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

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Abstract

Many households lack the sophistication required to make complex financial decision, which exposes them to the risk of being exploited when seeking advice from intermediares. We set up a structural model of financial advice, in which banks aim at issuing their ideal mix of fixed and adjustable rate mortgages and can achieve such goal by setting rates and providing advice to their clientele. "Sophisticated" households know the mortgage type best for them, whereas "naive" are susceptible to bank's advice. Using the data on the universe of Italian mortgages, we recover the primitives of the model and quantify the welfare implications of distorted financial advice. The cost of the distortion is equivalent to increasing the annual mortgage payment by 1,177 euros. Losses are bigger for the naive, but sophisticated households suffer as well. However, since even distorted advice conveys information, banning advice altogether is not welfare improving and would instead result in a loss of 736 euros per year on average. A financial literacy campaign is beneficial for all, though in different degrees.

JEL Classification: G21, D18, D12

Keywords: distorted financial advice, mortgage market, consumer protection

1 Introduction

Households frequently seek expert advice when they lack the knowledge or sophistication to determine what financial product is best for their needs.[1] However, advisors may have incentives to distort their recommendations in a way that serves their own needs rather than those of their customers. This is especially likely when households solicit advice from the seller of the financial product itself. We call financial advice "distorted" when it is provided in the interest of advisors, which need not be fully aligned with the customer's interest. The goal of this paper is to assess the prominence of this phenomenon and quantify its impact on households' welfare.

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.[2] Randomized field experiments (Anagol et al. (2017); 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 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

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

[2] 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.

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 in which a large fraction of the population participate in all advanced economies and a certain degree of sophistication is required from mortgage takers to appreciate the pros and cons of different products available. Therefore, expert opinion is potentially valuable. Furthermore, both banks and brokers have interest in taking advantage of customers' lack of knowledge and experience (Woodward and Hall (2012)). Our data consist of administrative records on the universe of mortgages originated between 2005 and 2008 by a sample of 175 Italian banks covering 90 percent of the market. In addition to information on the terms of the loans and characteristics of the borrowers, the data identifies the bank originating the mortgage, allowing us to match rich data on the balance sheet of the originator. On top of the high quality of the data we can access, studying the Italian mortgage market provides important advantages due to the institutional characteristics which make it well suited to the purpose of this study. Namely, there are only two main products available to customers (plain vanilla fixed and adjustable rate mortgages); advice is usually provided by the banks issuing the mortgages (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 spread between fixed and adjustable contracts. Naive borrowers lack sophistication to compare fixed and adjustable rate mortgages. Instead, they can get

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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 then provide advice to the customers they manage to attract.

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 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, we obtain a welfare loss of 736 euros per household per year. We find that banning advice, while very costly for the naive borrowers (2,025 euros per year) is also costly for the sophisticated ones who end up paying 71 euros more per year. The second counterfactual measures the costs of distorted advice; if banks could be forced to provide only undistorted advice the welfare gain would be 1,177 euros. Even in this case, both naive and sophisticated households suffer a welfare loss. Finally, we also study the consumer welfare gains of a financial education campaign that halves the fraction of naive households and find them to be substantial. Not surprisingly, the lion's share of the welfare gains accrue to households who were naive and become sophisticated thanks to the campaign. However, because the policy affects equilibrium spreads, it benefits also the naive households not directly treated by the financial education campaign as well as, to a smaller extent, sophisticated households.

Related Literature 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, 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). Besides the interest on credit markets, we are linked to these studies by a common methodological approach which follows a growing literature applying tools developed in Industrial Organization to the analysis of financial markets (Aguirregabiria et al. (2016); Cassola et al. (2013); Egan et al. (2017)). Finally, we contribute to the literature on financial advice games that rely on the presence of both sophisticated and naive investors (Ottaviani and Squintani (2006); Kartik et al. (2007)).[3] Whereas we do not aim at making a theoretical contribution, our estimates point to a large fraction of households with limited financial literacy engaging in high stakes transactions vindicating the tenet of these models.

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

2 Setting the Stage: Features of the Italian Mortgage Market and Data

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 key features of the Italian mortgage market and argue that, compared to other markets (most notably the US market), its simple structure provides a suitable environment for empirically studying distorted advice in financial markets. Second, we stress how the institutional characteristics of the Italian mortgage market inform our choices in the construction of the model we will present in Section 3.

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[3]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.

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.[4] Regulation sets the maximum loan to value ratio at 80% but can be 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, unlike what it is customary in the US (Fuster and Vickery (2015)), Italian 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 reflecting the cost of hedging or even the difficulty of accessing 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

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

that they have both opportunity and motive to distort 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 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.[5] 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. A 2007 reform (the "Bersani law") regulated re-negotiation and pre-payment fees setting them at a mandated

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[5]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

level common to all banks, which thus cannot compete on this margin. Re-negotiation fees were abolished by the reform 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[6], 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 do 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 an excellent 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

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[6]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.

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.

adopt as our definition of the consumer market. Since we do not model the choice of the maturity of the mortgage, for our analysis we focus on mortgages homogeneous under this dimension, with maturity between 25 and 30 years. We also restrict attention to only plain vanilla ARM or FRM mortgages (excluding partially adjustable rate mortgages, loans to sole proprietorships, etc.). These mortgages represent the overwhelming majority of the mortgages originated during our sample. The final dataset includes information from nearly 1,000,000 mortgages.

We merge this information with data from SLIR on the average rate for the FRM and ARM mortgages originated in each bank-quarter-province triplet. A subset of 175 banks reports interest rate data to SLIR but this includes all the main banking groups active in Italy covering more than 90 percent of the market. Some of our markets are quite small and only a handful of mortgages are originated in a quarter; this results in missing data on the interest rate since the rate is reported only by banks that actually issued a mortgage in the quarter. To alleviate this problem, we calculate interest rates for each bank-quarter as averages at the regional level, rather than at the province one.[7] This choice is unlikely to introduce significant distortion in our estimation of the supply side decisions as the bulk of the competitors faced by a bank is the same in all the provinces of a given region (although it can change significantly across regions due to the importance of regional banks) and there is evidence that the pricing is indeed set at the regional level: in 25% of the observations a bank sets the exact same rate in all the provinces within a region and, conditional on observing some difference between rates in provinces of the same region, the median deviation from the regional mean is 12 basis points for ARMs and 8 basis points for FRMs.

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

3 Model

In this section, we capture key aspects of the Italian mortgage market described in the previous section in a theoretical model of households' mortgage choice and banks' choice

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

of rate and advice policies. As discussed in Section 2, banks set rates at the regional level, while households search at the level of province. For simplicity of notation, we present the model for a single market where the definition of the region and the province coincide, but we take the distinction between the two 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 present in the market. The timeline is as follows:

1. In the beginning of quarter t, banks simultaneously set rates.

2. Each household h chooses the bank from which it takes the mortgage. We say that a household becomes a customer of the bank it picked.

3. Banks optimally provide advice to their customers about the mortgage type.

4. Households choose the mortgage type.

We next describe households' and banks' choices.

3.1 Households

Households are heterogenous in several dimensions. First, a fraction μ of households is *naive* and a fraction $1 - \mu$ is *sophisticated.* This is the key dimension of household heterogeneity given the objective of our study: naive households are susceptible to the bank's advice on the mortgage type they should pick, whereas sophisticated households make the choice based on their own knowledge and do not listen to the advice provided by the bank.

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

Finally, households differ in the size of their mortgage H, the degree of risk aversion γ, their beliefs about the volatility of real interest rate shocks σ_ε^2 and inflation shocks σ_π^2, and their future (stochastic) income y. For ease of notation, we omit indexing these characteristics by h, although they vary across households. Our data does not allow us to separately identify the distribution of $\gamma, H, \sigma_\varepsilon^2$, and σ_π^2. Instead, we can identify the distribution of a function of these parameters

$$\delta \equiv H\gamma(\sigma_\varepsilon^2 - \sigma_\pi^2), \tag{3.1}$$

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

Mortgage Choice Each household finances the home purchase with a mortgage. We focus on the households' choice of the bank and the mortgage type, but abstract from the decision to buy versus rent, the choice of the house size and the mortgage size.

The choice of the bank and the mortgage type differs between naive and sophisticated households. Sophisticated households choose considering the trade-off between interest rate and inflation risk embedded in the ARM-FRM decision. By taking an ARM, the household hedges against inflation risk, as interest payments adjust with inflation, but is exposed to interest rate risk. The reverse is true, when it takes a FRM.

