# Distorted Advice in the Mortgage Market: Theory and Structural Estimation*

Luigi Guiso   Andrea Pozzi   Anton Tsoy
Leonardo Gambacorta   Paolo Mistrulli†

December 2016

*Preliminary and Incomplete. Do Not Cite or Circulate.*

**Abstract**

Complex financial decisions require sophistication which not all households possess. This exposes them to the risk of being exploited when seeking advice from intermediares. We set up a structural model of financial advice and estimate it using administrative data on the universe of Italian mortgages. In the model banks have an ideal mix of fixed and adjustable rate mortgages and achieve it by both setting rates and providing advice to their clientele. "Sophisticated" households know which mortgage is best for them; "naive" households are instead susceptible to advice and will take the type of mortgage recommended by the bank. We recover the primitives of the model and use them to quantify the welfare implications of biased financial advice. The cost of the bias is equivalent to increasing the annual mortgage payment by 1,183 euros. Losses are bigger for the naive but also the sophisticated lose. Because even distorted advice conveys information, banning it altogether would result in a loss of 738 euros per year on average, mostly paid by the naive consumers. A financial education campaign is beneficial for all, though in different degrees.

*We thank Fernando Alvarez, Steffen Andersen, Francesco Decarolis, Liran Einav, Claudio Michelacci, Franco Peracchi, and seminar audiences at EIEF, LSE, Tilburg, WU, Conference CREST–ECODEC (Paris), Research in Behavioral Finance Conference (Amsterdam), FCA/Brevan Howard Conference on Consumer Choice in Mortgage Market (Imperial) for comments and discussions.

†Luigi Guiso: EIEF and CEPR, guiso@tin.it; Andrea Pozzi: EIEF and CEPR, andrea.pozzi@eief.it; Anton Tsoy: EIEF, tsoianton.ru@gmail.com; Leonardo Gambacorta: Bank of International Settlement and CEPR, leonardo.gambacorta@bis.org; Paolo Mistrulli: Bank of Italy, paolo.mistrulli@gmail.com.

# 1 Introduction

Households frequently seek expert advice when they lack the necessary knowledge to determine what financial product is best for their needs. For instance, 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. However, sometimes advisors may have an incentive to distort their recommendations in a way that serves their own needs rather than those of their customers. This is, for instance, often the case when households solicit advice from the seller of the financial product itself. A rich literature (Carlin and Manso, 2011; Inderst, 2010; Inderst and Ottaviani, 2012a,b,c; Kartik et al., 2007; Ottaviani and Squintani, 2006) has provided the theoretical underpinnings on how advice affects unsophisticated households' financial choices when brokers and/or intermediaries, with their informational advantage, are in conflict of interest. In this paper we assess the prominence of this phenomenon and quantify its impact on households' welfare.

Empirically documenting the presence of distorted advice is a challenging task. The finding that the investment performance of individuals who rely on advice is worse than that of those who do not (Hackethal et al., 2010, 2012) or than some benchmark (Foerster et al. (forthcoming)) has been claimed as evidence of biased advice. However, this result is also consistent with less capable investors being more keen to get advice but nevertheless unable to overcome the deficit in ability or to make proper use of the advice received.[1] Randomized field experiments (Anagol et al. (forthcoming); Mullainathan et al. (2012)) deal with the endogeneity of the choice to seek advice. However, the experimental setting may alter the behavior of the advisors with respect to the conduct they would keep in real world situations. Finally, common to both types of studies is the fact that only cases where advice is sought by the investors are observed. In practice, however, advice - especially distorted advice – may be offered even when it is not actually 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 households' choice to the

[1] Indeed, there is some evidence that investors fail to heed advice even when it is free of charge and where it is, by construction, unbiased (Bhattacharya et al., 2012). Moreover, even though advised investors do worse than the unadvised or the benchmark, they may nevertheless do better than they would have by choosing on their own. Advice may still help unsophisticated investors to avoid common investment mistakes or mitigate behavioral biases (Shapira and Venezia (2001); Gennaioli et al. (2015)). This possible benefit cannot be detected by comparing investors who rely on advice with those who do not.

intermediary's advantage. If so, comparing customers who do and do not solicit advice may fail to detect supply-side distortions or produce 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 cost of its distortion depend on the distribution in the population of sophisticated and unsophisticated consumers, a parameter that neither of the two approaches described above could identify.

To overcome these problems, in this paper we build and estimate an explicit 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 to which 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 available. Therefore, expert opinion is potentially valuable. Furthermore, both banks and brokers have interest in taking advantage of costumers' lack of knowledge and experience (Woodward and Hall (2012)). Our data consist of administrative records on the universe of mortgages originated between 2005 and 2008 by a sample of 175 Italian banks. In addition to information on the terms of the loans and characteristics of the households, 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 (no 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 that they need to trade off in order to choose the mortgage type, given the relative price of fixed and adjustable mortgages. Therefore, they choose the best mortgage type given their characteristics and the price gap between fixed and adjustable contracts. Naive borrowers instead are completely uninformed. They are unable to quantify inflation and interest rate risk and, therefore, cannot determine whether a fixed or an adjustable mortgage is better for them. However, they can get advice from the intermediary they choose to borrow from and follow whatever recommendation they receive from their chosen bank on the type of contract to pick. Banks are heterogenous in the target (ideal) adjustable/fixed composition of their mortgage portfolio and compete with each other by setting rates to attract borrowers. They provide advice to their customers without being able to observe whether each of them is naive or sophisticated.

Estimating the parameters of the model allows us to identify the fraction of naive and sophisticated households in the economy. We estimate the fraction of naive at 34% of the borrowers, 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 a public program meant to reduce the distortion.

Armed with this information we compute the welfare effect (in mortgage annual payment equivalent) of two counterfactual exercises that inform us about the costs and benefits of advice. The first shows that households can benefit even from distorted advice. In fact, if we restrict the banks' ability to provide advice, the welfare loss is 738 euros per household per year. We find that banning advice, while very costly for the naive borrowers (2,673 euros per year) is also costly for the sophisticated ones who end up paying 413 euros more per year. The second counterfactual measures the costs of distorted advice; if banks were forced to provide only undistorted advice the welfare gain is 1,183 euros. While distorting advice is most costly for the naive borrowers (2,030 euros per year per borrower), it is also somewhat costly for the sophisticated (71 euros). Finally, we also study the 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 affected by the financial education campaign as well as to a smaller extent the sophisticated households.

This study contributes to several strands of literature. First and foremost, it is related to the household finance literature showing evidence of distorted advice (Egan, 2015; Foa et al., 2015; Ru and Schoar, 2015; Egan et al., 2016). The main challenge faced by this line of research is the endogenous nature of advice and of its unobservability when not explicitly solicited. We deal with this issue imposing a structure on the data explicitly modeling the advice provision by the banks. Second, we contribute to the literature on financial advice games that rely on the presence of both sophisticated and naive investors as in Ottaviani and Squintani (2006); Kartik et al. (2007). We enrich the setting typically analyzed in these models by introducing price competition between banks and borrowers' search. This is a necessary extension in order to disentangle the role of price setting and advice as instruments that intermediaries may use to attract and steer customers choices. Finally, 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 (Crawford et al., 2015; Einav et al., 2012) and bargaining negotiation (Allen et al., 2014).

The rest of the paper is organized as follows. Section 2 describes the data and the convenient institutional features of the Italian mortgage markets. There we also present some evidence suggestive of the presence of advice distortion. In Section 3 we build and analyze a theoretical model where households search for banks where to borrow and decide on the type of mortgage to take while banks set interest rates for each type of contract and influence borrowers' decisions through advice. Section 4 provides details on the identification and the estimation of the model whose results are discussed in Section 5. Section 6 presents the results of the policy experiments measuring the welfare effects of distorted advice. Section 7 concludes.

## 2 Setting the Stage: Features of the Italian Mortgage Market, Data and Reduced Form Evidence

The working of the mortgage market, perhaps more than other segments of the credit market, is greatly affected by a number of institutional features (see Campbell (2013)), which are in turn relevant for the structure of incentives that mortgage originators may face when providing advice to borrowers. Accordingly, we start with a description of key features of the Italian mortgage market with two purposes in mind. First, we mean to highlight the differences between the Italian and the US mortgage markets and argue that features of the former provide a suitable environment for empirically studying distorted advice in financial markets more generally. Second, we stress how the institutional characteristics of the Italian mortgage market inform our choices in the construction of the model we will present in Section 3.

## 2.1 The Italian Mortgage Market

Despite Italy's high homeownership rate, the size of the household mortgage market is smaller than in comparable countries. Total household debt amounts to 63 percent of disposable income, compared to 95% in the euro area and 103% in the US. Based on data from the Bank of Italy Survey of Households Income and Wealth (SHIW) only 12 percent 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 00s. 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 a pure adjustable rate mortgage (henceforth, ARM), where the bank charges a spread over an underlying interest rate index (usually the Euribor 1 month); or a pure 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. 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.[2] Regulation sets the maximum loan to value ratio at 80% but can be adjusted and rise up to 100% if additional guarantees are provided. The actual 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 not customary 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, banks usually retain the mortgages they originated 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 Rampini et al. (2016) using US data and by Esposito et al. (2015) for Italian banks and it may be due to the cost of hedging or even to the difficulty of accessing to the relevant market for some banks. The fact that banks provide advice to customers and retain a chunk of the risk linked to maturity transformation, implies that they have both opportunity and motive to distort

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

advice to mortgage takers.

Banks fund their loans both through deposits and long term bonds placed in the market. As we show in Table 1, the relative importance of these two sources varies substantially across banks. 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) will be 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 loan with less concerns about fluctuations in the cost of their funding sources. Not only are banks heterogeneous in the extent to which they depend on the market for financing but also in the price they pay for it. The spread between fixed and variable rate 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. This is yet another reason that could 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 important source of risk taken by banks when issuing mortgages compared to credit and pre-payment risk. Like in many other European countries, households in Italy are personally liable for their debt and cannot walk away if the value of the house falls short of the value of the mortgage. Hence, the incidence of mortgage defaults in the Italian is rather limited: the fraction of mortgages with late repayment or default is between 1% and 1.5%. Even in the years of the financial crisis, which starts in Italy after the end of our sample, delinquency never climbs higher than 3%. This is partly a reflection of tight screening policies with high rejection rates of risky loan applicants.[3] For this reason we disregard 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)).

Pre-payment and re-negotiation of mortgages are also both limited. For most of the time span in our analysis, both were burdened by unregulated fees. The Bersani law in 2007 regulated re-negotiation and pre-payment fees setting them at a mandated level

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

common to all banks, which thus cannot compete on this margin. Re-negotiation fees were by the reform abolished but still only 4% of potential beneficiaries renegotiated their mortgages (Bajo and Barbi (2015)) after the bill was enacted. This is even more striking since rates were falling rapidly, providing a strong incentive to renegotiate. The new limits for pre-payment penalties vary between 0.2% and 1.9% depending on the nature of the contract (higher for FRM) and the residual length of the mortgage. The effect of the change in the cost of re-negotiation appears also to have been somewhat limited (Beltratti et al. (2016)). Before the bill was passed (that is over our sample period) pre-payment was limited also by positive prepayment fees. These were set by the law and common to all banks.

