

Distorted Advice in Financial Markets: Evidence from the Mortgage Market*

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Abstract

Many households lack the sophistication required to make complex financial decisions and risk being exploited when seeking advice from intermediaries. We build a structural model of financial advice, in which banks attain their optimal mix of fixed and adjustable rate mortgages by both setting rates and providing advice to their clientele. “Sophisticated” households know the mortgage type best for them, whereas “naive” are susceptible to the bank’s advice. Using data on the universe of Italian mortgages, we recover the primitives of the model and quantify the welfare implications of distorted financial advice. The cost of the distortion is equivalent to increasing the annual mortgage payment by 1,145 euros. Losses are bigger for naive households, but sophisticated households suffer as well. However, since even distorted advice conveys information, banning advice altogether results in a loss of 723 euros per year on average. A financial literacy campaign is beneficial for all, though to a different extent.

JEL Classification: G21, D18, D12

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1 Introduction

Households frequently seek expert advice when they lack the knowledge or sophistication to determine what financial product is best for their needs.¹ However, advisors might have incentives to distort their recommendations. This is especially likely when households solicit advice from the seller of the financial product itself. We call financial advice “distorted” when the advisor provides it in its own interest, which need not be fully aligned with the customer’s interest. The goal of this paper is to assess the prominence of this phenomenon and quantify its impact on households’ welfare.

Prior studies document the presence of distorted advice by comparing the investment performance of advised households to that of households who do not rely on advice (Hackethal et al., 2010, 2012; Foerster et al., forthcoming) or randomizing the advice through field experiments (Mullainathan et al. (2012); Anagol et al. (2017)). Their focus is on cases when advice is sought by the investors. However, advice – especially distorted advice – might be offered even when it is not solicited by the customer. The intermediary or broker may emphasize a given financial product, or highlight some features while hiding others in order to steer the customer’s choice to the intermediary’s advantage. If so, comparing customers who do and do not solicit advice may fail to detect supply-side distortions and underestimate their importance. Assessing the economic relevance of distorted advice is an even harder task than simply detecting its existence. In fact, the welfare benefit of undistorted advice and welfare implications of different policies depend on the distribution in the population of sophisticated and unsophisticated consumers, a parameter that the studies described above do not identify.

To overcome these limitations, in this paper we build and estimate a model of households’ choice of a financial instrument where some households are responsive to the advice of the seller of the product. Our application is to the mortgage market, which is an excellent setting to study distorted financial advice. It is a financial market in which a large fraction of the population participate in all advanced economies and a certain degree of sophistication is required from mortgage takers to appreciate the pros and cons of different products. Therefore, expert opinion is potentially valuable. Furthermore, both banks and brokers have interest in taking advantage of customers’ lack of knowledge and experience (Woodward and Hall (2012)).

¹For 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.

Our data consist of administrative records on the universe of mortgages originated between 2005 and 2008 by a sample of 175 Italian banks covering 90 percent of the market. In addition to information on the terms of the loans and characteristics of the borrowers, the data identifies the bank originating the mortgage, allowing us to match rich data on the balance sheet of the originator. On top of the high quality of the data we can access, studying the Italian mortgage market provides important advantages due to the institutional characteristics which make it well suited to the purpose of this study. Namely, there are only two main products available to customers (plain vanilla fixed and adjustable rate mortgages); advice is usually provided by the banks issuing the mortgages (rather than brokers); and banks retain on their balance sheets significant portion of the interest rate risk linked to the mortgages they originate. This means that Italian banks have both motive and opportunity to provide biased advice.

In our model, households make two choices: they pick a bank where they take a mortgage and they decide between a fixed and an adjustable rate mortgage. Choosing a fixed rate mortgage protects the household against the interest rate risk but exposes it to the inflation risk; the opposite is true for adjustable mortgages. There are two types of borrowers in the population: “sophisticated” and “naive”. When deciding about the mortgage type, sophisticated borrowers are perfectly informed about the risks associated with each mortgage type. Therefore, they choose the best mortgage type given their characteristics and the spread between fixed and adjustable contracts. Naive borrowers lack sophistication to compare fixed and adjustable rate mortgages. Instead, they can get advice from the intermediary they choose to borrow from and follow the recommendation on the mortgage type that they receive from their chosen bank. Banks are heterogenous in the target fixed/adjustable composition of their mortgage portfolio and compete with each other by setting rates to attract borrowers. They then provide advice to the customers they manage to attract.

We estimate the fraction of naive borrowers at 34%, which squares with survey measures of financial sophistication of the Italian population. This parameter is key to assess the economic effect of distorted advice as well as to evaluate the potential welfare gains of public policies meant to reduce the distortion. Our first counterfactual exercise shows that households can benefit even from distorted advice. In fact, if we restrict the banks’ ability to provide advice, we obtain a welfare loss of 723 euros per household per year. We find that banning advice, while very costly for the naive borrowers (1,838 euros per year) is also costly for the sophisticated ones who end up paying 147 euros more per year. The second counterfactual measures the costs of distorted advice. If banks could be forced

to provide undistorted advice the welfare gain would be 1,145 euros per household per year with benefits to both naive and sophisticated households. Finally, we also study the consumer welfare gains of a financial education campaign that halves the fraction of naive households and find them to be substantial. Not surprisingly, the lion's share of the welfare gains accrue to households who were naive and become sophisticated thanks to the campaign. However, because the policy affects equilibrium spreads, it benefits also the naive households not directly treated by the financial education campaign as well as, to a smaller extent, sophisticated households.

This study relates to several strands of literature. Spurred by the finding in Foa et al. (2015), who exploit similar data to find reduced form evidence of advice distortion in mortgage origination, we contribute to the household finance literature on distorted advice (Egan, 2015; Ru and Schoar, 2015; Egan et al., 2016) by explicitly modeling the advice provision by the 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 advice ties in to the empirical literature studying the interaction between borrowers and lenders in credit markets which has documented the relevance of other dimensions of these interactions such as information asymmetry (Einav et al., 2012; Crawford et al., 2015), inattention and inertia (Andersen et al. (2017)) and bargaining negotiation (Allen et al., 2014). Besides the focus on credit markets, we are linked to these studies by a common methodological approach which follows a growing literature applying tools developed in Industrial Organization to the analysis of financial markets (Aguirregabiria et al. (2016); Cassola et al. (2013); 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)).² Whereas we do not aim at making a theoretical contribution, our estimates point to a large fraction of households with limited financial literacy engaging in high stakes transactions vindicating the tenet of these models.

The rest of the paper is organized as follows. Section 2 describes the data and the institutional features of the Italian mortgage markets. In Section 3 we present the model. Section 4 discusses the identification of the model. Section 5 reports estimation results and provides evidence of distorted advice. Section 6 presents the results of the policy experiments measuring the welfare effects of distorted advice. Section 7 concludes.

²A 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.

2 Features of the Italian Mortgage Market and Data

The working of the mortgage market is greatly affected by a number of institutional characteristics (see Campbell (2013)). Therefore, this section describes the Italian mortgage market with two purposes in mind. First, we mean to highlight the differences between the Italian mortgage market and other markets (most notably the US) and argue that its simple structure provides a suitable environment for the empirical study of distorted advice in financial markets. Second, we stress how the institutional characteristics of the Italian mortgage market inform our choices in the construction of the model in Section 3. A more extensive description of the salient characteristics of the Italian market we illustrate below can be found in Appendix A.1.

2.1 The Italian Mortgage Market

Despite Italy's high homeownership rate, the size of the household mortgage market is smaller than in 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 (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 the period covered in our sample nearly 250,000 mortgages with maturity 25 to 30 years are originated on average each year.

The two most common types of contracts are either an adjustable rate mortgage (henceforth, ARM) where the bank charges a spread over an underlying benchmark rate (usually the 1- or 3-month Euribor); or a fixed rate mortgage (henceforth, FRM) where an interest rate is agreed upon when the contract is signed leading to fixed amount to be repaid in each installment for the whole length of the mortgage. Together, these represent over 90% of the mortgages issued in our sample.³ Unlike in other countries, both of these 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.⁴ The Italian regulation sets the maximum loan to value ratio at 80%, and exceeding this

³Italian 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.

⁴Consistent with Badarinza et al. (forthcoming), Foa et al. (2015) show using microdata from our same source that fluctuations in the ARM share are highly correlated with the FRM/ARM spread.

threshold requires banks to hold more regulatory capital. The average LTV over our sample period lies between 63% and 70%.

Two institutional features make the Italian mortgage market an ideal laboratory to study the effect of distorted financial advice. First, it is uncommon for Italian households in the process of obtaining a mortgage to hire a professional broker to advise them. This means that the most easily accessible expert opinion for a customer during the process is that of the (loan officer of the) bank which is issuing her the mortgage. Second, unlike in the US (Fuster and Vickery (2015)), in Italy banks retain most of the mortgages they originate on their balance sheets, bearing thus interest rate, pre-payment and credit risk. Although a securitization market exists, banks do not heavily rely on securitization: between 2000 and 2006 only 5% of the outstanding mortgages were securitized. Evidence of incomplete hedging of the interest risk on loans by financial institutions has been provided, for example, by Begeau et al. (2015); Gomez et al. (2016) and Rampini et al. (2016) using US data and by Esposito et al. (2015) and Cerrone et al. (2017) for Italian banks. The fact that banks retain the risk linked to maturity transformation explains why they might want to distort advice to mortgage takers.

Banks fund their loans both through deposits and long term bonds placed in the market. The relative importance of these two sources varies substantially across banks. (See Table 1). For some banks, deposits account for as little as a third of total liabilities. These are typically the large banking groups that are more keen on issuing bonds and therefore (given the higher volatility of bond compared to deposits funding) are more exposed to the risk of maturity mismatch between items on their balance sheets. For other banks in our sample, deposits represent nearly the totality of their funding suggesting that they will be able to 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 factors shape the preference of banks towards issuing fixed or adjustable rate mortgages.

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 relatively more prominent source of risk taken by banks when issuing mortgages compared to credit and pre-payment risks. Like in many other European countries, mortgages loans 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 around 1% without significant

spikes even in the years of the financial crisis, which anyway starts in Italy after the end of our sample. This also reflects banks' tight screening policies with high rejection rates of risky loan applicants.⁵ 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 for 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 even 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 (2015); Beltratti et al. (2017)). The share of refinanced mortgages is close to zero up until 2007 and consistently below 1% after. Therefore, we do not include renegotiation and prepayment risks in the problem of the bank.

