The Cost of Distorted Financial Advice: Evidence from the Mortgage Market*

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Abstract

Many households lack the sophistication required to make complex financial decisions and risk being exploited when seeking advice from intermediaries. We build a model of financial advice, in which banks attain their optimal mortgage portfolio by setting rates and providing advice to their clientele. "Sophisticated" households know which mortgage type is best for them; "naive" are susceptible to the bank's advice. Using data on the universe of Italian mortgages, we estimate the model and quantify the welfare implications of distorted financial advice. The average cost of the distortion is equivalent to an increase in the annual mortgage payment by 11%. However, since even distorted advice conveys information, banning advice altogether results in a loss of 998 euros per year on average. A financial literacy campaign is beneficial for naive households, but hurts sophisticated ones.

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 might have incentives to distort their recommendations. This is especially likely when households solicit advice from the seller of the financial product itself. We call financial advice "distorted" when the advisor provides it in its own interest, which need not be fully aligned with the customer's interest. The goal of this paper is to assess the prominence of this phenomenon and quantify its impact on households' welfare.

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

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

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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.

experience.

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 loan terms, 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, studying the Italian mortgage market is well suited to the purpose of this study due to a number of institutional characteristics. Namely, there are only two main products available to customers, plain vanilla fixed and adjustable rate mortgages, and both are popular; advice is usually provided by the banks issuing the mortgages (rather than brokers); and banks retain on their balance sheets mortgages that they originate. This means that Italian banks have both motive and opportunity to provide biased advice.

In our model, households make two choices: they pick a bank where they take a mortgage and they decide between a fixed and an adjustable rate mortgage. Choosing a fixed rate mortgage protects the household against the interest rate risk but exposes it to the inflation risk; the opposite is true for adjustable mortgages. There are two types of borrowers in the population: "sophisticated" and "naive". When deciding about the mortgage type, sophisticated borrowers are perfectly informed about the risks associated with each mortgage type. Therefore, they choose the best mortgage type given their characteristics and the spread between fixed and adjustable contracts. Naive borrowers lack sophistication to compare fixed and adjustable rate mortgages. Like in Gennaioli et al. (2015), absent advice they choose the easy to grasp (but potentially more costly) fixed rate mortgage. Banks are heterogenous in the target fixed/adjustable composition of their mortgage portfolio and compete with each other by setting rates to attract borrowers. They then provide advice to the customers they manage to attract, and naive customers follow their counsel. One key feature of the model is that advice might be valuable to households even when it may be distorted, because it expands the naive households' choice set.

We estimate the fraction of naive borrowers at 48%, which squares with survey measures of financial sophistication of the Italian population. This parameter is key to assess the economic effect of distorted advice as well as to evaluate the potential welfare gains of public policies meant to reduce the distortion. We calculate that the welfare cost of providing distorted advice is 661 euros per year for the average household (about 11% of the annual mortgage payment). But it is markedly heterogeneous across households. While the cost is positive for naive households (1,705 euros on average), sophisticated

households benefit (295 euros on average). Because banks can adjust by distorting naive households' choices, they rely less on rates to achieve their desired mortgage mix. At the estimated parameters this results in cheaper mortgages for the average sophisticated borrower. In essence, there is an implicit subsidy from naive to sophisticated households. It follows that a policy that forces banks to provide undistorted advice benefits the naive but hurts the sophisticated.

We find that the welfare effects of a financial education campaign that halves the fraction of naive households are also heterogeneous. Households on average gain 304 euros per year. Most of the welfare gain accrues to households who were naive and become sophisticated thanks to the campaign (1,845 euros per year). However, because banks react to the policy, the campaign benefits also naive households who are not directly affected by the financial education program. Instead, sophisticated households lose on average (314 euros per year).

Hence, these policies are not necessarily Pareto improving even ignoring the cost of funding them. On the other hand, we show that banning (even partially) advice from banks results in a welfare loss for both naive and sophisticated borrowers. On average this policy entails a welfare loss as large as 998 euros per year. It is very large for the naive households (1,444 euros per year), because the information value of even distorted advice exceeds the distortion costs. Because of the effect on rates, the loss is also significant for the sophisticated (590 euros per year). In sum, simply banning advice is too costly a policy.

This study relates to several strands of literature. Spurred by the finding in Foa et al. (2015), who exploit similar data to find reduced form evidence of advice distortion in mortgage origination, we contribute to the household finance literature on distorted advice (Egan, 2015; Ru and Schoar, 2017; Egan et al., forthcoming) by explicitly modeling the advice provision by the banks and quantifying its welfare consequences and the implications of several policies that can be adopted to deal with it. Second, our evidence on the role of advice ties in to the empirical literature studying the interaction between borrowers and lenders in credit markets which has documented the relevance of other dimensions of these interactions such as information asymmetry (Einav et al., 2012; Crawford et al., 2015), inattention and inertia (Woodward and Hall (2012); Andersen et al. (2017)) and bargaining negotiation (Allen et al., 2014). Besides the focus on credit markets, we are linked to these studies by a common methodological approach which follows a growing literature applying tools developed in Industrial Organization to the analysis of financial markets (Aguirregabiria et al. (2016); Cassola et al. (2013); Egan et al. (2017)). Further,

we relate to the literature on financial advice games that rely on the presence of both sophisticated and naive investors (Ottaviani and Squintani (2006); Kartik et al. (2007)).[2] Whereas we do not aim at making a theoretical contribution, our estimates point to a large fraction of households with limited financial sophistication engaging in high stakes transactions vindicating the tenet of these models.

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

2 The Italian Mortgage Market

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

Despite Italy's high homeownership rate, the size of the household mortgage market is smaller than in other developed countries. Total household debt amounts to 63% of disposable income, compared to 95% in the euro area and 103% in the US. Based on data from the Survey of Households Income and Wealth (henceforth, SHIW) – a comprehensive survey administered every two years by the Bank of Italy to a representative sample of Italian households – only 12% of Italian households have a mortgage, half the average figure for households in the euro area. Yet, reliance on mortgages to finance a purchase of a house has become increasingly popular in the 90s and early 2000. In our sample, nearly 250,000 mortgages with maturity 25 to 30 years are originated on average each year.

Types of mortgages   The two most common types of contracts are an adjustable rate mortgage (henceforth, ARM) where the bank charges a spread over an underlying benchmark rate (usually the 1- or 3-month Euribor); and a fixed rate mortgage (henceforth,

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

FRM) where an interest rate is agreed upon when the contract is signed and a fixed amount is repaid in each installment for the whole length of the mortgage. Together, these products represent over 90% of the mortgages issued in our sample.[3] Unlike in other countries, both of these types of loans are popular. In our data just over 30% of the mortgages issued are FRMs but in some years in the sample FRMs represent nearly 70% of the mortgages issued. The presence of only two mortgage types eases the identification of steering by banks. The Italian regulation sets the maximum loan to value ratio at 80%, and exceeding this threshold requires banks to hold more regulatory capital. The average LTV over our sample period lies between 63% and 70%.