We model this trade-off according to the following setup, introduced in Koijen et al. (2009). Households take a mortgage whose principal and interests are paid after Δ quarters, without 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 benchmark rate 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 the payment at date $t + \Delta$ is

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

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

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

where r_{it} is the FRM rate set by bank i at date t.

Sophisticated households have mean-variance utility function with the degree of risk aversion γ, i.e., their utility from the stochastic future wealth W equals $\mathbb{E}[W] - \gamma\mathbb{V}[W]$. Given this setting, it is optimal for households to follow what Koijen et al. (2009) call the *spread rule* in choosing the mortgage type. Let r_t^h and s_t^h be the lowest FRM rate and the lowest ARM-EURIBOR spreads, respectively, available to household h. If the household is un-attached to the home bank, then its choice set contains all rates in the market and r_t^h and s_t^h will be the lowest fixed and adjustable rates in the market (i.e., $r_t^h = \min_{i \in \{1,...,N\}} r_{it}$ and $s_t^h = \min_{i \in \{1,...,N\}} s_{it}$). If the household is attached to the home bank, then its choice contains only rates set by its home bank, and r_t^h and s_t^h equal to r_{it} and s_{it} in the home bank i of the household. The sophisticated household prefers an ARM if and only if

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\begin{aligned}
\mathbb{E}\left[y - (1 + s_t^h + r_t + \varepsilon)H\right] &- \gamma\mathbb{V}\left[y - (1 + s_t^h + r_t + \varepsilon)H\right] \\
&\geq \mathbb{E}\left[y - (1 + r_t^h - \pi)H\right] - \gamma\mathbb{V}\left[y - (1 + r_t^h - \pi)H\right], \quad (3.2)
\end{aligned}
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Recalling (3.1), we can rewrite (3.2) as

$$
r_t^h - (s_t^h + r_t) \geq \delta. \tag{3.3}
$$

The spread rule implies that the households chooses ARM if and only if the spread they face (i.e., the left-hand side of (3.3)) is above the cut-off δ. Thus, (3.1) and (3.3) imply that 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.

The behavior of naive households departs from the spread rule. We follow the "money doctors" framework of Gennaioli et al. (2015) to model their choice assuming that before receiving advice, naive households prefer FRM, which is a more familiar option with a pre-fixed installment plan, to a more complex option, ARM. Hence, naive un-attached households always become customers of the bank with the lowest FRM rate, ignoring ARM rates. Naive attached households become customers of their home bank. After they become customers of a bank, however, both un-attached and attached naive households will follow the bank's advice in their mortgage choice. Thus, naive households could be "convinced" to take a mortgage type different from the one that they intended to take before receiving the advice. Household choices are summarized in Table 2.

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

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

Interpretation and Discussion of Assumptions Here we comment and motivate our assumptions about the behavior of naive borrowers and our reduced form model of market frictions.

Our assumption that naive households purchase fixed rates in the absence of advice can be microfounded using the "money doctors" model by Gennaioli et al. (2015), as we show in Appendix A.1. In Gennaioli et al. (2015), households choose between two investment opportunities: the deposit, which is a more familiar option, and the stock market, which is a more rewarding, but more complex option that requires certain sophistication and skill. Investors experience anxiety when investing in more complex products, and may choose to stay out of the market. This is consistent with the low participation to the stock market by less sophisticated households (Calvet et al. (2007)). In this situation, financial intermediaries can provide information about more rewarding options, acting as "money doctors" in reducing the investors' anxiety. There is a parallel between retail investment choice and mortgage ones. In our model, FRM, represents the more familiar and easy to understand option; whereas ARM is similar to the stock market investment in that it is more complex and requires sophistication in order to acquire and process information about future rates and associated risks. [8] In absence of advice, naive households suffer anxiety when taking the ARM on their own and, therefore, prefer taking FRMs. However, banks can alleviate the households' anxiety and convince them to take ARM. Unlike in Gennaioli et al. (2015), in our model intermediaries can manipulate naive customers into taking ARMs, even when FRM is better for them. (See Appendix A.1 for details).

As we mentioned, the attached/un-attached status captures different market frictions that prevent households from taking a mortgage at the best market terms. These frictions

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[8]This is consistent with the empirical evidence that households taking ARMs tend to underestimate or not fully understand the terms of the ARMs (see Bucks and Pence (2008)). Appendix A.2 reports the results of surveys on financial literacy of Italian households indicating that there is a significant fraction of mortgage takers failing to answer basic questions measuring their financial literacy, and that households with outstanding FRMs are those less financially literate.

are a general feature of the mortgage market (Woodward and Hall (2012); Deuflhard (2016); Ater and Landsman (forthcoming)), and are present in Italy as documented by prior literature (Barone et al. (2011)) and witnessed by the large dispersion in rates observed in our data (see Figure 7 in Appendix $A.7$). Our data are, however, not rich enough to pinpoint the precise nature of the frictions preventing households to flow to the bank offering the best rates in the market. Therefore, the model is agnostic on the source of this phenomenon and instead includes a generic friction which binds for a fraction $1 - \psi$ of the households. One could interpret it as a switching cost, in which case, the home bank would be the bank where the household has its primary checking account, and for a fraction $1 - \psi$ of households the cost of switching bank is prohibitively high.[9] Alternatively, one could think of it as reflecting search frictions. In this case, the home bank is the bank from which the households starts its search and the search cost are so high for a fraction $1 - \psi$ of households that they do not search past their first inquiry, whereas a fraction ψ of households screens all rates in the market and finds the best available. If present, our estimate will reflect both.

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

3.2   Banks

We next describe bank's choice of rates and advice policy.

The central trade-off for banks in issuing mortgages is that FRMs typically earn banks

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[9]Italian banks require that in order to get a mortgage, a customer must have an account with them. Households that wish to take mortgage from a bank different from the bank where they hold their primary checking accounts have to incur switching costs (both financial and opportunity costs of time) of opening a new account, relocating funds between accounts or ensuring regular transfers between accounts, etc.

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

better margins but expose them to interest rate risk. To manage this risk, banks use two tools: rates and advice.

We capture the trade-off in the following specification of bank's profit. Let m_{it} be the mass of bank i's customers, x_{it} the fraction of FRMs issued by bank i in quarter t, and denote by $\phi_{it} \equiv r_{it} - (s_{it} + r_t)$ 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

$$\underbrace{\left(\alpha s_{it} + \phi_{it} x_{it} - \lambda (x_{it} - \theta_{it})^2 \right)}_{\text{net profit margin}} \times \underbrace{m_{it}}_{\text{customer base}} \times \underbrace{e^{-\beta r_{it}}}_{\text{penalty for high rates}} . \tag{3.4}$$

The first term reflects the net profit margin in basis points on one euro lent through mortgage. The bank earns a fraction $\alpha \in [0, 1]$ of the spread s_{it} between the ARM rate and the EURIBOR benchmark rate. This is motivated by the fact that banks themselves borrow in the interbank market at a certain spread over the EURIBOR and so, earn only a fraction of the ARM-Euribor spread. In addition to the spread between the ARM rate and the EURIBOR, the bank earns a spread ϕ_{it} on FRMs. As shown in Table 1, this spread is mostly positive in our sample reflecting the premium for the insurance against interest rate shocks.

Issuing too many FRMs, however, may cause a maturity mismatch whose costs are captured in a reduced form by the quadratic term $\lambda (x_{it} - \theta_{it})^2$. When the bank's fraction of FRMs in the mortgage portfolio equals θ_{it}, such costs are zero, and a Δ increase in the deviation of the fraction of FRMs issued by bank i from θ_{it} leads to a reduction in the profit margin by $\lambda \Delta^2$ basis points. We refer to θ_{it} as the bank i's *cost efficient fraction of FRMs*, which is the fraction of FRMs that bank i can issue without suffering maturity mismatch costs. Parameter $\lambda > 0$ reflects how severe these costs are.

The last factor $e^{-\beta r_{it}}, \beta > 0$, penalizes banks for offering very high fixed rates to their customers and captures in a reduced form the fact that excessive mortgage rates could turn away even attached customers to some outside option (e.g., renting).[11]

The timing of the game is as follows. At the beginning of quarter t, all banks observe all adjustable rates of their competitors. Each bank privately observes its θ_{it}, which are i.i.d. (across i and t) draws from a normal distribution with mean μ_θ and variance σ_θ^2 truncated from below at 0 and from above at 1. Banks simultaneously post FRM-ARM spreads ϕ_{it}. After that, all banks retain the attached households for whom they are the home bank. In addition, the bank attracts un-attached naive households if it posts the

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

lowest fixed rate, and un-attached sophisticated customers for whom one of its mortgages is the best option in the market. Given its customer base, each bank chooses its advice policy $\omega_{it} \in [0,1]$, where $1 - \omega_{it}$ represents the fraction of bank's customers that 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.