In sum, the Italian mortgage market is characterized by the prevalence of plain vanilla FRM and ARM mortgages with long maturity originated and commercialized by banks that also act as advisors for their customers and which retain most of the mortgage risk. Because origination fees are small (in the order of 0.1% of the value of the mortgage over the period we analyze) and independent of the type of contract (FRM vs ARM), banks have little incentive to originate mortgages just to cash in fees. However, because of the maturity transformation risk and costly long term funding and hedging, banks have an incentive to steer customers choice either towards FRM or ARM at the time of the origination to manage their exposure to interest rate risk. These features of the market and the properties of the data that we discuss below offer an excellent setting for testing whether this is actually the case and measure the consequences of such behavior.

<i>Variable</i>	<i>Obs.</i>	<i>Mean</i>	<i>Std.dev.</i>	<i>25th pctile</i>	<i>50th pctile</i>	<i>75th pctile</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
Num. mortgages	13,747	47.41	95.09	8	20	48
% lowest ARM	13,747	0.12	0.16	0	0.06	0.20
% 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 FRM 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						
Num. 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 % *lowest ARM* and % *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 the fraction of deposits and 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.

2.2 Data

We use data from two main administrative sources: the Italian Credit Register (CR) and the Survey on Loan Interest Rates (SLIR). Both datasets are maintained by the Bank of Italy. CR 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 (mortgage, credit line, etc.), the size of the loan, the identity of the bank originating the loan and several characteristics of the borrower. We have obtained data aggregated 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. Since we do not model the choice of the maturity of the mortgage, for our analysis we focus on mortgages homogeneous under this dimension, with maturity between 25 and 30 years. We also restrict attention to only plain vanilla ARM or FRM mortgages (excluding partially adjustable rate mortgages, loans to sole proprietorships, etc.). These mortgages represent the overwhelming majority of the mortgages originated during our sample. The final dataset includes information from nearly 1,000,000 mortgages.

We merge this information with data from SLIR on the average rate for the FRM and ARM mortgages originated in each bank-quarter-province triplet. A subset of 175 banks reports interest rate data to SLIR but this includes all the main banking groups active in Italy covering more than 90 percent of the market. Some of our markets 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 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.⁶ This choice is unlikely to introduce significant distortion in our estimation of the supply side decisions as the bulk of the competitors faced by a bank is the same in all the provinces of a given region (although it can change significantly across regions due to the importance of regional banks) and there is evidence that the pricing is 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 some difference between rates in provinces of the

⁵Based on SHIW data, on average 13% of the households have had a rejected loan application in 2004; the figure rises to 27% in 2008

⁶Regions 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).

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 and foremost, we are able to merge the mortgage dataset with detailed supervisory data on banks characteristics and balance sheets. Moreover, we obtain information at the bank-year-province level on the share of deposits in the market held by each bank. Table 1 displays summary statistics on our main data.

3 Model

In this section, we capture the key aspects of the Italian mortgage market described in the previous section in a model of households' mortgage choice and banks' choice of rate and advice policies. As discussed in Section 2, 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 indexed by h of mass M_t take up a mortgage in quarter t from one of N banks in the market. The timeline is as follows:

1. In the beginning of quarter t , banks simultaneously set rates.
2. Each household h chooses the bank from which it takes the mortgage. We say that the household becomes a *customer* of this bank.
3. Banks optimally provide advice to their customers about the mortgage type.
4. Households choose the mortgage type.

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

3.1 Households

Households are heterogenous in several dimensions. First, a fraction μ of households is *naive* and a fraction $1 - \mu$ is *sophisticated*. This is the key dimension of household heterogeneity given the objective of our study: naive households are susceptible to the bank's advice on the mortgage type they should pick, whereas sophisticated households make their choices based only on their own knowledge.

Second, each household enters the period 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 the households are *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 the households are *un-attached* in the sense that they can take a mortgage at any of the banks 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 shocks are ν_ε and σ_ε^2 , respectively, and that the mean and the volatility of inflation shocks 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 distribution of

$$\delta \equiv \nu_\varepsilon + \nu_\pi + H\gamma(\sigma_\varepsilon^2 - \sigma_\pi^2). \quad (3.1)$$

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 Each household finances the home purchase with a mortgage. The choice of the bank and the mortgage type differs between naive and sophisticated households.

Sophisticated households consider in their choice 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 interest rate risk. The reverse is true, when it takes a FRM.

We model this trade-off according to the following setup introduced in Kojien et al. (2009). Households take a mortgage whose principal and interest are paid after Δ quarters, without intermediate payments. Let $\pi \sim N(\nu_\pi, \sigma_\pi^2)$ be the inflation shock and $\varepsilon \sim N(\nu_\varepsilon, \sigma_\varepsilon^2)$ be the real interest rate shock at time $t + \Delta$. Thus, if r_t^{eurbr} is the Euribor

benchmark rate at date t , then $r_{t+\Delta}^{eurbr} = r_t^{eurbr} + \pi + \varepsilon$ is the Euribor at date $t + \Delta$. Consider the choice of a household who is a customer of bank i . Let r_{it}^f be the FRM rate and s_{it}^a be the spread between the adjustable rate and the Euribor benchmark rate set by bank i on mortgages issued at date t . Then when the household takes the ARM, the payment at date $t + \Delta$ is $(1 + s_{it}^a + r_{t+\Delta}^{eurbr})H$. When the household takes the FRM, the payment at date $t + \Delta$ is $(1 + r_{it}^f)H$.

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 what Kojien et al. (2009) call 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 $r_t^f(h)$ and $s_t^a(h)$ will be the lowest fixed and adjustable rates in the market, i.e., $r_t^f(h) = \min_{i \in \{1, \dots, N\}} r_{it}^f$ 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

$$\begin{aligned} \mathbb{E} \left[y - (1 + s_t^a(h) + r_{t+\Delta}^{eurbr} - \pi)H \right] - \gamma\mathbb{V} \left[y - (1 + s_t^a(h) + r_{t+\Delta}^{eurbr} - \pi)H \right] \\ \geq \mathbb{E} \left[y - (1 + r_t^f(h) - \pi)H \right] - \gamma\mathbb{V} \left[y - (1 + r_t^f(h) - \pi)H \right], \end{aligned} \quad (3.2)$$

Recalling (3.1), we can rewrite (3.2) as

$$r_t^f(h) - \left(s_t^a(h) + r_t^{eurbr} \right) \geq \delta. \quad (3.3)$$

The spread rule implies that the households chooses ARM if and only if the spread they face (the left-hand side of (3.3)) 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.

For simplicity, in our model, we focus on the households' choice of the bank and the mortgage type, but abstract from many relevant aspects of the mortgage choice, such as intermediate mortgage payments, the decision to buy versus rent, the choice of the house size and the mortgage size, or the comovements in rates and income. However, it has been shown empirically and theoretically in Campbell and Cocco (2003); Kojien et al. (2009);

	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 recommended mortgage type	home bank recommended mortgage type

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

Badarinza et al. (forthcoming) that the spread between FRMs and ARMs is the most important determinant of the mortgage choice and the spread rule (3.3) is approximately optimal in much richer models.

The behavior of naive households departs from the spread rule. We follow the “money doctors” framework of Gennaioli et al. (2015) and suppose that before receiving advice, 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. After they become customers of a bank, however, both un-attached and attached naive households follow the bank’s advice 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 before receiving the advice. Households’ choices are summarized in Table 2.

Discussion of Assumptions Next, we motivate our assumptions about the behavior of naive borrowers and our reduced form model of market frictions.

Our assumption that naive households purchase fixed rates in the absence of advice can be microfounded using the “money doctors” model by Gennaioli et al. (2015), as we show in Appendix A.3. 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 underparticipation 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 bank deposits and represents a more familiar and easy to understand option.⁷ 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.⁸ Similar to Gennaioli et al. (2015), in the absence of advice, 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 manipulate naive customers into taking ARMs, even when FRM is better for them. (See Appendix A.3 for details).

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 (forthcoming)), 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 12 in Appendix A.9). However, our data are not rich enough to pinpoint the precise nature of the frictions preventing households to flow to the bank offering the best rates in the market. 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.⁹ 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 cost 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

⁷Indeed, 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.

⁸This 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.4 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.

⁹Italian 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 opening a new account, relocating funds between accounts or ensuring regular transfers between accounts, etc.

best available.

Further, we assume that once the household becomes the customer of a certain bank, it cannot switch after receiving the advice. This assumption is binding only for naive un-attached households: they pick their bank based on convenience of the fixed rates, but are sometimes steered towards ARMs. They may then have incentives to withdraw their applications in the current bank and become a customer of the bank with a lower ARM rate.¹⁰ We justify this assumption with the presence of high fixed costs of application (e.g., collecting documentation, filing in the application and getting it approved), which reduce the incentives to re-optimize. Further, naive households may also believe (or be led to believe by banks) that a bank posting the lowest fixed rate is also posting a low adjustable rate, in which case the expected benefits from doing a new search would be low.

3.2 Banks

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

$$\underbrace{\left(s_{it}^a(1 - x_{it}) + s_{it}^f x_{it} - \lambda(x_{it} - \theta_{it})^2 \right)}_{\text{net profit margin}} \times \underbrace{m_{it}}_{\text{customer base}} \times \underbrace{e^{-\beta r_{it}^f}}_{\text{penalty for excessive rates}}. \quad (3.4)$$

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 (3.8) 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.¹¹

The net profit margin increases with the average spread of rates over benchmarks. We denote by s_{it}^a and s_{it}^f are the spreads of the ARM and FRM rates over the standard benchmarks: the 1-month Euribor (r_t^{eurbr}) for the ARM and the 25-year swap rates (r_t^{swap25}) for the FRM. Intuitively, 1-month Euribor rate is the relevant benchmark for ARMs, because the bank can finance ARMs by short-term borrowing in the interbank market in which

¹⁰This issue does not arise for sophisticated un-attached households, as they are not affected by advice and always choose the bank with the best rate and type of mortgage for them.