Banks as sources of advice   Banks are by far the main provider of financial information for Italian households, and therefore, have ample opportunity to influence their choices.

Several factors make banks prominent in advising households about their mortgage choices. First, banks are main originators of mortgages: 80% of mortgages (Wyman (2005)) are sold directly to customers at the local branch. Second, the Italian retail banking system is characterized by a tight relationship between a customer and its home bank. Data from the SHIW show that over 80% of the households carry on all of their financial transactions at a single bank and for nearly 60% of them the relationship with their main bank has been ongoing for more than 10 years. Therefore, the advice of the (loan officer of the) bank that issues the mortgage is the most easily accessible expert opinion for a household.[4]

To document that banks are key providers of information to their customers, we present evidence from a survey administered by a major Italian bank to a sample of 1,686 of its customers in the summer of 2007.[5] One of the questions in the survey asks how often the respondent resorts to various sources of financial information when making a financial decision. Banks emerge as the leading source of information for customers: over 63% of customers consult them "sometimes", "often", or "very often". This is a 20 percentage

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[3]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.

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

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

points gap with the second most popular source, the broker.[6] Friends and relatives, and media outlets, such as newspapers, magazines, TV, Internet, etc., are used to gather information by 12% and 18% of the interviewees, respectively.

Exposure to interest rate risk   Unlike in the US (Fuster and Vickery (2015)), in Italy banks retain most of the mortgages they originate on their balance sheets bearing all associated risk. Italian 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 rate risk on loans by financial institutions has been provided, for example, by Begenau et al. (2015); Gomez et al. (2016) and Rampini et al. (2016) using US data and by Esposito et al. (2015) and Cerrone et al. (2017) for Italian banks. Since FRMs and ARMs create different exposure to the interest rate risk for banks, the fact that banks retain the risk linked to maturity transformation explains why they might want to distort advice to mortgage takers.

Banks fund their loans both through deposits and long term bonds placed in the market. The relative importance of these two sources varies substantially across banks and shapes their preference towards issuing fixed or adjustable rate mortgages. As shown in Table 1, for some banks deposits account for as little as a third of total liabilities. These are typically large banking groups that are more keen on issuing bonds and therefore (given the higher volatility of bond funding compared to deposits funding) are more exposed to the risk of maturity mismatch between items on their balance sheets. Other banks are primarily funded through deposits suggesting that they can finance their loans with fewer concerns about fluctuations in the cost of their funding sources. Further, the spread between fixed and variable rate bank bonds varies substantially between banks in our sample: it averages 28 basis points but goes up to 100 basis points for banks in the top decile of the distribution.

Other risks   Our discussion of the bank incentives to influence mortgages choice centered on interest rate risk. This is because in the Italian setting this appears to be a more prominent source of risk taken by banks when issuing mortgages compared to credit and pre-payment risks. Like in many other European countries, mortgages are full recourse in

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[6]This figure overstates the importance of brokers in providing mortgage advice, because it includes sources of information about investment in stocks, retirement funds, insurance, etc., where the role of brokers is more prominent than for mortgages. Moreover, households could refer to as "broker" to the employee of the bank managing their investment and brokers often work for a company tightly linked to some bank.

Italy: households cannot walk away if the value of the property falls short of the outstanding mortgage. Hence, the incidence of mortgage defaults is rather limited: the fraction of mortgages with late repayment or default is around 1% without significant spikes even in the years of the financial crisis. This also reflects banks' tight screening policies with high rejection rates of risky loan applicants.[7] For this reason we do not include in our analysis the risk of default and also abstract from sophisticated pricing policies conditioning the mortgage rate offered on individual characteristics. In fact, banks submit applications to severe screening to minimize the default risk but then tend to ignore differences in accepted borrowers riskiness setting flat rates, with the exception of a recent attention to loan size or LTV (Liberati and Vacca (2016)).

Most Italian mortgages are held until maturity and it is relatively uncommon that households renegotiate the terms of the mortgage or transfer it to another bank. For most of the time span in our analysis, both prepayment and renegotiation were burdened by unregulated fees in the order of at least 3% of the remaining debt (Brunetti et al. (2016)). A reform enacted in April 2007 (the "Bersani law") removed prepayment penalty fees for all new mortgages and capped them at a mandated level for existing ones. The reform bill also removed additional cost of renegotiation such as notary fees. Still, the effect of these changes on renegotiation has been modest (Bajo and Barbi (2015); Beltratti et al. (2017)). The share of refinanced mortgages is close to zero up until 2007 and consistently below 1% after. Therefore, we do not include renegotiation and prepayment risks in the problem of the bank.

To summarize, the Italian mortgage market is characterized by the prevalence of plain vanilla FRM and ARM mortgages with long maturity. Banks originate mortgages and act as advisors for their customers. Because origination fees are small (in the order of 0.1% of the value of the mortgage over our sample period) and independent of the type of contract, banks have little motive to originate mortgages just to cash in fees. However, because they bear the interest rate risk, banks have incentives to steer customers either towards FRM or ARM at origination. These institutional features and the properties of the data that we discuss below make the Italian mortgage market an ideal laboratory to study distorted financial advice.

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[7]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

3 Data and Descriptive Evidence

3.1 Data

We use data from two administrative sources: the Italian Credit Register (CR) and the Survey on Loan Interest Rates (SLIR). Both datasets are maintained by the Bank of Italy. 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, the loan size, the identity of the bank originating the loan and several characteristics of the borrower. We use aggregated data on the total number of fixed and adjustable rate mortgages issued in each quarter between 2005 and 2008 by each bank in each Italian province, a geographical unit roughly equivalent to a US county which we adopt as our definition of the consumer market. We focus on mortgages with similar maturities between 25 and 30 years. We also restrict attention to plain vanilla ARM or FRM mortgages. The final dataset includes information from nearly 1,000,000 mortgages.

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. This set includes all main banking groups active in Italy and covers more than 90 percent of the market.[8] Some provinces are quite small and only a handful of mortgages are originated in a quarter. This results in missing data on the interest rate since the rate is reported only by banks that actually issued a mortgage in the province in the quarter. To alleviate this problem, we calculate interest rates for each bank-quarter as averages at the regional level, rather than at the province one.[9] This choice is unlikely to introduce significant distortions 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. Further, there is evidence that the rates are indeed set at the regional level: in 25% of the observations a bank sets the exact same rate in all the provinces within a region, and conditional on observing differences in rates between provinces of the same region, the median deviation from the regional mean is 12 basis points for ARMs and 8 basis points for FRMs.