Interpretation and Discussion of Assumptions   In modelling the banks' objective, we intentionally take a reduced form approach and only capture how given the cost efficient fraction of FRMs, θ_{it}, each bank optimally uses rate setting and advice to manage interest rate risk. In particular, at this point, we are agnostic about what drives θ_{it}. For example, θ_{it} could depend on supply factors, e.g. reflect the ability of the bank to securitize loans or borrow long-term at better terms. If shifts in θ_{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. The advantage of our approach is that it allows us to retrieve an estimate of the bank's θ_{it} without imposing assumptions on its nature. Then, we will be able to use our estimates to provide evidence on which variables influence the bank's cost efficient fraction of FRMs.

The assumption that adjustable rates are determined outside of our model, and banks compete only by setting FRM-ARM spreads ϕ_{it} is motivated by the common practice of rate setting in the industry. Figure 1 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.[12] We observe a similar pattern when we average rates over all the banks in our sample.[13]

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[12]Unlike the ARM-EURIBOR spread, there is a large time series variation in the spread of FRM over 5, 10, 30 years bond benchmark rates.

[13]The nature of the rate setting for ARMs and FRMs provides another justification for holding ARM-EURIBOR spread fixed. Recent evolutions of adjustable rates are 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. This may motivate banks to avoid tinkering with adjustable rate. In contrast, this incentive is not present for fixed rates and banks can
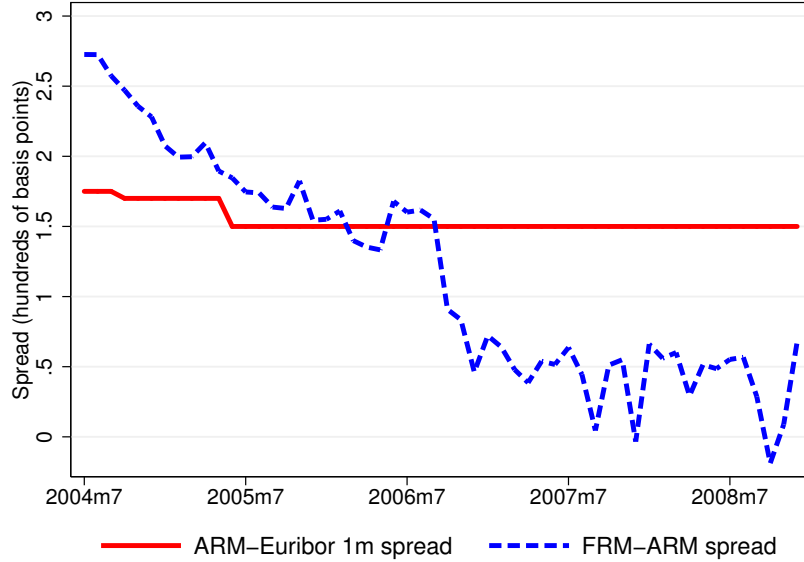
Figure 1: **Rate Spreads on a 25-year Mortgage Set by a Major Italian Bank**

3.3 Equilibrium

The solution concept is the perfect Bayesian equilibrium (PBE). We next derive explicit expressions for bank's optimality conditions.

Consider the subgame, in which bank i gives its customers advice about the type of the mortgage. Suppose that in this subgame, the ARM-EURIBOR spread is s_{it}, the FRM-ARM spread is ϕ_{it}, bank i attracts mass m_{it} of customers. Bank i advises to take the ARM a fraction $1 - \omega_{it}$ of its customers. This advice affects only the choice of naive customers, while sophisticated customers ignore the advice and choose 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 (these depend on the realization of the customer base attracted by the bank).[14] Observe that the choice of ω_{it} is equivalent to the direct choice of the fraction of FRMs issued, x_{it}, subject to the constraint that $\underline{x}_{it} \leq x_{it} \leq \overline{x}_{it}$. Hence, the bank solves

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

freely vary fixed-rates spread to attract more customers today, without worrying about the effect on future demand.

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

The optimal choice of x_{it} is given by

$$x(\phi_{it}|\theta_{it}) = \max\left\{\min\left\{\theta_{it} + \frac{\phi_{it}}{2\lambda}, \overline{x}_{it}\right\}, \underline{x}_{it}\right\}, \qquad (3.5)$$

from which we can recover the optimal advice policy:

$$\omega(\phi_{it}|\theta_{it}) = \max\left\{\min\left\{\frac{1}{\overline{x}_{it} - \underline{x}_{it}}\left(\theta_{it} + \frac{\phi_{it}}{2\lambda} - \underline{x}_{it}\right), 1\right\}, 0\right\}. \qquad (3.6)$$

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

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

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

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

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

where $G_i(\cdot|\mathbf{s}_t)$ is the distribution of $\underline{r}_{-it} = \min_{j\neq i}\{r_{jt}\}$ given $\mathbf{s}_t$ and the equilibrium rate setting strategies of other banks. Appendix $A.4$ derives a more explicit formula for (3.8) that we use in our estimation.

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

4   Identification

Our goal is to estimate the following parameters of the model: the fraction of naive households, μ, the fraction of un-attached households, ψ, the distribution of the optimal cut-off on the rate spread, δ, banks' cost efficient FRM fraction θ, and the parameters of

banks' profit function (λ, β, α).

4.1 Identification of Demand Parameters

The identification of demand parameters $w^d = (\mu, \psi, \mu_\delta, \sigma_\delta)$ exploits the differences in the reaction of sophisticated and naive as well as attached and un-attached households to the variation in the fixed-adjustable rate 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. Hence, we index all observables by the superscript d to indicate that they are at the level of aggregation we use for demand, where a market is a province. For every quarter $t = 1, \ldots, T$ and province $j = 1, \ldots, J$, our data includes

- the set of banks actively issuing mortgages in the province, $i = 1, \ldots, N_j^d$;

- the number of mortgages issued by every bank, $\mathbf{M}_{jt}^d = (M_{1jt}^d, \ldots, M_{N_j^d jt}^d)$;

- FRM rates posted by banks, $\mathbf{r}_{jt}^d = (r_{1jt}, \ldots, r_{N_j^d jt})$;

- ARM-EURIBOR spread of banks, $\mathbf{s}_{jt}^d = (s_{1jt}, \ldots, s_{N_j^d jt})$;

- banks' shares in the province depositor market, $\mathbf{p}_{jt}^d = (p_{1jt}, \ldots, p_{N_j^d jt})$.

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

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

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

Equation (4.1) consists of four terms. With probability $(1 - \psi)p_{ijt}$ a household is attached and i is its home bank. With probability $\psi\mu$ a household is un-attached and naive. Then it takes a mortgage from bank i only if $r_{ijt} = \underline{r}_{jt}$. With probability $\psi(1 - \mu)$ a household is un-attached and sophisticated. Then it takes a mortgage from bank i if

and only if bank i offers the best mortgage (type and rate) in the market. The likelihood of observing a particular realization $\mathbf{M}_{jt}^d$ is given by

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

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

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

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

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

The fraction of naive households is identified exploiting differences in the elasticity of banks market shares to the event that a bank posts the best fixed or the best adjustable rate in a market. Suppose for example that $\underline{r}_{jt} - \underline{s}_{jt} > \delta$, meaning that all sophisticated un-attached take the mortgage from the bank with the lowest ARM rate. 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 behavior of naive and

sophisticated households, we can recover μ from variation in market shares of the banks 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.

As documented by Figure 1, our sample spans a period when the FRM-ARM spread starts off as relatively high and then declines.[15] This shift provides useful variation to identify the optimal cutoff in the FRM-ARM decision for a sophisticated household (δ). Table 1 documents that our data provide ample variation over time and\or across markets in the spread between adjustable and fixed rates so that the type of mortgage preferred by sophisticated households varies. The standard deviation of the FRM-ARM spread is 0.63 with an interquartile rage of over 50 basis points.