In sum, the Italian mortgage market is characterized by the prevalence of plain vanilla FRM and ARM mortgages[4], 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, since banks face maturity transformation risk and long term funding and hedging to cope with it are costly, they may have an incentive to steer customers choice either towards FRM or ARM at time of origination. The features of the market just described and the properties of the data that we discuss below offer a good setting for testing whether this is actually the case and measure the consequences of such behavior.

## 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

[4]Italian banks de facto do not originate non-standard mortgages, e.g., interest only, negative amortization, balloon payment. They issue very few partially adjustable mortgages; accordingly, teaser rates are not common.

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. Only 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.[5] 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 in 75% of the cases the gap is no larger than 50 basis points.

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.

## 2.3 Reduced Form

In this section we build on Foa et al. (2015), who designed a reduced form test of biased advice using the same mortgage data used in this paper, to provide some evidence that the data support the existence of the type of bank behavior at the center of our model.Foa et al. (2015) test the presence of distorted advice based on the premise that if households

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

| *Variable* | *Obs.* | *Mean* | *Std.dev.* | *10th pctile* | *25th pctile* | *50th pctile* | *75th pctile* | *90th pctile* |
|---|---|---|---|---|---|---|---|---|
| **Branch level variables** | | | | | | | | |
| FRM-ARM Spread | 13,747 | 0.54 | 0.63 | -0.14 | 0.23 | 0.54 | 0.84 | 1.19 |
| FRM rate | 13,747 | 5.47 | 0.62 | 4.77 | 5.17 | 5.58 | 5.91 | 6.11 |
| ARM rate | 13,747 | 4.63 | 0.87 | 3.56 | 3.80 | 4.66 | 5.36 | 5.79 |
| Num. mortgages | 13,747 | 47.41 | 95.09 | 4 | 8 | 20 | 48 | 104 |
| % lowest ARM | 13,747 | 0.12 | 0.16 | 0 | 0 | 0.06 | 0.20 | 0.36 |
| % lowest FRM | 13,747 | 0.16 | 0.19 | 0 | 0 | 0.12 | 0.25 | 0.44 |
| Share of deposit market | 13,747 | 0.10 | 0.12 | 0.01 | 0.02 | 0.05 | 0.13 | 0.25 |
| Share of mortgage market | 13,747 | 0.10 | 0.09 | 0.02 | 0.03 | 0.06 | 0.13 | 0.23 |
| Share of FRM issued | 13,747 | 0.37 | 0.34 | 0 | 0.03 | 0.27 | 0.67 | 0.91 |
| **Bank level variables** | | | | | | | | |
| Total assets (millions €) | 268 | 39,495 | 45,098 | 6,428 | 11,737 | 17,169 | 57,768 | 103,838 |
| Deposits/Total assets | 268 | 0.46 | 0.11 | 0.33 | 0.38 | 0.45 | 0.53 | 0.98 |
| Bank bond spread | 280 | 0.27 | 0.52 | -0.46 | -0.07 | 0.28 | 0.64 | 0.98 |
| **Market variables** | | | | | | | | |
| Num. banks in the mkt. | 1,350 | 10.18 | 1.98 | 7 | 9 | 10 | 11 | 13 |

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.

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" buyers 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.

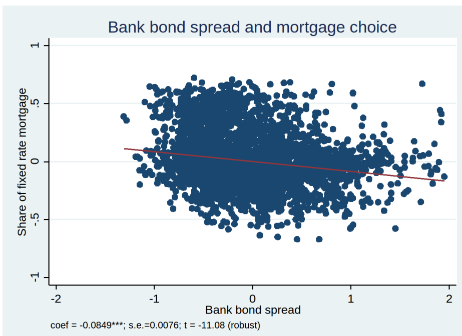
Applying this idea to administrative data on a large sample of Italian households taking a mortgage Foa et al. (2015) show that the choice between ARM and FRM is systematically correlated, not only with the relative costs of the two type of mortgages but also with time varying characteristics of the bank that originates the mortgage at the time the decision is made. For instance, they find that, after controlling for relative cost of the two type of mortgages they face, households borrowing from a given bank are more likely to choose an ARM in a given quarter if in that quarter the bank faces a higher cost of raising long term funding compared to households borrowing from the same bank in a quarter when the bank can more cheaply obtain long-term funding.

In Figure 1 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

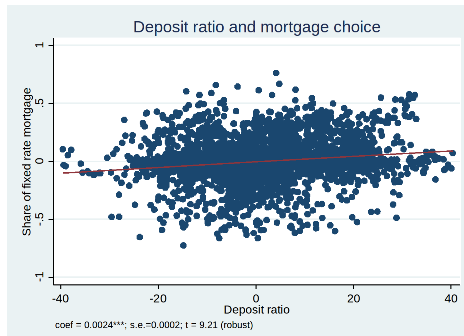
$$shareFRM_{it} = a_0 + a_1 LTFP_{it} + u_{it},$$
$$BankChar_{it} = b_0 + b_1 LTFP_{it} + v_{it},$$

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 1 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.

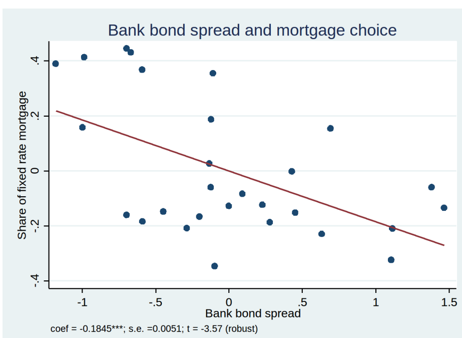
The figure shows that, for both choices of bank characteristic, once we control for the level of the fixed-adjustable spread the balance sheet condition of a bank is significantly correlated with the fraction of fixed rate mortgages it issues. A higher cost of fixed rate financing (that is a high spread on fixed vs variable rate corporate bonds) is associated



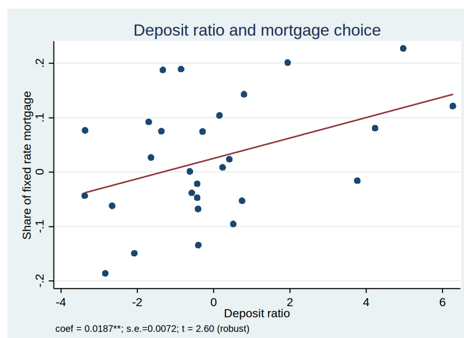

(a) Bond spread, all banks




(b) Deposit ratio, all banks




(c) Bond spread, major bank




(d) Deposit ratio, major bank

Figure 1: **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.

with a lower fraction of fixed rate mortgages; a higher incidence of deposits over total funding is positively correlated with the fraction of FRM. 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 1, 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, probably due to the smaller sample size, less statistically significant.

This evidence is consistent with the idea that at least a fraction of the borrowers follows distorted advice provided by their banks. However, the size of the correlation between residuals we documented bears no direct implications for the importance of this phenomenon and does not allow to identify the share of households affected. In the next section, we introduce a model that complements this reduced form tests providing a way to quantify the extent of distorted financial advice in our data and to assess the welfare impact of this phenomenon.

# 3 Model

This section builds a theoretical model of households' mortgage choice and bank rate/advice policy that captures key aspects of the Italian mortgage market described in the previous section.

As we explained in Section 2, banks set rates at a regional level, while households search at a provincial level. For notation simplicity, we present the model for a single market where the definition of the region and the province coincide, but take this distinction into account when we estimate the model.

A continuum of households indexed by $h$ of mass $M_t$ take up a mortgage in quarter $t$ from one of $N$ banks. The timeline is as follows:

1. At the beginning of quarter $t$, banks simultaneously set fixed rates taking as given the spread of adjustable rates over EURIBOR, the benchmark rate in the interbank borrowing market. Banks also decide on their advice policy.

2. Each household $h$ is randomly assigned to the *home bank* in its province.

3. Each household $h$ observes a subset of rates in its province and chooses the bank. We say that household $h$ becomes a *customer* of this bank.

4. Banks provide advice to their customers about the mortgage type.

5. Based on the advice and observed rates, households choose the mortgage type (adjustable or fixed rate).

**Household Heterogeneity** Households are heterogenous on several dimensions. First, each household $h$ is initially assigned to a bank $i$ in quarter $t$ with probability $p_{it}$. We refer to bank $i$ as the *home bank* of household $h$. The characteristic of the home bank is that it is always part of the household's choice set. It may be natural to assume that the home bank for household is the bank where it has its primary checking account (as it is required to open an account in the bank that issues the mortgage). Another way of thinking about the home bank is that larger banks are more likely to play this role as they typically have more branches, and hence, are more likely to be conveniently located for the household. Under either assumption, the share of depositors held by a bank should affect its probability of being the home bank for a household. Therefore, in the estimation we will use the share of bank $i$ in the deposits market in quarter $t$ as a proxy for $p_{it}$.

Second, a fraction $\mu$ 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. As we describe in detail below, naïveté determines whether banks can affect the household's choice of the mortgage type. Third, a fraction $\psi$ of households are searchers and a fraction $1-\psi$ are non-searchers. Searcher/non-searcher status is independent of the sophistication.[6] Searchers see the rates posted by every bank in the market; whereas non-searchers only observe rates at their home bank, i.e., they do not search past their first inquiry. Although we refer to the parameter $\psi$ as the fraction of searchers, once we move to the estimation its interpretation will differ from the typical meaning of this term in the consumer search literature. In the data, we do not observe the number of banks a household has considered as potential originators of its mortgage. The only evidence of search occurs when a household finds a better rate in a bank other than its home banks and takes the mortgage there. A simple inquiry in alternative rates which does not translate in a transaction goes undetected by our data. Hence, $\psi$ will combine the features of both search and switching costs.

[6]While one can argue that sophisticated households might be more inclined to search, as they better understand the future consequences of their mortgage choice, the opposite is also plausible in an environment where households have limited time and can either learn about the difference between FRMs and ARMs or screen the market for the best rates. In the absence of any supportive empirical evidence on the positive/negative correlation of the two, we assume that they are independent.