The main dataset is complemented by other ancillary sources of data. First, we merge the mortgage dataset with detailed supervisory data on banks characteristics and balance

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[8]Additional details on sample construction are relegated to Appendix *A*.2.

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

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

Table 1: **Summary Statistics**

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

sheets. Second, we obtain information at the bank-year-province level on the share of deposits in the market held by each bank. Further, SHIW documents several characteristics of households' behavior in financial transactions. Table 1 displays summary statistics on our main data.

3.2 Descriptive Evidence of Distorted Advice

There is abundant anecdotal evidence that banks distorts advice in Italy.[10] For instance, a report by the Italian Securities and Exchange Commission (Grasso et al. (2010)) documents that several banks have systematically diverted retail customers towards bonds issued by the bank or an affiliate, even when a dominant alternative (e.g., a government bond of same maturity and higher yield) was present in the market. Another source of anecdotal evidence of distorted advice are customers' complaints and lawsuits alleging unscrupulous practices by Italian mortgage originators. Data obtained from the Arbitro Bancario Finanziario, the Italian ombudsman dealing with financial disputes between customers and banks, show that during our sample period, over 70% of the complaints are related to mortgage issues.[11]

While suggestive, anecdotal evidence is hard to generalize. Foa et al. (2015) use data similar to ours to provide reduced form evidence that banks' advice slants customers' mortgage choices. For completeness, we reproduce their main findings and refer to Foa et al. (2015) for additional robustness.

The Foa et al. (2015) test is based on the idea that if households are savvy, then 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 is able to steer their behavior to its own advantage, for given prices their choice could also be affected by characteristics of the suppliers (possibly unobservable to the borrower) that affect the incentive of the bank to "push" buyers towards a certain product. In this case, the direction of the effect should be consistent with the bank's interest.

We exploit microdata covering 40% of mortgage transactions during our sample span that contain characteristics of the borrow and the lending bank as well as conditions of

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

[11]One recent example is a court ruling against Barclays Bank for advising customers to take ARM mortgages with a complex indexation to the Swiss Franc between 2006 and 2010 (http://www.repubblica.it/economia/2017/01/13/news/barclays_condannamutuo_franchi_svizzeri-155899009/).

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

Table 2: **The Effect of Lenders' Characteristics on Mortgage Choices**

Notes: Each observation is a new mortgage contract between a household and a bank. The dependent variable is an indicator taking value 1 if the household chose a FRM. Long Term Financial Premium defined as in Foa et al. (2015) is the difference between the FRM rate and the expected ARM rate based on borrowers' actual ARM rate and one year moving average of the one month interbank rate. The Bank Bond Spread is the difference between fixed and adjustable rate bank bonds. Standard errors are in parentheses and are clustered at the bank level. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
	Mortgage size	*Joint Mortgage*	*Italian*	*Cohabitation*	*Age*	*Female*
Bank bond spread	0.0110	-0.0018	0.0011	-0.0004	-0.0131	-0.0007
	(0.0072)	(0.0041)	(0.0081)	(0.0036)	(0.1500)	(0.0024)
Observations	631,993	631,993	631,993	631,993	631,993	631,993
R-squared	0.0220	0.0154	0.0385	0.0091	0.0231	0.0016

Table 3: **Lack of Dynamic Sorting**

Notes: Each observation is a new mortgage contract between a household and a bank. Each column refers to a different regression where a different dependent variable is regressed on the Bank Bond Spread, that is the difference between fixed and adjustable rate bank bonds. All specifications include bank and year-region fixed effects. Standard errors are in parentheses and are clustered at the bank-date-province level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

the contract. In Table 2, we use it to show that the choice between ARM and FRM is systematically correlated not only with the relative costs of the two types of mortgages, but also with time varying characteristics of the bank that originates the mortgage. We estimate a linear probability model where the indicator takes value 1 if the household chooses a FRM is regressed on a measure of the spread between FRM and ARM, household characteristics and the Bank Bond Premium, which measures the relative cost for the bank of securing funds at a fixed rate. We also include bank fixed effects to capture time-invariant unobserved heterogeneity across banks and systematic sorting. Region-quarter fixed effects capture aggregate market effects.

As expected, the FRM-ARM spread negatively affects the probability that the household picks a fixed rate. However, the negative and significant coefficient on the Bank Bond Spread implies that households borrowing from a given bank are less likely to choose a FRM in a given quarter if in that quarter the bank faces a higher cost of raising long term funding compared to households borrowing from the same bank in a quarter where the bank faces a lower costs of long-term funding. The finding is confirmed in column (2) when we control for aggregate trends at a finer level of geography (a province).

To interpret the result described above as evidence of bank manipulating customers through advice, we need to rule out the possibility that customers sort across banks based on the type of mortgage they tend to sell.[12] First, the banks in our sample are not highly

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[12]Foa et al. (2015) provide evidence that rules out other alternative explanations, such as rationing and advertising.

specialized. The same bank can predominantly issue ARMs in one quarter and originate more FRMs in the following one. Second, in Table 3 we replicate the exercise performed in Foa et al. (2015) running a set of linear regressions with bank fixed effects to assess whether several characteristics of the borrower (size of loan needed, age, gender, etc.) co-vary with the lender's cost of long term funding. The result is that, whereas the cost of securing fixed rate funding influences the probability of a mortgage being fixed rate, it does not correlate with any of the characteristics of the pool of borrowers included in our data, despite the fact that these characteristics affect mortgage choice. This evidence suggests that the effect documented in Table 2 is not due to sorting of borrowers across banks and is instead fully consistent with banks distorting advice.

4 Model

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

A continuum of households of mass M_t indexed by h take up a mortgage in quarter t from one of N banks in the market. The timeline is as follows. First, in the beginning of quarter t, banks simultaneously set rates. Second, each household h chooses the bank from which it takes the mortgage. We say that the household becomes a *customer* of this bank. Third, banks provide advice to their customers about the mortgage type. Forth, households choose the mortgage type.

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

4.1 Households

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

Second, each household enters the quarter with a *home bank,* which one can think of as the default option for the household to do business with (e.g., the bank where the

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

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

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

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

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

We capture this trade-off according to the following setup introduced in Koijen et al. (2009). Households take a mortgage whose principal and interest are fully repaid after Δ quarters without intermediate payments. Thus, if r_t^{eurbr} is the 1-month Euribor benchmark rate at date t, then $r_{t+\Delta}^{eurbr} = r_t^{eurbr} + \pi + \varepsilon$ is the 1-month Euribor at date $t + \Delta$, where π and ε are inflation and real interest rate shocks at time $t + \Delta$. Let r_{it}^f be the FRM rate and s_{it}^a be the spread between the ARM and the 1-month Euribor benchmark rate set by

bank i on mortgages issued at date t. Then, for a customer of bank i the payment at date $t + \Delta$ is equal to $(1 + s_{it}^a + r_{t+\Delta}^{eurbr})H$ when she takes the ARM and to $(1 + r_{it}^f)H$ when she takes the FRM.

