it}^a the spread of the ARM rate over the 1-month Euribor (r_t^{eurbr}) and by s_{it}^f the spread of the FRM rate over the 25-year swap rates (r_t^{swap25}). We use 1-month Euribor rate as the benchmark for ARMs, because the bank can finance ARMs by short-term borrowing in the interbank market in which case the bank's profit from ARMs equals the spread over Euribor that the bank charges. Similarly, the 25-year swap rate is the benchmark for FRMs, because the bank can finance FRMs by borrowing short-term in the interbank market and entering an interest rate swap contract in which case the bank's profit from FRMs equals the spread over the 25-year swap rate. Figure 10 in Appendix A.9 documents using data from one of the largest bank in Italy that FRM and ARM rates track corresponding benchmarks.

A recent literature argues that banks maintain significant exposure to the interest rate risk (Begenau et al. (2015); Gomez et al. (2016)) due to the limited use of derivative

opening a new account, relocating funds between accounts or ensuring regular transfers between accounts, etc.

hedging (Rampini et al. (2016)) or banks' relative efficiency in managing the maturity mismatch (Drechsler et al. (2017)). The quadratic cost term in (4.7) captures the fact that issuing too many FRMs causes a potential maturity mismatch. We refer to θ_{it} as bank i 's *cost efficient fraction of FRMs*, which is the fraction of FRMs that bank i can issue without suffering maturity mismatch costs. When the bank's fraction of FRMs in the mortgage portfolio equals θ_{it} , such costs are zero. A deviation of x_{it} from θ_{it} leads to a reduction in the profit margin by $\lambda(x_{it} - \theta_{it})^2$ basis points. The parameter $\lambda > 0$ reflects how severe these costs are.

The timing of the game is as follows. At the beginning of quarter t , each bank privately observes its θ_{it} , which is an i.i.d. draw for each banks in each period from a normal distribution with mean μ_θ and variance σ_θ^2 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_{it}^f of FRM rates over the 25-year swap rate. After that, the customer base is determined: the bank retains the attached households for whom it is the home bank. In addition, the bank attracts un-attached naive households if it posts the lowest fixed rate, and un-attached sophisticated customers for whom one of its mortgages is the best option in the market.

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.

Interpretation of steering We do not explicitly model the particular mechanism of how banks steer their customers. However, our model captures in a reduced form many types of steering such as distorted advice, advertising, strategic rationing, etc. During the personal interaction with customers, bank employees can provide distorted advice by highlighting some features, while hiding others to make one mortgage type more appealing to the customer. For example, bank employee can stress lower current mortgage payments for ARMs and downplay the risk that interest payments may go up in the future to steer some customers towards ARMs. In terms of our model, $1 - \omega_{it}$ is the fraction of households that get the biased advice from the bank employee to take ARM, and this advice affects only naive households. Importantly, what makes distorted advice particularly attractive is that it is virtually costless and it does not require the knowledge on the side of the bank of whether the customer is naive or sophisticated.

There are two ways how the effect of advertising is captured by our model. First, shrouding of certain mortgage attributes in the marketing materials that bank employees

provide to customers is analogous in how it affects mortgage choices to the distorted advice. Namely, $1 - \omega_{it}$ is the fraction of households that receive extra advertising materials about the advantages of ARMs, and only naive households pay attention to these materials. Second, banks can conduct advertising campaigns to educate the public about the advantages of ARMs. Unlike in Gabaix and Laibson (2006), certain banks (e.g., those with the lowest ARM-Euribor spread) may find it beneficial to hold such campaigns. We can capture this in our model by assuming that if some bank does a campaign promoting advantages of ARMs, then a certain fraction of naive households becomes sophisticated. This would affect only the interpretation of μ as the fraction of naive households after the ad campaign, but otherwise would not change the model.

Finally, banks can ration customers by strategically rejecting applications for FRMs and offering instead to apply for ARMs. If naive households take such an offer, then the effect on naive households of such strategic rejection is identical to the effect of distorted advice or shrouded attributes. However, such a policy is potentially costly, because rejected sophisticated customers may prefer to switch the bank rather than take ARMs. Given that according to the SHIW, 80% of households in Italy do all their financial transactions with only a single bank, the costs of losing a customer because of strategic rejection of the mortgage application are arguably very high.

Discussion of other assumptions The assumption that adjustable rates are determined outside of our model, and banks compete only by setting spreads s_{it}^f is motivated by the common practice of rate setting in the industry. Figure 2 plots the spread between the 25-year FRM and ARM rates and corresponding benchmarks at a monthly frequency between 2004 and 2008 for one of the largest banks in Italy. The ARM spread over the Euribor is held constant over very long time intervals; whereas the spread of FRM rate over the swap rate adjusts at much higher frequency. We observe a similar pattern when we average rates over all the banks in our sample.

In modeling the banks' objective function, we intentionally take a reduced form approach and only capture how given the cost efficient fraction of FRMs (θ_{it}) each bank optimally uses rate setting and steering to manage the interest rate risk. The evidence from Section 3 suggests that θ_{it} depends on supply factors. For example, it reflects the ability of the bank to borrow long-term at better terms. If shifts in banks' supply factors drive θ_{it} , then banks' steering distorts households' mortgage choices. However, our approach allows us to retrieve an estimate of the bank's θ_{it} without imposing assumptions on its nature. In particular, θ_{it} could also be affected by other factors, such as reputa-

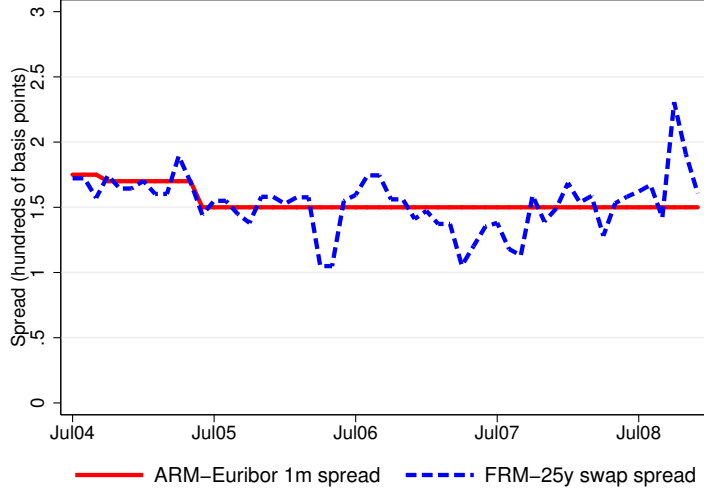


Figure 2: **Rate Spreads on a 25-year Mortgage Set by a Major Italian Bank**

tion concerns. In Section 6, we use our estimates to provide evidence on which variables influence the bank’s cost efficient fraction of FRMs.

4.3 Equilibrium

The solution concept is the perfect Bayesian equilibrium (PBE).

We next derive explicit expressions for bank’s optimality conditions. Consider the subgame, in which bank i gives its customers advice about the type of the mortgage. Suppose that in this subgame, the spreads of ARM and FRM over benchmarks are s_{it}^a and s_{it}^f , respectively, and bank i attracts mass m_{it} of customers. Bank i steers a fraction $1 - \omega_{it}$ of its customers to take the ARM. This steering 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} and \bar{x}_{it} respectively the minimal and maximal fractions of FRMs that can be attained through steering.²⁷ The choice of ω_{it} is equivalent to the direct choice of the fraction of FRMs issued, x_{it} , subject to the constraint that $\underline{x}_{it} \leq x_{it} \leq \bar{x}_{it}$. Hence, the bank solves

$$\max_{x_{it} \in [\underline{x}_{it}, \bar{x}_{it}]} \left(s_{it}^a (1 - x_{it}) + s_{it}^f x_{it} - \lambda (x_{it} - \theta_{it})^2 \right) m_{it} e^{-\beta r_{it}^f}.$$

We rewrite the profit function in terms of the FRM-ARM spread $\phi_{it} = r_{it}^f - (s_{it}^a + r_t^{eurbr})$,

²⁷More precisely, \underline{x}_{it} can be attained by setting $\omega_{it} = 0$ and \bar{x}_{it} can be attained by setting $\omega_{it} = 1$.

which is the relevant spread for the sophisticated households' choice:

$$\max_{x_{it} \in [\underline{x}_{it}, \bar{x}_{it}]} \left(s_{it}^a + (\phi_{it} - r_t^{swap25} + r_t^{eurbr}) x_{it} - \lambda (x_{it} - \theta_{it})^2 \right) m_{it} e^{-\beta(\phi_{it} + s_{it}^a + r_t^{eurbr})}.$$

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

$$x(\phi_{it}|\theta_{it}) = \max \left\{ \min \left\{ \theta_{it} + \frac{1}{2\lambda} \left(\phi_{it} - r_t^{swap25} + r_t^{eurbr} \right), \bar{x}_{it} \right\}, \underline{x}_{it} \right\}, \quad (4.5)$$

from which we can recover the optimal steering policy: $\omega(\phi_{it}|\theta_{it}) = (x(\phi_{it}|\theta_{it}) - \underline{x}_{it}) / (\bar{x}_{it} - \underline{x}_{it})$.