¹¹Given that naive households follow bank's advice, such a punishment is necessary in our model to rule out equilibria where the bank only sells FRM at outrageous rates to its naive un-attached customers.

case the bank’s profit from ARMs equals the spread over Euribor that the bank charges. Similarly, the 25-year swap rate is the relevant benchmark for FRMs, because the bank can finance FRMs by borrowing short-term in the interbank market and entering the interest rate swap contract in which case the bank’s profit from FRMs equals the spread over the 25-year swap rate.

However, it is documented 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 hedging (Rampini et al. (2016)) or banks’ relative efficiency in managing the maturity mismatch (Drechsler et al. (2017)). We capture the fact that issuing too many FRMs causes a potential maturity mismatch in a reduced form by the quadratic cost term $\lambda(x_{it} - \theta_{it})^2$ in the objective function (3.8). 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, and a Δ increase in the deviation of the fraction of FRMs issued by bank i from θ_{it} leads to a reduction in the profit margin by $\lambda\Delta^2$ basis points. 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 its advice policy $\omega_{it} \in [0, 1]$, and recommends to a fraction $1 - \omega_{it}$ of its customers to take the ARM. This advice only affects a fraction $1 - \omega_{it}$ of the naive customers of the bank, as sophisticated customers are not susceptible to advice.

Discussion of Assumptions 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 advice to manage the interest rate risk. In particular, we are agnostic about what drives θ_{it} . For example, θ_{it} could depend on supply factors, e.g., reflect the ability of the bank to borrow long-term at better terms. If shifts in θ_{it} are driven by banks’ supply conditions, the advice banks provide is

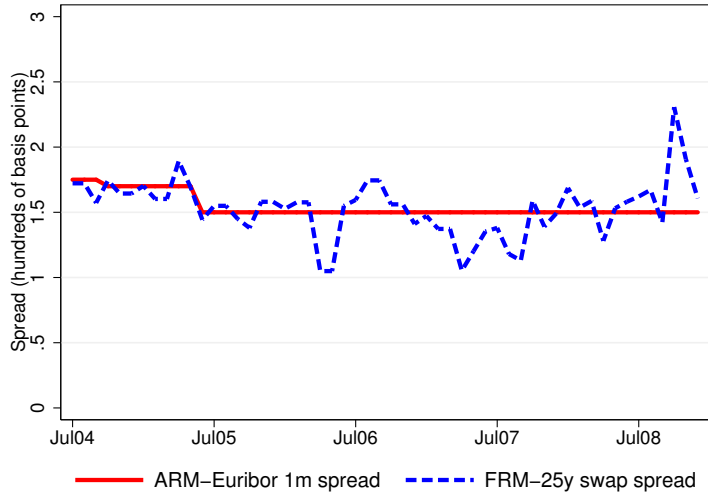


Figure 1: **Rate Spreads on a 25-year Mortgage Set by a Major Italian Bank**

distorted. In fact, it is motivated by the desire to improve their own maturity mismatch and not by the convenience of their customers. Conversely, the bank type could reflect a bank’s expectation of the optimal FRM/ARM choice for the household, which could differ across banks and times depending on the forecasted evolution of inflation and interest rate. In this case one would interpret the advice coming from the bank as provided in the customer best interest, possibly as a result of reputation concerns. The advantage of our approach is that it allows us to retrieve an estimate of the bank’s θ_{it} without imposing assumptions on its nature. Then, we will be able to use our estimates to provide evidence on which variables influence the bank’s cost efficient fraction of FRMs.

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 1 plots the spread between the 25-year FRM and the 25-year swap rate, as well as the spread between the ARM rates and the 1-month Euribor at a monthly frequency between 2004 and 2008 for one of the largest banks in Italy. As it can be seen, 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 essentially every month. We observe a similar pattern when we average rates over all the banks in our sample.

3.3 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 advises to take the ARM a fraction $1 - \omega_{it}$ of its customers. This advice affects only the choice of naive customers, while sophisticated customers ignore the advice 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 advice (these depend on the realization of the customer base attracted by the bank).¹² 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 $\phi_{it} = r_{it}^f - (s_{it}^a + r_t^{eurbr})$, 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:

$$x(\phi_{it} | \theta_{it}) = \max \left\{ \min \left\{ \theta_{it} + \frac{1}{2\lambda} \left(\phi_{it} - r_t^{swap25} + r_t^{eurbr} \right), \bar{x}_{it} \right\}, \underline{x}_{it} \right\}, \quad (3.5)$$

from which we can recover the optimal advice policy:

$$\omega(\phi_{it} | \theta_{it}) = \max \left\{ \min \left\{ \frac{1}{\bar{x}_{it} - \underline{x}_{it}} \left(\theta_{it} + \frac{1}{2\lambda} \left(\phi_{it} - r_t^{swap25} + r_t^{eurbr} \right) - \underline{x}_{it} \right), 1 \right\}, 0 \right\}. \quad (3.6)$$

The fraction of naive households advised 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

¹²More precisely, \underline{x}_{it} can be attained by setting $\omega_{it} = 0$ and \bar{x}_{it} can be attained by setting $\omega_{it} = 1$.

$x(\phi_{it}|\theta_{it})$, the bank's profit per customer is given by

$$V(\phi_{it}|\theta_{it}) = \left(s_{it} + \left(\phi_{it} - r_t^{swap25} + r_t^{eurbr} \right) x(\phi_{it}|\theta_{it}) - \lambda \left(x(\phi_{it}|\theta_{it}) - \theta_{it} \right)^2 \right) e^{-\beta(\phi_{it} + s_{it}^a + r_t^{eurbr})}. \quad (3.7)$$

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

$$\int m_{it} V(\phi_{it}|\theta_{it}) dG_i(\underline{s}_{-it}^f | \mathbf{s}_t), \quad (3.8)$$

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.5 derives a more explicit formula for (3.8) that we use in our estimation.

It is useful to point out 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.

4 Identification

Our goal is to 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 rate spread (δ), banks' cost efficient FRM fraction (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. We index all observables in the demand estimation by the superscript d and those in the supply estimation by the superscript s to indicate this distinction.

4.1 Identification of Demand Parameters

The identification of demand parameters $w^d = (\mu, \psi, \mu_\delta, \sigma_\delta)$ exploits the differences in the reaction of sophisticated and naive as well as attached and un-attached households to the variation in the fixed and adjustable mortgage 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, $i = 1, \dots, N_j^d$;
- 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, $\mathbf{r}_{jt}^d = (r_{1jt}^f, \dots, r_{N_j^d jt}^f)$;
- ARM-Euribor spreads of banks, $\mathbf{s}_{jt}^d = (s_{1jt}^a, \dots, s_{N_j^d jt}^a)$;
- banks' shares in the province depositor market, $\mathbf{p}_{jt}^d = (p_{1jt}, \dots, p_{N_j^d jt})$.

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

$$\begin{aligned} \ell_{ijt} = & (1 - \psi)p_{ijt} + \psi\mu 1\{r_{ijt}^f = \underline{r}_{jt}^f\} + \\ & \psi(1 - \mu) 1\{s_{ijt}^a = \underline{s}_{jt}^a\} \Phi\left(\frac{1}{\sigma_\delta}(r_{ijt}^f - \underline{s}_{jt}^a - r_t^{eurbr} - \mu_\delta)\right) + \\ & \psi(1 - \mu) 1\{r_{ijt}^f = \underline{r}_{jt}^f\} \left(1 - \Phi\left(\frac{1}{\sigma_\delta}(\underline{r}_{jt}^f - \underline{s}_{jt}^a - r_t^{eurbr} - \mu_\delta)\right)\right), \end{aligned} \quad (4.1)$$

where $1\{\cdot\}$ is the indicator function and Φ is the CDF of the standard normal distribution.

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Equation (4.1) 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) in the market. The likelihood

¹³The likelihood in (4.1) ignores ties, because they do not occur in our data.

of observing a particular realization \mathbf{M}_{jt}^d is given by

$$L\left(\mathbf{M}_{jt}^d \mid w^d, \mathbf{r}_{jt}^d, \mathbf{s}_{jt}^d, \mathbf{p}_{jt}^d\right) = \left(M_{1jt}^d, M_{2jt}^d, \dots, M_{N_j^d jt}^d\right)^{M_{jt}^d} \prod_{i=1}^{N_j^d} \ell_{ijt}^{M_{ijt}^d},$$

where $M_{jt}^d \equiv \sum_{i=1}^{N_j^d} M_{ijt}^d$. The log-likelihood is given by

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

where C is a constant that does not depend on w^d . We maximize \mathcal{L} over $\mu, \psi, \mu_\delta, \sigma_\delta$ to find estimates $\hat{w}^d = (\hat{\mu}, \hat{\psi}, \hat{\mu}_\delta, \hat{\sigma}_\delta)$.

To illustrate how the identification works, we abstract from the heterogeneity not due to differences in naivete and attachment to home bank so that δ is equal across households. Inference on the fraction of un-attached households (ψ) requires some knowledge on the identity of a household's home bank, which is not observed in our data. Therefore, we assume a distribution for the probability that a particular bank is a home bank to a household. We proxy this probability using data on banks' market shares in deposits, based on the assumption that a household would experience the least frictions in obtaining a mortgage from the bank where it holds its checking account. We can then identify the fraction of un-attached households from the correlation between banks market shares in the deposit and mortgage markets. Intuitively, if all households are attached to their home bank, every bank will have the same market share in the two segments, no matter the rates posted. The extent to which posted rates can drive a wedge between the market shares in the depositors and mortgage markets is informative on the prevalence of un-attached households.

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 a market. Suppose for example that $r_{jt}^f - \left(s_{jt}^a + r_t^{eurbr}\right) > \delta$, meaning that 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 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 fixed mortgage rate, then its market share increases by $\psi(1-\mu)$ because it attracts sophisticated un-attached households. Therefore, given the differences in the behavior of naive and sophisticated households, we can recover

μ from the variation in market shares of the banks as the lowest adjustable and fixed rates are occasionally posted by different banks. In Table 1 shows that in our data there is substantial variation in the identity of the firm 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.¹⁴

4.2 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, $i = 1, \dots, N_k^s$,¹⁵
- the distribution of households taking up mortgages at each bank, $\mathbf{M}_{kt}^s = (M_{1kt}^s, \dots, M_{N_k^s kt}^s)$,¹⁶
- the fraction of FRMs over 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, $\phi_{kt} = (\phi_{1kt}, \dots, \phi_{N_k^s kt})$;
- the ARM-Euribor spread of banks, $\mathbf{s}_{kt}^s = (s_{1kt}^a, \dots, s_{N_k^s kt}^a)$;
- banks' shares in the regional depositor market, $\mathbf{p}_{kt}^s = (p_{1kt}^s, \dots, p_{N_k^s kt}^s)$.