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

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

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

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

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

The behavior of naive households departs from the spread rule. By the analogy with the "money doctors" framework of Gennaioli et al. (2015), 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. However, after they become customers of some bank both un-attached and attached naive households follow the bank's advice in their choice of mortgage type. Thus, naive households can be "convinced" to take a mortgage type different from the one that they intended to take before receiving the

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

advice. Households' choices are summarized in Table 4.

Discussion of assumptions In our model of sophisticated households' choices, we abstract from several aspects of the mortgage choice, such as intermediate mortgage payments, the decision to buy versus rent, the choice of the house size and the mortgage size, or the comovements in rates and income. However, it has been shown empirically and theoretically in Campbell and Cocco (2003); Koijen et al. (2009); Badarinza et al. (forthcoming) that the spread between FRMs and ARMs is indeed the most important determinant of the mortgage choice, and the spread rule in (4.3) is approximately optimal in much richer models.

Our assumption that naive households purchase FRMs in the absence of advice can be microfounded using the "money doctors" model by Gennaioli et al. (2015). Below, we outline the similarities between our setup and theirs. The formal treatment is in Appendix *A*.3. In Gennaioli et al. (2015), households choose between two investment opportunities: the bank deposit, which is a more familiar option, and the stock market, which is a more rewarding, but more complex option that requires certain sophistication and skill. Investors experience "anxiety" when investing in a more complex product, and might choose to stay out of the market, which is consistent with well-documented under-participation in the stock market by less sophisticated households (Calvet et al. (2007)). Financial intermediaries act as "money doctors" by providing information about more rewarding options and reducing the investors' anxiety.

We draw a parallel between the household's decision about the mortgage type and the retail investor's portfolio decision. FRM is conceptually similar to bank deposits and represents a more familiar and easy to understand option.[13] ARM is similar to the

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

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.[14] Similar to Gennaioli et al. (2015), in the absence of advice, naive households suffer anxiety when taking the ARM on their own and therefore prefer taking FRMs. However, banks can alleviate the households' anxiety and convince them to take ARM. Unlike in Gennaioli et al. (2015), in our model intermediaries can manipulate naive customers into taking ARMs, even when FRM is better for them.

As we mentioned, the attached/un-attached status captures different market frictions that prevent households from taking a mortgage at the best market terms. These frictions are a general feature of the retail financial sector (Woodward and Hall (2012); 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 8 in Appendix $A.8$). However, our data is not rich enough to pinpoint the precise nature of these frictions. Therefore, the model is agnostic on the source of this phenomenon and instead includes a generic friction which binds for a fraction $1 - \psi$ of the households. One could interpret it as a switching cost, in which case, the home bank would be the bank where the household has its primary checking account, and for a fraction $1 - \psi$ of households the cost of switching bank is prohibitively high.[15] Alternatively, the attached/un-attached status could reflect search frictions. In this case, the home bank is the bank from which the household starts its search and the search cost are so high for a fraction $1 - \psi$ of households that they do not search past their first inquiry, whereas a fraction ψ of households screens all rates in the market and finds the best available.

Further, we assume that once the household becomes the customer of a certain bank, it cannot switch after receiving the advice. This assumption is binding only for naive un-attached households: they pick their bank based on fixed rates, but are sometimes steered towards ARMs. They might then have incentives to withdraw their applications

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[14]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 $A.4$ reports the results of surveys on financial literacy of Italian households indicating that there is a significant fraction of mortgage takers failing to answer basic questions measuring their financial literacy, and that households with outstanding FRMs are those less financially literate.

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

in the current bank and become a customer of the bank with a lower ARM rate.[16] We justify this assumption with the presence of high fixed costs of application (e.g., collecting documentation, filing in the application and getting it approved), which reduce the incentives to re-optimize. Further, naive households may also believe (or be led to believe by banks) that a bank posting the lowest fixed rate is also posting a low adjustable rate, in which case the expected benefits from doing a new search would be low.

4.2 Banks

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

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

where m_{it} is the mass of bank i's customers and x_{it} is the fraction of FRMs issued by bank i in quarter t.

The first term in (4.7) reflects the net profit margin in basis points on one euro lent through mortgages. This margin is multiplied by the size of the bank's customer base m_{it} to obtain the total profit from all mortgages issued. The last term $e^{-\beta r_{it}^f}, \beta>0$, penalizes banks for offering very high fixed rates to their customers and captures in a reduced form the fact that excessive mortgage rates could turn away even attached customers to some outside option, e.g., renting.

The net profit margin increases with the average spread of rates over benchmarks. We denote by s_{it}^a the spread of the ARM rate over the 1-month Euribor (r_t^{eurbr}) and by s_{it}^f the spread of the FRM rate over the 25-year swap rates (r_t^{swap25}). We use 1-month Euribor rate as the benchmark for ARMs, because the bank can finance ARMs by short-term borrowing in the interbank market in which case the bank's profit from ARMs equals the spread over Euribor that the bank charges. Similarly, the 25-year swap rate is the benchmark for FRMs, because the bank can finance FRMs by borrowing short-term in the interbank market and entering an interest rate swap contract in which case the bank's profit from FRMs equals the spread over the 25-year swap rate. Figure 9 in Appendix A.8 documents using data from one of the largest bank in Italy that FRM and ARM rates track corresponding benchmarks.

A recent literature argues that banks maintain significant exposure to the interest

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[16]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.

rate risk (Begenau et al. (2015); Gomez et al. (2016)) due to the limited use of derivative hedging (Rampini et al. (2016)) or banks' relative efficiency in managing the maturity mismatch (Drechsler et al. (2017)). The quadratic cost term in (4.7) captures the fact that issuing too many FRMs causes a potential maturity mismatch. We refer to θ_{it} as bank i's *cost efficient fraction of FRMs*, which is the fraction of FRMs that bank i can issue without suffering maturity mismatch costs. When the bank's fraction of FRMs in the mortgage portfolio equals θ_{it}, such costs are zero. A deviation of x_{it} from θ_{it} leads to a reduction in the profit margin by $\lambda(x_{it} - \theta_{it})^2$ basis points. The parameter $\lambda > 0$ reflects how severe these costs are.

The timing of the game is as follows. At the beginning of quarter t, each bank privately observes its θ_{it}, which is an i.i.d. draw for each banks in each period from a normal distribution with mean μ_θ and variance σ_θ^2 truncated from below at 0 and from above at 1. All banks observe all the adjustable rate spreads of their competitors and simultaneously set spreads s_{it}^f of FRM rates over the 25-year swap rate. After that, the customer base is determined: the bank retains the attached households for whom it is the home bank. In addition, the bank attracts un-attached naive households if it posts the lowest fixed rate, and un-attached sophisticated customers for whom one of its mortgages is the best option in the market. Given its customer base, each bank chooses its advice policy $\omega_{it} \in [0, 1]$, and recommends to a fraction $1 - \omega_{it}$ of its customers to take the ARM. This advice only affects a fraction $1 - \omega_{it}$ of the naive customers of the bank, as sophisticated customers are not susceptible to advice.