The explanation provided above also serves as the rationale for the identification of the parameters of the optimal cutoff distribution once we allow δ to vary across households. Abundant variation in spreads faced by households (especially the variation across different banks in the same market) helps tracing the distribution of individual cutoffs. It is important to point out that, although naive households behave similarly to sophisticated households with high δ (extremely risk averse/leveraged/pessimistic about volatility of real rates), the variance of the distribution of δ is separately identified from the fraction of naive. In fact, a higher variance in δ implies that both very high and very low realizations of δ in the population are more likely. Thus, it need not necessarily lead to an increase in the share of households who prefer fixed rate mortgages. In contrast, a higher μ implies an increase in popularity of fixed rate mortgages.

4.2   Identification of Supply Parameters

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

As explained in Section 2, to estimate the supply parameters it is convenient for us to aggregate the level of observation from the province (used in the estimation of the demand

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[15]The spread portrayed in Figure 1 is constructed from data from a single, albeit large, bank. However, its evolution is broadly representative as it can be confirmed by looking at Figure 12 (page 21) in Felici et al. (2012) which plot the average FRM-ARM spread across all banks for a sample period including the years we analyze.

parameters) to the region. To denote the different level of aggregation, observables will be indexed by the superscript s.[16]

For every quarter $t = 1, \ldots, T$ and region $k = 1, \ldots, K$, our data includes

- the set of banks actively issuing FRM mortgages in the region, $i = 1, \ldots, N_k^s$;[17]

- the distribution of households taking up mortgages at each bank, $\mathbf{M}_{kt}^s = (M_{1kt}^s, \ldots, M_{N_k^s kt}^s)$;

- the fraction of FRMs over the total number of mortgages issued by each bank, $\mathbf{x}_{kt} = (x_{1kt}, \ldots, x_{N_k^s kt})$;

- the FRM-ARM spreads posted by banks, $\boldsymbol{\phi}_{kt} = (\phi_{1kt}, \ldots, \phi_{N_k^s kt})$;

- the ARM-EURIBOR spread of banks, $\mathbf{s}_{kt}^s = (s_{1kt}, \ldots, s_{N_k^s kt})$;

- banks' shares in the province depositor market, $\mathbf{p}_{kt}^s = (p_{1kt}, \ldots, p_{N_k^s kt})$.

The supply side estimation uses as inputs the estimates of the demand side of the model ($\hat{w}^d$). The main challenge is retrieving each bank 's cost efficient fractions of FRMs, θ_{ikt}, which is not observable and determines the advice policy of the bank. We exploit a parallel between our setting and the auction structural estimation literature as the rate setting stage is an English auction and the bank 's cost efficient fractions of FRMs can be thought of as the type of the bidder in an auction. We follow the methodology used in the structural estimation of auctions (Athey and Haile (2007)) inverting the optimality condition for advice (3.5) to obtain θ_{ikt} as a function of data and supply parameters w^s. Then, we express banks' predicted shares of FRMs and FRM-ARM spreads as functions of only data and supply parameter w^s, but not of θ_{ikt}. Finally, we find estimates of w^s that minimize the discrepancy between predicted and actual quantities.

The key to identify the unobserved cost efficient fraction of FRM for each bank in every period is the mapping the model creates between the θ's and the realized fraction of FRMs issued by a bank. For this approach to work well it is necessary that the distribution of characteristics of customers faced by banks do not change during our sample span. In

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[16]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., $M_{ikt}^s = \sum_{j \in k} M_{ijt}^d$); we similarly obtain regional figures for the number of account holders at a bank. Regional ARM-EURIBOR spreads and FRM rates for a bank are calculated averaging the bank's provincial ARM-EURIBOR spreads and FRM rates across provinces of the same region weighting them by the number of mortgages issued by the bank in the province (e.g., $s_{ikt} = \frac{1}{M_{ikt}^d} \sum_{j \in k} s_{ijt} M_{ijt}^d$).

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

particular, we need the distribution of δ to be stationary. If that were not the case, swings in the fraction of FRMs issued could be due to changes in the composition of demand without necessarily implying changes in the cost efficient fraction of FRMs for the banks. In Appendix $A.5$, we exploit a survey of retail investors as well as microdata from the credit registry to show that both the distribution of risk aversion and that of the mortgage size, which are the two main elements entering δ, stay the same throughout the period we analyze. Foa et al. (2015) also show that the distribution of customer characteristics is the same across banks regardless of the bank propensity towards issuing fixed or adjustable mortgages, justifying our use of cross-sectional as well as panel variation in the share of FRMs issued.

Step 1: Invert the Optimality Condition for Advice   For a given guess of the supply parameters w^s, we can obtain estimates of the cost efficient fraction of FRM issued for each bank $(\hat{\theta}(w^s, \mathbf{x}_{kt}, \boldsymbol{\phi}_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s))$ by picking the θ_{ikt} that minimizes the discrepancy between the fraction of FRM issued by a bank observed in the data and that predicted by the model

$$\left(x_{ikt} - \max \left\{ \min \left\{ \theta_{ikt} + \tfrac{\phi_{ikt}}{2\lambda}, \overline{x}_{ikt} \right\}, \underline{x}_{ikt} \right\} \right)^2. \tag{4.2}$$

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 (4.2). To obtain an estimate of θ_{ikt} for those cases, we rely on the assumption that the θ's are distributed according to a truncated normal with truncation points at 0 and 1, mean μ_θ and standard deviation σ_θ. We estimate the parameters of this distribution maximizing the following likelihood of the observed fraction of FRMs issued

$$\sum_{t,k} \left[\sum_{x_{ikt} \in (\underline{x}_{ikt}, \overline{x}_{ikt})} \ln \left(\frac{1}{\sigma_\theta} \phi \left(\frac{x_{ikt} - \frac{\phi_{ikt}}{2\lambda} - \mu_\theta}{\sigma_\theta} \right) \right) + \sum_{x_{ikt} \in (\underline{x}_{ikt}, \overline{x}_{ikt})} \ln \left(\frac{1}{\sigma_\theta} \phi \left(\frac{x_{ikt} - \frac{\phi_{ikt}}{2\lambda} - \mu_\theta}{\sigma_\theta} \right) \right) + \right.$$

$$\left. \sum_{x_{ikt} \geq \overline{x}_{ikt}} \ln \left(\Phi \left(\frac{1 - \mu_\theta}{\sigma_\theta} \right) - \Phi \left(\frac{\overline{x}_{ikt} - \frac{\phi_{ikt}}{2\lambda} - \mu_\theta}{\sigma_\theta} \right) \right) - N_k^s \ln \left(\Phi \left(\frac{1 - \mu_\theta}{\sigma_\theta} \right) - \Phi \left(\frac{-\mu_\theta}{\sigma_\theta} \right) \right) \right].$$

Then, we use the estimated distribution of θ's to simulate θ_{ikt} for the cases in which it cannot be uniquely inferred by minimizing expression (4.2). In particular, we impute $\hat{\theta}_{ikt} = \mathbb{E}[\theta | \theta \leq \underline{x}_{ikt} - \frac{\phi_{ikt}}{2\lambda}]$ 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: Predicted FRM Fractions and FRM-ARM Spreads Conditional on $\theta_{ikt}, \phi_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s$ and parameters w^s, we can compute the predicted share of FRMs from equation (3.5). Denote it by $\hat{x}(\theta_{ikt}|w^s, \phi_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s)$.

We then compute the predicted FRM-ARM spread, $\hat{\phi}(\theta_{ikt}|w^s, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s)$, from maximizing equation (3.8). In order to do so, we need an estimate of the distribution of the minimum of $N_k^s - 1$ FRM rates for each region, $\hat{G}_k(\cdot)$. 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 spreads posted in the market, i.e., $G_{ik}(\cdot|\mathbf{s}_{kt}^s)$. 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 1, the ARM-EURIBOR spreads are fairly persistent and proxy the conditional distribution with the unconditional one.[18]

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

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

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

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

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.

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[18]In any case, given that we find that the fraction of un-attached households is small, this assumption is unlikely to have a quantitatively relevant impact on our results.

	Demand		Supply	
Parameter	Estimate		Parameter	Estimate
μ	0.34 (0.0115)		λ	26.88 (7.43)
ψ	0.02 (0.0003)		α	0.058 (0.011)
μ_δ	-0.19 (0.074)		β	0.729 (0.052)
σ_δ	0.92 (0.089)			

Table 3: **Estimates of the Parameters**

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

5 Estimation Results

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

5.1 Estimates

Table 3 reports estimates for the parameters of the model.

Two main facts emerge from the estimates of the demand parameters: the fraction of naive households is large (34%) and the fraction of un-attached households is small (2%). Our estimate of a 34% share of naive borrowers is consistent with the evidence relying on independent data measuring the sophistication of Italian households we discuss in Appendix A.2, which points to a very low level of basic financial knowledge by Italian households, providing wide opportunity for banks to distort advice.