¹⁴Note 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.

¹⁵For the estimation of the supply side of the model, we restrict the sample to banks that are active in the FRM regional market. We cannot derive the optimal rate setting and advice policies for banks that only sell ARMs. The sample size loss due to this restriction is minimal.

¹⁶The number of mortgages issued by a bank in a region is obtained by summing the number of mortgages issued by the bank in each province belonging to that region (e.g., $M_{ikt}^s = \sum_{j \in k} M_{ijt}^d$ where the summation is over all provinces j in the region k); we similarly obtain regional figures for the number of account holders at a bank. Regional ARM-Euribor spreads and FRM rates for a bank are calculated averaging the bank's provincial ARM-Euribor spreads and FRM rates across provinces of the same region weighting them by the number of mortgages issued by the bank in the province (e.g., $s_{ikt}^a = \frac{1}{M_{ikt}^d} \sum_{j \in k} s_{ijt}^a M_{ijt}^d$).

The supply side estimation uses as inputs the estimates of the demand side of the model (\hat{w}^d). The main challenge is retrieving each bank's unobserved cost efficient fractions of FRMs, θ_{ikt} . We invert the optimality condition for advice (3.5) to obtain θ_{ikt} as a function of data and supply parameters w^s . Then, we express banks' predicted shares of FRMs and FRM-ARM spreads as functions of only data and supply parameter w^s , but not of θ_{ikt} . Further, we find estimates of w^s that minimize the discrepancy between the model 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 the supply parameters w^s , we obtain estimates of the cost efficient fraction of FRM issued for each bank, which we denote by $\hat{\theta}(w^s, \mathbf{x}_{kt}, \phi_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s)$, 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

$$\left(x_{ikt} - \max \left\{ \min \left\{ \theta_{ikt} + \frac{1}{2\lambda} \left(\phi_{it} - r_t^{swap25} + r_t^{eurbr} \right), \bar{x}_{ikt} \right\}, \underline{x}_{ikt} \right\} \right)^2. \quad (4.2)$$

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 (4.2). To obtain an estimate of θ_{ikt} for those cases, we estimate the parameters μ_θ and σ_θ of the distribution of θ_{ikt} by maximizing the likelihood of the observed fraction of FRMs issued:

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

Then, we use the estimated distribution of θ 's to impute θ_{ikt} for the cases in which it cannot be uniquely inferred by minimizing expression (4.2). In particular, we impute $\hat{\theta}_{ikt} = \mathbb{E}[\theta | \theta \leq \underline{x}_{ikt} - \frac{\phi_{it} - r_t^{swap25} + r_t^{eurbr}}{2\lambda}]$ when the bank specific lower bound is hit and

$\hat{\theta}_{ikt} = \mathbb{E}[\theta | \theta \geq \bar{x}_{ikt} - \frac{\phi_{it} - r_t^{swap25} + r_t^{eurbr}}{2\lambda}]$ for observations at the upper bound.

Step 2: Predicted FRM Fractions and FRM-ARM Spreads Conditional on $\theta_{ikt}, \phi_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s$ and parameters w^s , we can compute the predicted share of FRMs from equation (3.5), which we denote by $\hat{x}(\theta_{ikt}|w^s, \phi_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s)$.

We then compute the predicted FRM-ARM spread, $\hat{\phi}(\theta_{ikt}|w^s, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s)$, from maximizing equation (3.8). 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, which we then use 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 1, the ARM-Euribor spreads are fairly persistent and proxy the conditional distribution with the unconditional one.¹⁷

Step 3: Estimation of w^s Summarizing steps 1 and 2, let us define

$$\begin{aligned}\hat{\theta}_{ikt}(w^s) &\equiv \hat{\theta}(w^s, \mathbf{x}_{kt}, \phi_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s), \\ \hat{x}_{ikt}(\theta_{ikt}, w^s) &\equiv \hat{x}(\theta_{ikt}|w^s, \phi_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s), \\ \hat{\phi}_{ikt}(\theta_{ikt}, w^s) &\equiv \hat{\phi}(\theta_{ikt}|w^s, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s).\end{aligned}$$

We find estimates $\hat{w}^s = (\hat{\lambda}, \hat{\beta})$ that minimize the function

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

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

¹⁷Given that we find that the fraction of un-attached households is small, this assumption is unlikely to have a quantitatively relevant impact on our results.

<i>Demand</i>		<i>Supply</i>	
Parameter	Estimate	Parameter	Estimate
μ	0.34 (0.0115)	λ	84.94 (14.78)
ψ	0.02 (0.0003)	β	0.212 (0.031)
μ_δ	-0.19 (0.074)		
σ_δ	0.92 (0.089)		

Table 3: **Estimates of the Parameters**

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

the mapping between the θ 's and the realized fraction of FRMs issued by a bank. This approach requires that the distribution of characteristics of customers, namely, the distribution of δ , faced by banks does not change during our sample span. In Appendix A.6, 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, Foa et al. (2015) document that in our data there is no significant sorting of customers across banks: the distribution of customer characteristics is the same across banks regardless of the bank propensity towards issuing fixed or adjustable mortgages and their cost of long term funding. 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 advice.

5 Estimation Results

In this section, we report the estimates of the parameters of our model and provide evidence of distorted advice in the Italian mortgage market.

5.1 Estimates

Table 3 reports estimates for the parameters of the model.

Two main facts emerge from the estimates of the demand parameters: the fraction of naive households is large (34%) and the fraction of un-attached households is small (2%). Our estimate of a 34% share of naive borrowers is consistent with the evidence relying

on independent data measuring the sophistication of Italian households we discuss in Appendix A.4. This points to a very low level of basic financial knowledge by Italian households, providing ample opportunity for banks to distort advice.

The estimate of ψ points to large frictions on the consumer side in the Italian mortgage market, which is further witnessed by the significant dispersion in both adjustable and fixed rates across banks in a market documented in Figure 12 in Appendix A.9.¹⁸ Furthermore, the low fraction of un-attached households that we estimate resonates with the extreme inertia documented in deposit markets (Deuffhard (2016); Ater and Landsman (forthcoming)).

The estimate of the distribution of the optimal spread cut-off δ for sophisticated households indicates that on average, ARM is 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 the real interest rate. The 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)).¹⁹

As a robustness exercise, in Appendix A.7, 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. 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 displayed in Figure 2. The distribution is fairly disperse but there is barely any mass for values of θ above 0.9, likely due to the fact that in our sample span ARM are on average more popular. Similarly, the mass close to $\theta = 0$ signals that a number of banks in our data are highly specialized in issuing adjustable rate mortgages.

To interpret the estimate of λ we take the net profit margin in equation (3.4) as a

¹⁸Recall, the parameter ψ reflects any friction in the banking market preventing households to take their mortgage at the bank offering the best rate. In fact, we identify it exploiting the wedge between banks' market shares in deposit and mortgage markets. Such a wedge is only created when households not only look for rates at banks other than the one where they hold their primary checking account but end up taking the mortgage there.

¹⁹Figure 13 in the appendix shows that the estimated distribution of δ has substantial overlap with the empirical distribution of the FRM-ARM spread in our data. This indicates that sophisticated households following the spread rule in (3.3) choose both types of mortgage.

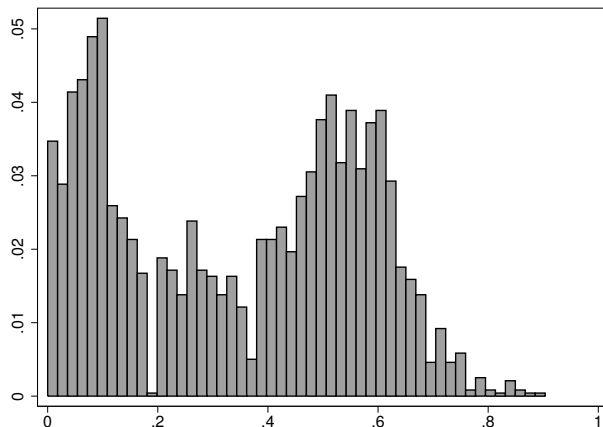


Figure 2: **Histogram of Estimated θ_{it}**

point of reference. The cost of deviating from the cost efficient fraction of FRMs issued paid by the median firm in our data represents 3% of its margin per euro lent. However, 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.

5.2 Evidence of Distorted Advice

Our structural model allows us to recover a time-varying, bank-specific parameter which determines the advice policy of the bank. We have been agnostic on the interpretation of this parameter throughout our illustration of the model and the identification. The θ 's could represent heterogeneity across banks in their beliefs about the evolution of nominal interest rates, which would lead them to push different types of mortgages when trying to faithfully advise their customers. However, this view is hard to reconcile with the wide dispersion in θ_{ikt} s across banks in the same period. Even though experts do disagree on their forecast of the evolution of economic variables, it is difficult to imagine that professional operators could have such extreme divergences as to lead one bank to recommend fixed rate to most of their customers while another does the opposite.

Our preferred interpretation of θ is that of the cost-efficient fraction of FRMs a bank aims at issuing. This implies that the push towards FRM or ARM is motivated by the structure of liabilities and the cost of financing of each bank. Hence, banks' effort to issue a fraction of FRMs close to their θ can be read as the provision of distorted advice. Such interpretation is consistent with Foa et al. (2015) who present reduced form evidence of

Variables	All sample	Deposit/ Liabilities < 75 pctlile	Deposit/ Liabilities < 50 pctlile	Deposit/ Liabilities < 25 pctlile
Bank bond spread	-0.042* (0.025)	-0.061** (0.03)	-0.076** (0.034)	-0.092 (0.064)
Observations	762	521	386	202
R-squared	0.6	0.6	0.6	0.52

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

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

distorted advice by financial intermediaries. In Appendix A.8 we follow their approach to document patterns in our data which are broadly consistent with banks actively steering their customers' mortgage choices in response to their financing needs.