Discussion of assumptions The assumption that adjustable rates are determined outside of our model, and banks compete only by setting spreads s_{it}^f is motivated by the common practice of rate setting in the industry. Figure 1 plots the spread between the 25-year FRM and ARM rates and corresponding benchmarks at a monthly frequency between 2004 and 2008 for one of the largest banks in Italy. The ARM spread over the Euribor is held constant over very long time intervals; whereas the spread of FRM rate over the swap rate adjusts at much higher frequency. We observe a similar pattern when we average rates over all the banks in our sample.

In modeling the banks' objective function, we intentionally take a reduced form approach and only capture how given the cost efficient fraction of FRMs (θ_{it}) each bank optimally uses rate setting and advice to manage the interest rate risk. The evidence from Section 3 suggests that θ_{it} depends on supply factors. For example, it reflects the ability of the bank to borrow long-term at better terms. If shifts in banks' supply factors
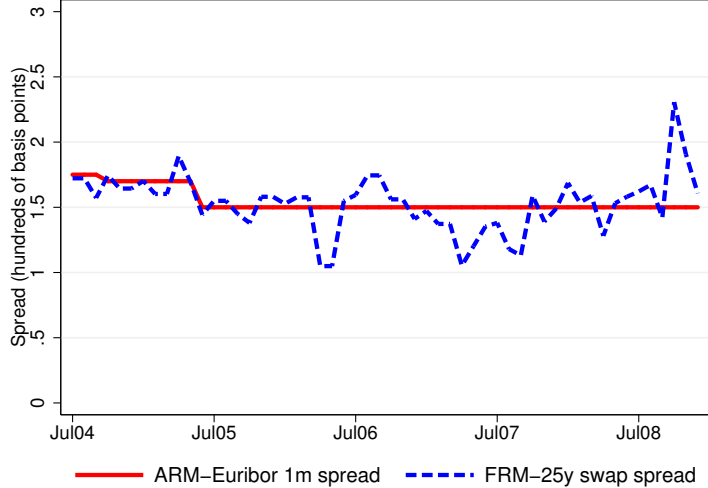
Figure 1: **Rate Spreads on a 25-year Mortgage Set by a Major Italian Bank**

drive θ_{it}, then banks' advice is distorted. However, our approach allows us to retrieve an estimate of the bank's θ_{it} without imposing assumptions on its nature. In particular, θ_{it} could also be affected by other factors, such as reputation concerns. In Section 6, we use our estimates to provide evidence on which variables influence the bank's cost efficient fraction of FRMs.

4.3 Equilibrium

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

We next derive explicit expressions for bank's optimality conditions. Consider the subgame, in which bank i gives its customers advice about the type of the mortgage. Suppose that in this subgame, the spreads of ARM and FRM over benchmarks are s_{it}^a and s_{it}^f, respectively, and bank i attracts mass m_{it} of customers. Bank i advises a fraction $1 - \omega_{it}$ of its customers to take the ARM. This advice affects only the choice of naive customers, while sophisticated customers ignore the advice and choose the mortgage type based on the spread rule. We denote by $\underline{x}_{it}$ and $\overline{x}_{it}$ respectively the minimal and maximal fractions of FRMs that can be attained through advice.[17] The choice of ω_{it} is equivalent to the direct choice of the fraction of FRMs issued, x_{it}, subject to the constraint that

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

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$\underline{x}_{it} \leq x_{it} \leq \overline{x}_{it}$. Hence, the bank solves

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

We rewrite the profit function in terms of the FRM-ARM spread $\phi_{it} = r_{it}^f - (s_{it}^a + r_t^{eurbr})$, which is the relevant spread for the sophisticated households' choice:

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

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

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

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

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

$$(4.6)$$

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

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

where $G_i\left(\cdot|\mathbf{s}_t\right)$ is the distribution of $\underline{s}_{-it}^f \equiv \min_{j\neq i}\{s_{jt}^f\}$ given $\mathbf{s}_t$ and the equilibrium rate setting strategies of other banks. Here, the FRM-ARM spread together with the stochastic fixed rates set by other banks affect the mass of customers of bank i, m_{it}, and the composition of this customer base, namely, bounds $\underline{x}_{it}$ and $\overline{x}_{it}$. Appendix $A.5$ derives a more explicit formula for (4.7) that we use in our estimation.[18]

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

5 Identification

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

5.1 Identification of Demand Parameters

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

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

- the set of banks actively issuing mortgages in the province, $i = 1, \ldots, N_j^{d}$;[19]

- 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, $\mathbf{r}_{jt}^d = (r_{1jt}^f, \ldots, r_{N_j^d jt}^f)$;

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

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

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

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

---

[19]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.

where $1\{\cdot\}$ is the indicator function and Φ is the cdf of the standard normal distribution. The identity of a household's home bank is not observed in our data. We use bank's share in the province depositor market p_{ijt}^d as proxy for the probability p_{ijt} that a particular bank i is a home bank to a household. This is based on the observation that a household would experience the least frictions in obtaining a mortgage from the bank where it holds its checking account.

The likelihood in (5.1) consists of four terms. With probability $(1-\psi)p_{ijt}$ a household is attached and i is its home bank. With probability $\psi\mu$ a household is un-attached and naive. Then it takes a mortgage from bank i only if $r_{ijt}^f = \underline{r}_{jt}^f$. With probability $\psi(1-\mu)$ a household is un-attached and sophisticated. Then it takes a mortgage from bank i if and only if bank i offers the best mortgage (type and rate) for the household.[20] The log-likelihood of the realization of issued mortgages, $\mathbf{M}_{jt}^d, j = 1, \ldots, J, t = 1 \ldots T$, equals up to a constant

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

We complement our main data with microdata from the SHIW survey that provides the additional information on households' attachment to their home bank. The 2006 wave of the survey asks respondents to report whether they took a mortgage in this year, which allows us to identify new borrowers. Furthermore, they are asked about the length of the relationship with their main bank. Given that 80% of Italian households only do business with one bank and the mortgage is one of the most important financial decisions for households, we assume that new mortgage takers with short relationships with their main bank ("less than 2 years") changed bank when taking the mortgage. This auxiliary information on the number of households that take mortgages outside of their home bank helps the identification of ψ, because being unattached is a necessary condition to do that. The likelihood that a household takes a mortgage at a bank which is not its home bank in province j and quarter t is

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

where p_{jt}^F and p_{jt}^A are the probabilities that the bank posting the lowest fixed rate and the