The estimate of ψ indicates the presence of large frictions on the consumer side in the Italian mortgage market, which is further witnessed by the significant dispersion in both adjustable and fixed rates across banks documented in Figure 7 in Appendix A.7.[19] The low fraction of un-attached households that we estimate resonates with the extreme inertia documented in deposit markets (Deuflhard (2016); Ater and Landsman (forthcoming)).

The estimate of the distribution of the optimal spread cut-off δ for sophisticated households indicates that on average, ARM is the preferred option in the market. The negative

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[19]Recall, the parameter ψ reflects any friction in the banking market preventing households to take their mortgage at the bank offering the best rate. In fact, we identify it exploiting the wedge between banks' market shares in deposit and mortgage markets. Such a wedge is only created when households not only look for rates at banks other than the one where they hold their primary checking account but end up taking the mortgage there.
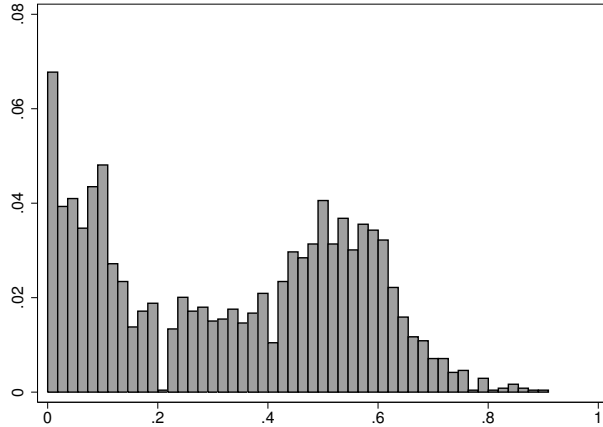
Figure 2: **Histogram of Estimated θ_{it}**

mean of the distribution of δ could be explained by households' higher expectation of the volatility of inflation compared to the real interest rate. The generation of mortgage takers in our data experienced highly volatile inflation in the 80s and 90s, which could have affected such expectations (Malmendier and Nagel (2011)).

In Figure 8 in Appendix A.7 we show that the estimated distribution of δ has substantial overlap with the empirical distribution of the FRM-ARM spread in our data. This indicates that sophisticated households choosing following the spread rule in (3.3), will vary in the type of mortage they prefer.

The key object estimated in the supply side is the distribution of the cost efficient fractions of FRMs. Figure 2 shows the distribution of θ_{ikt}. The distribution is fairly disperse but there is barely any mass for values of θ above 0.9, likely due to the fact that in our sample span ARM are on average more popular. Similarly, the mass point at $\theta = 0$ signals that a number of banks in our data are highly specialized in issuing adjustable rate mortgages.

The estimates of λ and α allow us to decompose the net profit margin in equation (3.4). Adjustable rate mortgages account for 27% of the margins accrued to the median bank from issuing mortgages, with the residual 73% being earned through issuing FRMs. The cost of deviating from the cost efficient fraction of FRMs issued paid by the median firm in our data represents 13% of its margin per euro lent. We will get further insight on the importance of these supply parameters in the context of the counterfactual exercises performed in Section 6.

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5.2 Evidence of Distorted Advice

Our structural model helped us recover a time-varying, bank-specific parameter which influences the advice policy of the bank. We have been agnostic on the interpretation of this parameter throughout our illustration of the model and the identification. The θ's could represent heterogeneity across banks in their beliefs about the evolution of interest rate and inflation, which would lead them to push different types of mortgages when trying to faithfully advise their customers. This view is, however, hard to reconcile with the wide dispersion documented in Figure 2. Even though experts do disagree on their forecast of the evolution of economic variables, it is difficult to imagine that professional operators could have such extreme divergences as to lead one bank to recommend fixed rate to most of their customers while another does the opposite.

Our preferred interpretation of θ is that of the cost-efficient fraction of FRMs a bank aims at issuing. This implies that the push towards FRM or ARM is motivated by the structure of liabilities and the cost of financing of each bank and that banks' effort to issue a fraction of FRMs close to their θ can be read as the provision of distorted advice. Such interpretation is consistent with several anecdotes on the behavior of financial intermediaries. Foa et al. (2015) present more formal evidence of the existence of this behavior and in Appendix A.6 we follow their approach to document patterns in our data which are broadly consistent with banks actively steering their customers' mortgage choices in response to their financing needs. Here, we exploit instead our model 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 FRMs they want to issue to reflect their convenience, their type θ 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 θ's belonging to branches of the same bank in a given quarter to obtain θ_{it}, the average cost-efficient share of mortgages for bank i in quarter t. We regress the θ_{it} on the bank bond spread, the difference between the rate of 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 instance, the decision to securitize or the structure of liabilities which the bank can adjust, perhaps with some delay.[20]

The results are reported in Table 4. Controlling for time and bank fixed effects, a

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[20]Banks are not important but not dominant players in the bond market and so, we can think of them as price takers.

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

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

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

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 subsamples where we dropped banks with very high ratio of deposits to total liabilities. When we focus on banks in the bottom three quartiles of the deposits/liabilities ratio, the relationships stays negative but it is now statistically significant; its point estimate grows in absolute value when we look at banks below the median of the deposits/liabilities ratio, which should be even more reliant on the bond market to secure financing. In the final subsample we examine (banks in the bottom quartile of the distribution of the deposits/liabilities ratio), the correlation is the most negative. However, it is not significant most likely because we are now obtaining our estimates from a relatively small sample.

These results bring our exercise full circle. We started from the premise that needs arising from shifts in their supply factors may affect banks' incentives to sell different mortgage types. We setup a model where banks can provide distorted advice to affect customers' choices and we structurally estimated time-varying, bank-specific factors that

drive the advice banks provide. We now showed that such bank factors 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 finds support in the data. This does not mean, however, that alternative determinants cannot also play a role in shaping banks behavior. For instance, it is perfectly plausible (and not inconsistent with our model) that θ reflects in part banks' reputation concerns: a bank would not want to distort too much advice for fear of customer backslash. In that case, our estimated θ will reflect the net effect on the preffered FRM share of the balance sheet and the reputation channel. Given a good proxy for reputation, it would be even possible to include it in regressions of the type we just presented and estimate the relative importance of the two channels in shaping advice.

6   Counterfactual Experiments

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

In order to conduct this exercise, we need to specify the utility of naive households and a measure of welfare. We suppose that both sophisticated and naive households are characterized by the parameters $H, \gamma, \sigma_\varepsilon^2$, and σ_π^2. Then, we evaluate the welfare of naive households using the same mean-variance utility function as for sophisticated households.[21]

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. The certainty equivalent of a FRM at rate r_t^h equals

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

and the certainty equivalent of a ARM at ARM-EURIBOR spread s_t^h equals

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

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[21]In the microfounded model of naive households in Appendix $A.1$, if we set $a = 1$ (remove anxiety) and let the distribution G be degenerate, we obtain the utility of sophistiated households. Thus, our welfare measure could be interpreted as the utility that households would have if they all were sophisticated.

	Limiting Advice	Undistorted Advice	Financial Literacy
All	-736	1,177	620
Sophisticated	-71	412	216
Naive	-2,025	2,659	1,400

Table 5: **Summary of Counterfactual Exercises**

Notes: The table reports the policy effect on consumer welfare as changes in the certainty equivalent in euros per household per year. Positive numbers correspond to gains, negative – to losses.

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 s_t^h to ARM with $\tilde{s}_t^h$, or from FRM with r_t^h to FRM with $\tilde{r}_t^h$, then the change in the certainty equivalent equals $H(s_t^h - \tilde{s}_t^h)$ and $H(r_t^h - \tilde{r}_t^h)$, respectively. If the household switches from the ARM with s_t^h to FRM with $\tilde{r}_t^h$ or from the FRM with r_t^h to ARM with $\tilde{s}_t^h$, then from (6.1) and (6.2), the change in the certainty equivalent equals $H(s_t^h + \delta - \tilde{r}_t^h)$ and $H(r_t^h - \tilde{s}_t^h - \delta)$, respectively.

To quantify the welfare impact of different policies, we use our estimates of μ, ψ and of the distribution of δ to simulate a population of customers equal in size to the number of mortgages issued in our data and calculate the consumer surplus induced by counterfactual exercise on this sample of simulated households.