Finally, households vary in the size of their mortgage $H$, the absolute risk aversion $\gamma$, and their beliefs about the relative volatility of real interest rate shocks ($\sigma_{\varepsilon}^2$) and inflation shocks ($\sigma_{\pi}^2$). We cannot separately identify the effect of $\gamma$,$H$,$\sigma_{\varepsilon}^2$ and $\sigma_{\pi}^2$ on a household's mortgage decision. Instead, we can identify the distribution of parameter $\delta \equiv \frac{1}{2}H\gamma(\sigma_{\varepsilon}^2 - \sigma_{\pi}^2)$ which as we will show next captures the decision rule of sophisticated households. We assume that $\delta$ is normally distributed with mean $\mu_{\delta}$ and variance $\sigma_{\delta}^2$ and independent from the other forms of household heterogeneity we described.[7]

**Mortgage Choice** Households finance the purchase of the house with the mortgage. We focus on the households' choice of the bank and the mortgage type, but abstract from their decision to buy versus rent, their choice of the size of the house and of the mortgage size. The distinction between naive and sophisticated households as well as between searchers and non-searchers shapes the way in which agents in our model choose their mortgage. We start describing the choice by sophisticated households, which follows a simple model of mortgage choice based on Koijen et al. (2009). While the model is stylized, it captures the main trade-offs in the mortgage choice and in our model sophisticated households recognize those trade-offs.

Households have CARA utility function $U(\cdot)$ with absolute risk aversion parameter $\gamma$. Suppose that the principal and the interest are paid after $\Delta$ quarters, and for simplicity, there are no intermediate payments. Let $\pi \sim N(0, \sigma_{\pi}^2)$ be the inflation shock and $\varepsilon \sim N(0, \sigma_{\varepsilon}^2)$ be the real interest rate shock at time $t + \Delta$. Thus, if $r_t$ is the EURIBOR at date $t$, then $r_t + \pi + \varepsilon$ is the EURIBOR at date $t + \Delta$. Consider the choice of a household who is a customer of bank $i$. If the household takes the ARM, then at date $t + \Delta$, it pays

$$(1 + s_{it} + r_t + \pi + \varepsilon)H,$$

where $s_{it}$ is the ARM spread between the adjustable rate and the EURIBOR 1-month rate set by bank $i$ on mortgages issued at date $t$. If the household takes the FRM, then at date $t + \Delta$, it pays

$$(1 + r_{it})H,$$

where $r_{it}$ is the FRM rate set by bank $i$ in quarter $t$. Recall that $\gamma$,$H$,$\sigma_{\varepsilon}^2$ and $\sigma_{\pi}^2$ vary across households but we omit this dependence on $h$ in the notation.

We denote by $\phi_{it} = r_{it} - (s_{it} + r_t)$ the FRM-ARM spread, i.e., the spread between

[7]Note that $\delta$ could take negative values. This may reflect risk-loving behavior or, more likely, the fact that some households view inflation shocks as more volatile than real interest rate shocks.

fixed and adjustable mortgage rates set by bank $i$ in quarter $t$. Household's income $y$ is distributed according to $G_y$ and is independent of the other random variables.

We next show that it is optimal for households to follow a simple *spread rule* in choosing the mortgage type. Specifically, suppose $\mathbf{r}_{ht}$ and $\mathbf{s}_{ht}$ are the lowest FRM rate and ARM-EURIBOR spreads, respectively, available to household $h$. If the household is a searcher, then $\mathbf{r}_{ht}$ and $\mathbf{s}_{ht}$ equal to the lowest $r_{it}$ and $s_{it}$ in the market, i.e., $\mathbf{r}_{ht} = \min_{i\in\{1,\dots,N\}} r_{it}$ and $\mathbf{s}_{ht} = \min_{i\in\{1,\dots,N\}} s_{it}$. If the household is a non-searcher, then $\mathbf{r}_{ht}$ and $\mathbf{s}_{ht}$ equal to $r_{it}$ and $s_{it}$ in the home bank of the household. The household prefers an ARM if and only if

$$\mathbb{E}_{\varepsilon}[-\exp(-\gamma(y-(1+\mathbf{s}_{ht}+r_t+\varepsilon)H))] \geq \mathbb{E}_{\pi}[-\exp(-\gamma(y-(1+\mathbf{r}_{ht}-\pi)H))], \tag{3.1}$$

Notice that by taking the 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 the FRM. Denoting by $\phi_{ht} \equiv \mathbf{r}_{ht} - (\mathbf{s}_{ht} + r_t)$ and recalling that $\delta = \frac{1}{2}H\gamma(\sigma_{\varepsilon}^2 - \sigma_{\pi}^2)$, we obtain that the ARM is preferred if and only if

$$\delta \leq \phi_{ht}. \tag{3.2}$$

This spread rule is quite intuitive: ARM is preferred whenever the household has low risk aversion, takes a relatively small mortgage, believes that inflation shocks are more volatile, and the spread between FRM and ARM rates is relatively large. This gives a natural interpretation to $\delta$ as the household cutoff spread below which ARM is chosen.

The behavior of naive households instead departs from the spread rule framework we just introduced. Before receiving advice, we assume that naive customers always prefer taking a fixed rate mortgage. However, they will take an ARM if their bank suggests so when providing advice. This implies that naive searchers only search for the bank with the lowest FRM rate, ignoring ARM rates. After the search, these households become a customers of the bank with the lowest fixed rate and will take the type of mortgage their bank advises them to take. Households only search once and cannot switch bank after receiving advice. Naive non-searchers take the mortgage at their home bank and pick the type the bank recommends. The difference between the choices of sophisticated/naive and searchers/non-searchers households is summarized in Table 2.

Our assumption that naive households purchase fixed rates in absence of advice can be motivated by the fact that FRMs are more similar to regular consumption goods in that the price is known in advance, and thus, no sophistication is required to predict

| | Searchers (frac. $\psi$) | Non-searchers (frac. $1-\psi$) |
|---|---|---|
| Sophisticated (frac. $\mu$) | best market rates<br>best mortgage type given rates | rates at home bank<br>best mortgage type given rates |
| Naive (frac. $1-\mu$) | best fixed rates<br>recommended mortgage type | rates at home bank<br>recommended mortgage type |

Table 2: **Household Choices**

future payments on the mortgage. In contrast, with ARM, the household must acquire information about future EURIBOR rates, needs a certain degree of sophistication to use this information to predict future mortgage payments, and should be aware of and understand different risks associated with each type of mortgage in order to compare them. Thus, it is natural to assume that naive households pay attention to a more simple (though potentially more expensive) product, the FRM, when comparing rates across banks. The idea that the ARM is a more complex instrument 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 $A.1$ reports the results of surveys on financial literacy of Italian household 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.

In Appendix $A.2$, we propose two models micro-founding the inclination of naive households towards FRMs. The first model builds on the money doctors framework by Gennaioli et al. (2015). In Gennaioli et al. (2015), household choose between various investment opportunities: the bank account is a more familiar option, while investment in the stock market is a more rewarding, but more complex option that requires certain knowledge and skill.[8] In this situation, financial intermediaries play an important role, as they provide information about more rewarding options as well as act as "money doctors" in reducing the anxiety of investing in more complex products. FRM and ARM are similar in this way to bank accounts and risky assets, resp., as one is more familiar, while the other is more complex and requires sophistication. Naive households suffer anxiety when taking the ARM (or investing in equities) on their own and so, ignore this option when they search, but can be convinced by banks to take ARM later who act as money doctors

[8]Calvet et al. (2007) document that less sophisticated households tend to stay out of the stock market

and alleviate the anxiety. The difference of our model from Gennaioli et al. (2015) is that banks can manipulate naive customers into taking ARMs, even when FRM is better for them. In the second model, naive households are ambiguity averse (in the sense of Gilboa and Schmeidler (1989)) and face Knightian uncertainty about the evolution of future real rates. Thus, they focus on FRM in their search behavior, but can choose ARM after the bank resolves the uncertainty about real rates. These two models operate similarly, but differ in the mechanism and interpretation of why naive households are averse to ARMs and how banks can resolve this aversion.

Finally, we assume that, once chosen a bank, households cannot switch. This assumption is binding for naive households: they pick their bank based on convenience of the fixed rates but are then sometimes steered towards ARMs. They may then have incentives to withdraw their applications in the current bank and go to a bank with a lower ARM rate.[9] We justify this assumption with the presence of high switching costs (e.g., the costs of putting together another mortgage application), which reduce the incentives to re-optimize. Further, if naive households also believe (or are led to believe by banks) that the bank posting the lowest fixed rate is also posting the lowest adjustable rate, then it is optimal for them not to redo the search.

**Banks** We next describe banks' profit function and their choice of rates and advice.

The main trade-off that banks face is that FRMs earn higher spread, as they ensure households against interest rate risk, but it is costly for banks to give out too many FRMs as they themselves become exposed to the interest rate risk. We capture this trade-off in reduced form in the following specification of banks' profits. Let $m_{it}$ be the mass of bank $i$'s customers and $x_{it}$ the fraction of FRMs issued by bank $i$ at time $t$. Denote by $\phi_{it} = r_{it} - (s_{it} + r_t)$ the spread between fixed and adjustable rates posted by bank $i$ in quarter $t$. The profit of bank $i$ in quarter $t$ is given by

$$\left(\alpha s_{it} + \phi_{it} x_{it} - \lambda (x_{it} - \theta_{it})^2\right) m_{it} e^{-\beta r_{it}}.$$

The bank earns a fraction $\alpha \in [0, 1]$ of the spread $s_{it}$ between the ARM rate and the EURIBOR rate. The fact that the bank only earns a share of this spread is motivated by the fact that banks themselves borrow on the interbank market at a certain spread over the EURIBOR and so, earn only a fraction of the spread $s_{it}$. In addition to the spread

[9]This issue does not arise for sophisticated households. They always purchase they type of mortgage they looked for in the search stage.

between the ARM rate and the EURIBOR, the bank earns spread $\phi_{it}$ on FRMs. This spread is mostly positive in our sample reflecting the premium for the insurance against interest rate shocks.

Issuing many FRMs, however, is costly because of maturity mismatch. The costs of the maturity mismatch are captured by the quadratic term $\lambda(x_{it} - \theta_{it})^2$, where $\theta_{it}$ is the cost efficient fractions of FRMs and $\lambda > 0$ reflects how severe are such costs. When the bank's fraction of FRMs in the mortgage portfolio equals $\theta_{it}$, such costs are zero, and they increase with the deviation of the bank from its ideal portfolio structure. We refer to $\theta_{it}$ as the *bank's type*; one could think of $\theta_{it}$ as the fraction of FRMs that bank $i$ can issue without suffering mismatch costs. Banks' types are privately observed and are i.i.d. (across $i$ and $t$) draws from a normal distribution with mean $\mu_\theta$ and variance $\sigma_\theta^2$ truncated from below at 0 and from above at 1.

At this stage, we are agnostic about what drives $\theta_{it}$. In Section 2 we introduced the idea that $\theta_{it}$ could depend on supply factors, e.g. reflect the ability of the bank to securitize loans or borrow long-term at better terms. If shifts in $\theta_{it}$ are driven by banks' supply conditions, the advice banks provide is 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. Once we estimate the model, we will be able to provide evidence on which variables influence the bank type.