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

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

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

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

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

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

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

Discussion of demand identification The main source of identification of the fraction of un-attached households is SHIW data documenting the number of people taking mortgages outside their home bank. The fraction of naive households is identified exploiting differences in the elasticity of banks market shares to the event that a bank posts the best fixed or the best adjustable rate in the market. This can be most clearly seen if we fix δ to be the same for all households. In this case, if for example $\underline{r}_{jt}^f - \left(\underline{s}_{jt}^a + r_t^{eurbr}\right) > \delta$, then all sophisticated un-attached households take the mortgage from the bank with the lowest ARM rate. If bank i posts the lowest fixed but not the lowest adjustable mortgage rate, then its market share increases by $\psi\mu$, because it attracts naive un-attached households. Instead, if bank i posts the lowest adjustable but not the lowest fixed mortgage rate, then its market share increases by $\psi(1 - \mu)$, because it attracts sophisticated un-attached households. This way we can recover μ from the variation in market shares of the banks when the lowest adjustable and fixed rates are occasionally posted by different

banks. In Table 1, we show that in our data there is substantial variation in the identity of the bank offering the best rates: The top decile for the fraction of times a bank offers the lowest rate is 0.36 for ARM and 0.44 for FRM.

Table 1 documents that in our data the FRM-ARM spread varies enough that the fraction of sophisticated households who prefer FRM to ARM differs across time and markets. This variation allows us to identify the distribution of δ. The standard deviation of the FRM-ARM spread is 0.63 with an interquartile range of over 50 basis points.[21]

5.2   Identification of Supply Parameters

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

- the set of banks actively issuing FRM mortgages in the region, $i = 1, \ldots, N_k^s$;[22]

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

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

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

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

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

The supply side estimation uses as inputs the estimates of the demand side of the model $(\hat{\Omega}^d)$. The main challenge is retrieving each bank's unobserved cost efficient fractions of FRMs, θ_{ikt}. We invert condition (4.5) for optimality of advice to obtain θ_{ikt} for each bank-region-quarter as a function of data and supply parameters Ω^s. Then, we express banks' predicted shares of FRMs and FRM-ARM spreads as functions of only data and supply parameters but not of θs. Further, we find estimates of Ω^s that minimize the discrepancy between the model's predictions for FRM shares issued and FRM-ARM spreads and the data.

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

[22]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.

Next, we describe the estimation procedure.

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

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

However, when the observed fraction lies below the lowest $(x_{ikt} < \underline{x}_{ikt})$ or above the highest $(x_{ikt} > \overline{x}_{ikt})$ fraction achievable by the bank according to the model, there is a range of $\hat{\theta}_{ikt}$ that minimizes expression (5.5). To obtain an estimate of θ for those cases, we estimate the parameters μ_θ and σ_θ of the distribution of θ by maximizing the likelihood of the observed fraction of FRMs issued.[23] Then, we use the estimated distribution of θs to impute $\hat{\theta}_{ikt} = \mathbb{E}[\theta | \theta \leq \underline{x}_{ikt} - (\phi_{it} - r_t^{swap25} + r_t^{eurbr})/(2\lambda)]$ when the bank specific lower bound is hit and $\hat{\theta}_{ikt} = \mathbb{E}[\theta | \theta \geq \overline{x}_{ikt} - (\phi_{it} - r_t^{swap25} + r_t^{eurbr})/(2\lambda)]$ for observations at the upper bound.

Step 2: Predicted FRM Fractions and FRM-ARM Spreads   Conditional on $\theta_{ikt}, \boldsymbol{\phi}_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s$ and parameters Ω^s, we can compute the predicted share of FRMs from equation (4.5), which we denote by $\hat{x}(\theta_{ikt}|\Omega^s, \boldsymbol{\phi}_{kt}, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s)$.

We then compute the predicted FRM-ARM spread, $\hat{\phi}(\theta_{ikt}|\Omega^s, \mathbf{s}_{kt}^s, \mathbf{p}_{kt}^s)$, from maximizing equation (4.7). In order to do so, we need an estimate of the distribution of the minimum of $N_k^s - 1$ FRM rates for each region, $\hat{G}_k(\cdot)$. Following the auction literature (Athey and Haile (2007)), we use the observed rates to obtain the kernel density estimator for the regional distribution of FRM rates. We use it to construct an estimate of the first-

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[23]The likelihood is given by

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

$$+ \sum_{x_{ikt} \leq \underline{x}_{ikt}} \ln\left(\Phi\left(\frac{\underline{x}_{ikt} - \frac{1}{2\lambda}(\phi_{it} - r_t^{swap25} + r_t^{eurbr}) - \mu_\theta}{\sigma_\theta} \right) - \Phi\left(\frac{-\mu_\theta}{\sigma_\theta} \right) \right)$$

$$+ \left. \sum_{x_{ikt} \geq \overline{x}_{ikt}} \ln\left(\Phi\left(\frac{1-\mu_\theta}{\sigma_\theta} \right) - \Phi\left(\frac{\overline{x}_{ikt} - \frac{1}{2\lambda}(\phi_{it} - r_t^{swap25} + r_t^{eurbr}) - \mu_\theta}{\sigma_\theta} \right) \right) \right].$$

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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., $G_{ik}\left(\cdot|\mathbf{s}_{kt}^s\right)$. This requirement is data intensive because it implies estimating a different function for each combination of adjustable rates posted by banks active in the market. We exploit the fact that, as shown in Figure 1, the ARM-Euribor spreads are fairly persistent and proxy the conditional distribution with the unconditional one.

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

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

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

Two remarks on the identification of the supply side are in order. First, to identify the unobserved cost efficient fraction of FRM for each bank in every period we exploit the mapping between the θs and the realized fraction of FRMs issued by a bank. This approach requires that the distribution of characteristics of customers, i.e., the distribution of δ, faced by banks does not change during our sample span. In Appendix $A.6$, we exploit a survey of retail investors as well as microdata from the credit registry to show that both the distribution of risk aversion and that of the mortgage size, which are the two main elements entering δ, stay the same throughout the period we analyze. Second, in Table 3 we show that there is no significant sorting of customers across banks. This rules out the alternative story that the dispersion in the share of FRM issued across banks is due to differences in the preferences of the clientele rather than to advice.

6   Estimation Results

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

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

Table 5: **Estimates of the Parameters**

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

6.1 Estimates

Table 5 reports estimates for the parameters of the model. The main fact emerging from the estimates of demand parameters is that the fraction of naive households is large (48%). Our estimate is consistent with the evidence relying on independent data measuring the sophistication of Italian households we discuss in Appendix A.4. This evidence points to a very low level of basic financial knowledge by Italian households, providing ample opportunity for banks to distort advice.