6.1 Restricting Advice

Our first counterfactual exercise investigates the effect of reducing the ability of banks to provide advice to their customers.[22] 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 ω_{it} is restricted to be between 0 and $\frac{1}{2}$, instead of 0 and 1 as in the baseline. It is important to notice that this experiment does not change the way households choose banks nor their decision rules: sophisticated borrowers will follow the spread rule; advised naive borrowers will follow the suggestion given to them by the bank, and unadvised naive borrowers will select fixed rate mortgages.

This experiment allows us to measure the value (or cost) of advice to households. The experiment could be interpreted as the regulator that monitors more closely banks,

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[22]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 for the customers, because it is undistorted. In our case, the welfare effects are ex-ante ambiguous.

but focuses only on the largest branches, thus, limiting, but not fully eliminating the scope for advice, or as the advent of online banking, which crowds out the advice by limiting direct interaction with clients. It can also be related to regulatory interventions tightening fiduciary standards, like the one introduced by the Obama administration for the US in 2016, which could induce financial intermediaires to provide less advice for fear of exposing themselves to lawsuits.

The overall effect of limiting advice is a loss of 736 euros per household per year over the entire course of the mortgage. This is about 17% of the total amount (principal and interest) a household would have to repay in a year for a 125,000 euros mortgage at the average FRM rate in our data (5.6%). If we decompose this loss, we observe that naive households suffer the most (they lose 2,025 euros per capita per year compared to the unrestricted advice scenario); but sophisticated customers are worse off too by 71 euros per year.

To obtain intuition for why restricting advice is costly, it is useful to decompose its effect on the population of naive into the information value of advice and the costs of distortion. Naive households take a FRM if left on their own. On the one hand, for naive households with sufficiently small δ, this decision is suboptimal, and the fact that a recommendation from their bank can steer them towards an ARM is beneficial for them (although such recommendation is provided in bank's self interest). This constitutes the information value of advice, as banks inform naive customers about the alternative product, which they did not consider before.[23] On the other hand, there are naive households who should take a FRM if they were to follow the spread rule. These households would make the correct choice in the absence of advice, but banks can instead distort it leading them to take an ARM. This causes the distortion costs. Given our estimate of the distribution of δ, 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 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

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[23]This is closely related to banks acting as "money doctors" that reduce the naive households' anxiety from choosing a more complex product, ARM.

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 merely 68 euros per household per year (with naive households gaining on average 112 euros per year and sophisticated households losing 18 euros 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: 1,177 euros per capita per year. As usual, naive households benefit the most gaining 2,659 euros per year each;[24] sophisticated households enjoy a gain of 412 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 θ_{it}). In the baseline model it was relatively easy for those banks to fill their quota as all the naive customers were willing to buy FRMs. Now, the share of customers who will take a FRM depends on the distribution of δ and our estimates imply that the majority of the customers favors ARMs. Therefore, banks who want to sell a significant fraction of FRMs must reduce their spread to achieve such goal. This affects both sophisticated and naive households with high values of δ 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 they choose the bank where to take the mortgage. Namely, if they are un-attached they still become customers of the bank offering the lowest FRM rate even though their δ implies that they

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

should take an adjustable one. However, due to the low fraction of un-attached in our data, the additional welfare gains if we were to make all households sophisticated in both decision stages would not be very large.

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 choosing the bank and type of mortgage. We assess the impact of a campaign that succeed in reducing the share of naive households in the population from 34% to 17% and find that the average households experiences a gain of 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 2,496 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 304 euros per year; the latter 216 euros. The mechanism is analogous to that described for the undistorted advice experiment: the reduction in μ makes selling FRMs harder and forces high θ_{it} banks to lower FRM rates to the benefit of customers buying fixed rate mortgages.

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 34% to 17%) in an economy where the share of un-attached (ψ) is as high as 70% we obtain an average yearly gain of 275 euros per customer. The welfare gains are about one half of those estimated when ψ is at its baseline value because in a more competitive environment, the negative effects of the distortion in advice is mitigated. 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 δ naive households who are taking an FRM: the possibility of taking the mortgage from the bank with the lowest FRM rate limits the extent to which they overpay to insure agains interest rate risk.

An interesting implication of this exercise, however, relates the decomposition of the gains between naive and sophisticated. The gain for the naive households is 838 euros per year; this is an average between the gain of the naive who become sophisticated (whose gains are more substantial) and the loss of 127 euros per year of 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 un-attached (who are many in the baseline) 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 un-attached households taking FRMs.

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.

References

AGUIRREGABIRIA, V., R. CLARK, AND H. WANG (2016): "Diversification of geographic risk in retail bank networks: Evidence from bank expansion after the Riegle-Neal act," *RAND Journal of Economics*, 47, 529–572.

ALLEN, J., R. CLARK, AND J.-F. HOUDE (2014): "Search frictions and market power in negotiated price markets," NBER working paper n.19883.

ANAGOL, S., S. A. COLE, AND S. SARKAR (2017): "Understanding the advice of commissions-motivated agents: Evidence from the Indian life insurance market," *Review of Economics and Statistics*, 99, 1–15.

ATER, I. AND V. LANDSMAN (forthcoming): "Testing alternative learning theories: Evidence from subscription contracts," *Journal of Industrial Economics.*

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

ATHEY, S. AND P. HAILE (2007): "Nonparametric approaches to auctions," in *Handbook of Econometrics*, ed. by J. Heckman and E. Leamer, North Holland, vol. 6, chap. 60, 3847–3965.

BADARINZA, C., J. Y. CAMPBELL, AND T. RAMADORAI (forthcoming): "What calls to ARMs? International evidence on interest rates and the choice of adjustable-rate mortgages," *Management Science.*

BAJO, E. AND M. BARBI (2015): "Out of sight, out of mind: Financial illiteracy, inattention, and sluggish mortgage refinancing," Working paper.

BARONE, G., R. FELICI, AND M. PAGNINI (2011): "Switching costs in local credit markets," *International Journal of Industrial Organization*, 29, 694–704.

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.

CASSOLA, N., A. HORTACSU, AND J. KASTL (2013): "The 2007 subprime market crisis in the EURO area through the lens of ECB repo auctions," *Econometrica*, 81, 1309–1345.

CHATER, N., S. HUCK, AND R. INDERST (2010): "Consumer decision-making in retail investment services: A behavioural economics perspective," *Report to the European Commission/SANCO.*

CRAWFORD, G., N. PAVANINI, AND F. SCHIVARDI (2015): "Asymmetric information and imperfect competition in lending markets," CEPR working paper DP10473.

DEUFLHARD, F. (2016): "Quantifying inertia in retail deposit markets," Working paper.

EGAN, M. (2015): "Brokers vs. retail investors: Conflicting interest and dominated products," Working paper.

EGAN, M., A. HORTACSU, AND G. MATVOS (2017): "Deposit competition and financial fragility: Evidence from the US banking sector," *American Economic Review*, 107, 169–216.

EGAN, M., G. MATVOS, AND A. SERU (2016): "The market for financial adviser misconduct," Working paper.

EINAV, L., M. JENKINS, AND J. LEVIN (2012): "Contract pricing in consumer credit markets," *Econometrica*, 80, 1387–1432.

ESPOSITO, L., A. NOBILI, AND T. ROPELE (2015): "The management of interest rate risk during the crisis: Evidence from Italian banks," *Journal of Banking & Finance*, 59, 486 – 504.

FELICI, R., E. MANZOLI, AND R. PICO (2012): "La crisi e le famiglie italiane: un'analisi microeconomica dei contratti di mutuo," *Questioni di Economia e Finanza*, 125.

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*.

FUSTER, A. AND J. VICKERY (2015): "Securitization and the fixed-rate mortage," *Review of Financial Studies*, 28, 176–211.

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

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.

MALMENDIER, U. AND S. NAGEL (2011): "Depression babies: Do macroeconomic experiences affect risk taking?" *The Quarterly Journal of Economics*, 126, 373–416.

MULLAINATHAN, S., M. NOETH, AND A. SCHOAR (2012): "The market for financial advice: An audit study," NBER working paper n.17929.

OECD (2016): "OECD/INFE International Survey of Adult Financial Literacy Competencies," http://www.oecd.org/finance/financial-education/oecd-infe-survey-adult-financial-literacy-competencies.htm.

OTTAVIANI, M. AND F. SQUINTANI (2006): "Naive audience and communication bias," *International Journal of Game Theory*, 35, 129–150.

RAMPINI, A., S. VISWANATHAN, AND G. VUILLEMEY (2016): "Risk management in financial institutions," Working paper.