The factor $e^{-\beta r_{it}}, \beta > 0$, in the profit function is a punishment to the bank for offering very high fixed rates to its customers. Such a punishment is necessary in our model given the assumption that naive households follow bank's advice. Without it, we could have equilibria where banks just charge infinitely high rates on FRM and only serve their naive non-searcher customers. In reality, a cap on the level of rates can come from the risk that naive households charged "excessive" rates end up defaulting or realize they have been exploited and badmouth the bank.[10] Since we do not model default or reputation concerns, we simply capture this trade-off in a reduced form.

Banks compete for customers by posting a fixed rate spread over EURIBOR. After households have chosen their bank, banks provide advice to their customers. The timing

[10] Another reason we do not observe outrageously high rates in our data is that a usury cap on interest rates exists.

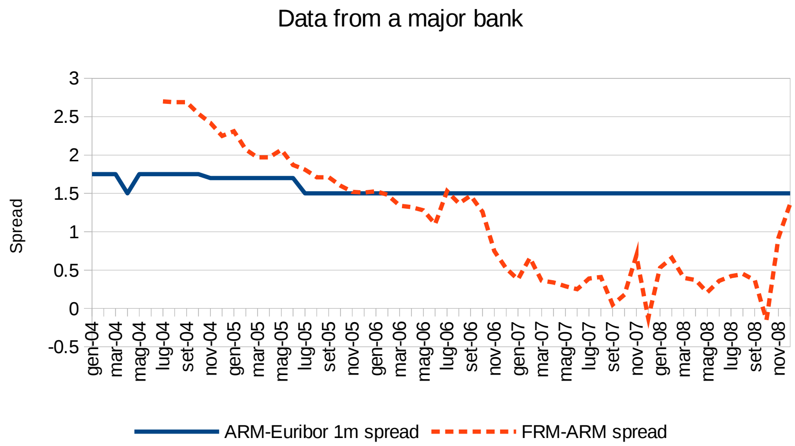



Figure 2: **Rate Spreads on a 25-year Mortgage Set by a Major Italian Bank**

of the game is as follows. At the beginning of quarter $t$, all banks observe all adjustable rates set by their competitors, but only their own type. They simultaneously post spreads $\phi_{it}$ between FRMs and ARMs, taking the spread between ARMs and EURIBOR $s_{it}$ as given. All banks retain the non-searchers for whom they are the home bank. In addition, the bank attracts searching naive households if it posts the lowest fixed rate, and searching sophisticated customers for whom one of its mortgages is the best option in the market. Given its customer base, each bank $i$ chooses the advice policy $\omega_{it} \in [0, 1]$: a fraction $1 - \omega_{it}$ of bank's customers are recommended to take ARMs. This advice only affects a fraction $1 - \omega_{it}$ of the naive customers of the bank, as sophisticated customers are not susceptible to advice.

We assume that the spread between adjustable rates and EURIBOR is determined outside of our model, and banks compete only by setting spreads $\phi_{it}$. This assumption is motivated by both the common practice of rate setting in the industry and the nature of the rate setting for ARMs and FRMs. Figure 2 plots the spread between the 25-year FRM and ARM, as well as the spread between ARM and 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 FRM-ARM spread adjusts up and down essentially every month. We observe a similar pattern when we average rates over all the banks in our sample.

The assumption that banks use FRM-ARM spread as a policy variable, rather than both FRM and ARM rates can also be motivated by the nature of ARMs. When households contemplate taking up an ARM, the recent evolution of adjustable rates is an important predictor of the future path of adjustable rates. By changing the spread on the ARM today, the bank affects decisions of households not only in the current period, but also in future periods. The rate setting problem becomes then inherently dynamic and quite involved, which could explain why banks adhere to a simple strategy of setting the adjustable rate spread constant for a prolonged period and adjust it infrequently (mainly because of liquidity considerations). In contrast, fixed rates in the current period do not affect the demand for FRMs in the future, and banks can freely vary fixed-rates spread to attract more customers today, without worrying about the effect on future demand.

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

Consider the subgame, in which bank $i$ gives its customers advice about the type of the mortgage. Suppose that in this subgame, the ARM-EURIBOR spread is $s_{it}$, the FRM-ARM spread is $\phi_{it}$, bank $i$ attracts mass $m_{it}$ of customers. Bank $i$ advices to take up 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 based on the spread rule. We denote by $\underline{x}_{it}$ and $\overline{x}_{it}$ respectively the minimal and maximal fractions of FRMs that can be attained through advice.[11] Observe that the choice of $\omega_{it}$ is equivalent to the direct choice of the fraction of FRMs issued, $x_{it}$, subject to the constraint that $\underline{x}_{it} \leq x_{it} \leq \overline{x}_{it}$. Hence, the bank solves

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

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

$$x(\phi_{it}|\theta_{it}) = \max\left\{\min\left\{\theta_{it}+\tfrac{\phi_{it}}{2\lambda}, \overline{x}_{it}\right\}, \underline{x}_{it}\right\}, \tag{3.3}$$

from which we can recover the optimal advice policy:

$$\omega(\phi_{it}|\theta_{it}) = \max\left\{\min\left\{\frac{1}{\overline{x}_{it}-\underline{x}_{it}}\left(\theta_{it}+\tfrac{\phi_{it}}{2\lambda}-\underline{x}_{it}\right), 1\right\}, 0\right\}. \tag{3.4}$$

The fraction of naive households advised to take FRM is increasing in the cost-efficient share of FRMs, $\theta_{it}$; in the FRM-ARM spread, $\phi_{it}$; and decreasing in the cost of portfolio imbalance, $\lambda$. Observe that the extent to which the bank can manipulate its customers depends on the gap between $\underline{x}_{it}$ and $\overline{x}_{it}$.

[11] More precisely, $\underline{x}_{it}$ can be attained by setting $\omega_{it}=0$ and $\overline{x}_{it}$ can be attained by setting $\omega_{it}=1$.

Given the optimal share of FRMs $x(\phi_{it}|\theta_{it})$ derived above, the bank's profit per customer is given by

$$V(\phi_{it}|\theta_{it}) = \left((\alpha s_{it} + \phi_{it} x(\phi_{it}|\theta_{it}) - \lambda \left(x(\phi_{it}|\theta_{it}) - \theta_{it}\right)^2\right) e^{-\beta(\phi_{it}+s_{it}+r_t)}. \tag{3.5}$$

We now turn to optimal spread setting by banks. Given $\theta_{it}$ and the profile of ARM-EURIBOR spreads across banks $S_t = \{s_{1t}, \ldots, s_{N_k t}, \}$, bank $i$ chooses $\phi_{it}$ to maximize

$$\int m_{it} V(\phi_{it}|\theta_{it}) dG_i(\underline{r}_{-it}|S_t), \tag{3.6}$$

where $G_i(\cdot|S_t)$ is the distribution of $\underline{r}_{-it} = \min_{j\neq i}\{r_{jt}\}$ given $S_t$. In the Appendix $A$.3, we derive more explicit formula for (3.6) that we use in our estimation.

Our model of competition among banks is similar to the first-price auction: the bank that posts the lowest fixed rate attracts searching households. Athey (2001); Reny and Zamir (2004) provide the existence and uniqueness results for equilibria in pure, monotone strategies in the first-price auction. Our model differs from the first-price auction however in the payoff structure. Thus, we simply assume that there exists a PBE in pure strategies in our model.

# 4 Identification

Our goal is to estimate the following parameters of the model: the fraction of naive households ($\mu$), the fraction of searchers ($\psi$), the distribution of the household residual heterogeneity $\delta$, the distribution of banks' types ($\theta$), and parameters $\lambda, \beta, \alpha$ of banks' profit functions.

**Identification of Demand Parameters** The identification of demand parameters $w^d = (\mu, \psi, \mu_\delta, \sigma_\delta)$ exploits our assumption on the differences in the way sophisticated and naive as well as searchers and non searchers react to variation in the fixed-adjustable spread. Since this amounts to estimating price elasticities, our strategy follows the classic approach of the demand estimation literature and relies on data on prices (spreads) and quantities (market shares in the mortgage market). We do not need to use our supply side model for identification.

As we mentioned in Section 2, the level of aggregation of the data is different between the demand and supply sides of the model. Therefore, we index all the observables by the superscript $d$ to signal that they are at the level of aggregation we use for demand, where a market is a province. Our data includes for every quarter $t = 1, \ldots, T$ and province $j = 1, \ldots, J$, the distribution of households taking up the mortgage across banks, $M^d_{jt} = (M^d_{1jt}, \ldots, M^d_{N^d_j jt})$ where $N^d_j$ is the number of banks in province $j$; the FRM rates posted by banks, $R^d_{jt} = (r_{1jt}, \ldots, r_{N^d_j jt})$; the ARM-EURIBOR spread of banks, $S^d_{jt} = (s_{1jt}, \ldots, s_{N^d_j jt})$; banks' shares in the province depositor market, $P^d_{jt} = (p_{1jt}, \ldots, p_{N^d_j jt})$. For $i = 1, \ldots, N^d_j$, the probability that a randomly drawn household takes a mortgage at bank $i$ is:

$$
\begin{aligned}
\ell_{ijt} =& (1-\psi)p_{ijt} \\
&+ \psi\mu 1\{r_{ijt} = \underline{r}_{jt}\} && (4.1) \\
&+ \psi(1-\mu)1\{r_{ijt} = \underline{r}_{jt}\}\left(1 - \Phi\left(\tfrac{1}{\sigma_\delta}(\underline{r}_{jt} - \underline{s}_{jt} - r_t - \mu_\delta)\right)\right) \\
&+ \psi(1-\mu)1\{s_{ijt} = \underline{s}_{jt}\}\Phi\left(\tfrac{1}{\sigma_\delta}(\underline{r}_{jt} - \underline{s}_{jt} - r_t - \mu_\delta)\right), && (4.2)
\end{aligned}
$$

where $\underline{r}_{jt} = \min_{i=1,\ldots,N^d_j} r_{ijt}$ and $\underline{s}_{jt} = \min_{i=1,\ldots,N^d_j} s_{ijt}$. Equation (4.2) consists of four terms. With probability $(1-\psi)p_{ijt}$ a household is non-searcher and $i$ is its home bank. With probability $\psi\mu$ a household is a searcher and naive. Then it takes a mortgage from bank $i$ only if $r_{ijt} = \underline{r}_{jt}$. With probability $\psi(1-\mu)$ a household is a searcher 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 of observing a particular realization $M^d_{jt}$ is given by

$$
L(M^d_{jt}|w^d, R^d_{jt}, S^d_{jt}, P^d_{jt}) = \binom{M^d_{jt}}{M^d_{1jt}, M^d_{2jt}, \ldots, M^d_{N^d_j jt}} \prod_{i=1}^{N^d_j} \ell_{ijt}^{M^d_{ijt}},
$$

where with a little abuse of notation we denote use $M^d_{jt}$ for $\sum_{i=1}^{N^d_j} M^d_{ijt}$. The log-likelihood is given by

$$
\mathcal{L} = \sum_{t=1}^{T}\sum_{j=1}^{J} \ln L(M^d_{jt}|w^d, R^d_{jt}, S^d_{jt}, P^d_{jt}) = C + \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{N^d_j} M^d_{ijt} \ln \ell_{ijt}.
$$

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, assume first that $\delta$ is equal across households ($\sigma_\delta = 0$), and the population is a continuum so that the exact Law of Large Numbers holds. The parameter $\psi$ represent the fraction of households that can shop for mortgages at banks other than their home bank. In our data we do not observe $p_{ijt}$, the fraction of households that have bank $i$ as their home bank. Instead, we construct the probability that a household has bank $i$ as its home bank using data on banks' market shares in deposits. This is a reasonable proxy, as households must have a checking account with the bank issuing them a mortgage. $\psi$ can then be identified off the correlation between banks market shares in the deposit and mortgage markets. Intuitively, if no household can search, every bank will have the same market share in the two segments, no matter the spreads posted. The extent to which posted rates can drive a wedge between the two is informative on the prominence of searchers.