The fraction of naive households steered to take FRM is increasing in the cost-efficient share of FRMs (θ_{it}); increasing in the FRM-ARM spread (ϕ_{it}); and decreasing in the cost of portfolio imbalance (λ). Observe that the extent to which the bank can manipulate its customers depends on the gap between \underline{x}_{it} and \bar{x}_{it} . Given the optimal share of FRMs $x(\phi_{it}|\theta_{it})$, the bank's profit per customer is given by

$$V(\phi_{it}|\theta_{it}) = \left(s_{it} + \left(\phi_{it} - r_t^{swap25} + r_t^{eurbr} \right) x(\phi_{it}|\theta_{it}) - \lambda (x(\phi_{it}|\theta_{it}) - \theta_{it})^2 \right) e^{-\beta(\phi_{it} + s_{it}^a + r_t^{eurbr})}. \quad (4.6)$$

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

$$\int m_{it} V(\phi_{it}|\theta_{it}) dG_i(\underline{s}_{-it}^f | \mathbf{s}_t), \quad (4.7)$$

where $G_i(\cdot | \mathbf{s}_t)$ is the distribution of $\underline{s}_{-it}^f \equiv \min_{j \neq i} \{s_{jt}^f\}$ given \mathbf{s}_t and the equilibrium rate setting strategies of other banks. Here, the FRM-ARM spread together with the stochastic fixed rates set by other banks affect the mass of customers of bank i , m_{it} , and the composition of this customer base, namely, bounds \underline{x}_{it} and \bar{x}_{it} . Appendix A.6 derives a more explicit formula for (4.7) that we use in our estimation.²⁸

5 Identification

We estimate the following parameters of the model: the fraction of naive households (μ), the fraction of un-attached households (ψ), the distribution of the optimal cut-off on the

²⁸Note that aside from differences in the payoff structure, our model of competition among banks bears similarities to first-price auctions whose equilibrium properties have been analyzed for instance by Athey (2001); Reny and Zamir (2004). In fact, the bank that posts the lowest fixed rate can be thought of as the lowest bidder in an auction and its reward is attracting the un-attached households.

rate spread (μ_δ and σ_δ), banks' cost efficient fraction of FRMs (θ), and the parameters of banks' profit function (λ and β). As we mentioned in Section 2, the level of aggregation of the data is different between the demand and supply sides of the model: The demand estimation is done at the provincial level, while the supply estimation aggregates the data to the regional level. To mark this distinction, we index all observables in the demand estimation by the superscript d and those in the supply estimation by the superscript s .

5.1 Identification of Demand Parameters

The identification of demand parameters $\Omega^d = (\mu, \psi, \mu_\delta, \sigma_\delta)$ exploits the differences in the reaction of sophisticated and naive as well as attached and un-attached households to the variation in rates. Since this amounts to estimating price elasticities, our strategy follows the classic approach of the demand estimation literature and relies on data on prices (rates) and quantities (market shares in the mortgage market). We do not need to use our supply side model for identification.

For every quarter $t = 1, \dots, T$ and province $j = 1, \dots, J$, our data include

- the set of banks actively issuing mortgages in the province, $i = 1, \dots, N_j^d$;²⁹
- the number of mortgages issued by every bank, $\mathbf{M}_{jt}^d = (M_{1jt}^d, \dots, M_{N_j^d jt}^d)$;
- FRM rates posted by banks, $\mathbf{r}_{jt}^d = (r_{1jt}^d, \dots, r_{N_j^d jt}^d)$;
- ARM-Euribor spreads of banks, $\mathbf{s}_{jt}^d = (s_{1jt}^d, \dots, s_{N_j^d jt}^d)$;
- banks' shares in the province depositor market, $\mathbf{p}_{jt}^d = (p_{1jt}^d, \dots, p_{N_j^d jt}^d)$.

Let $\underline{r}_{jt}^f \equiv \min_{i=1, \dots, N_j^d} r_{ijt}^f$ and $\underline{s}_{jt}^a \equiv \min_{i=1, \dots, N_j^d} s_{ijt}^a$. For $i = 1, \dots, N_j^d$, the probability that a randomly drawn household takes a mortgage at bank i is given by

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

where $1\{\cdot\}$ is the indicator function and Φ is the cdf of the standard normal distribution. The identity of a household's home bank is not observed in our data. We use bank's share

²⁹To 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.

in the province depositor market p_{ijt}^d as proxy for the probability p_{ijt} that a particular bank i is a home bank to a household. This is based on the observation that a household would experience the least frictions in obtaining a mortgage from the bank where it holds its checking account.

The likelihood in (5.1) consists of four terms. With probability $(1 - \psi)p_{ijt}$ a household is attached and i is its home bank. With probability $\psi\mu$ a household is un-attached and naive. Then it takes a mortgage from bank i only if $r_{ijt}^f = \underline{r}_{jt}^f$. With probability $\psi(1 - \mu)$ a household is un-attached and sophisticated. Then it takes a mortgage from bank i if and only if bank i offers the best mortgage (type and rate) for the household.³⁰ The log-likelihood of the realization of issued mortgages, $\mathbf{M}_{jt}^d, j = 1, \dots, J, t = 1 \dots T$, equals up to a constant

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

We complement our main data with microdata from the SHIW survey that provides the additional information on households' attachment to their home bank. The 2006 wave of the survey asks respondents to report whether they took a mortgage in the year, which allows us to identify new borrowers. Furthermore, they are asked about the length of the relationship with their main bank. Given that 80% of Italian households only do business with 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. The likelihood that a household takes a mortgage at a bank which is not its home bank in province j and quarter t is

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

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 yearly rather than quarterly frequency. Thus, for each province we average the

³⁰In (5.1), we ignore ties between banks, because they do not occur in our data.

quarterly likelihood in (5.3) weighting 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 $j = 1, \dots, J$, 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 in a new bank. The log-likelihood of the realization $\mathbf{M}_{2006}^{SHIW} = (S_{j2006}, M_{j2006}, j = 1, \dots, J)$ equals up to a constant to

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

Given that SHIW is a survey 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

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

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

Discussion of demand identification The main source of identification of the fraction of un-attached households is SHIW data documenting the number of people taking mortgages outside their home bank. The fraction of naive households is identified 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 $r_{jt}^f - (\underline{s}_{jt}^a + r_t^{eurbr}) > \delta$, 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 $\psi\mu$, 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 $\psi(1 - \mu)$, because it attracts sophisticated un-attached households. This way we can recover μ 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 ARM and 0.44 for FRM.

Table 1 documents that in our data the FRM-ARM spread varies enough that the fraction of sophisticated households who prefer FRM to ARM 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.³¹

We want to stress that our focus is on identifying the share of naive and attached households. As we showed in Section 4, the parameter δ absorbs any residual heterogeneity among households in our sample beyond naivete and attachment. Since we are not interested in isolating the impact of different components of unobserved heterogeneity (e.g., risk aversion, wealth, etc.) on mortgage choice, we do not need to account for multiple dimension of heterogeneity in the estimation. In fact, allowing for an heterogeneous cutoff parameter provides a parsimonious way to take care of all unobserved factors and ensures that the other parameters of the demand side are identified.

5.2 Identification of Supply Parameters

We now turn to the estimation of supply parameters $w^s = (\lambda, \beta)$ and the distribution of θ s. For every quarter $t = 1, \dots, T$ and region $k = 1, \dots, K$, our data include

- the set of banks actively issuing FRM mortgages in the region, $i = 1, \dots, N_k^s$;³²
- the distribution of households taking mortgages at each bank, $\mathbf{M}_{kt}^s = (M_{1kt}^s, \dots, M_{N_k^s kt}^s)$;
- the fraction of FRMs in the total number of mortgages issued by each bank, $\mathbf{x}_{kt} = (x_{1kt}, \dots, x_{N_k^s kt})$;
- the FRM-ARM spreads posted by banks, $\boldsymbol{\phi}_{kt} = (\phi_{1kt}, \dots, \phi_{N_k^s kt})$;
- the ARM-Euribor spreads of banks, $\mathbf{s}_{kt}^s = (s_{1kt}^a, \dots, s_{N_k^s kt}^a)$;
- banks' shares in the regional depositor market, $\mathbf{p}_{kt}^s = (p_{1kt}^s, \dots, p_{N_k^s kt}^s)$.

The supply side estimation uses as inputs the estimates of the demand side of the model ($\hat{\Omega}^d$). The main challenge is retrieving each bank's unobserved cost efficient fractions

³¹Note that although naive households behave similarly to sophisticated households with high δ , the variance of the distribution of δ is separately identified from the fraction of naive. In fact, a higher variance in δ implies that both very high and very low realizations of δ in the population are more likely. Thus, it does not necessarily increase the mortgage share of the bank that posts the lowest fixed rate. Instead, this would be the consequence of having a large share of naive households in the market.

³²Since 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.

of FRMs, θ_{ikt} . We invert condition (4.5) for optimality of steering policy to obtain θ_{ikt} for each bank-region-quarter as a function of data and supply parameters Ω^s . Then, we express banks' predicted shares of FRMs and FRM-ARM spreads as functions of only data and supply parameters but not of θ s. Further, we find estimates of Ω^s that minimize the discrepancy between the model's predictions for FRM shares issued and FRM-ARM spreads and the data.

Next, we describe the estimation procedure.