RENY, P. J. AND S. ZAMIR (2004): "On the Existence of Pure Strategy Monotone Equilibria in Asymmetric First-Price Auctions," *Econometrica*, 72, 1105–1125.

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.

A   Appendix

A.1   Microfoundation for Naive Households' Behavior

In this appendix, we use the "money doctors" framework introduced in Gennaioli et al. (2015) to microfound the behavior of naive households. We draw a parallel between the household's decision about the mortgage type studied in our paper and the retail investor's portfolio decision studied in Gennaioli et al. (2015). FRM is essentially the reverse of the bank deposit and is a more familiar option, while ARM is a more complex (but potentially more beneficial) option, which, similarly to the investment in the stock market, requires certain degree of knowledge and sophistication. It is well documented (e.g., Calvet et al. (2007)) that households that lack such sophistication tend to invest in deposits. Gennaioli et al. (2015) capture this phenomenon by assuming that investors experience anxiety, when they invest in less familiar option, which could be "relieved" by financial intermediaries. In parallel, we suppose that naive households experience anxiety when taking ARM.

Specifically, suppose that naive households are uncertain about σ_π^2 and σ_ε^2, and have some full-support beliefs G about their joint distribution. Conditional on σ_π^2 and σ_ε^2, the utility of naive households from taking FRM is the same as of sophisticated households and is given by $\mathbb{E}[y - (1 + r_t^h - \pi)H] - \gamma \mathbb{V}[y - (1 + r_t^h - \pi)H]$.[25] However, conditional on σ_π^2 and σ_ε^2, their utility from ARM is given by

$$\mathbb{E}[y - (1 + s_t^h + r_t + \varepsilon)H] - a\gamma \mathbb{V}[y - (1 + s_t^h + r_t + \varepsilon)H].$$

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

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

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[25]Thus, their unconditional utility equals

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

where the outside expectation is with respect to household's beliefs about σ_π^2 and σ_ε^2.

A.2 Evidence of Limited Sophistication

In this appendix, we present some evidence on the limited sophistication using measures of the level of financial literacy among Italian households, and show that it 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, to understand the difference between real and nominal interest, the concept of compound interest, the wealth consequence of stock prices fluctuations, and the properties of fixed and adjustable rates. For each question, four options are offered: one of them is correct; two incorrect and a fourth option allowing the interviewee to profess his cluelessness about the topic.[26]

We construct a summary index of sophistication 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 3, we shows the distribution of the Summary Sophistication Index among the whole sample and for the subset of those who have a mortgage outstanding (information about mortgages and other forms of debt is collected in another section of SHIW). Only 3% of the households interviewed answers correctly all the questions, 18% does not get a single one right and 42% does not do better than two correct answers out of six. Compared to the distribution of the index for the whole sample, mortgage holders show higher sophistication (80% of them answer at least two questions correctly).

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

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[26]The questionnaire of the 2006 wave of SHIW is available (in Italian) at `https://www.bancaditalia.it/statistiche/tematiche/indagini-famiglie-imprese/bilanci-famiglie/documentazione/documenti/2006/Quest_it2006.pdf`.
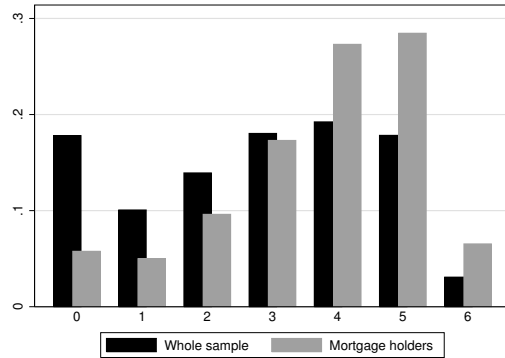
Figure 3: **Distribution of the Sophistication Index**

Notes: The Summary Sophistication Index is constructed as the number of correct answers to the six financial literacy questions contained in the 2006 wave of SHIW. The whole sample includes all the SHIW interviewees in 2006 who were administered the financial literacy section of the questionnaire; the mortgage holders sample consists of all the households who answered the financial literacy questions and also reported elsewhere in the survey to have an outstanding mortgage.
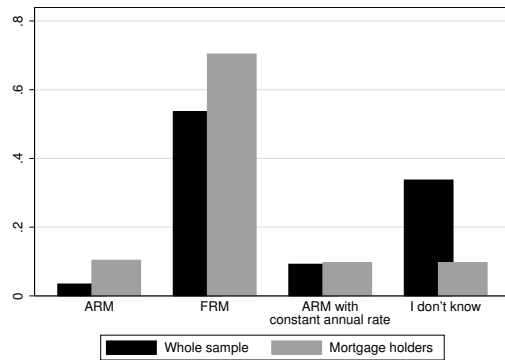
Figure 4: **Understanding of Mortgage Characteristics**

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

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

Table 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.

Finally, Table 6 provides some evidence in support of our assumption that unsophisticated borrowers tend to opt for fixed rate mortgages. 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 buy a lower amount; 3) No, I could buy a higher amount; 4) I do not know.

We define *Sophisticated* all those who provide the correct answer (answer 2); *Naive* those who provide either of the wrong answers (answer 1 or 3); and *Clueless* those who cannot answer (answer 4). We tabulate the type of mortgage that households in these different groups 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 among the clueless.

A.3   Sample Selection

As we explained in the main text, whereas we have information on the universe of mortgages issued in Italy, the interest rate of the loan is also known to us if the bank issuing the mortgage is among the 125 regularly surveyed by the Bank of Italy for information on rates of the loans they issued. Therefore, we exclude from our analysis the banks not participating in the survey, which anyway represent a small fraction of the market.

To avoid dealing with banks intermittently active in a market, we retain in our sample only banks issuing at least 2% of the mortgages in the market. This requirement is strengthened for the sample we use to estimate the supply side of the model. Since we need variation in the

FRM-ARM spread, we only consider banks that are regularly active in issuing FRMs and hold a market share of at least 1% in the FRM segment in the market where they are located.

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

Finally, some restrictions are imposed by our need of having information on the amount of the deposits (in Euros) held by each bank in a given market. Such data are missing for some bank-quarter-province triplet and we exclude from the sample banks for which either no or only one year of data on the amount of deposits is available. For banks with less severe missing data problems, we extrapolate the amount of deposits for a given bank in a given province in a given year using a linear regression to fill the gaps between available observations. When the time series ends without resuming later on, we impute for all the missing province-year the last amount of deposits recorded in the data. We remove from the sample three small provinces where 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 exceeded 30%.

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.

A.4 Optimal Spread Setting

We derive an explicit formula for (3.8) that we use in the estimation. We distinguish two cases depending on whether bank i has the lowest ARM-EURIBOR spread on the market ($s_{it} < \underline{s}_{-it}$) 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

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

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

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

Then ϕ_{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

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

   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,

   $$\underline{x}_{it}^{AF} = (1-\mu)\kappa(\phi_{it}), \qquad (A.4)$$
   $$\overline{x}_{it}^{AF} = (1-\mu)\kappa(\phi_{it}) + \mu. \qquad (A.5)$$

   (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

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

   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

(a) Distribution of Risk Aversion

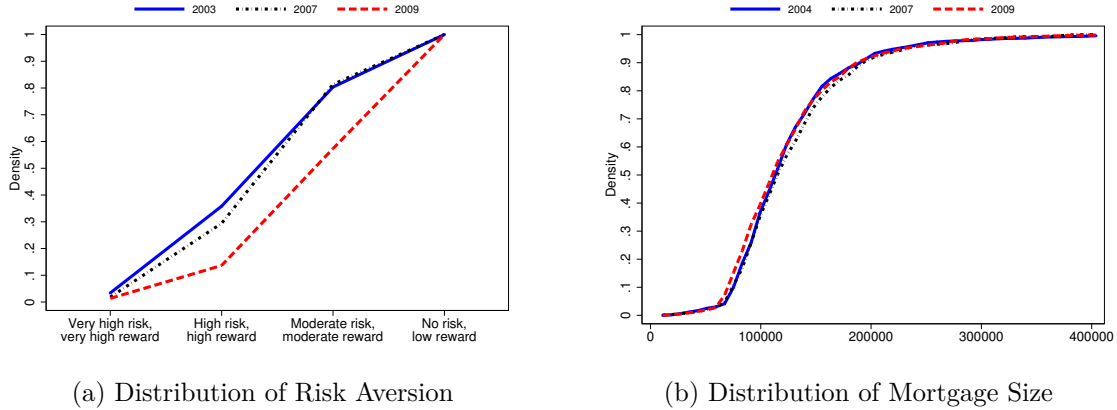(b) Distribution of Mortgage Size

Figure 5: **Cumulative Distribution of Households Characteristics**

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

searchers. The total mass of bank i's customers is then

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

and

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

A.5 Stationarity of Households Characteristics

In Figure 5 we plot the cumulative distribution of a proxy of risk aversion and of the mortgage size for the beginning and the end of the time span covered by our data. Our aim is to show that the distribution of these variables experienced negligible changes in the period we analyze. Since they represent the main element determining the optimal spread cutoff, this evidence should reassure on the stationarity of the distribution of δ which is an assumption underlying our identification of the bank cost-efficient fraction of FRMs (δ).