The fraction of naive households is identified exploiting different sensitivity 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 $\underline{r}_{jt} - \underline{s}_{jt} > \delta$, meaning all sophisticated searchers will be looking for ARMs. If bank $i$ posts the lowest fixed rate, while another bank $\tilde{i}$ posts the lowest adjustable rate, bank $i$'s market share will increase by $\psi\mu$ with respect to the share it would have had if it had not offered the cheapest fixed mortgage $((1-\psi)p_{ijt})$. Instead, bank $\tilde{i}$'s market share will increases by $\psi(1-\mu)$. Therefore, given the differences in the search behavior of naive and sophisticated households, we can recover $\mu$ from variation in market shares of the banks in a market as long as the lowest adjustable and fixed rates are occasionally posted by different banks. In Table 1 we have shown that this is the case: although a quarter of the banks active in a given market never manage to post the lowest fixed or adjustable rate, 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 adjustable rate is 0.36; the same figure is 0.44 for the fixed rate mortgages.

Recall further that if $\underline{r}_{jt} < \underline{s}_{jt} + \delta$ sophisticated households will be searching for fixed rate mortgages. Hence, there is a range of rates $\underline{r}_{jt}$ and $\underline{s}_{jt}$ such that naive and sophisticated agents have the same search behavior, as the latter also search for the lowest fixed rate. Therefore, we can identify $\delta$ if there is variation over time and\or across markets in the lowest adjustable and fixed rates so that the type of mortgage preferred by sophisticated households varies. Table 1 documents that our data provide ample scope for such event. The standard deviation of rates is 0.87 for adjustable rate mortgages and 0.67 for fixed rate mortgages. This is the product of both cross-sectional variation in the rates set by different banks at a given point in time[12] and changes in the rates set by each bank over time. As 2 illustrate, our sample span covers a period when the FRM-ARM spread starts off as relatively high only to steadily decline. This shift provides useful variation to

[12]Variation in rates set by a same banks in different geographical markets is instead quite limited.

identify $\delta$ as it affects the fraction of households who should prefer a fixed rate mortgage absent naïveté.

Once we allow $\delta$ to vary in the population, we also need to identify the parameters of its distribution. In particular, it is important to understand how the variance of this distribution ($\sigma_\delta$) is separately identified from the fraction of naive. Although it is true that naive households search similarly to sophisticated households with high $\delta$ (extremely risk averse/leveraged/pessimistic about volatility of real rates), a higher variance in $\delta$ implies that both very high and very low realizations of $\delta$ in the population are more likely. Thus, it need not necessarily lead to an increase in households who prefer and search for fixed rate mortgages. In contrast, higher $\mu$ implies an increase in popularity of fixed rate mortgages.

**Identification of Supply Parameters** We now turn to the estimation of supply parameters $w^s = (\lambda, \alpha, \beta)$ and the distribution of $\theta$.

For reasons explained in Section 2, it is convenient for us to aggregate level from the provincial level, which we used in the demand, to the regional level. To denote the different level of aggregation, observables will be indexed by the superscript $s$.[13]

Our data includes for every quarter $t = 1, \ldots, T$ and region $k = 1, \ldots, K$, the distribution of households taking up the mortgage across banks, $M^s_{kt} = (M^s_{1kt}, \ldots, M^s_{N^s_k kt})$ where $N^s_k$ is the number of banks in region $k$; the fraction of FRMs over the total number of mortgages issued by each bank, $X_{kt} = (x_{1kt}, \ldots, x_{N^s_k kt})$; the FRM-ARM spreads posted by banks, $\Phi_{kt} = (\phi_{1kt}, \ldots, \phi_{N^s_k kt})$; the ARM-EURIBOR spread of banks, $S^s_{kt} = (s_{1kt}, \ldots, s_{N^s_k kt})$; and banks' shares in the province depositor market, $P^s_{kt} = (p_{1kt}, \ldots, p_{N^s_k kt})$.

The supply side estimation uses as inputs the estimates of the demand side of the model ($\hat{w}^d$) and unfolds in three steps. First for given parameters $w^s$,we construct estimates $\hat{\theta}_{ikt}(w^s)$ of unobserved bank types $\theta_{ikt}$ using the optimality condition for advice (equation (3.3)) and obtain predictions for the fraction of FRMs issued by each bank as predicted by the model. Next, we obtain an estimate for the distribution of the minimum FRM rate offered in the market and obtain model predictions on the rates banks set. Finally, we estimate $w^s$ matching for each bank the fraction of fixed rate mortgages issued and

[13] The 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. $M^s_{ikt} = \sum_{j \in k} M^d_{ijt}$); 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 a same region weighting by the number of mortgages issued by the bank in the province (e.g., $s_{ikt} = \frac{1}{M^d_{ikt}} \sum_{j \in k} s_{ijt} M^d_{ijt}$).

the FRM-ARM spread to the model's predictions.

*Step 1:* For a given guess of the supply parameters $w^s$, we can obtain a estimates of the type for each bank ($\hat{\theta}(w^s|X_{kt}, \Phi_{kt}, S^s_{kt}, P^s_{kt})$) by picking the $\theta_{ikt}$ that minimizes the discrepancy between the fraction of FRM issued by a bank observed in the data and predicted by the model

$$\left(x_{ikt} - \max\left\{\min\left\{\theta_{ikt} + \tfrac{\phi_{ikt}}{2\lambda}, \overline{x}_{ikt}\right\}, \underline{x}_{ikt}\right\}\right)^2. \tag{4.3}$$

However, when the observed fraction lies below the lowest ($x_{ikt} < \underline{x}_{ikt}$) or above the highest ($x_{ikt} > \overline{x}_{ikt}$) fraction achivable by the bank according to the model, there is a range of $\hat{\theta}_{ikt}$ that minimizes expression (4.3). To obtain an estimate of $\theta_{ikt}$ for those cases, we rely on the assumption that the $\theta$'s are distributed according to a normal truncated between 0 and 1, with parameters $\mu_\theta$ and $\sigma_\theta$. We estimate the parameters of this distribution maximizing the following likelihood of the observed fraction of FRMs issued

$$\begin{aligned}
&\sum_{t,k} \sum_{x_{ikt} \in (\underline{x}_{ikt}, \overline{x}_{ikt})} \ln\left(\frac{1}{\sigma_\theta}\phi\left(\frac{x_{ikt} - \frac{\phi_{ikt}}{2\lambda} - \mu_\theta}{\sigma_\theta}\right)\right) + \\
&\sum_{t,k} \sum_{x_{ikt} \leq \underline{x}_{ikt}} \ln\left(\Phi\left(\frac{\underline{x}_{ikt} - \frac{\phi_{ikt}}{2\lambda} - \mu_\theta}{\sigma_\theta}\right) - \Phi\left(\frac{-\mu_\theta}{\sigma_\theta}\right)\right) + \\
&\sum_{t,k} \sum_{x_{ikt} \geq \overline{x}_{ikt}} \ln\left(\Phi\left(\frac{1-\mu_\theta}{\sigma_\theta}\right) - \Phi\left(\frac{\overline{x}_{ikt} - \frac{\phi_{ikt}}{2\lambda} - \mu_\theta}{\sigma_\theta}\right)\right) - \\
&\sum_{t,k} \sum_{i} \ln\left(\Phi\left(\frac{1-\mu_\theta}{\sigma_\theta}\right) - \Phi\left(\frac{-\mu_\theta}{\sigma_\theta}\right)\right).
\end{aligned}$$

Then, we use the estimated distribution of $\theta$'s to draw bank types for the instances in which a unique $\theta_{ikt}$ cannot be inferred by minimizing expression (4.3). In particular, we impute $\hat{\theta}_{ikt} = \mathbb{E}[\theta|\theta \leq \underline{x}_{ikt} - \frac{\phi_{ikt}}{2\lambda}]$ when the bank specific lower bound is hit and $\hat{\theta}_{ikt} = \mathbb{E}[\theta|\theta \geq \overline{x}_{ikt} - \frac{\phi_{ikt}}{2\lambda}]$ for observations at the upper bound.

*Step 2:* Conditional on $\theta_{ikt}, \Phi_{kt}, S^s_{kt}, P^s_{kt}$ and parameters $w^s$, we can compute the predicted share of FRMs from eq. (3.3), $\hat{x}(\theta_{ikt}|w^s, \Phi_{kt}, S^s_{kt}, P^s_{kt})$. We then compute the predicted FRM-ARM spread, $\hat{\phi}(\theta_{ikt}|w^s, S^s_{kt}, P^s_{kt})$, from maximizing eq. (3.6) In order to do so, we need an estimate of the distribution of the minimum of $N^s_k - 1$ FRM rates for each region, $\hat{G}_k(\cdot)$. We use a kernel density estimator on the observed FRM rates to obtain an estimate 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

| *Demand* | | *Supply* | |
|---|---|---|---|
| Parameter | Estimate | Parameter | Estimate |
| $\mu$ | 0.34 (0.0115) | $\lambda$ | 27.78 (6.43) |
| $\psi$ | 0.02 (0.0003) | $\alpha$ | 0.057 (0.013) |
| $\mu_\delta$ | $-0.19$ (0.074) | $\beta$ | 0.733 (0.079) |
| $\sigma_\delta$ | 0.92 (0.089) | | |

Table 3: **Estimates of the Parameters**

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

spreads posted in the market, i.e., $G_{ik}(\cdot|S^s_{kt})$. However, this requirement is data intensive because it implies estimating a different function for each different combination of adjustable rates posted by banks active in the market. We exploit the fact that, as shown in Figure 2, the ARM-EURIBOR spreads are fairly persistent and proxy the conditional distribution with the unconditional one.