Step 1: Invert the optimality condition for advice For a given guess of supply parameters Ω^s , we obtain estimates of the cost efficient fraction of FRM 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 FRM issued by a bank observed in the data and that predicted by the model

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

However, when the observed fraction lies below the lowest ($x_{ikt} < \underline{x}_{ikt}$) or above the highest ($x_{ikt} > \bar{x}_{ikt}$) 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.³³ Then, we use the estimated distribution of θ s 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 $\hat{\theta}_{ikt} = \mathbb{E}[\theta | \theta \geq \bar{x}_{ikt} - (\phi_{it} - r_t^{swap25} + r_t^{eurbr})/(2\lambda)]$ for observations at the upper bound.

Step 2: Predicted FRM fractions and FRM-ARM spreads Conditional on $\theta_{ikt}, \boldsymbol{\phi}_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s$ and parameters Ω^s , we can compute the predicted share of FRMs from

³³The likelihood is given by

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

equation (4.5), which we denote by $\hat{x}(\theta_{ikt}|\Omega^s, \phi_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s)$.

We then compute the predicted FRM-ARM spread, $\hat{\phi}(\theta_{ikt}|\Omega^s, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s)$, from maximizing equation (4.7). In order to do so, we need an estimate of the distribution of the minimum of $N_k^s - 1$ 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. We use it to construct an estimate of the first-order statistic of this distribution for each region k . The banks' value function involves such a distribution conditional on the entire vector of ARM-Euribor spreads posted in the market, i.e., $G_{ik}(\cdot|\mathbf{s}_{kt}^s)$. 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 2, the ARM-Euribor spreads are fairly persistent and proxy the conditional distribution with the unconditional one.

Step 3: Estimation of Ω^s Let us define $\hat{\theta}_{ikt}(\Omega^s) \equiv \hat{\theta}(\Omega^s, \mathbf{x}_{kt}, \phi_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s)$, $\hat{x}_{ikt}(\theta_{ikt}, \Omega^s) \equiv \hat{x}(\theta_{ikt}|\Omega^s, \phi_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s)$, and $\hat{\phi}_{ikt}(\theta_{ikt}, \Omega^s) \equiv \hat{\phi}(\theta_{ikt}|\Omega^s, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s)$. We find estimates $\hat{\Omega}^s = (\hat{\lambda}, \hat{\beta})$ that minimize the function

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

We minimize the discrepancies between fraction of FRMs issued and spreads set as predicted in the model and observed in the data. We adjust the objective function so that the importance of matching a particular moment is inversely proportional to its volatility.

Two remarks on the identification of the supply side are in order. First, to identify the unobserved cost efficient fraction of FRM for each bank in every period we exploit the mapping between the θ s and the realized fraction of FRMs issued by a bank. This approach requires that the distribution of customers' characteristics, i.e., the distribution of δ faced by banks does not change during our sample span. In Online Appendix A.7, we exploit a survey of retail investors as well as microdata from the credit registry to show that both the distribution of risk aversion and that of the mortgage size, which are the two main elements entering δ , stay the same throughout the period we analyze. Second, as we mentioned in Section 3, Foà et al. (2019) show that there is no significant sorting of customers across banks. This rules out the alternative story that the dispersion in the share of FRM issued across banks is due to differences in the preferences of the clientele rather than to steering.

	<i>Demand</i>				<i>Supply</i>	
Parameter	μ	ψ	μ_δ	σ_δ	λ	β
Estimate	0.48 [0.46;0.49]	0.0884 [0.0879;0.0891]	-0.68 [-0.88;-0.56]	0.9 [0.81;1.01]	2.5 [2.36;13.15]	0.46 [0.38;0.52]

Table 5: **Estimates of the Parameters**

Notes: 99% confidence intervals estimated from 200 bootstrap replications are in parentheses.

6 Estimation Results

In this section, we report the estimates of the parameters of our model and provide evidence of steering through non-price channels in the Italian mortgage market.

6.1 Estimates

Table 5 reports estimates for the parameters of the model. The first fact emerging from the estimates of demand parameters is that the fraction of naive households is large (48%). Our estimate is consistent with the evidence relying on independent data measuring the sophistication of Italian households that we discuss in Online Appendix A.2. This evidence points to a very low level of basic financial knowledge by Italian households, providing ample opportunity for banks to steer customers.

We also find that there is a limited fraction of un-attached households (8.8%). This estimate suggests relevant frictions on the consumer side in the Italian mortgage market, which is further witnessed by the significant within market dispersion in both adjustable and fixed rates across banks documented in Figure 9 in Online Appendix A.9. Furthermore, the low fraction of un-attached households that we estimate resonates with the extreme inertia in the deposit market (Bhutta et al. (2018); Ater and Landsman (2018)).

The main implication of these two estimates is that banks have enough scope to use both pricing and steering in order to manage the maturity risk of their mortgage portfolios. Specifically, the presence of a significant fraction of naive households allows banks to use steering in order to affect the maturity of mortgages at origination, and hence, reduce the exposure to the interest rate risk. Further, the significant market power allows banks to use relative pricing in order to discourage sophisticated households from taking a certain mortgage type. This results resonates with the recent findings that banks use their market power over depositors in order to manage the maturity of their liabilities (Drechsler et al. (2017)).

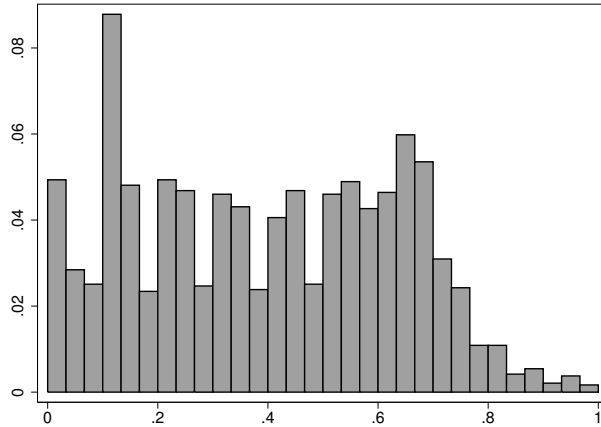


Figure 3: **Histogram of Estimated θ_s**

The estimate of the distribution of the optimal spread cut-off δ for sophisticated households indicates that ARM is on average the preferred option in the market. The negative mean of the distribution of δ could be explained by households' expectation of declining nominal rates, or alternatively, higher expectation of the volatility of inflation compared to that of the real interest rate.³⁴ Figure 11 in Online Appendix A.9 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 mortgage.

As a robustness exercise, in Online Appendix A.8 we consider an alternative specification for the demand side where the fraction of naive and un-attached households differ across regions and are functions of region characteristics, such as education level and the length of relationship with the bank. The estimation result are consistent with our baseline specification. We find that the education level in the region reduces the fraction of naive households, and the higher share of households with long relationship with their bank increases the fraction of attached households.

The key object estimated in the supply side is the distribution of the cost efficient fractions of FRMs, θ_s , displayed in Figure 3. The distribution is fairly disperse but there is barely any mass for values of θ above 0.9, likely due to the fact that more ARMs are issued in our sample span.

To interpret the estimate of λ we take the net profit margin in equation (4.4) as a

³⁴The generation of mortgage takers in our data experienced highly volatile inflation in the 80s and 90s, which could have affected such expectations (Malmendier and Nagel (2011)).

<i>Variables</i>	<i>All sample</i>	<i>Deposit/ Liabilities < 75 pctile</i>	<i>Deposit/ Liabilities < 50 pctile</i>	<i>Deposit/ Liabilities < 25 pctile</i>
Bank bond spread	-0.042* (0.025)	-0.069** (0.028)	-0.078** (0.033)	-0.089 (0.055)
Observations	762	521	386	202
R-squared	0.40	0.44	0.45	0.36

Table 6: **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.

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 cost has a fat right tail: banks with large deviations from their cost-efficient share of FRM suffer significant reductions in their margins.

6.2 Evidence of Steering

Our structural model allows us to recover a time-varying, bank-specific parameter which determines the rate setting and steering policies of the bank. So far, we have been agnostic on the interpretation of this parameter. Our preferred interpretation of θ is that it reflects the structure of liabilities and the cost of financing. Hence, banks' effort to issue a fraction of FRMs close to their 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 of steering by financial intermediaries in Foà et al. (2019).

Here, we exploit our estimates of the bank θ s to provide additional evidence consistent with steering.³⁵ We regress θ s on the bank bond spread, which is the difference between the rate of long- and short-term bonds issued by the bank. We focus on this particular measure because it varies often and it is outside the control of the bank.³⁶

In Table 6, we show that controlling for time and bank fixed effects, a higher level of

³⁵Since supply factors listed in the balance sheets vary only at the bank and not at the branch level, we average all the θ 's 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 .

³⁶In the bond market, banks are important but not dominant players and we can think of them as price takers.

bond spread is associated with a lower cost-effective fraction of FRMs issued. When it is more costly for a bank to finance itself through fixed rate bonds, it will be less keen on issuing fixed rate mortgages, because it finds it expensive to match them with fixed rate liabilities. As our model predicts, such banks would steer their customers towards ARMs.