In the left panel of Figure 5, we plot the cumulative distribution of the answer to a question meant to elicit risk aversion. The sample of people interviewed does not coincide with the population of new mortgage holders covered in our data. The data come from a relatively large survey conducted by a major Italian bank on its retail customers. The question we are

focussing on asks responders about the investment strategy that best identifies their approach. The four options offered span a profile consistent with high risk tolerance (households pursuing "very high reward" and willing to be exposed to "very high risk" to achieve it) to extreme risk aversion (households content to obtain "low reward" as long as it entails "no risk" at all). The survey counts several waves and is a repreated cross section (though a panel dimension was created keeping a subset of households interviewed in 2007 in the 2009 wave). The distribtion of answers in 2003 (before the beginning of our sample) and 2007 (the next to last year we consider) is nearly identical. The risk aversion of Italian investors seems instead profoundly affected by the explosion of the financial crisis which dates to the second semester of 2009 in Italy. The investors surveyed in 2009 report a much more risk averse attitude than measured before. This evidence explains why, although we have obtained data on mortgages issued in 2009 and 2010, we elected to limit our end our analysis before the effects of the financial crisis were felt in Italy.

The right panel prooses a similar exercise by showing the distribution of the real mortgages size (in 2004 euros) exploting microdata on a random subsample covering 40% of the mortgages issued between 2004 and 2009. Conditional on the mortgage being issued, the distribution of mortgage size does not change throught our sample. Interestingly, this variable does not seem to be affected even by the intervention of the financial crisis: the distribution in 2009 is nearly identical to the 2004 and 2007 ones.

A.6   Reduced Form Evidence of Distorted Advice

Foa et al. (2015) design a reduced form test of the presence of distorted advice of the type introduced in our model and implement it exploiting the same mortgage data we use for our estimates. Their test is based on the premise that if households are savvy, the relative price of different financial products should be a sufficient statistic for their choice. On the other hand, if some households lack sophistication and the intermediary steers their behavior to its own advantage, their choice could also be affected by characteristics of the suppliers (possibly unobservable to the borrower) that affect the incentive of the supplier to "push" 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.
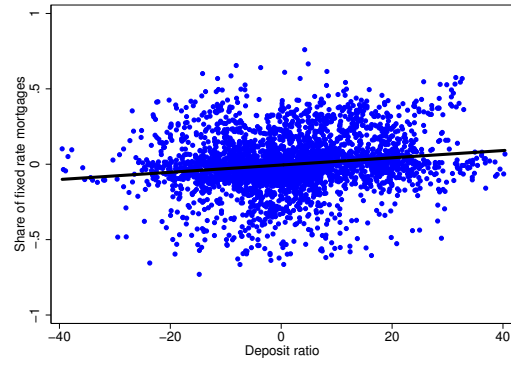
In Figure 6 we present some graphical evidence based on the same logic. In particular, the two top panels portray the correlation between the residuals of the following regression equations

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

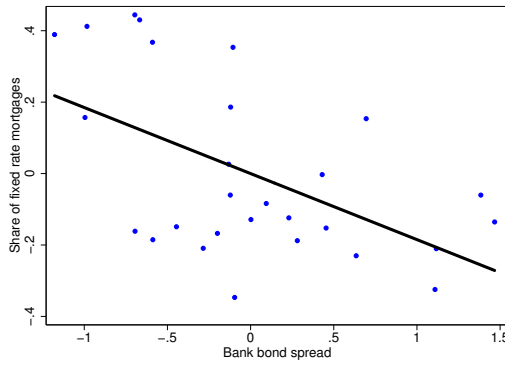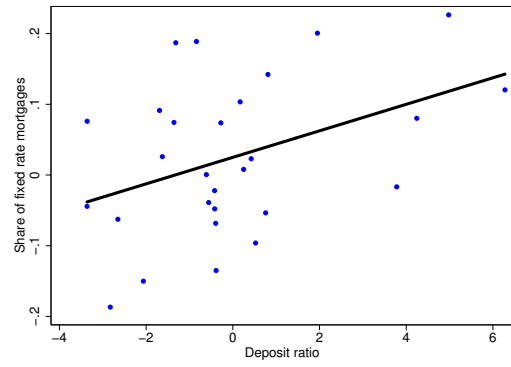where $shareFRM$ is the proportion of fixed rate mortgages over the total number of mortgages
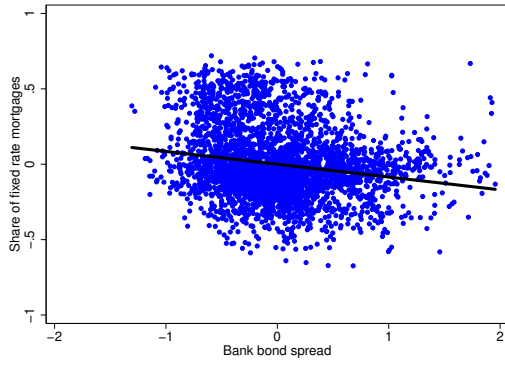
Figure 6: **Banks Balance Sheet and Mortgage Type Prevalence**

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.

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 6 is the spread between the cost of fixed rate bank bonds and variable rate bonds; whereas in the top right plot we use the deposits as a fraction of the bank total liabilities.

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

rate mortgages; a higher incidence of deposits over total funding is positively correlated with the fraction of FRM. In both cases the correlation is statistically significant. Since customers should not care about the liabilities structure of the bank beyond its effect on the mortgage spread, which is already controlled for, this results is consistent with the presence of advice by the bank which influences the households' decision. In the bottom panels of Figure 6, 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.
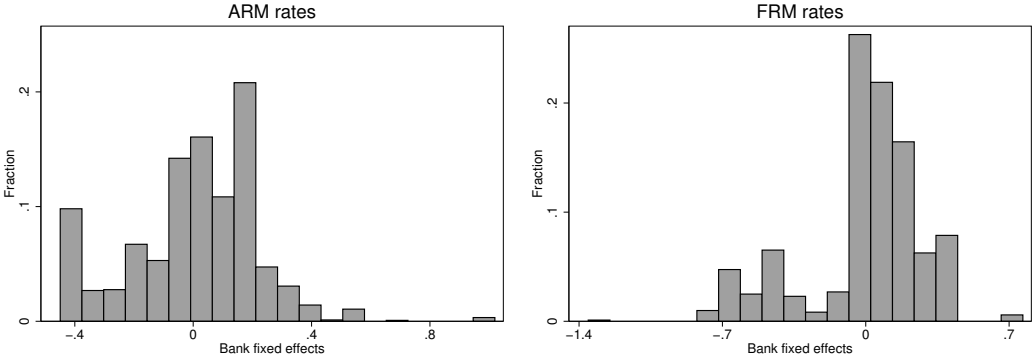
A.7 Additional Figures

Figure 7: **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.
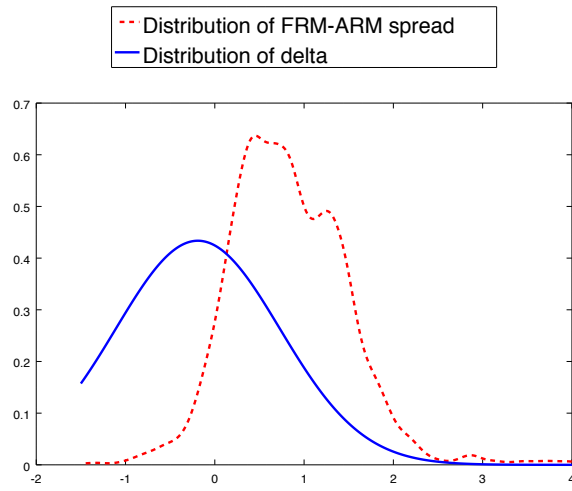
Figure 8: **Estimated Distribution of δ and Kernel Density of ϕ_{it}**