We also find that there is a limited fraction of un-attached households (8.8%). This estimate suggests relevant frictions on the consumer side in the Italian mortgage market, which is further witnessed by the significant within market dispersion in both adjustable and fixed rates across banks documented in Figure 8 in Appendix A.8. Furthermore, the low fraction of un-attached households that we estimate resonates with the extreme inertia in the deposit market (Deuflhard (2016); Ater and Landsman (forthcoming)).

The estimate of the distribution of the optimal spread cut-off δ for sophisticated households indicates that ARM is on average the preferred option in the market. The negative mean of the distribution of δ could be explained by households' expectation of declining nominal rates, or alternatively, higher expectation of the volatility of inflation compared to that of the real interest rate.[24] Figure 10 in Appendix *A*.8 shows that the estimated distribution of δ has substantial overlap with the empirical distribution of the FRM-ARM spread in our data. This indicates that sophisticated households following the spread rule choose both types of mortgage.

As a robustness exercise, in Appendix A.7 we consider an alternative specification for the demand side where the fraction of naive and un-attached households differ across regions and are functions of region characteristics, such as education level and the length of relationship with the bank. The estimation result are consistent with our baseline

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[24]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)).
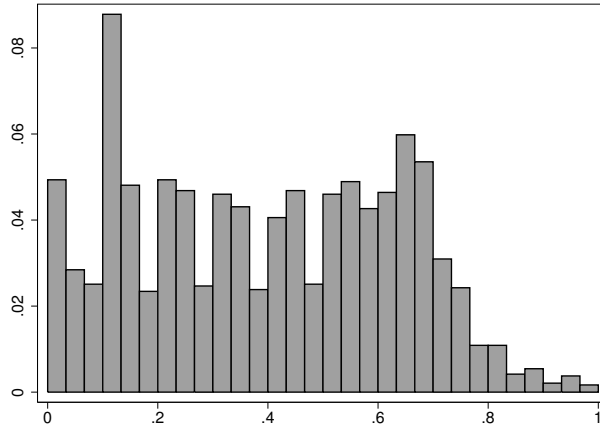
Figure 2: **Histogram of Estimated θs**

specification. We find that the education level in the region reduces the fraction of naive households, and the higher share of households with long relationship with their bank increases the fraction of attached households.

The key object estimated in the supply side is the distribution of the cost efficient fractions of FRMs, θs, displayed in Figure 2. The distribution is fairly disperse but there is barely any mass for values of θ above 0.9, likely due to the fact that more ARMs are issued in our sample span.

To interpret the estimate of λ we take the net profit margin in equation (4.4) as a point of reference. For the median bank in our data, the loss due to the deviation from the cost efficient fraction of FRMs issued represents 1.8% of its margin per euro lent. The distribution of such cost has a fat right tail: banks with large deviations from their cost-efficient share of FRM suffer significant reductions in their margins.

6.2 Evidence of Distorted Advice

Our structural model allows us to recover a time-varying, bank-specific parameter which determines the rate setting and advice policies of the bank. So far, we have been agnostic on the interpretation of this parameter. Our preferred interpretation of θ is that it reflects the structure of liabilities and the cost of financing. Hence, banks' effort to issue a fraction of FRMs close to their θ can be read as the provision of distorted advice. Such interpretation is consistent with the reduced form evidence of distorted advice by financial intermediaries in Foa et al. (2015).

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

Table 6: **Correlation between θ and Supply Factors**

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

Here, we exploit our estimates of the bank θs to provide additional evidence of distorted advice.[25] We regress θs on the bank bond spread, which is the difference between the rate of long- and short-term bonds issued by the bank. We focus on this particular measure because it varies often and it is outside the control of the bank.[26]

In Table 6, we show that controlling for time and bank fixed effects, a higher level of bond spread is associated with a lower cost-effective fraction of FRMs issued. When it is more costly for a bank to finance itself through fixed rate bonds, it will be less keen on issuing fixed rate mortgages, because it finds it expensive to match them with fixed rate liabilities. As our model predicts, such banks would advise their customers to take ARMs.

As we documented in Table 1, banks differ in their reliance on the market for financing. Some banks, usually small ones, are able to finance their operations using almost exclusively cash collected from their depositors. For these banks, the cost of financing is not an important factor and should not affect their goals in terms of how many fixed rate mortgages to issue. If θ reflects distorted advise, the relationship between θ and the bank bond spread should be stronger for banks with higher reliance on bond financing. In the other columns of Table 6, we repeat the exercise focusing on subsamples that exclude banks with very high ratio of deposits to total liabilities. For banks in the bottom three quartiles of the deposits/liabilities ratio, the relationships becomes more negative

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

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

and more statistically significant; its point estimate grows in absolute value when we look at banks below the median of the deposits/liabilities ratio, which should be even more reliant on the bond market to secure financing. Further, for banks in the bottom quartile of the distribution of the deposits/liabilities ratio the correlation is the most negative. However, it is not significant most likely because of a relatively small sample.

7   Policy Experiments

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

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

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

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

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

We set the mortgage size H to the median mortgage size in our sample (125,000 euros) and compute the change in the certainty equivalent for every household as follows. If the household switches from ARM with $s_t^a(h)$ to ARM with $\tilde{s}_t^a(h)$, or from FRM with $r_t^f(h)$ to FRM with $\tilde{r}_t^f(h)$, then the change in the certainty equivalent equals $H\left(s_t^a(h) - \tilde{s}_t^a(h)\right)$ and $H\left(r_t^f(h) - \tilde{r}_t^f(h)\right)$, respectively. If the household switches from the ARM with $s_t^a(h)$ to FRM with $\tilde{r}_t^f(h)$ or from the FRM with $r_t^f(h)$ to ARM with $\tilde{s}_t^a(h)$, then it follows from $(7.1) - (7.2)$ that the change in the certainty equivalent equals $H\left(s_t^a(h) + r_t^{eurbr} + \delta - \tilde{r}_t^f(h)\right)$ and $H\left(r_t^f(h) - \tilde{s}_t^a(h) - r_t^{eurbr} - \delta\right)$, respectively.

We use our estimates of μ, ψ, and the distribution of δ to simulate a population of customers equal in size to the number of mortgages issued in our data. We then use our estimates of λ, β, and θ_{ikt} to compute the banks' responses to various policies. Further,

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

Table 7: **Summary of Counterfactual Exercises**

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

we calculate the consumer surplus induced by counterfactual exercises on the sample of simulated households. To be conservative on the impact of advice on welfare, we assume that banks provide advice minimizing the welfare loss caused to their customers. This means that if a bank decides to recommend ARM to 30% of its naive customers, it will pick those customers for which the switch from FRM to ARM is the least harmful.