As we documented in Table 1, banks differ in their reliance on the market for financing. Some banks, usually small ones, are able to finance their operations using almost exclusively cash collected from their depositors. For these banks, the cost of financing is not an important factor and should not affect their goals in terms of how many fixed rate mortgages to issue. If θ reflects steering, the relationship between θ and the bank bond spread should be stronger for banks with higher reliance on bond financing. In the other columns of Table 6, we repeat the exercise focusing on subsamples that exclude banks with very high ratio of deposits to total liabilities. For banks in the bottom three quartiles of the deposits/liabilities ratio, the relationships becomes more negative and more statistically significant. Although the point estimates in columns 2-4 of Table 6 are not statistically different from each other, it is telling that they grow in absolute value when we look at banks below the median of the deposits/liabilities ratio, which should be even more reliant on the bond market to secure financing. For banks in the bottom quartile of the distribution of the deposits/liabilities ratio the correlation is the most negative, though it is not significant most likely because of a relatively small sample.

7 Policy Experiments

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

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 before and after 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

$$CE\left(r_t^f(h)\right) = \mathbb{E}[y] - \gamma\mathbb{V}[y] - H\left(1 + r_t^f(h) - \nu_\pi + \gamma H\sigma_\pi^2\right). \quad (7.1)$$

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

$$CE(s_t^a(h)) = \mathbb{E}[y] - \gamma \mathbb{V}[y] - H \left(1 + s_t^a(h) + r_t^{eurbr} + \nu_\varepsilon + \gamma H \sigma_\varepsilon^2 \right). \quad (7.2)$$

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 $H(s_t^a(h) - \tilde{s}_t^a(h))$ and $H(r_t^f(h) - \tilde{r}_t^f(h))$, respectively. If the household switches from the ARM with $s_t^a(h)$ to FRM with $\tilde{r}_t^f(h)$ or from the FRM with $r_t^f(h)$ to ARM with $\tilde{s}_t^a(h)$, then it follows from (7.1) – (7.2) that the change in the certainty equivalent equals $H(s_t^a(h) + r_t^{eurbr} + \delta - \tilde{r}_t^f(h))$ and $H(r_t^f(h) - \tilde{s}_t^a(h) - r_t^{eurbr} - \delta)$, respectively.

We use our estimates of μ , ψ , and the distribution of δ to simulate a population of customers equal in size to the number of mortgages issued in our data. We then use our estimates of λ , β , and θ_{ikt} to compute the banks' responses to various policies. Further, we calculate the consumer surplus induced by counterfactual exercises on the sample of simulated households. To be conservative on the impact of steering on welfare, we assume that banks minimize the welfare loss caused to their customers by steering. This means that if a bank decides to steer a certain fraction of naive customers towards ARM, it will pick those customers for which the switch from FRM to ARM is the least harmful.

7.1 Restricting Steering

We first investigate the effect of reducing the ability of banks to steer their customers. Whereas in the baseline model, the bank could influence all of its naive customers, we now suppose that it can steer only to a half of them. Formally, $\omega_{it} \in [0, \frac{1}{2}]$ instead of $\omega_{it} \in [0, 1]$. We can interpret this experiment as an increase in the level of monitoring by the regulator, which limits the scope for advice or shrouding, or as the advent of online banking, which reduces direct one-on-one interaction with clients. It can also be related to regulatory interventions tightening fiduciary standards, like the one introduced by the Obama administration for the US in 2016, which could induce financial intermediaries to provide less distorted advice for fear of exposing themselves to lawsuits. Note that this experiment does not change either the way households choose banks or their decision rules: sophisticated borrowers follow the spread rule; naive borrowers, who are steered by the bank, follow the suggestion given to them by the bank, and naive borrowers, who are not steered by the bank, select FRMs.

	Limiting Advice	Undistorted Advice	Financial Literacy
All	-998	661	304
Sophisticated	-590	-295	-314
Naive	-1,444	1,705	980

Table 7: **Summary of Counterfactual Exercises**

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.

This experiment allows us to measure the welfare consequences of steering to households.³⁷ The overall effect of limiting steering is a loss of 998 euros per household per year over the entire course of the mortgage. This is about 17% 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%).³⁸ If we decompose this loss, we observe that naive households suffer the most (they lose 1,444 euros per capita per year compared to the unrestricted steering scenario); but sophisticated customers are also worse off by 590 euros per year.

To obtain intuition for why restricting steering is costly, we separate two effects of steering on naive households. Recall that naive households would take an FRM if left on their own. On the one hand, for naive households with sufficiently small δ , this decision is suboptimal. Hence, they benefit when the bank steers them towards an ARM, even though such a recommendation is provided in the bank’s self interest. We call this the *information value* of steering, as banks inform naive customers about the alternative product, which they did not consider before.³⁹ On the other hand, there are naive households who should take an FRM if they were to follow the spread rule. These households would make the correct choice in the absence of steering, but banks can instead distort their choice through steering. This causes the *distortion costs*. At our parameter estimates, before the policy, for 52% of naive households the bank’s recommendation coincides with their optimal choice, while the remaining naive household make suboptimal choices. After the

³⁷As already discussed in Section 4, our model bears resemblances to the “money doctors” framework in Gennaioli et al. (2015). In their model, financial intermediaries are always beneficial to their customers, because they expand their customers’ choice sets. In our model, because of potential distortions introduced by steering, the welfare effects are ex-ante ambiguous.

³⁸The total amount paid in a year was computed using the mortgage calculator <http://www.mutuonline.it/guide-mutui/calcolo-rata-mutuo.asp>.

³⁹The information value is closely related to banks acting as “money doctors” that reduce the naive households’ anxiety from choosing the more complex product, namely, the ARM.

policy, a half of naive households are still affected by steering and 33% of them make suboptimal choices. The other half is not affected by banks' steering and 80% of them make suboptimal choices. Thus, the fraction of households making suboptimal choices increases. Therefore, the information value outweighs the distortion costs, and restricting steering reduces welfare of naive households.

The conclusion on the effect of partially banning steering is robust to the assumption about the choice of naive households when banks do not interfere with their choice. In our baseline model, when they make the choice on their own, they choose an FRM. As a robustness exercise, we consider an alternative specification in which 40% of naive households turn to other sources of information and advice, such as media, friends, family, etc. As we mentioned in Section 2, 40% is an upper bound on the fraction of households that consults sources of information other than banks. We suppose that the recommendation from these sources is equally likely to be for FRM or ARM (essentially, a random recommendation). This modification reduces the number of households who should take the ARM but instead take the FRM because of the lack of steering by banks; whereas the set of households whose choice is negatively distorted (i.e., households who should take the FRM and are instead led to take the ARM) stays the same. As a consequence, steering by banks is less valuable: restricting it in this scenario still leads to a considerable average welfare loss of 633 euros per household per year (with naive households losing on average 797 euros per year and sophisticated households losing 484 euros per year).

7.2 Undistorted Steering and Financial Literacy Campaign

We next study the effect of forcing banks to steer their customers only to each customer's best mortgage type. This means that banks make naive households follow the same spread rule that guides the decision of sophisticated households. This way banks have to rely solely on pricing to manage the portfolio of mortgages.

In this scenario, every household takes the "right" mortgage and the average welfare gain is very large: 661 euros per capita per year, which amounts to 11% of the annual mortgage payment for the average household. Interestingly, not all households gain. While naive households benefit the most gaining 1,705 euros per year each, sophisticated households lose 295 euros.⁴⁰

Whereas the effect for naive households comes mostly from them making better

⁴⁰The gain for naive households from picking the optimal type of mortgage is comparable to the figures reported in Campbell and Cocco (2003).

choices, the losses for sophisticated households are due to the adjustment of FRM rates by banks. If the steering becomes undistorted but rates do not change, then many naive households will switch to FRMs. In the baseline specification, banks on average bias naive households' decisions towards ARM: 34% of sophisticated households take FRM, while only 23% of naive households take FRM. Hence, this shift is on average costly for banks. Because banks can no longer use steering, they increase FRM rates (median FRM rate increases from 4.15% to 4.47%) to avoid issuing too many FRMs. This hurts sophisticated households who took cheaper FRMs before the policy intervention.

Our third counterfactual experiment simulates the effect of a financial literacy campaign aimed at increasing knowledge of the basic factors that should be taken into account when choosing the bank and type of mortgage. We assess the impact of a campaign that halves the share of naive households in the population. The average households experiences a gain of 304 euros per year. 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 1,845 euros per year. But sophisticated households lose on average 314 euros per year. As in the previous exercise, this is due to an increase in the median FRM rate from 4.15% to 4.42%.

Even naive households who are not affected by the campaign (and stay naive) gain 117 euros per year. Perhaps surprisingly, both the loss of sophisticated and the gain of naive households unaffected by the campaign come mostly from the effect on households who take FRM both before and after the campaign. The key to this result is that this policy affects different banks differently. When more households become sophisticated, in order to achieve an optimal fraction of FRMs, banks rely more on the rate setting. Banks with a strong preference for ARMs (low θ_{ikt}) increase FRM rates, and banks with a strong preference for FRMs (high θ_{ikt}) lower FRM rates. The correlation coefficient between the FRM rate change and banks' types is -0.11. Thus, the effect on sophisticated households is ambiguous and depends on the distribution of banks' θ s. At our parameter estimates, this effect is negative.