Here, we exploit our estimates of the bank θ s to provide additional evidence of distorted advice. If banks use distorted advice opportunistically to adjust the fraction of FRMs, then their θ should reflect bank supply factors. We exploit balance sheet data on the banks in our sample to verify whether such a correlation exists. Since 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 . We regress the θ_{it} on the bank bond spread, 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.²⁰

The results are reported in Table 4. Controlling for time and bank fixed effects, a higher level of bond spread is associated with a lower cost-effective fraction of FRMs issued. This result is natural to explain: 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 we documented, 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. This suggests there could

²⁰In the bond market, banks are important but not dominant players and we can think of them as price takers.

be heterogeneity in the relationship between θ and the bank bond spread. Therefore, in the other columns of Table 4 we repeat the exercise focusing on subsamples where we dropped banks with very high ratio of deposits to total liabilities. When we focus on banks in the bottom three quartiles of the deposits/liabilities ratio, the relationships becomes more negative and more statistically significant; its point estimate grows 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. Further, for banks in the bottom quartile of the distribution of the deposits/liabilities ratio the correlation is the most negative. However, it is not significant most likely because of a relatively small sample.

Our evidence of the presence of advice distortions does not rule out alternative determinants of bank behavior. For instance, it is perfectly plausible (and not inconsistent with our model) that θ reflects in part banks' reputation concerns: a bank does not want to distort too much advice for fear of customer backlash. In that case, our estimated θ will reflect the net effect on the preferred FRM share of the balance sheet and the reputation channel. Given a good proxy for reputation, it would be possible to include it in the regressions we just presented and estimate the relative importance of the two channels in shaping advice.

6 Counterfactual Experiments

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

In order to conduct this exercise, we need to specify the welfare of sophisticated and naive households. We follow Kahneman et al. (1997) and assume that naive households' welfare is evaluated according to the *experienced* utility function, which is the same as the mean-variance utility function of sophisticated households. We use as a welfare measure 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 a FRM at rate $r_t^f(h)$ equals

$$CE\left(r_t^f(h)\right) = \mathbb{E}[y] - \gamma\mathbb{V}[y] - H\left(1 + r_t^f(h) - \nu_\pi + \gamma H\sigma_\pi^2\right), \quad (6.1)$$

and the certainty equivalent of an ARM at ARM-EURIBOR spread $s_t^a(h)$ equals

$$CE(s_t^a(h)) = \mathbb{E}[y] - \gamma \mathbb{V}[y] - H \left(1 + s_t^a(h) + r_t^{eurbr} + \nu_\varepsilon + \gamma H \sigma_\varepsilon^2 \right). \quad (6.2)$$

We set the mortgage size H to the median size of the mortgage 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 from (6.1) and (6.2), 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 quantify the welfare impact of different policies using our estimates of μ , ψ and of the distribution of δ to simulate a population of customers equal in size to the number of mortgages issued in our data and calculate the consumer surplus induced by counterfactual exercises on this sample of simulated households. To be conservative on the impact of advice on welfare, we assume that banks provide advice minimizing the welfare loss caused to their customers. This means that if a bank decides to recommend ARM to 30% of its naive customers, it will pick those customers for which the switch from FRM to ARM is the least harmful.

6.1 Restricting Advice

Our first counterfactual exercise investigates the effect of reducing the ability of banks to provide advice to their customers. Whereas in the baseline model, the bank could influence all of its naive customers, we now assume that it can only provide advice to a half of them. Formally, ω_{it} is restricted to be between 0 and $\frac{1}{2}$, instead of 0 and 1 as in the baseline. It is important to notice that this experiment does not change the way households choose banks nor their decision rules: sophisticated borrowers will follow the spread rule; advised naive borrowers will follow the suggestion given to them by the bank, and unadvised naive borrowers will select fixed rate mortgages.

This experiment allows us to measure the value or cost of advice to households.²¹ The experiment could be interpreted as an increase in the level of monitoring by the

²¹As already discussed in Section 3, our model bears resemblances to the “money doctors” framework in Gennaioli et al. (2015). In their case, advice is indisputably welfare improving for the customers, because it is undistorted. In our case, the welfare effects are ex-ante ambiguous.

	Limiting Advice	Undistorted Advice	Financial Literacy
All	-723	1,145	679
Sophisticated	-147	423	203
Naive	-1,838	2,547	1,603

Table 5: **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.

regulator which limits the scope for advice or as the advent of online banking, which crowds out the advice by reducing direct 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 advice for fear of exposing themselves to lawsuits.

The overall effect of limiting advice is a loss of 723 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%). If we decompose this loss, we observe that naive households suffer the most (they lose 1,838 euros per capita per year compared to the unrestricted advice scenario); but sophisticated customers are also worse off by 147 euros per year.

To obtain intuition for why restricting advice is costly, it is useful to decompose its effect on the population of naive into the information value of advice and the costs of distortion. Naive households take a FRM if left on their own. On the one hand, for naive households with sufficiently small δ , this decision is suboptimal, and the fact that a recommendation from their bank can steer them towards an ARM is beneficial for them despite such recommendation being provided in bank’s self interest. This constitutes the information value of advice, as banks inform naive customers about the alternative product, which they did not consider before.²² On the other hand, there are naive households who should take a FRM if they were to follow the spread rule. These households would make the correct choice in the absence of advice, but banks can instead distort it leading them to take an ARM. This causes the distortion costs. At our parameter estimates the benefits outweigh the costs and banning advice delivers a welfare loss.

²²This is closely related to banks acting as “money doctors” that reduce the naive households’ anxiety from choosing a more complex product, ARM.

The conclusion on the effect of banning advice is robust to the assumption we make on the default behavior of the naive households when they are not advised. In our baseline model, we posit that they make the choice on their own and therefore choose a FRM. As a robustness exercise we consider an alternative specification in which 40% of naive household in the absence of bank advice about the mortgage type turn to other sources of advice such as friends and family or media.²³ We suppose that the recommendation from these sources is equally likely to be for FRM or ARM. This modification reduces the number of households who should take ARM and take instead FRM because of lack of advice; whereas the set of households whose choice is negatively distorted (i.e., households who should take the fixed rate and are instead led to take the adjustable rate) stays the same. As a consequence advice from banks is less valuable: restricting advice in this scenario leads to an average welfare loss of 360 euros per household per year (with naive households losing on average 948 euros per year and sophisticated households losing 55 euros per year).

6.2 Undistorted Advice and Financial Literacy Campaign

Our second experiment simulates the effect of forcing banks to provide undistorted advice to their customers. This means that banks will make naive households follow the same spread rule that guides the decision of sophisticated households. In this scenario, every household takes the “right” mortgage and the welfare gains are very large: 1,145 euros per capita per year. As usual, naive households benefit the most gaining 2,547 euros per year each;²⁴ sophisticated households enjoy a gain of 423 euros.

Whereas the effect for naive households comes mostly from them making better choices, the gains for sophisticated households are entirely due to adjustment of optimal spreads by banks. The inability to distort advice raises a particularly pressing concern for banks with higher propensity to issue FRMs (high θ_{it}). In the baseline model it was relatively easy for those banks to fill their quota as all the naive customers were willing to buy FRMs. Now, the share of customers who take a FRM depends on the distribution of δ and our estimates imply that the majority of the customers favors ARMs. Therefore, banks who want to sell a significant fraction of FRMs must reduce their spread to achieve such a goal. This affects both sophisticated and naive households with high values of δ

²³In Figure 4, 40% is an upper bound on the fraction of households obtaining advice from sources other than banks.

²⁴The gain for naive households from picking the optimal type of mortgage is comparable to the figures reported in Campbell and Cocco (2003).

who are paying less for their fixed rate mortgages.²⁵

Our final 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 succeed in reducing the share of naive households in the population from 34% to 17% and find that the average households experiences a gain of 679 euros per year. The lion's share of the welfare gains accrue to households who were naive and become sophisticated thanks to the financial literacy campaign: they gain on average 2,341 euros per year. The effect on spreads, however, has consequences also for the naive households unaffected by the financial literacy campaign as well as on the sophisticated households: the former gain 866 euros per year; the latter 203 euros. The mechanism is analogous to that described for the undistorted advice experiment: the reduction in μ makes selling FRMs harder and forces high θ_{it} banks to lower FRM rates to the benefit of customers buying fixed rate mortgages.

7 Conclusion

The goal of this paper is twofold: to assess the relevance of distorted financial advice and to quantify its impact on borrowers' welfare. On the first count, we are able to identify that a large fraction of the population of borrowers lacks the sophistication to make independent choices on financial instruments. This finding is relevant both from a practical standpoint, as it implies that there is large scope for intermediaries to supply biased advice. In terms of the welfare relevance of advice distortion, a set of counterfactual exercises leads us to conclude that advice manipulation has a critical impact. The gains from forcing intermediaries to provide only honest advice or from educating borrowers so that they no longer need to rely on advice are sizable. Interestingly, we also find that banning advice altogether might not be recommendable, especially if this implies leaving unsophisticated households on their own. This reveals that advice can be beneficial to customers even it is not provided with their best interest in mind.

²⁵Note that this experiment is not the same as making all households sophisticated. In fact, even though naive households are advised so that they behave as sophisticated in their choice of mortgage type, they still behave as naive when they choose the bank where to take the mortgage. Namely, if they are un-attached they still become customers of the bank offering the lowest FRM rate even though their δ indicates that they should take an adjustable one. However, due to the low fraction of un-attached in our data, the additional welfare gains if we were to make all households sophisticated in both decision stages would not be very large.

References

- 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.
- ALLEN, J., R. CLARK, AND J.-F. HOUDE (2014): “Search frictions and market power in negotiated price markets,” NBER working paper n.19883.
- 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 (forthcoming): “Testing alternative learning theories: Evidence from subscription contracts,” *Journal of Industrial Economics*.
- 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 (forthcoming): “What calls to ARMs? International evidence on interest rates and the choice of adjustable-rate mortgages,” *Management Science*.
- BAJO, E. AND M. BARBI (2015): “Out of sight, out of mind: Financial illiteracy, inattention, and sluggish mortgage refinancing,” Working paper.
- 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.
- 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.
- 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*.
- CRAWFORD, G., N. PAVANINI, AND F. SCHIVARDI (2015): “Asymmetric information and imperfect competition in lending markets,” CEPR working paper DP10473.
- 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. (2015): “Brokers vs. retail investors: Conflicting interest and dominated products,” Working paper.
- 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 (2016): “The market for financial adviser misconduct,” Working paper.
- 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.
- FOA, G., L. GAMBACORTA, L. GUIISO, AND P. MISTRULLI (2015): “The supply side of household finance,” CEPR working paper DP10714.
- FOERSTER, S., J. T. LINNAINMAA, B. T. MELZER, AND A. PREVITERO (forthcoming): “Retail financial advice: does one size fit all?” *Journal of Finance*.
- FUSTER, A. AND J. VICKERY (2015): “Securitization and the fixed-rate mortgage,” *Review of Financial Studies*, 28, 176–211.
- 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.
- GUIISO, L., P. SAPIENZA, AND L. ZINGALES (forthcoming): “Time Varying Risk Aversion,” *Journal of Financial Economics*.
- HACKETHAL, A., M. HALIASSOS, AND T. JAPPELLI (2012): “Financial advisors: A case of babysitters?” *Journal of Banking & Finance*, 36, 509–524.
- HACKETHAL, A., R. INDERST, AND S. MEYER (2010): “Trading on advice,” Working paper.
- 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.
- 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>.
- 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.