*Step 3:* Denote $\hat{\theta}_{ikt}(w^s) \equiv \hat{\theta}(w^s|X_{kt}, \Phi_{kt}, S^s_{kt}, P^s_{kt})$, $\hat{x}_{ikt}(\theta_{ikt}, w^s) \equiv \hat{x}(\theta_{ikt}|w^s, \Phi_{kt}, S^s_{kt}, P^s_{kt})$, and $\hat{\phi}_{ikt}(\theta_{ikt}, w^s) \equiv \hat{\phi}(\theta_{ikt}|w^s, S^s_{kt}, P^s_{kt})$. We find estimates $\hat{w}^s = (\hat{\xi}, \hat{\alpha}, \hat{\beta})$ that minimize the function

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

In practice, we aim at minimizing 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.

# 5 Estimation Results

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

## 5.1 Estimates

Table 3 reports estimates for the parameters of the model.

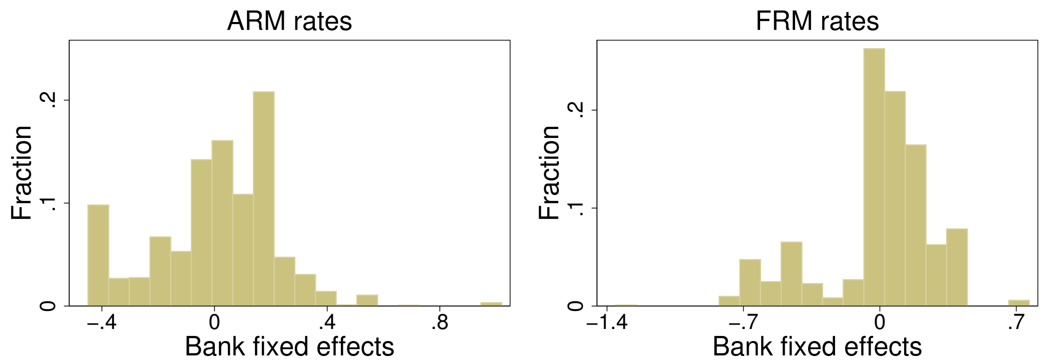



Figure 3: **Dispersion of rates**

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

Two main facts emerge from the estimates of the demand parameters: the fraction of naive households is large (34%) and the fraction of searchers 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.1, which points to a very low level of basic financial knowledge by Italian households, providing wide opportunity for banks to distort advice.

The low fraction of searchers is consistent with the significant interest rate dispersion in our sample. Figure 3 displays the distribution of bank fixed effects estimated from regressions of adjustable (left) and fixed (right) rate mortgages (in percentage points) controlling for market and time effects. The dispersion is significant, especially for fixed rates, which suggests the presence of large frictions in the market: the standard deviation of the bank fixed effects is 0.23 for adjustable mortgages and 0.28 for fixed mortgages. It is also important to recall, that the variation identifying the parameter $\psi$ really reflects both search and switching frictions. In fact, we only count as searchers households who looked around for rates at banks other than the one where they hold their primary checking account and end up taking the mortgage there. Search effort that does not translate ina switch of the bank chosen does not contribute to identify $\psi$. Hence, our estimate is also influenced by the level of switching cost across banks, which is anecdotally reported to be high in Italy.

The final parameters of the demand side of the model are the mean and standard deviation of the distribution of the household cutoff spread $\delta$. Figure 4 shows that the estimated distribution of $\delta$ is shifted to the left of the empirical distribution of the FRM-

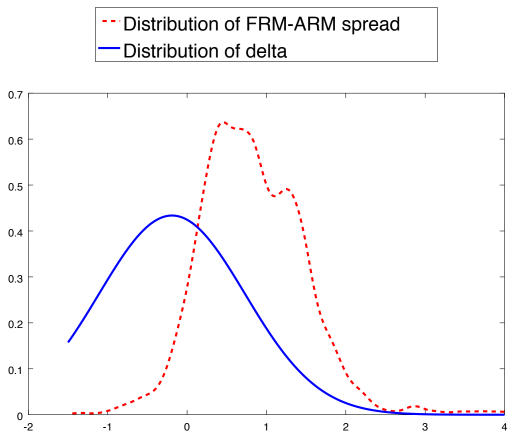



Figure 4: **Estimated distribution of $\delta$ and kernel density of $\phi_{it}$.**

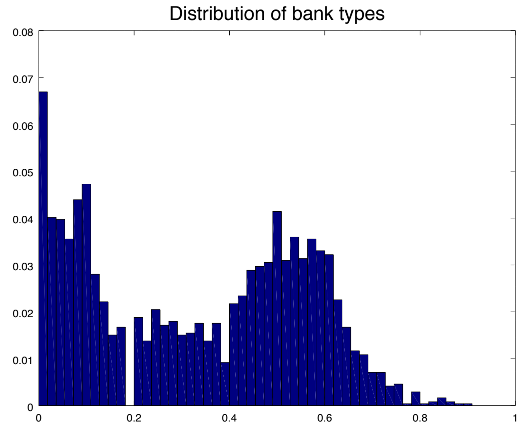



Figure 5: **Histogram of estimated $\theta_{it}$.**

ARM spread in our data, but still has a substantial overlap with it. Given the spread rule (3.2), this indicates that while sophisticated households on average prefer the ARM, there is still a variation in the type of mortage chosen across sophisticated households.

As far as the supply side parameters are concerned, the interpretation of $\lambda, \beta, \alpha$ is also not immediate. We will better grasp the importance of these parameters in the context of the counterfactual exercises performed in the next section. In Figure 5 we instead show the distribution of $\theta_{ikt}$, the parameter capturing heterogeneity among banks in their cost efficient fraction of FRM issued. The distribution is fairly dispersed but there is barely any mass for values of $\theta$ above 0.9, likely due to the fact that in our sample span ARM are on average more popular. Similarly, the mass point at $\theta = 0$ derives from the fact that there is a number of banks in our data which are barely active in the fixed rate market.

## 5.2 Evidence of the Distorted Advice

Our structural model helped us recover a time-varying bank-specific parameter which, in principle, lends itself to different interpretations. For instance, it could represent heterogeneity across banks in their beliefs about the evolution of interest rate and inflation, which would lead them to push different types of mortgages when trying to faithfully advise their customers. This interpretation is, however, hard to reconcile with the wide dispersion in the bank types we estimated. Even though experts do disagree on their forecast of the evolution of economic variables, it is hard to imagine that professional operators could have such extreme divergences as to lead one bank to recommend fixed

| VARIABLES | All sample | Deposit/ Liabilities < 75 pctile | Deposit/ Liabilities < 50 pctile | Deposit/ Liabilities < 25 pctile |
|---|---|---|---|---|
| Bank bond spread | −0.035 | −0.056** | −0.070** | −0.086 |
| | (0.023) | (0.027) | (0.031) | (0.053) |
| Observations | 762 | 521 | 386 | 202 |
| R-squared | 0.747 | 0.746 | 0.734 | 0.678 |

Table 4: **Correlation between $\theta$ 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.

rate to most of their customers and another one to do the opposite.

Our preferred interpretation of $\theta$ has been that of the cost-efficient fraction of FRM 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 and that banks' effort to issue a fraction of FRMs close to their $\theta$ can be read as the provision of distorted advice. Such interpretation is consistent with both several anecdotes on the behavior of financial intermediaries and the more formal evidence provided by Foa et al. (2015). Here, we exploit our estimates of the bank types to provide additional indication that our distorted advice narrative is indeed supported in the data.

If banks are opportunistically adjusting the "ideal" fraction of FRM they want to issue to reflect their convenience, their type $\theta$ should be a function of 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 $\theta$'s belonging to branches of the same bank in a given quarter to obtain $\theta_{it}$, the average cost-efficient share of mortgages for bank $i$ in quarter $t$. We regress the $\theta_{it}$ on the bank bond spread, the difference between the rate of fixed and floating bonds issued by the bank. We focus on this particular measure because it varies often and it is outside the control of the bank unlike, for instace, the decision to securitize or the structure of liabilities which the bank can adjust, perhaps with some delay.

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. However, the relationship is not significant when we look at our entire sample of banks. This is to be expected: 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. Therefore, in the other columns of Table 4 we repeat the exercise focusing on smaller samples 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 stays negative but it is now statistically significant; its point estimate grows in absolute value when we focus on banks below the median, which should be even more reliant on the bond market to secure financing. In the final subsample we examine (banks in the bottom quartile of the distribution), the correlation is the most negative. However, it is not significant most likely because we are now obtaining our estimates from a relatively small sample.

These results bring our exercise full circle. We structurally estimated bank types based on a model where banks were giving distorted advice to match needs arising from shifts in their supply factors. We now showed that such bank types do indeed respond to variation in the supply conditions faced by the banks. We take this as evidence that our story of distorted finacial advice, as opposed to alternative interpretations such as divergence across banks on expectations about the economy, finds support in the data.

# 6 Counterfactual Experiments

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

To study the impact of different policies, we assume that each of the mortgages in our sample was taken by a different household and take as many draws from the distribution of the residual heterogeneity parameter $\delta$ as mortgages in our data. This delivers a set of simulated households we can use to quantify shifts in welfare before and after policy changes. As a welfare measure we use 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. Recall that $\underline{s}_{ht}$ and $\underline{r}_{ht}$ denote respectively the minimum ARM-EURIBOR and

| | Limiting Advice | Undistorted Advice | Financial Literacy |
|---|---|---|---|
| All | -738 | 1183 | 620 |
| Sophisticated | -71 | 413 | 217 |
| Naive | -2030 | 2673 | 1403 |
| Searchers | -515 | 687 | 587 |
| Non-Searchers | -743 | 1193 | 621 |

Table 5: **Summary of Counterfactual Exercises**

**Notes:** Welfare effects are reported as changes in the certainty equivalent in euros per household per year.

FRM-EURIBOR spreads available to household $h$. Then for household $h$, the certainty equivalents from taking the ARM and FRM are given by

$$CE(\underline{r}_{ht}) = -\frac{1}{\gamma}\log(\mathbb{E}[\exp(-\gamma y)]) - H(1 + \underline{r}_{ht} + r_t + \tfrac{1}{2}\gamma H\sigma_\pi^2),$$
$$CE(\underline{s}_{ht}) = -\frac{1}{\gamma}\log(\mathbb{E}[\exp(-\gamma y)]) - H(1 + \underline{s}_{ht} + r_t + \tfrac{1}{2}\gamma H\sigma_\varepsilon^2).$$

We use the median size of the mortgage in our sample (125,000 euros) for $H$ and compute the change in the certainty equivalent for every household as follows. If the household switches from ARM with $\underline{s}_{ht}$ to ARM with $\tilde{\underline{s}}_{ht}$, or from FRM with $\underline{r}_{ht}$ to FRM with $\tilde{\underline{r}}_{ht}$, then the change in the certainty equivalent equals $H(\underline{s}_{ht} - \tilde{\underline{s}}_{ht})$ and $H(\underline{r}_{ht} - \tilde{\underline{r}}_{ht})$, respectively. If the household switches from the ARM with $\underline{s}_{ht}$ to FRM with $\tilde{\underline{r}}_{ht}$ or from the FRM with $\underline{r}_{ht}$ to ARM with $\tilde{\underline{s}}_{ht}$, then the change in the certainty equivalent equals $H(\underline{s}_{ht} + \delta - \tilde{\underline{r}}_{ht})$ and $H(\underline{r}_{ht} - \tilde{\underline{s}}_{ht} - \delta)$, respectively.