The welfare effect on naive attached households is asymmetrical depending on the preferences of their home bank. If the naive household is a customer of a bank with preferences for ARMs, then the increase in FRM rates will not affect them, because such a bank does not steer its customers toward FRMs. However, if the naive household is a customer of a bank that prefers issuing FRMs, then they might benefit from cheaper FRMs, because such a bank does recommend FRMs. As a result, naive households who stay naive stand to gain.

8 Conclusion

In this paper, we pursue two aims. First, we quantify the costs of steering in financial markets. We estimate that a large fraction of borrowers (48%) lacks the sophistication to make independent financial decisions. This finding is relevant from a practical standpoint, as it implies that there is ample scope for intermediaries to steer their customers' choices. Consistently, we estimate that the cost of the distortion is significant, amounting to 11% of the annual mortgage payment for the average household.

Second, we assess the consequences of different policies to address this distortion. A set of counterfactual exercises leads us to conclude that the gains from forcing intermediaries to steer customers only to their optimal choices, or from educating borrowers, are sizable. Importantly, they are also unequally distributed. While the naive gain, the sophisticated lose. On the other hand, we find that severely restricting steering is not to be recommended. All households lose, especially the unsophisticated ones, which are then left on their own devices. This reveals that steering actually benefit customers even if it is potentially distortive because it may also contain useful information.

We applied our methodology to the mortgage market. However, it might be fruitfully extended to study the cost of steering in other financial markets, for example, the market for financial investments. Such an extension, while valuable in itself, would also allow us to quantify the disciplining role of repeated interactions between intermediaries and customers.

References

- AGARWAL, S., B. AMBROSE, AND V. YAO (forthcoming): "Lender Steering in Residential Mortgage Markets," *Real Estate Economics*.
- AGARWAL, S., G. AMROMIN, I. BEN-DAVID, S. CHOMSISENGPHET, AND D. D. EVANOFF (2010): "Learning to cope: Voluntary financial education and loan performance during a housing crisis," *American Economic Review*, 100, 495–500.
- AGUIRREGABIRIA, V., R. CLARK, AND H. WANG (2016): "Diversification of geographic risk in retail bank networks: Evidence from bank expansion after the Riegle-Neal act," *RAND Journal of Economics*, 47, 529–572.
- ALBERTAZZI, U., F. FRINGUELLOTTI, AND S. ONGENA (2018): "Fixed rate versus adjustable rate mortgages: evidence from euro area banks," Tech. rep., Bank of Italy, Economic Research and International Relations Area.

- ALLEN, J., R. CLARK, AND J.-F. HOUDE (2019): “Search frictions and market power in negotiated price markets,” *Journal of Political Economy*, 127, 1550–1598.
- ANAGOL, S., S. A. COLE, AND S. SARKAR (2017): “Understanding the advice of commissions-motivated agents: Evidence from the Indian life insurance market,” *Review of Economics and Statistics*, 99, 1–15.
- ANDERSEN, S., J. CAMPBELL, K. NIELSEN, AND T. RAMADORAI (2017): “Inattention and Inertia in Household Finance: Evidence from the Danish Mortgage Market,” Working paper.
- ATER, I. AND V. LANDSMAN (2018): “Testing alternative learning theories: Evidence from subscription contracts,” *Journal of Industrial Economics*, 66, 763–815.
- ATHEY, S. (2001): “Single crossing properties and the existence of pure strategy equilibria in games of incomplete information,” *Econometrica*, 69, 861–889.
- ATHEY, S. AND P. HAILE (2007): “Nonparametric approaches to auctions,” in *Handbook of Econometrics*, ed. by J. Heckman and E. Leamer, North Holland, vol. 6, chap. 60, 3847–3965.
- BADARINZA, C., J. Y. CAMPBELL, AND T. RAMADORAI (2018): “What calls to ARMs? International evidence on interest rates and the choice of adjustable-rate mortgages,” *Management Science*, 64, 2275–2288.
- BAJO, E. AND M. BARBI (2018): “Financial illiteracy and mortgage refinancing decisions,” *Journal of Banking & Finance*, 94, 279–296.
- BARONE, G., R. FELICI, AND M. PAGNINI (2011): “Switching costs in local credit markets,” *International Journal of Industrial Organization*, 29, 694–704.
- BEGENAU, J., M. PIAZZESI, AND M. SCHNEIDER (2015): “Banks’ Risk Exposures,” Working paper.
- BELTRATTI, A., M. T. BENETTON, AND A. GAVAZZA (2017): “The role of prepayment penalties in mortgage loans,” *Journal of Banking & Finance*, 82, 165–179.
- BERGSTRESSER, D., J. CHALMERS, AND P. TUFANO (2009): “Assessing the Costs and Benefits of Brokers in the Mutual Fund Industry,” *Review of Financial Studies*, 22, 4129–4156.
- BHUTTA, N., A. FUSTER, AND A. HIZMO (2018): “Paying Too Much? Price Dispersion in the US Mortgage Market,” Working paper.
- BRUNETTI, M., R. CICIRETTI, AND L. DJORDJEVIC (2016): “Till Mortgage Do Us Part: Refinancing Costs and Mortgage Shopping,” Working paper.
- BUCKS, B. AND K. PENCE (2008): “Do borrowers know their mortgage terms?” *Journal of Urban Economics*, 64, 218 – 233.
- CALVET, L. E., J. Y. CAMPBELL, AND P. SODINI (2007): “Down or out: Assessing the welfare costs of household investment mistakes,” *Journal of Political Economy*, 115, 707–747.

- CAMPBELL, J. Y. (2013): “Mortgage market design,” *Review of Finance*, 17, 1–33.
- CAMPBELL, J. Y. AND J. F. COCCO (2003): “Household risk management and optimal mortgage choice,” *Quarterly Journal of Economics*, 118.
- CASSOLA, N., A. HORTACSU, AND J. KASTL (2013): “The 2007 subprime market crisis in the EURO area through the lens of ECB repo auctions,” *Econometrica*, 81, 1309–1345.
- CERRONE, R., R. COCOZZA, D. CURCIO, AND I. GIANFRANCESCO (2017): “Does prudential regulation contribute to effective measurement and management of interest rate risk? Evidence from Italian banks,” *Journal of Financial Stability*, 30, 126–138.
- CHALMERS, J. AND J. REUTER (2017): “Is Conflicted Investment Advice Better than No Advice?” NBER WP 18158.
- CHATER, N., S. HUCK, AND R. INDERST (2010): “Consumer decision-making in retail investment services: A behavioural economics perspective,” *Report to the European Commission/SANCO*.
- CHRISTOFFERSEN, S., R. EVANS, AND D. MUSTO (2013): “What do consumers’ fund flows maximize? Evidence from their brokers’ incentives,” *Journal of Finance*, 68, 201–235.
- CIOCCHETTA, F., W. CORNACCHIA, R. FELICI, AND M. LOBERTO (2016): “Assessing financial stability risks arising from the real estate market in Italy,” *Questioni di Economia e Finanza*, 323.
- CRAWFORD, G., N. PAVANINI, AND F. SCHIVARDI (2018): “Asymmetric information and imperfect competition in lending markets,” *American Economic Review*, 108, 1659–1701.
- DEUFLHARD, F. (2016): “Quantifying inertia in retail deposit markets,” Working paper.
- DRECHSLER, I., A. SAVOV, AND P. SCHNABL (2017): “Banking on Deposits: Maturity Transformation without Interest Rate Risk,” Working paper.
- EGAN, M. (2019): “Brokers versus retail investors: Conflicting interest and dominated products,” *Journal of Finance*, 74, 1217–1260.
- EGAN, M., A. HORTACSU, AND G. MATVOS (2017): “Deposit competition and financial fragility: Evidence from the US banking sector,” *American Economic Review*, 107, 169–216.
- EGAN, M., G. MATVOS, AND A. SERU (2019): “The market for financial adviser misconduct,” *Journal of Political Economy*, 127, 233–295.
- EINAV, L., M. JENKINS, AND J. LEVIN (2012): “Contract pricing in consumer credit markets,” *Econometrica*, 80, 1387–1432.
- ESPOSITO, L., A. NOBILI, AND T. ROPELE (2015): “The management of interest rate risk during the crisis: Evidence from Italian banks,” *Journal of Banking & Finance*, 59, 486 – 504.
- FINANCIAL SERVICES AUTHORITY (2009): “Mortgage market review,” Discussion Paper.