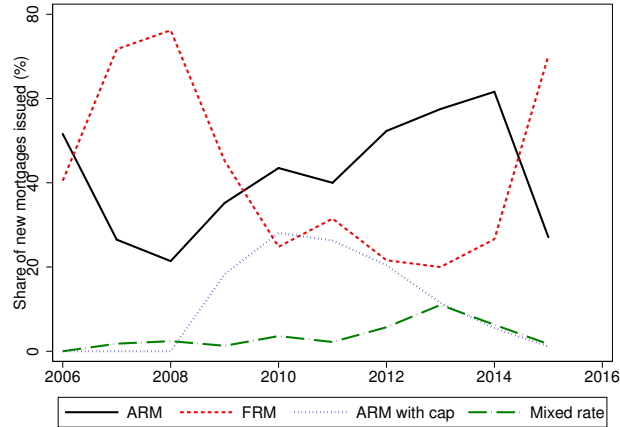


Figure 3: Market Share by Type of Mortgage

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.

RU, H. AND A. SCHOAR (2015): “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 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 3, 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%. The second 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.

Banks as Providers of Advice A first important characteristic of the Italian retail banking system is the tight relationship between a customer and its home bank. From the answers to the SHIW section devoted to the household financial choices, it emerges that over 80% of the households do all of their financial transactions at a single bank and nearly 60% of them have a relationship with their main bank that lasts more than 10 years. The existence of long term relationship between banks and their customers justifies the prominent role that banks play in advising them.

To document that banks are important provider 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 2007.²⁶ One of the questions in the survey offers a list of potential sources of financial information: the bank, the broker, friends and family, newspapers, magazines, TV, Internet, etc. For each one of them the respondent is asked how frequently she resort to it to obtain information when making a financial decision. In Figure 4, we display the fraction of respondents reporting that they consult either “sometimes”, “often” or “very often” a specific source. Banks emerge from the responses as the leading source of information for customers: over 60% of customers consults them. This is a 20 percentage points gap with the second most popular source, the broker.²⁷ Friends and relatives and media outlets are used to gather information by less than 20% of the interviewees. Hence, the survey evidence confirms that banks are by far the main provider of financial information for households and have, therefore, ample opportunity to influence their choices.

Exposure to Interest Rate Risk The US market is dominated by mortgage banks which offload mortgages from their balance sheets shortly after origination. Banks issuing mortgages in Europe are instead portfolio lenders: they fund loans using the deposits they raise or by issuing bonds and keep mortgage loans on their balance sheets. In particular, Italian banks not only retain a large chunk of the mortgages they originate on their balance sheets but also carry a substantial fraction of the associated interest rate risk as they appear not to hedge perfectly their position with derivatives. This distinction is important because it implies that Italian banks have the incentive to steer customers towards ARM or FRM to manage their exposure to interest rate risk.

In Figure 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

²⁶More details on the survey can be found in Guiso et al. (forthcoming).

²⁷The figures are likely to overstate the importance of brokers in providing advice in the context of our application as they refer to households sourcing information for the purpose of a generic financial transaction, including investment in stocks, retirement funds, insurance, etc., where the role of brokers is more prominent than for mortgages. Moreover, households could refer as broker to the employee of the bank managing their investment and brokers often work for a company tightly linked to a bank.

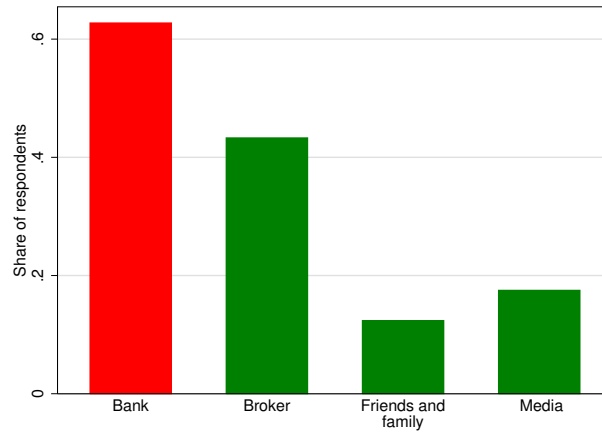


Figure 4: Sources of Financial Advice

Notes: The histogram reports the fraction of customers who report consulting “sometimes”, “often” or “very often” a specific source to obtain financial information. The category “Media” aggregates the options “Newspapers”, “Specialized newspapers”, “Magazines”, “Specialized magazines”, “TV and radio” and “Internet”. The source is a survey run by a large Italian bank between June and September 2007.

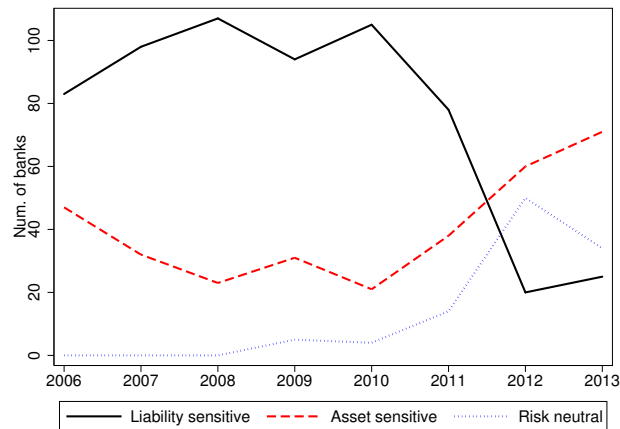


Figure 5: Exposure of Italian Banks to Interest Rate Risk

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.

implement a duration gap approach based 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. At any point in time, however, at least 60% of the banks in the sample bear interest rate risk. 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.

Even though this evidence does not identify interest rate risk exposure deriving from mortgages specifically, the mere fact that banks tend to have an overall mismatch between their assets and liabilities, which is not offset with the use of derivatives, is enough to justify why they would want to skew the share of FRM they originate to possibly mitigate this problem.

Default and Refinancing Risk Our analysis focuses on the incentives to distort advice provided by the need to manage banks’ exposure to interest rate risk. However, mortgages expose the financial intermediary to other types of risk, namely default risk and renegotiation risk. We do not include default or renegotiation risk in the model on the ground that they are far less important in Italy than in other countries.

One important reason for the low incidence of refinancing in Italy is that unrestricted prepayment penalty fees were allowed until midway through 2007. In April 2007, the Bersani law abolished prepayment penalty fees for mortgages finalized to purchase of the house of residence issued after February 2007 and for all the mortgages issued after April 2007. For mortgages issued after 2001, the penalty fees were capped at 1.9% of the outstanding debt which further reduced to 0.2% for mortgages three years from maturity. Fees were removed for all mortgages in their last two years.

Figure 6 shows the percentage share of mortgages which are defaulted upon or refinanced each year as a fraction of the total value in euros of the outstanding mortgages. Default rates are low, typically below 1% and surging only marginally during the 2009 financial crises. The share of existing mortgages which are refinanced is consistently below 1% during the time span we analyze. Refinanced mortgages represent between 10% and 15% of newly issued mortgages

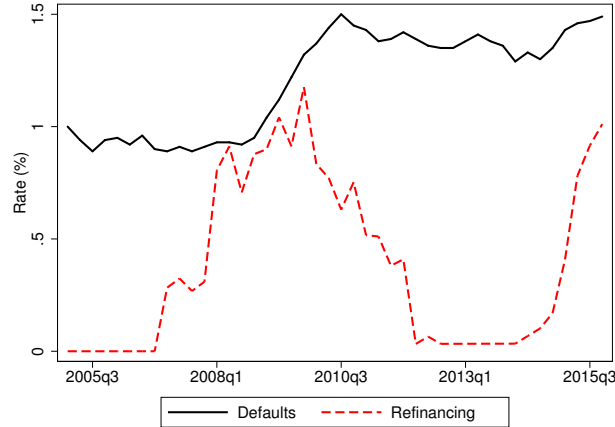


Figure 6: **Incidence of Defaults and Refinancing**

Notes: The figure reports the annual share of mortgages defaulted or renegotiated, in percentage terms. The share of defaults is calculated as the number of loans defaulted over the total number of mortgages. The share of refinanced loans is calculated as the fraction of the value (in euros) of refinanced mortgages in the the total value of the outstanding 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, at least for the years we analyze. 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 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 advertised rate for the type of mortgage in that market in that period. We then attribute to bargaining and pricing of individual characteristics the dispersion of the rates away from the modal rate and quantify it. This approach is prone to understate the adherence of banks to posted rates because the frequency of the data is quarterly. Hence, some of the changes in the rate paid by households is due to changes in the price set by the bank within the quarter.

Table 6 shows the results of this exercise. Over 50% of the mortgages of the same type issued in the same branch in the same quarter 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

	% 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. (2016)	25	50	75	95

Table 6: **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. (2014).

discount whose quartiles are 16, 38 and 76 basis points.²⁸ These figures, especially the first two quartiles, are substantially lower than those reported by Allen et al. (2014) for the Canadian market where negotiation on mortgage rates is customary.

A.2 Sample Selection

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 known to us 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 the banks not participating in the survey, which represent a small fraction of the market.

To avoid dealing with banks intermittently active in a market, we retain in our sample only banks issuing at least 2% of the mortgages in the market. This requirement is strengthened for the sample we use to estimate the supply side of the model. Since we need variation in the FRM-ARM spread, we only consider banks that are regularly active in issuing FRMs and hold a market share of at least 1% in the FRM segment in the market.