## 6.1 Limiting Distorted Advice

The first counterfactual exercise entails reducing the ability of banks to provide advice to their customers.[14] Whereas in the baseline model, the bank could influence all of its naive customers, we now assume that it can only provide advice to half of them. Formally, we assume that $\omega_{it}$ 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 customers search, nor their decision rules: sophisticated borrowers will follow the spread rule; advised naive

[14] As 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, because it is undistorted. In our case, the welfare effects are ex-ante ambiguous.

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. The experiment could be interpreted as the regulator that monitors more closely banks, but focuses only on the largest branches, thus, limiting, but not fully eliminating the scope for advice. An alternative interpretation is that the advent of online banking leads to more mortgages being issued online, where the scope for manipulative advice is limited due to the absence of human interaction with clients.

The overall effect of limiting advice is a loss of 738 euros per household per year over the entire course of the mortgage. This is around 16.7% 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 2,030 euros per capita per year compared to the unrestricted advice scenario); but sophisticated customers are worse off too by 71 euros per year.

To illustrate the reason why restricting advice is costly we further decompose its effect on the population of naive. First, we have naive households whose $\delta$ would suggest taking an ARM. If left on their own, they will take a FRM. The fact that a recommendation from their bank can steer them towards an ARM is hugely beneficial for these households who save 6,957 euros per year by avoiding the product which is typically more expensive and that they should not value more given their preferences. 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 them a loss of 2,377 euros per year. Given our estimate of the distribution of $\delta$, the number of households in the first group exceeds that of the households in the second group. Hence, advice turns out to be valuable on average and banning it delivers a welfare loss. The gain for naive households from picking the optimal type of mortgage is comparable to the figures reported in Campbell and Cocco (2003).

The conclusion on the effect of banning advice depends on the assumption we make on the default behavior of the naive households when they are not advised. In our baseline model, we posited that they make the choice on their own and therefore choose a FRM. However, if they tried to substitute for the bank advice, for instance by asking friends, the picture would change. To capture this, we have simulated the same experiment on advice restriction but assuming that naive households who do not receive any advice choose between ARM and FRM by flipping a (fair) coin. This tweak 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 gain of 145 euros per household per year.

## 6.2 Undistorted Advice

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 the sophisticated households. In this scenario, every household takes the "right" mortgage and the welfare gains are very large: 1,183 euros per capita per year. As usual, naive households benefit the most gaining 2,673 euros per year each; sophisticated households enjoy a gain of 413 euros.

Whereas the effect for naive households comes mostly from them making better choices, the gains for sophisticated households are entirely due to the "general equilibrium" channel through the adjustment of optimal spreads by banks. In the case we are examining, the impossibility to distort advice raises a particularly pressing concern for banks with higher propensity to issue FRMs (high $\theta_{it}$). 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 will take a FRM depends on the distribution of $\delta$ 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 goal. This affects both sophisticated and naive households with high values of $\delta$ who are paying less for their fixed rate mortgages.

It is useful to point out 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 choose the mortgage type, they still behave as naive when searching for the bank where to take the mortgage. Namely, if they are searchers they still look for the bank offering the lowest FRM rate even though their $\delta$ implies that they should take an adjustable one. However, due to the low fraction of searchers in our data, the additional welfare gains if we were to make all households sophisticated in both decision stages would not be very large.

## 6.3 Financial Literacy Campaign

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 searching for a mortgage in the general population. 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 620 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 1,403 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 289 euros per year; the latter 217 euros. The mechanism is analogous to that described for the undistorted advice experiment: the reduction in $\mu$ makes selling FRMs harder and forces high $\theta_{it}$ banks to price more competitively to the benefit of customers buying fixed rate mortgages.

Repeated in a context much more competitive than the Italian mortgage market, the financial literacy campaign delivers further interesting insights. If we halve the share of naive households (from 35% to 17%) in an economy where the share of searchers ($\psi$) is as high as 70% we obtain an average yearly gain of 277 euros per customer. The welfare gains are about one-fourth of those estimated when $\psi$ is at its baseline value because the possibility of searching mitigates the negative effects of the distortion in advice. In fact, there is still a cost due to the fact that households take the wrong type of mortgage for them, but at least most of them will have access to the least expensive option. This is particularly salient for low $\delta$ naive households who are taking an FRM: the possibility of searching limits the extent to which they overpay to insure agains interest rate risk.

The most interesting result of this exercise, however, comes when looking at the decomposition of the gains between naive and sophisticated. The gain for the naive households is 846 euros per year; this is an average between the gains of the naive who become sophisticated (whose gains are more substantial) and those who remain naive. The sophisticated households instead experience a loss of 16 euros per capita per year. In the baseline model a bank setting the lowest spread was able to attract all the naive searchers (who are many in this simulations) and naive households are useful to have in the customer base because they can be steered and make it easier for a bank to exactly meet its desired fraction of originated fixed rate. Once the number of naive decreases, it makes it less valuable to issue FRMs at the best rate causing the left tail of the distribution of spreads to shift to the right. This hurts sophisticated and naive searchers taking fixed rates.

# 7 Conclusion

The goal of this paper was twofold: estimate the relevance of distorted financial advice and 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, and because it provides support to a large theoretical literature on expert advice which stands on the premise that some of the agents in the economy are susceptible to suggestions coming from third parties. In terms of the welfare relevance of advice distortion, a battery 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 may 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.

# A Appendix

## A.1 Evidence of Financial Literacy

In this appendix we present some evidence on the level of financial literacy among Italian households and show that they not only suggest a prevalence of unsophisticated households, which provides scope for banks to distort advice, but also reflect differences in the behavior of financially literated and illitterated households which is broadly consistent with some of our key modeling assumptions.

The evidence relies on the 2006 wave of SHIW (Survey of Households Income and Wealth), a biannual survey of a representative sample of Italian households run by the Bank of Italy. Half of the interviewees in 2006 (3,992 households) were administered a section of the questionnaire meant to elicit financial capabilities/literacy using a set of questions following the standards of the literature measuring financial literacy (e.g., Van Rooij et al. (2011),OECD (2016)). The section consisted of six questions testing the ability to recognize the balance of a checking account statement, to compare the returns of two mutual funds, and to understand the difference between real and nominal interest, the concept of compound interest, the wealth consequence of stock

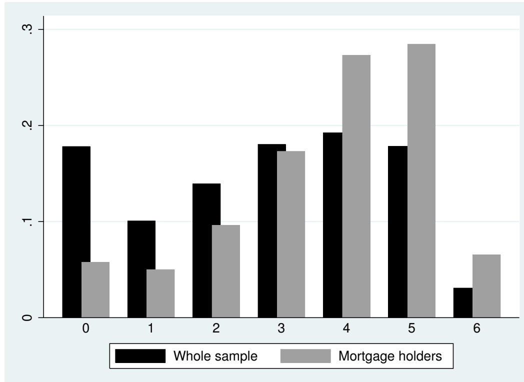



Figure 6: **Distribution of the sophistication index**

**Notes:** The SSI 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.

prices fluctuations, and the properties of fixed and adjustable rates. For each question, four options are offered: only one of them is correct; two are incorrect and the fourth option is "I Do not know", allowing the interviewee to profess his cluelessness about the topic.[15]

We construct a summary index of sophistication (SSI) by counting the number of correct answers given by an individual. The index would then range from zero (least financially literate households) to six (most sophisticated). In Figure 6, we shows the distribution of the Summary Sophistication Index among those who have a mortgage outstanding (information about mortgages and other forms of debt is collected in anther section of SHIW). No one answers correctly all the questions and 27.5% of the interviewees does not do better than two correct answers out of six; the mean and median number of right answers is 3. Compared to the distribution of the index for the whole sample, mortgage holders show higher sophistication (the average number or correct answers in the whole sample is 2.3).

Figure 7 uses the second indicator of sophistication that provides information on peoples ability to understand the properties of FRM and ARM. It shows the distribution of the answers to the question : "*Which of the following mortgage types allows you to know since the very beginning the maximum amount that you will paying annually and for how many years before you extinguish the mortgage?*" The answers offered are: (1) Adjustable rate mortgage ; (2) Fixed rate mortgage; (3) Adjustable rate mortgage with constant annual payment; and (4) I do not know. Whereas 70% of the interviewees holding a mortgage provides the right answer, nearly one third of the interviewees are either clueless or provide a wrong answer. However, mortgage

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

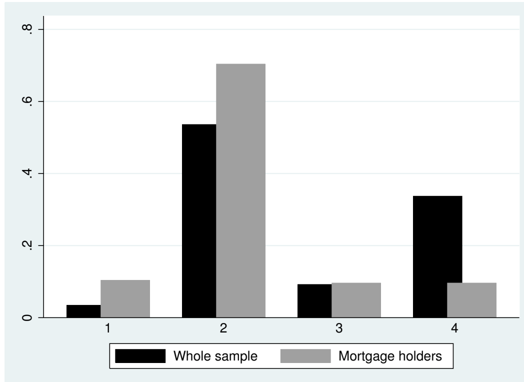



Figure 7: **Understanding of mortgage characteristics**

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

holders are more likely to correctly identify the type of mortgage insuring against instalments fluctuations than the general population.

Finally, Table 6 provides some evidence in support of our assumption that unsophisticated borrowers tend to opt for fixed rate mortgages as they have troubles in figuring out inflation and interest rate volatility and perceive FRM as less ambiguous than ARM. We exploit 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 by a lower amount; 3) No, I could by 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 (1 or 3); and *Clueless* those who cannot answer (answer 4). We tabulate the type of mortgage that households in these different groups with the caveat that SHIW reports the mortgage chosen by the household (i.e. picked after the bank provided advice) and not what it wanted to buy before advice was provided (which is the 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 the clueless.

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

Table 6: **Sophistication and mortgage choice**

**Notes:** The classification in the table is based on the answers to the following question: *"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?"* Answers: 1: Yes I would be able; 2: No, I could only by a lower amount; 3: No, I could by 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 (1 or 3); and *Clueless* those who cannot answer (answer 4). The sample consists the set of SHIW interviewees in the 2006 wave who were administered the section on financial literacy and reported to have a mortgage.

## A.2 Two Microfoundations for Naive Households' Behavior

In this subsecion, we offer two models that microfound the behavior of naive households. In both models, naive household's utility from FRMs is similar to that of sophisticated households, however, their utility from ARMs is much lower because they either suffer from an anxiety in the money doctors framework, or face Knightian uncertainty about real rates in the ambiguity aversion framework.