- FOÀ, G., L. GAMBACORTA, L. GUISO, AND P. MISTRULLI (2019): “The supply side of household finance,” *Review of Financial Studies*, 32, 3762–3798.
- FOERSTER, S., J. T. LINNAINMAA, B. T. MELZER, AND A. PREVITERO (2017): “Retail financial advice: does one size fit all?” *Journal of Finance*, 72, 1441–1482.
- FORNERO, E., C. MONTICONE, AND S. TRUCCHI (2011): “The effect of financial literacy on mortgage choices,” Netspar Discussion Paper 09/2011-085.
- FUSTER, A. AND J. VICKERY (2015): “Securitization and the fixed-rate mortgage,” *Review of Financial Studies*, 28, 176–211.
- GABAIX, X. AND D. LAIBSON (2006): “Shrouded attributes, consumer myopia, and information suppression in competitive markets,” *Quarterly Journal of Economics*, 121, 505–540.
- GATHERGOOD, J. AND J. WEBER (2017): “Financial literacy, present bias and alternative mortgage products,” *Journal of Banking & Finance*, 78, 58–83.
- GENNAIOLI, N., A. SHLEIFER, AND R. VISHNY (2015): “Money doctors,” *Journal of Finance*, 70, 91–114.
- GOMEZ, M., A. LANDIER, D. SRAER, D. THESMAR, ET AL. (2016): “Banks’ exposure to interest rate risk and the transmission of monetary policy,” Working paper.
- GRASSO, R., N. LINCIANO, L. PIERANTONI, AND G. SICILIANO (2010): “Le obbligazioni emesse da banche italiane,” *Quaderno di Finanza Consob* n.67.
- GUISO, L., P. SAPIENZA, AND L. ZINGALES (2018): “Time Varying Risk Aversion,” *Journal of Financial Economics*, 128, 403–421.
- GUISO, L. AND E. VIVIANO (2015): “How Much can Financial Literacy Help?” *Review of Finance*, 19, 1347–1382.
- GURUN, U. G., G. MATVOS, AND A. SERU (2016): “Advertising expensive mortgages,” Working paper.
- HACKETHAL, A., M. HALIASSOS, AND T. JAPPELLI (2012): “Financial advisors: A case of babysitters?” *Journal of Banking & Finance*, 36, 509–524.
- HOECHLE, D., S. RUENZI, N. SCHAUB, AND N. SCHMID (2018): “Financial Advice and Bank Profits,” *Review of Financial Studies*, 31, 4447–4492.
- HOFFMANN, P., S. LANGFIELD, F. PIEROBON, AND G. VUILLEMAY (2019): “Who bears interest rate risk?” *Review of Financial Studies*, 32, 2921–2954.
- HUNG, A. AND J. YOONG (2013): “Asking for help: Survey and experimental evidence on financial advice and behavior change,” in *The Market for Retirement Financial Advice*, ed. by O. S. Mitchell and K. Smetters, Oxford University Press, chap. 9.

- INDERST, R. AND M. OTTAVIANI (2012): “Financial advice,” *Journal of Economic Literature*, 50, 494–512.
- KAHNEMAN, D., P. P. WAKKER, AND R. SARIN (1997): “Back to Bentham? Explorations of experienced utility,” *Quarterly Journal of Economics*, 112, 375–406.
- KARTIK, N., M. OTTAVIANI, AND F. SQUINTANI (2007): “Credulity, lies, and costly talk,” *Journal of Economic Theory*, 134, 93–116.
- KASHYAP, A. K. AND J. C. STEIN (1995): “The impact of monetary policy on bank balance sheets,” *Carnegie-Rochester Conference Series on Public Policy*, 42, 151–195.
- KOIJEN, R. S., O. VAN HEMERT, AND S. VAN NIEUWERBURGH (2009): “Mortgage timing,” *Journal of Financial Economics*, 93, 292–324.
- LIBERATI, D. AND V. P. VACCA (2016): “With (more than) a little help from my bank. Loan-to-value ratios and access to mortgages in Italy,” Bank of Italy Occasional Paper N.315.
- MALMENDIER, U. AND S. NAGEL (2011): “Depression babies: Do macroeconomic experiences affect risk taking?” *Quarterly Journal of Economics*, 126, 373–416.
- MULLAINATHAN, S., M. NOETH, AND A. SCHOAR (2012): “The market for financial advice: An audit study,” NBER working paper n.17929.
- OECD (2016): “OECD/INFE International Survey of Adult Financial Literacy Competencies,” <http://www.oecd.org/finance/financial-education/oecd-infe-survey-adult-financial-literacy-competencies.htm>.
- OLIVER WYMAN (2003): “Study on the financial integration of European mortgage markets,” *European Mortgage Federation*.
- (2005): “European mortgage distribution: Changing channel choice,” technical report.
- OTTAVIANI, M. AND F. SQUINTANI (2006): “Naive audience and communication bias,” *International Journal of Game Theory*, 35, 129–150.
- RAMPINI, A., S. VISWANATHAN, AND G. VUILLEMEY (2016): “Risk management in financial institutions,” Working paper.
- RENY, P. J. AND S. ZAMIR (2004): “On the Existence of Pure Strategy Monotone Equilibria in Asymmetric First-Price Auctions,” *Econometrica*, 72, 1105–1125.
- ROBLES-GARCIA, C. (2019): “Competition and Incentives in Mortgage Markets: The Role of Brokers,” Working paper.
- RU, H. AND A. SCHOAR (2017): “Do credit card companies screen for behavioral biases?” NBER working paper n.22360.

VAN ROOIJ, M., A. LUSARDI, AND R. ALESSIE (2011): “Financial literacy and stock market participation,” *Journal of Financial Economics*, 101, 449–472.

WOODWARD, S. E. AND R. E. HALL (2012): “Diagnosing consumer confusion and sub-optimal shopping effort: Theory and mortgage-market evidence,” *American Economic Review*, 102, 3249–3276.

A Online Appendix

A.1 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 4, 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.

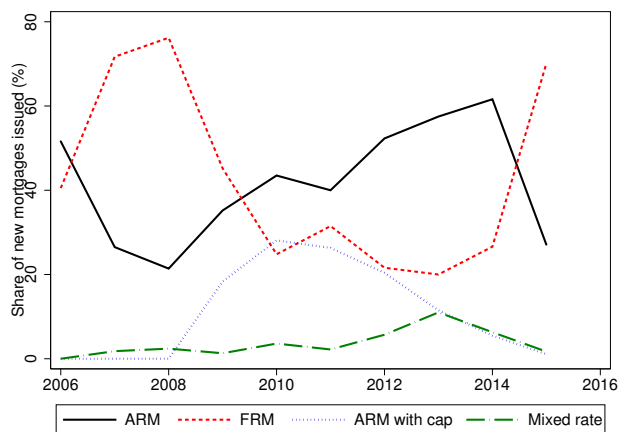


Figure 4: Market Share by Type of Mortgage

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 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

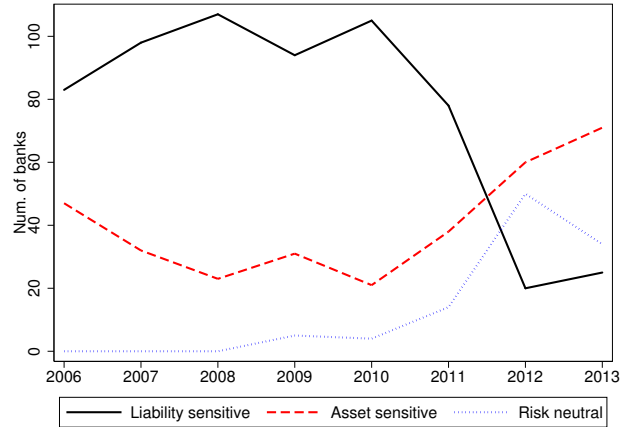


Figure 5: **Exposure of Italian Banks to Interest Rate Risk**

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.

incentive to steer customers towards ARM or FRM to manage their exposure to interest rate risk.

In Figure 5, 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 prepayment 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. (2016)). 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.

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

	% 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 8: **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).

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 8 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.

A.2 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

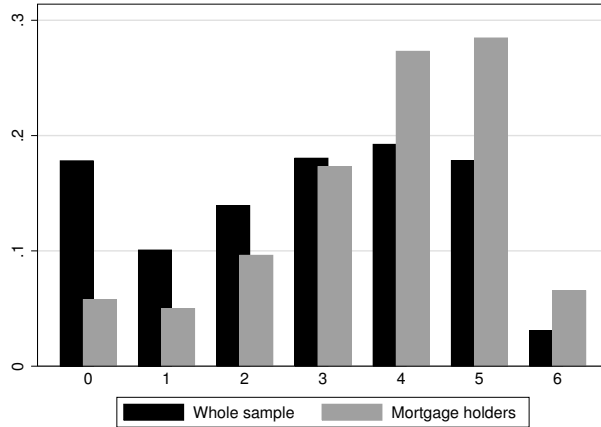


Figure 6: Distribution of the Sophistication Index

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.

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.⁴¹

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 6, 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).

Figure 7 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

⁴¹The 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.

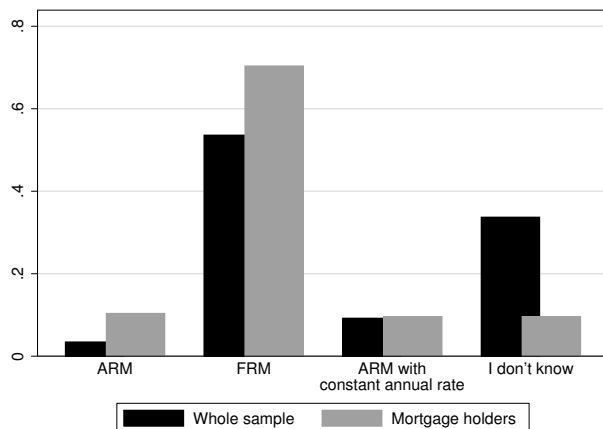


Figure 7: Understanding of Mortgage Characteristics

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.