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, we eliminate provincial banks

²⁸The modal interest rate is invariably on the high end of the distribution of interest rates within a bank-quarter-type of mortgage bin. There are usually 5% to 10% of mortgages which are taken at rates higher than the modal rate. These observations are discarded when computing the size of the discount.

from the sample we use to estimate supply by retaining only banks issuing mortgages in at least 40% of the provinces belonging to the region where the bank is located.

Finally, some restrictions are imposed by our need to have 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 either no or only 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.3 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. Specifically, suppose that naive households are uncertain about $\nu_\pi, \sigma_\pi^2, \nu_\varepsilon$, and σ_ε^2 , and have some full-support beliefs F about their joint distribution. Conditional on $\nu_\pi, \sigma_\pi^2, \nu_\varepsilon$, and σ_ε^2 , the decision utility of naive households from taking FRM is the same as of sophisticated households and is given by $\mathbb{E}[y - (1 + r_t^f(h) - \pi)H] - \gamma\mathbb{V}[y - (1 + r_t^f(h) - \pi)H]$.²⁹ However, conditional on $\nu_\pi, \sigma_\pi^2, \nu_\varepsilon$, and σ_ε^2 , their decision 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 $a \geq 1$, which reflects 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 the 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

²⁹Thus, 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 .

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.4 Evidence of Limited Sophistication

In this appendix, we present some evidence on the limited sophistication of Italian households using measures of the financial literacy from SHIW. It points to a prevalence of unsophisticated households, which provides scope for banks to distort advice, 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 (e.g., Van Rooij et al. (2011); OECD (2016)). The section consists of six questions testing the ability to recognize the balance of a checking account statement, to compare the returns of two mutual funds, to understand the difference between real and nominal interest, the concept of compound interest, the wealth consequence of stock prices fluctuations, and the properties of fixed and adjustable rates. For each question, four options are offered: one of them is correct; two incorrect and a fourth option allowing the interviewee to profess his cluelessness about the topic.³⁰

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 7, 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 8 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;

³⁰The 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.

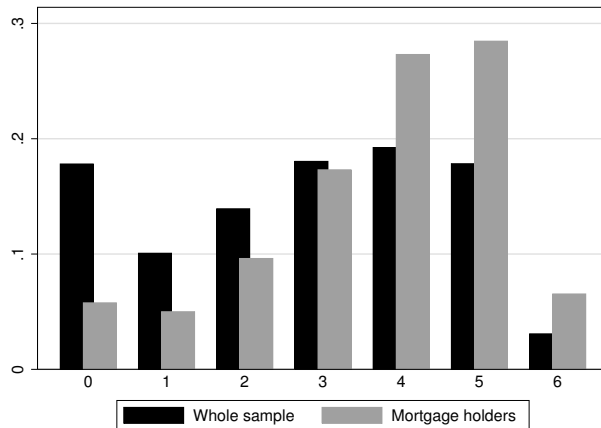


Figure 7: Distribution of the Sophistication Index

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

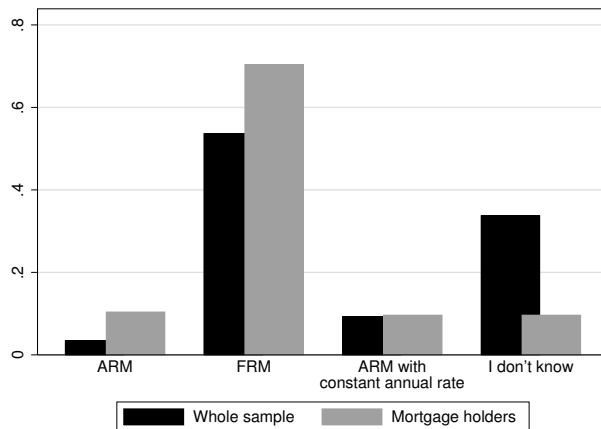


Figure 8: Understanding of Mortgage Characteristics

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.

2) Fixed rate mortgage; 3) Adjustable rate mortgage with constant annual payment; and 4) I do not know. Only 50% of the interviewees provide the right answer. Even among mortgage holders, nearly one third of the interviewees are either clueless or provide a wrong answer.

Further, we provide support to our assumption that unsophisticated borrowers tend to opt for fixed rate mortgages by exploiting a question meant to elicit people’s ability to understand the link between interest rates and inflation. Specifically, they are asked: “*Suppose you have 1000 Euros in an account 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.5 Optimal Spread Setting

We derive an explicit formula for (3.8) 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 ($s_{it}^a > \underline{s}_{-it}^a$). We abstract from ties as they are not observed in our data. 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

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

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

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

Then ϕ_{it} is determined by maximizing either (A.1) or (A.2) depending on whether $s_{it}^a > \underline{s}_{-it}^a$ 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 $1 - \mu$ of sophisticated, and among sophisticated, a fraction $\kappa(\phi_{it})$ chooses the FRM. Thus, $\underline{x}_{it}^{AF} = (1 - \mu)\kappa(\phi_{it})$ and $\bar{x}_{it}^{AF} = (1 - \mu)\kappa(\phi_{it}) + \mu$.
 - (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 $\psi\mu$, the mass of the latter is $\psi(1 - \mu)\kappa(\phi_t)$. Thus, the total mass of bank i 's customers equals

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

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

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

The fraction of naive households is given by

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

and so,

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

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

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

Among those, there is a fraction

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

of naive households. Further,

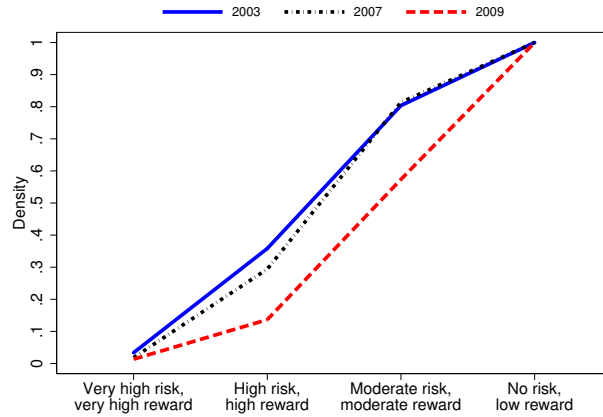
$$\begin{aligned} \underline{x}_{it}^{aF} &= \frac{(1 - \mu)(1 - \psi)p_{it}\kappa(\phi_{it})}{(1 - \psi)p_{it} + (1 - \mu)\psi(1 - \kappa(\phi_t))}, \\ \bar{x}_{it}^{aF} &= \frac{(1 - \mu)(1 - \psi)p_{it}\kappa(\phi_{it}) + \mu(1 - \psi)p_{it}}{(1 - \psi)p_{it} + (1 - \mu)\psi(1 - \kappa(\phi_t))} \end{aligned}$$

- (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 $\underline{x}_{it}^{af} = (1 - \mu)\kappa(\phi_{it})$ and $\bar{x}_{it}^{af} = (1 - \mu)\kappa(\phi_{it}) + \mu$.

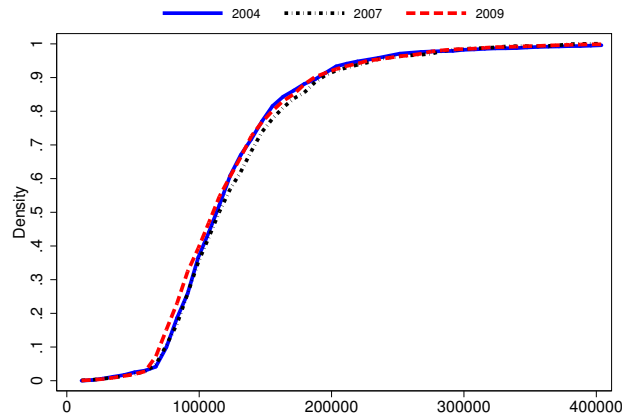
A.6 Stationarity of Households Characteristics

Here, we show that the distribution of risk aversion and mortgage size experienced negligible changes in the period that we analyze. Figure 9 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 9a plots the cumulative distribution of the answer to a question meant to elicit risk aversion. The data come from a relatively large survey conducted by a major Italian bank on its retail customers. The question we are focusing on asks responders 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 9: 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 we choose to limit our analysis before the financial crisis in Italy, although we have obtained data on mortgages issued in 2009 and 2010.

Figure 9b 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.7 Heterogeneity in Demand Parameters

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

In particular, 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:

$$\mu_r = \frac{\exp(a_0 + a_1 Education_r)}{1 + \exp(a_0 + a_1 Education_r)},$$

$$\psi_r = \frac{\exp(b_0 + b_1 RelationshipLength_r)}{1 + \exp(b_0 + b_1 RelationshipLength_r)},$$

where r denotes an Italian region and the logistic functional form is imposed so that μ and ψ 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; *RelationshipLength* 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 7 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

Coefficients	Estimates
a_0	2.67 (0.262)
a_1	-8.54 (0.646)
b_0	-3.17 (0.224)
b_1	-0.88 (0.278)
μ_d	-0.35 (0.106)
σ_d	-0.07 (0.523)

Table 7: Demand with Regional Heterogeneity

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

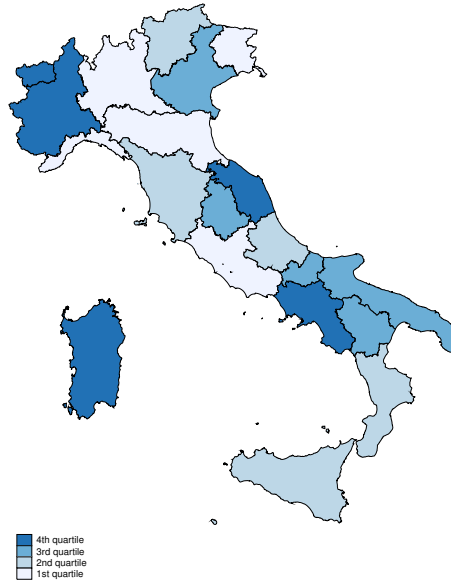


Figure 10: Geographical Heterogeneity in Naivete

Notes: The figure displays a map of Italy where regions are colored in different shades of blue according to the region-specific fraction of naive households predicted on the basis of the estimates in Table 7. Regions in the lighter shade have an estimate of μ in the bottom quartile of the cross-sectional distribution; regions in the darkest shade are in the top quartile for the estimated fraction of naive.

minimal: the estimates of ψ across regions range between 1.9% and 2.2%. There is, instead, dispersion in the fraction of naive with some regions having as few 15% of them and others reaching 70%.