**Money Doctors Framework** The utility from FRM of both sophisticated and naive households is given by $\mathbb{E}[y-(1+\underline{r}_{ht}-\pi)H]-\gamma\mathbb{V}[y-(1+\underline{r}_{ht}-\pi)H]$. The utility from ARM of sophisticated households is given by $\mathbb{E}[y-(1+\underline{r}_{ht}-\pi)H]-\gamma\mathbb{V}[y-(1+\underline{r}_{ht}-\pi)H]$ and so, their preference over the type of mortgage is given by the spread rule (3.2). The utility from ARM of naive households is given by $\mathbb{E}[y-(1+\underline{r}_{ht}-\pi)H]-\bar{\gamma}\mathbb{V}[y-(1+\underline{r}_{ht}-\pi)H]$, where $\bar{\gamma}$ is some large number that reflects naive households' anxiety about investing in the less familiar product. As a result, naive households when they are on their own only search for FRMs in the market, and they rule out ARMs altogether in their search process. Banks can aleviate the anxiety (lower $\bar{\gamma}$) from taking ARMs, and this way can steer naive households toward taking ARM.

**Ambiguity Aversion Framework** The preferences of sophisticated households are as in the baseline model. Naive households have CARA utility with absolute risk aversion $\gamma$. Naive households have know the volatility of inflation $\sigma_\pi^2$ (e.g., due to the fact that they observe the dynamics of prices in their everyday life), but face Knightian uncertainty with respect to the distribution of $\sigma_\varepsilon^2$ at the search stage. Specifically, they believe that the distribution of $\sigma_\varepsilon^2$ is chosen by the adversary Nature to minimize their expected payoff. This captures the ambiguity aversion of naive households in the sense of Gilboa and Schmeidler (1989). The assumption that naive households face Knightian uncertainty captures their lack of knowledge about the evolution of real rates in the future. (In subsection $A.1$ of this Appendix, we provide survey evidence that households have trouble even understanding the concept of real rates). Then the utility from FRM is given by $\mathbb{E}_\pi[-\exp(-\gamma(y-(1+\underline{r}_{ht}-\pi)H))]$ as for the sophisticated households. However, the utility from ARM is given by

$$\min_{\sigma_\varepsilon^2} \mathbb{E}_\varepsilon[-\exp(-\gamma(y-(1+\underline{s}_{ht}+r_t+\varepsilon)H))] = -\infty.$$

As a result, naive households only search for FRMs in the market, and they rule out ARMs altogether. The banks' advice is in the form of the upper bound on $\sigma_\varepsilon^2$. We assume that naive households believe that this information is undistorted, i.e., they ignore the potential conflict of interest of banks. This allows banks to steer naive households toward ARMs.

## A.3 Optimal Spread Setting

We derive an explicit formula for (3.6) that we use in the estimation. We distinguish two cases depending on whether bank $i$ has the lowest ARM-EURIBOR spread on the market ($s_{it} < \underline{s}_{-it}$) or not ($s_{it} > \underline{s}_{-it}$). (We abstract from ties as they are not observed in our data). We will use super-index $a$ for the former case and super-index $A$ for the latter. After banks post spreads, bank $i$ has either the lowest FRM rate ($r_{it} < \underline{r}_{-it}$) or not ($r_{it} > \underline{r}_{-it}$). We will use super-index $f$ for the former case and super-index $F$ for the latter.

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

$$m_{it}^{AF} V^{AF}(\phi_{it}|\theta_{it}) G(\phi_{it}+s_{it}|S_t) + m_{it}^{Af} V^{Af}(\phi_{it}|\theta_{it})(1-G(\phi_{it}+s_{it}|S_t))), \tag{A.1}$$

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

$$m_{it}^{aF} V^{aF}(\phi_{it}|\theta_{it}) G(\phi_{it}+s_{it}|S_t) + m_{it}^{af} V^{af}(\phi_{it}|\theta_{it})(1-G(\phi_{it}+s_{it}|S_t))). \tag{A.2}$$

Then $\phi_{it}$ is determined by maximizing either $(A.1)$ or $(A.2)$ depending on whether $s_{it} > \underline{s}_{-it}$ or $s_{it} < \underline{s}_{-it}$, resp. To complete the characterization of the optimal rate setting, we determine functions $m_{it}, \underline{x}_{it}$, and $\overline{x}_{it}$ for different cases, which we do next. Let $\kappa(\phi) = 1 - \Phi\left(\frac{\phi-\mu_\delta}{\sigma_\delta}\right)$.

1. Bank $i$ does not have the lowest ARM-EURIBOR spread on the market ($s_{it} > \underline{s}_{-it}$)

    (a) If $r_{it} > \underline{r}_{-it}$, then bank $i$ keeps only non-searching households initially assigned to it. The mass of them is

    $$m_{it}^{AF} = (1-\psi)p_{it}. \tag{A.3}$$

    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,

$$\underline{x}_{it}^{AF} = (1-\mu)\kappa(\phi_{it}), \tag{A.4}$$

$$\overline{x}_{it}^{AF} = (1-\mu)\kappa(\phi_{it}) + \mu. \tag{A.5}$$

(b) If $r_{it} < \underline{r}_{-it}$, then bank $i$ in addition to its non-searching customers attracts all naive searchers and sophisticated searchers that prefer to take FRM in the market. The mass of the former is $\psi\mu$, the mass of the latter is $\psi(1-\mu)\kappa(\phi_t)$ where $\phi_t = \underline{r}_t - (\underline{s}_t + r_t)$. Observe that when $r_{it} < \underline{r}_{-it}$,

$$\phi_t = r_{it} - \min_i\{s_{it} + r_t\} = \phi_{it} + s_{it} - \min_i s_{it}.$$

Then the total mass of bank $i$'s customers equals

$$m_{it}^{Af} = (1-\psi)p_{it} + \psi\mu + \psi(1-\mu)\kappa(\phi_t) \tag{A.6}$$

Sophistictiated non-searchers take FRM with probability $\kappa(\phi_{it})$, while all sophisticated searchers that bank $i$ attracts take FRM. Thus,

$$\underline{x}_{it}^{Af} = \frac{(1-\psi)p_{it}(1-\mu)\kappa(\phi_{it}) + \psi(1-\mu)\kappa(\phi_t)}{(1-\psi)p_{it} + \psi\mu + \psi(1-\mu)\kappa(\phi_t)}. \tag{A.7}$$

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,

$$\overline{x}_{it}^{Af} = \underline{x}_{it}^{Af} + \frac{\mu((1-\psi)p_{it}+\psi)}{(1-\psi)p_{it} + \psi\mu + \psi(1-\mu)\kappa(\phi_t)}. \tag{A.8}$$

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

(a) If $r_{it} > \underline{r}_{-it}$, then bank $i$ in addition to its non-searching customers attracts all sophisticated searchers who prefer to take ARM in the market. They constitute a fraction $1-\kappa(\phi_t)$ of sophisticated searchers where

$$\begin{aligned}\phi_t &= \underline{r}_t - (\underline{s}_t + r_t)\\ &= \underline{r}_t - (s_{it} + r_t)\\ &= \min_i\{\phi_{it} + s_{it}\} - s_{it}.\end{aligned}$$

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. Finally,

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

(b) If $r_{it} < \underline{r}_{-it}$, then bank $i$ in addition to its non-searching customers attracts all searchers. The total mass of bank $i$'s customers is then

$$m_{it}^{af} = (1-\psi)p_{it} + \psi,$$

and

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

## A.4 Data Cleaning

The data on the amount (in Euros) of the deposits held by each bank in a given market are missing for some bank-quarter-province triplet. 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 provinces where banks missing deposit data were either a major player, issuing more than 15% of the mortgages or where the market share held in the mortgage market by banks with missing data on the amount of deposits exceded 30%.

## A.5 Alternative Definition of Best Rate in the Market

We compute the rates for fixed and adjustable mortgages posted by each bank in each market-quarter as the average of the rates of the underlying mortgages issued. Although there is little scope for bargaining on rates in the Italian market, it may still be the case that some mortgages are issued at special conditions. This could affect the average rate for banks that issued a low number of mortgages in the period. The issue could prove particularly problematic if it affected the determination of the bank posting the lowest fixed or adjustable rate in the market. We therefore performed a robustness check exploiting a way to determine the best rate in a market which takes into account the possible error in the average rates.

For every average rate (fixed or adjustable) we have an associated standard deviation. We use it to construct a one-sided t-test where the null hypothesis is that a certain average rate is equal to the best average rate in the market versus the alternative that it is strictly higher than the minimum rate in the market. We then determine that all the banks for which we cannot reject the null at 1% confidence are tied as issuers of the best rate. We modify accordingly the likelihood function so that the extra customers attracted by the bank issuing the best fixed or adjustable rate are spread equally among all the banks with rates not statistically different from the minimum rate in the market.

# References


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 (forthcoming): "Understanding the advice of commissions-motivated agents: Evidence from the Indian life insurance market," *Review of Economics and Statistics*.

Athey, S. (2001): "Single crossing properties and the existence of pure strategy equilibria in games of incomplete information," *Econometrica*, 69, 861–889.

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.

Beltratti, A., M. T. Benetton, and A. Gavazza (2016): "The Role of Prepayment Penalties in Mortgage Loans," Working paper.

Bhattacharya, U., A. Hackethal, S. Kaesler, B. Loos, and S. Meyer (2012): "Is unbiased financial advice to retail investors sufficient? Answers from a large field study," *Review of Financial Studies*, 975–1032.

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.

CARLIN, B. I. AND G. MANSO (2011): "Obfuscation, learning, and the evolution of investor sophistication," *Review of Financial Studies*, 24, 754–785.

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.

EGAN, M. (2015): "Brokers vs. Retail Investors," Working paper.

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. GUISO, 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*.

GENNAIOLI, N., A. SHLEIFER, AND R. VISHNY (2015): "Money doctors," *Journal of Finance*, 70, 91–114.

GILBOA, I. AND D. SCHMEIDLER (1989): "Maxmin expected utility with non-unique prior," *Journal of Mathematical Economics*, 18, 141–153.

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. (2010): "Misselling (financial) products: The limits for internal compliance," *Economics Letters*, 106, 35–37.

Inderst, R. and M. Ottaviani (2012a): "Competition through Commissions and Kickbacks," *American Economic Review*, 102, 780–809.

——— (2012b): "Financial advice," *Journal of Economic Literature*, 50, 494–512.

——— (2012c): "How (not) to pay for advice: A framework for consumer financial protection," *Journal of Financial Economics*, 105, 393–411.

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.

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.

Ru, H. and A. Schoar (2015): "Do credit card companies screen for behavioral biases?" NBER working paper n.22360.

Shapira, Z. and I. Venezia (2001): "Patterns of behavior of professionally managed and independent investors," *Journal of Banking & Finance*, 25, 1573–1587.

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.