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 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:

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

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.

A.3 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%.

A.4 Evidence from Foà et al. (2019)

Foà et al. (2019) devise a test for the presence of steering on the part of the financial intermediary and apply it to our same data on mortgage choices made by Italian households. The test relies on the availability of data on the type of mortgage each household selects and on the balance sheets of the bank where it is taking the mortgage. In the main text, we replicated their key result establishing that, even controlling for the FRM-ARM spread, bank balance sheet variables (such as the cost of fixed rate funding) contribute to explain households' mortgage decisions (see Table 2). Since banks balance sheets should influence households decision only through their

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 9: **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.

impact on the FRM-ARM spread, this is interpreted as evidence that banks use tools other than price to influence their customers. Here 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 9) 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 unobservable 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 10 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 capital protection;

⁴²Static sorting is not a plausible explanation of the correlations presented in Table 2 since it would be taken care of by the bank fixed effects.

Explanatory variables	Dependent variable is individual risk aversion		Dependent variable is bank rejection rate	
	(1)	(2)	(3)	(4)
	Baseline	adding bank and time fixed effects	baseline	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 10: **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.

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 10 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

⁴³The 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.

	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 11: **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.

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 11) and the fixed effects are not correlated with the supply factors of the bank.

A.5 Microfoundation for Naive Households' Behavior

In this appendix, 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 ν_π , σ_π^2 , ν_ε , and σ_ε^2 , and have some full-support beliefs F about their joint distribution. Conditional on ν_π , σ_π^2 , ν_ε , and σ_ε^2 , the utility of naive households from taking FRM is the same

as of sophisticated households and is given by $\mathbb{E}[y - (1 + r_t^f(h) - \pi)H] - \gamma \mathbb{V}[y - (1 + r_t^f(h) - \pi)H]$.⁴⁴ 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 un-attached, 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.

A.6 Optimal Spread Setting

We derive an explicit formula for (4.7) 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 ($s_{it}^a > \underline{s}_{-it}^a$).⁴⁵ We use super-index a for the former case and super-index A for the latter. After banks post FRM-ARM spreads, bank i has either the lowest FRM rate ($s_{it}^f < \underline{s}_{-it}^f$) or not ($s_{it}^f > \underline{s}_{-it}^f$). We use super-index f for the former case and super-index F for the latter.

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

$$m_{it}^{AF} V^{AF}(\phi_{it}|\theta_{it})G(s_{it}^f|\mathbf{s}_t) + m_{it}^{Af} V^{Af}(\phi_{it}|\theta_{it}) \left(1 - G(s_{it}^f|\mathbf{s}_t)\right), \quad (\text{A.1})$$

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

$$m_{it}^{aF} V^{aF}(\phi_{it}|\theta_{it})G(s_{it}^f|\mathbf{s}_t) + m_{it}^{af} V^{af}(\phi_{it}|\theta_{it}) \left(1 - G(s_{it}^f|\mathbf{s}_t)\right). \quad (\text{A.2})$$

Then ϕ_{it} is determined by maximizing either (A.1) or (A.2) depending on whether $s_{it}^a > \underline{s}_{-it}^a$

⁴⁴Thus, their unconditional utility equals

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

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

⁴⁵We abstract from ties as they are not observed in our data.

or $s_{it}^a < \underline{s}_{-it}^a$, respectively. To complete the characterization of the optimal rate setting, we determine functions m_{it} , \underline{x}_{it} , and \bar{x}_{it} for different cases. Let

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

and $\phi_t \equiv \underline{s}_t^f + r_t^{swap25} - (\underline{s}_t^a + r_t^{eurbr})$ 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 ($s_{it}^a > \underline{s}_{-it}^a$)
 - (a) If $s_{it}^f > \underline{s}_{-it}^f$, then bank i keeps only attached households initially assigned to it. The mass of them is $m_{it}^{AF} = (1 - \psi)p_{it}$. 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, $\underline{x}_{it}^{AF} = (1 - \mu_a)\kappa(\phi_{it})$ and $\bar{x}_{it}^{AF} = (1 - \mu_a)\kappa(\phi_{it}) + \mu_a$.
 - (b) If $s_{it}^f < \underline{s}_{-it}^f$, then bank i , in addition to its attached customers, attracts all naive un-attached households and sophisticated un-attached households that prefer to take FRM in the market. The mass of the former is $\psi\mu_u$, the mass of the latter is $(1 - \mu_u)\kappa(\phi_t)$. Thus, the total mass of bank i 's customers equals

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

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

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

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,

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

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 un-attached households who prefer to take ARM in the market. They constitute a fraction $1 - \kappa(\phi_t)$ of sophisticated un-attached 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,

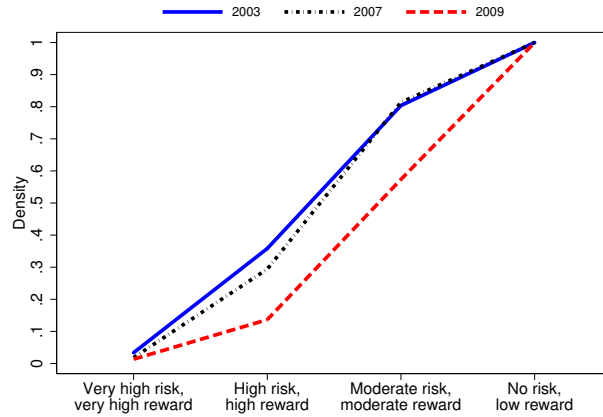
$$\begin{aligned} \underline{x}_{it}^{aF} &= \frac{(1 - \mu_a)(1 - \psi)p_{it}\kappa(\phi_{it})}{(1 - \psi)p_{it} + (1 - \mu_u)\psi(1 - \kappa(\phi_t))}, \\ \bar{x}_{it}^{aF} &= \frac{(1 - \mu_a)(1 - \psi)p_{it}\kappa(\phi_{it}) + \mu_a(1 - \psi)p_{it}}{(1 - \psi)p_{it} + (1 - \mu_u)\psi(1 - \kappa(\phi_t))}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

- (b) If $s_{it}^f < \underline{s}_{it}^f$, then bank i in addition to its attached customers attracts all un-attached 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 $\bar{x}_{it}^{af} = ((1 - \psi)(1 - \mu_a) + \psi(1 - \mu_u))\kappa(\phi_{it}) + ((1 - \psi)\mu_a + \psi\mu_u)$.

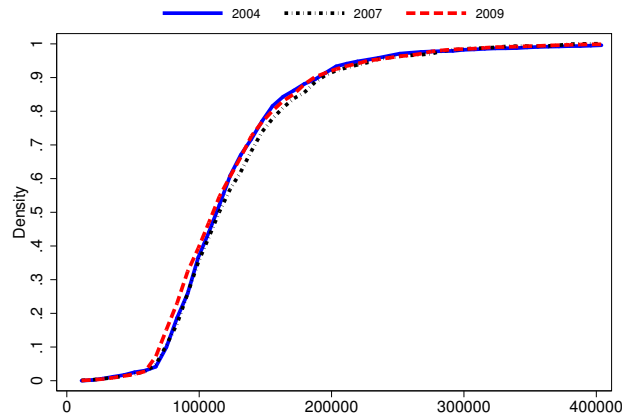
A.7 Stationarity of Households Characteristics

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 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



(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.

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.

A.8 Heterogeneity in Demand Parameters

In our baseline estimates, we assume that all parameters are the same across all markets. Here, we implement an alternative estimation where the fraction of naive households and the share of households who are un-attached to their home banks differ across Italian regions. We leave instead the parameters of the distribution of the optimal cutoff homogeneous across markets.

We assume that the fraction of naive households depends on the level of education in the population resident in the region as more educated people should be able to make informed choice sourcing and understanding information on their own and relying less on the opinion of experts. We model the share of un-attached households as a function of the length of the relationship between a customer and its main bank. This captures the well known fact that switching costs are increasing in time: new customers are overwhelmingly more likely to shop around than long time ones. The specification we estimates is as follows:

$$\begin{aligned}\mu_r &= \frac{\exp(a_0 + a_1 Education_r)}{1 + \exp(a_0 + a_1 Education_r)}, \\ r &= \frac{\exp(b_0 + b_1 RelationLength_r)}{1 + \exp(b_0 + b_1 RelationLength_r)},\end{aligned}$$

where r denotes an Italian region and the logistic functional form is imposed so that μ and r are guaranteed to be between 0 and 1. The covariates are simple averages at the regional level from SHIW waves 2004, 2006 and 2008. For *Education* we use the share of households reporting to have obtained a bachelor or a postgraduate degree; *RelationLength* represents the share of households who have a 10 years or longer relationship with their main bank.

The maximum likelihood estimates are displayed in Table 12 and line up with intuition. A larger share of highly educated is associated with fewer naive households. Further, regions where the relationships between customers and banks are tighter have a lower fraction of un-attached households. In quantitative terms, the dispersion estimated in the fraction of un-attached is minimal: the estimates of ψ across regions range between 8.5% and 9.3%. Dispersion in the fraction of naive is also moderate: the share ranges from 45% to 52%.