Figure 10 portrays the regions of Italy in different shades of blue: Darker shades correspond to regions in higher quartiles of the predicted fraction of naive households. Households living in Northern regions are better financially educated, with the exception of the Northwest. The peninsular South and the island of Sardinia display instead a lower level of financial literacy.

A.8 Reduced Form Evidence of Distorted Advice

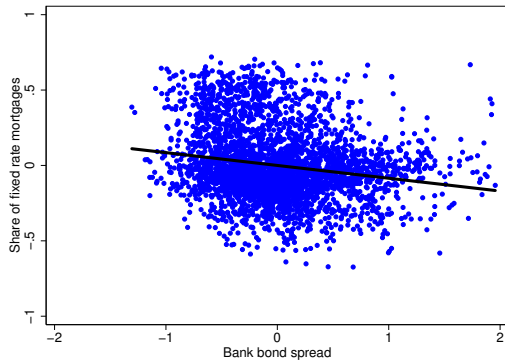
Foa et al. (2015) design a reduced form test of the presence of distorted advice of the type introduced in our model and implement it exploiting mortgage data similar to those we use for our estimates. Their test is based on the premise that if households are savvy, the relative price of different financial products should be a sufficient statistic for their choice. On the other hand, if some households lack sophistication and the intermediary steers their behavior to its own advantage, their choice could also be affected by characteristics of the suppliers (possibly unobservable to the borrower) that affect the incentive of the supplier to “push” customers to buy one product rather than the other, for given prices. Hence, the choices of buyers susceptible to the bank advice would be affected not only by the relative prices but also by attributes of the supplier.

In Figure 11 we present some graphical evidence based on the same logic. In particular, the two top panels portray the correlation between the residuals of the following regression equations

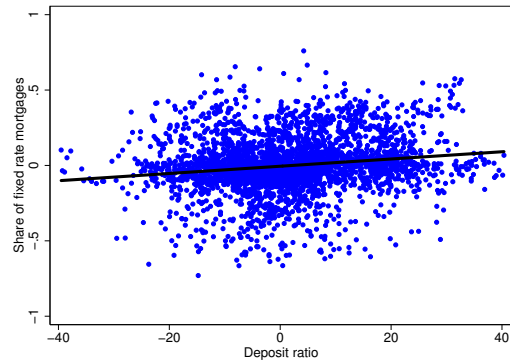
$$\begin{aligned} shareFRM_{it} &= a_0 + a_1 LTFP_{it} + u_{it}, \\ BankChar_{it} &= b_0 + b_1 LTFP_{it} + v_{it}, \end{aligned}$$

where *shareFRM* is the proportion of fixed rate mortgages over the total number of mortgages issued by the bank i in quarter t and *LTFP* is the Long Term Finance Premium that is the spread between fixed and adjustable mortgages rates posted by the bank. *BankChar* is a bank characteristic with the potential of influencing the convenience of the bank between issuing FRMs or ARMs. The bank characteristic used in the top left plot in Figure 11 is the spread between the cost of fixed rate bank bonds and variable rate bonds; whereas in the top right plot we use the deposits as a fraction of the bank total liabilities.

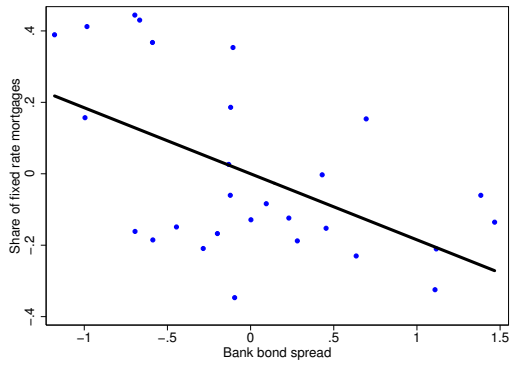
The figure shows that, for both bank characteristics, once we control for the level of the fixed-adjustable mortgage spread the balance sheet condition of a bank is correlated with the fraction of fixed rate mortgages it issues. A higher cost of fixed rate financing (that is a high spread on fixed vs variable rate corporate bonds) is associated with a lower fraction of fixed rate mortgages; a higher incidence of deposits over total funding is positively correlated with



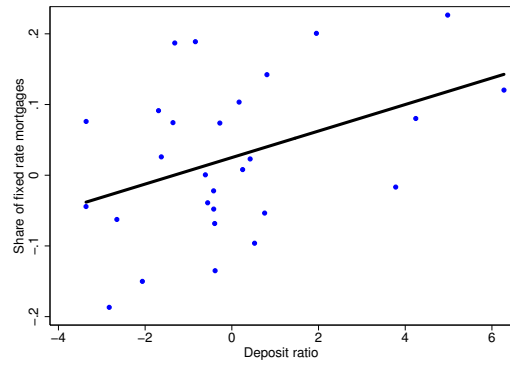
(a) Bond spread, all banks



(b) Deposit ratio, all banks



(c) Bond spread, major bank



(d) Deposit ratio, major bank

Figure 11: Banks Balance Sheet and Mortgage Type Prevalence

Notes: In all plots, the variable on the y-axis is the fraction of a bank's mortgage which is fixed rate. The plots on the left have on the x-axis the spread between short and long term bonds issued by the bank; the plot on the left have the ratio of deposits to assets on the x-axis. The top plots show the relationship in the entire sample; the bottom plots only use observations on the largest bank in our data.

the fraction of FRMs. In both cases the correlation is statistically significant. Since customers should not care about the liabilities structure of the bank beyond its effect on the mortgage spread, which is already controlled for, this results is consistent with the presence of advice by the bank which influences the households' decision. In the bottom panels of Figure 11, we repeat the same exercise using observations on the largest bank in our sample, whose market share ranges between 10% and 15%. The qualitative results are in line with those we just presented: the correlations are bigger in magnitude but less statistically significant due to the smaller sample size.

A.9 Additional Figures

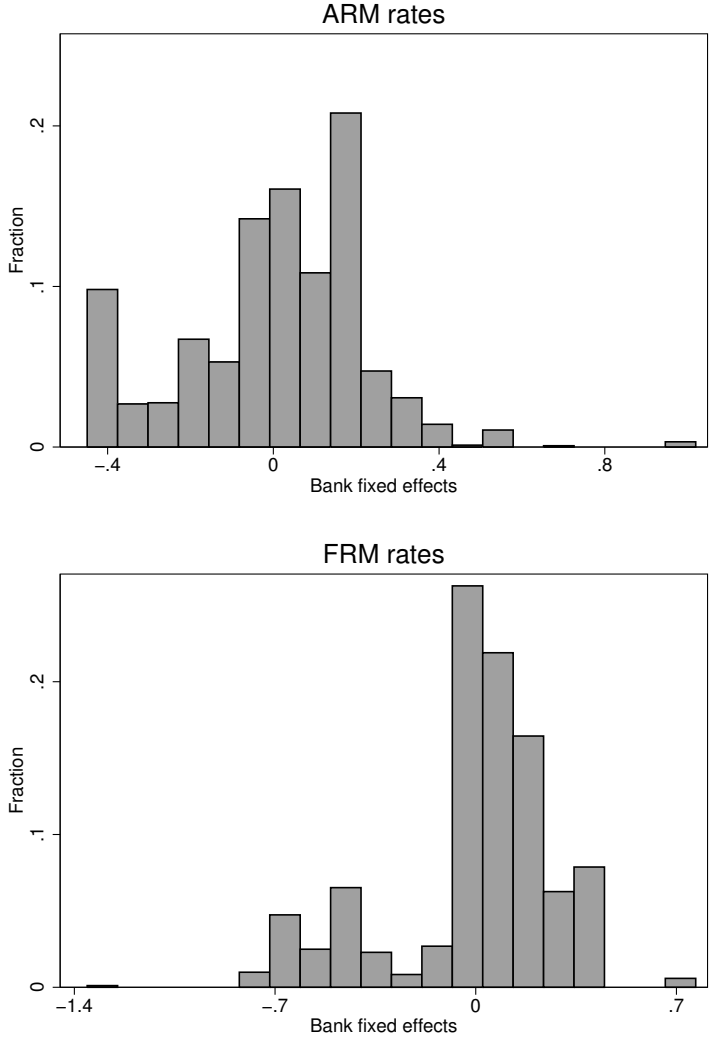


Figure 12: Dispersion of Rates

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.

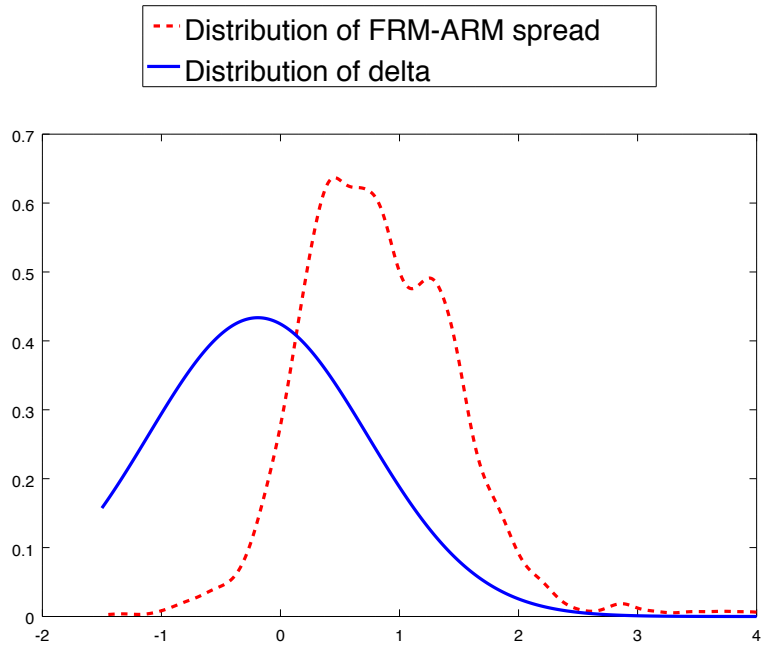


Figure 13: **Estimated Distribution of δ and Kernel Density of ϕ_{it}**