Coefficients	Estimates
a_0	0.34 [0.18;0.57]
a_1	-1.15 [-1.76;-0.76]
b_0	-1.83 [-1.93;-1.76]
b_1	-0.62 [-0.74;-0.54]
μ_d	-0.74 [-0.94;-0.56]
σ_d	0.91 [0.81;1.03]

Table 12: Demand with Regional Heterogeneity

Notes: The table reports the maximum likelihood estimates of the demand model where μ and ψ are functions of observables. 99% confidence intervals estimated from 200 bootstrap replications are in parentheses.

A.9 Additional Figures

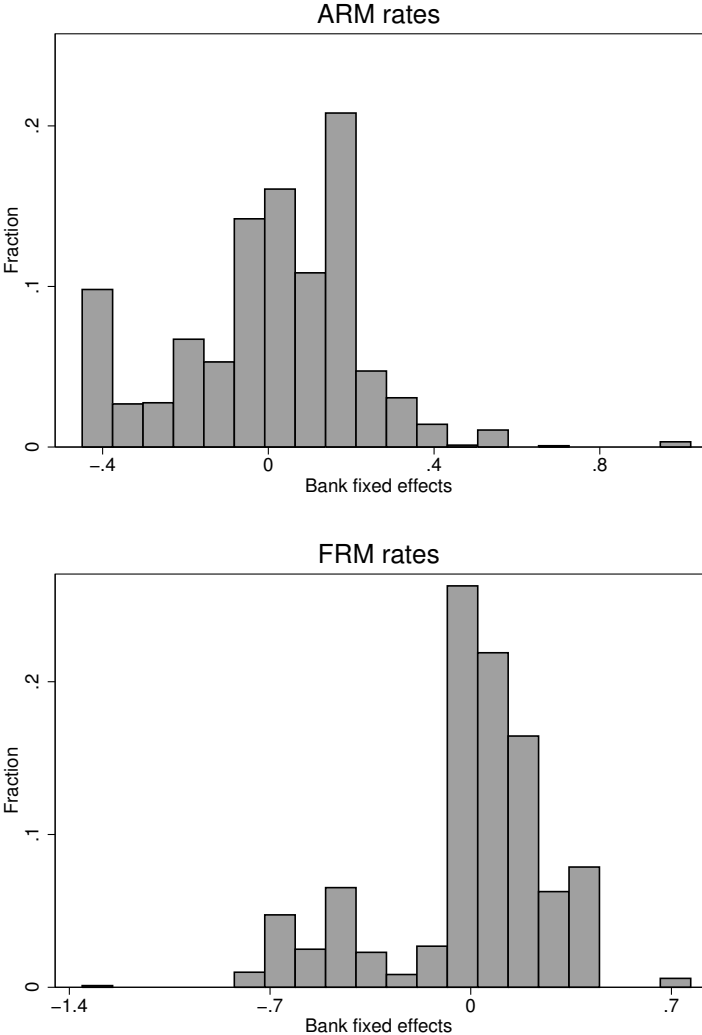


Figure 9: Dispersion of Rates

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.

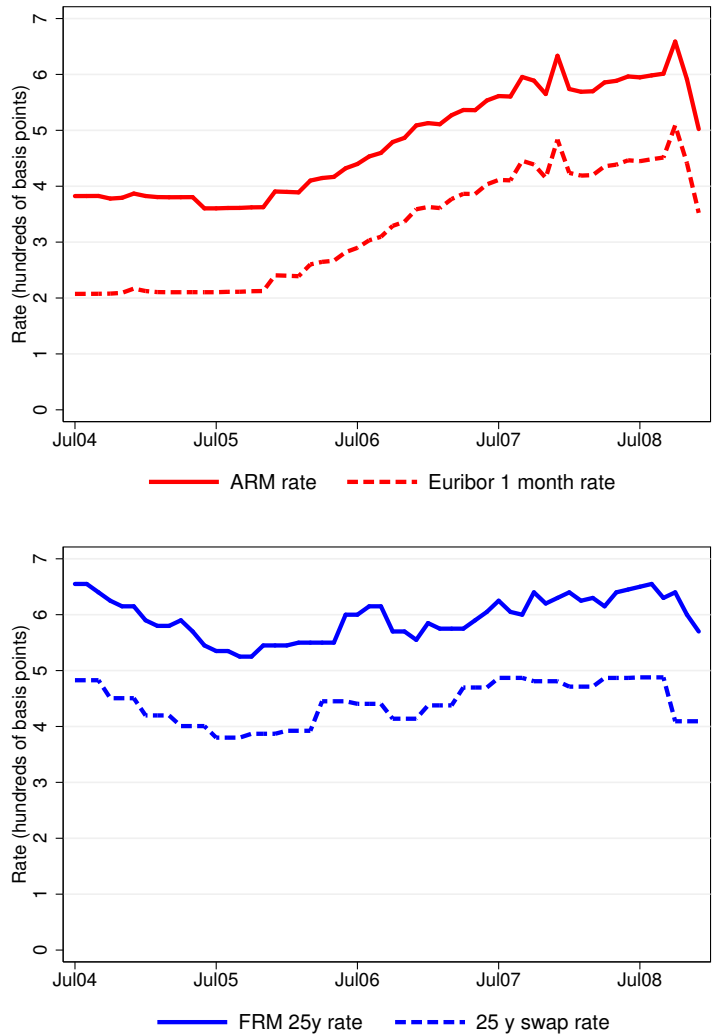


Figure 10: **Benchmark Rates for adjustable and fixed rate mortgages**

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 portrayed alongside the rate of a 25 years interest rate swap.

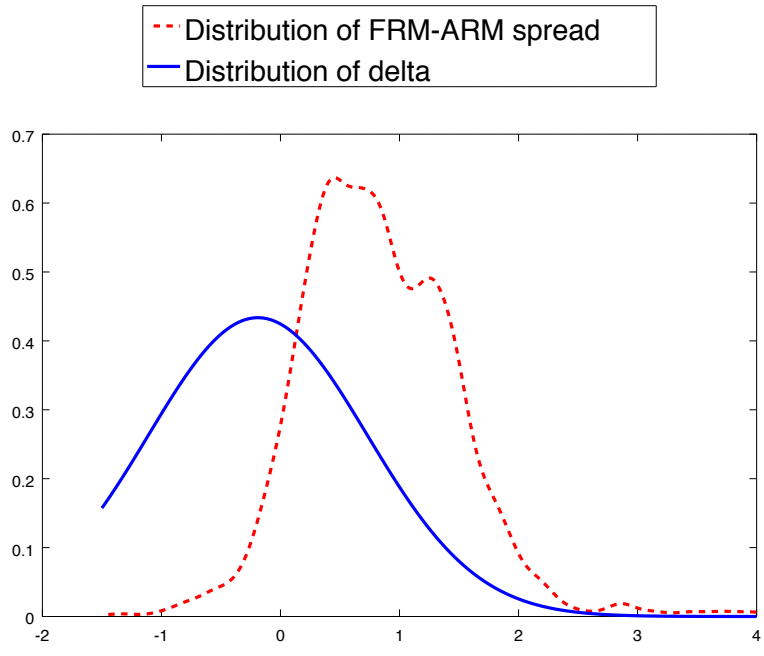


Figure 11: **Estimated Distribution of δ and Kernel Density of ϕ_{it}**

Previous volumes in this series

834 December 2019	How do machine learning and non-traditional data affect credit scoring? New evidence from a Chinese fintech firm	Leonardo Gambacorta, Yiping Huang, Han Qiu and Jingyi Wang
833 December 2019	Central Counterparty Exposure in Stressed Markets	Wenqian Huang, Albert J. Menkveld and Shihao Yu
832 December 2019	Hedger of Last Resort: Evidence from Brazilian FX Interventions, Local Credit and Global Financial Cycles	Rodrigo Barbone Gonzalez, Dmitry Khametshin, José-Luis Peydró and Andrea Polo
831 December 2019	Believing in bail-in? Market discipline and the pricing of bail-in bonds	Ulf Lewrick, José Maria Serena and Grant Turner
830 December 2019	De jure benchmark bonds	Eli Remolona and James Yetman
829 December 2019	Central banking in challenging times	Claudio Borio
828 December 2019	The currency composition of foreign exchange reserves	Hiro Ito, Robert N McCauley
827 December 2019	Bank Loan Supply during Crises: The Importance of Geographic Diversification	Sebastian Doerr, Philipp Schaz
826 December 2019	The cost of Clearing Fragmentation	Evangelos Benos, Wenqian Huang, Albert Menkveld and Michalis Vasios
825 December 2019	Examining macroprudential policy and its macroeconomic effects – some new evidence	Soyoung Kim, Aaron Mehrotra
824 December 2019	Spread the Word: International Spillovers from Central Bank Communication	Hanna Armelius, Christoph Bertsch, Isaiah Hull and Xin Zhang
823 November 2019	Unintended Side Effects: Stress Tests, Entrepreneurship, and Innovation	Sebastian Doerr
822 November 2019	China's Shadow Banking: Bank's Shadow and Traditional Shadow Banking	Guofeng Sun
821 November 2019	What do almost 20 years of micro data and two crises say about the relationship between central bank and interbank market liquidity? Evidence from Italy	Massimiliano Affinito

All volumes are available on our website www.bis.org.