7.1 Restricting Advice

We first investigate the effect of reducing the ability of banks to provide advice to their customers. Whereas in the baseline model, the bank could influence all of its naive customers, we now suppose that it can provide advice only to a half of them. Formally, $\omega_{it} \in [0, \frac{1}{2}]$ instead of $\omega_{it} \in [0, 1]$. We can interpret this experiment as an increase in the level of monitoring by the regulator, which limits the scope for advice, or as the advent of online banking, which crowds out the advice by reducing direct interaction with clients. It can also be related to regulatory interventions tightening fiduciary standards, like the one introduced by the Obama administration for the US in 2016, which could induce financial intermediaries to provide less advice for fear of exposing themselves to lawsuits. Note that this experiment does not change the way households choose banks nor their decision rules: sophisticated borrowers follow the spread rule; advised naive borrowers follow the suggestion given to them by the bank, and unadvised naive borrowers select FRMs.

This experiment allows us to measure the welfare consequences of advice to households.[27] The overall effect of limiting advice is a loss of 998 euros per household per year over the entire course of the mortgage. This is about 17% of the total amount (principal and interest) a household would have to repay in a year for a 125,000 euros mortgage at

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[27]As already discussed in Section 4, our model bears resemblances to the "money doctors" framework in Gennaioli et al. (2015). In their model, advice is undistorted and so, is indisputably welfare improving for the customers. In our model, because of the distorted advice, the welfare effects are ex-ante ambiguous.

the average FRM rate in our data (5.6%).[28] If we decompose this loss, we observe that naive households suffer the most (they lose 1,444 euros per capita per year compared to the unrestricted advice scenario); but sophisticated customers are also worse off by 590 euros per year.

To obtain intuition for why restricting advice is costly, we separate two effects of advice on naive households. 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. Hence, they benefit when the bank steers them towards an ARM, even though such a recommendation is provided in the bank's self interest. We call this the *information value* of advice, as banks inform naive customers about the alternative product, which they did not consider before.[29] On the other hand, there are naive households who should take a FRM if they were to follow the spread rule. These households would make the correct choice in the absence of advice, but banks can instead distort it leading them to take an ARM. This causes the *distortion costs*. At our parameter estimates, before the policy, for 52% of naive households the bank's recommendation coincides with their optimal choice, while the remaining naive household make suboptimal choices. After the policy, a half of naive households are still affected by advice and 33% of them make suboptimal choices. The other half does not receive advice and 80% of them make suboptimal choices. Thus, the fraction of households making suboptimal choices increases. Therefore, the information value outweighs the distortion costs and restricting advice reduces welfare of naive households.

The conclusion on the effect of partially banning advice is robust to the assumption about the choice of naive households in the absence of advice. In our baseline model, when they make the choice on their own, they choose a FRM. As a robustness exercise, we consider an alternative specification in which 40% of naive household in the absence of bank advice about the mortgage type turn to other sources of advice, such as media, friends, family, etc. As we mentioned in Section 2, 40% is an upper bound on the fraction of households obtaining advice from sources other than banks. We suppose that the recommendation from these sources is equally likely to be for FRM or ARM. This modification reduces the number of households who should take the ARM but instead take the FRM because of the lack of advice; whereas the set of households whose choice is negatively distorted (i.e., households who should take the FRM and are instead led to

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[28]The total amount paid in a year was computed using the mortgage calculator http://www.mutuionline.it/guide-mutui/calcolo-rata-mutuo.asp.

[29]The information value is closely related to banks acting as "money doctors" that reduce the naive households' anxiety from choosing the more complex product, namely, the ARM.

take the ARM) stays the same. As a consequence, advice from banks is less valuable: restricting advice in this scenario still leads to a considerable average welfare loss of 633 euros per household per year (with naive households losing on average 797 euros per year and sophisticated households losing 484 euros per year).

7.2 Undistorted Advice and Financial Literacy Campaign

We next study the effect of forcing banks to provide undistorted advice to their customers. This means that banks make naive households follow the same spread rule that guides the decision of sophisticated households. In this scenario, every household takes the "right" mortgage and the average welfare gain is very large: 661 euros per capita per year, which amounts to 11% of the annual mortgage payment for the average household. Interestingly, not all households gain. While naive households benefit the most gaining 1,705 euros per year each, sophisticated households lose 295 euros.[30]

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

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

Even naive households who are not affected by the campaign (and stay naive) also gain

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

117 euros per year. Perhaps surprisingly, both the loss of sophisticated and the gain of naive households unaffected by the campaign come mostly from the effect on households who take FRM both before and after the campaign. The key to this result is that this policy affects differently different banks. When more households become sophisticated, in order to achieve an optimal fraction of FRMs, banks rely more on the rate setting. Banks with a strong preference for ARMs (low θ_{ikt}) increase FRM rates, and banks with a strong preference for FRMs (high θ_{ikt}) lower FRM rates. The correlation coefficient between the FRM rate change and banks' types is -0.11. Thus, the effect on sophisticated households is ambiguous and depends on the distribution of banks' θs. At our parameter estimates, this effect is negative.

The effect on naive attached households is asymmetric. Banks with a strong preference for ARMs bias their advice towards ARMs, while banks with a strong preference for ARMs bias their advice towards FRMs. If the naive household is a customer of the former type of bank, then the increase in FRM rates does not affect her, because such a bank does not recommend FRMs. However, if the naive household is a customer of the latter type of bank, then she might benefit from cheaper FRMs, because such a bank does recommend FRMs. As a result, naive households who stay naive gain.

8 Conclusion

In this paper, we pursue two objectives. First, we quantify the costs of distorted financial advice. Second, we assess the consequences of different policies to address it. We identify that a large fraction of borrowers lacks the sophistication to make independent choices on financial decisions. This finding is relevant from a practical standpoint, as it implies that there is large scope for intermediaries to supply biased advice. Consistently, we estimate that the cost of the distortion is significant and amounts to 11% of the annual mortgage payment for the average household.

A set of counterfactual exercises leads us to conclude that the gains from forcing intermediaries to provide only honest advice or from educating borrowers are sizable. Importantly, they are also unequally distributed: While the naive gain, the sophisticated lose. This exposes financial education campaigns and policies that force undistorted advice to non-trivial political economy implementation problems. On the other hand, we find that restricting advice is not recommendable. All households lose, especially the unsophisticated ones which are left on their own. This reveals that advice can be beneficial to customers even when it is not provided with their best interest in mind.

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

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A   Appendix

A.1   Characteristics of the Italian Mortgage Market

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

Adjustable and fixed rate mortgages in Italy   Our data include only plain vanilla adjustable and fixed rate mortgages. As can be seen in Figure 3, these types represent the majority of mortgages issued in Italy. In the years of our sample, other types of mortgages had a negligible market share. In the period 2006-2015, the combined market share of fixed and adjustable mortgages was on average close to 85%. Another feature emerging from the picture is that both adjustable and fixed rate mortgages are popular. They each represent no less than 20% of the mortgages issued every year.
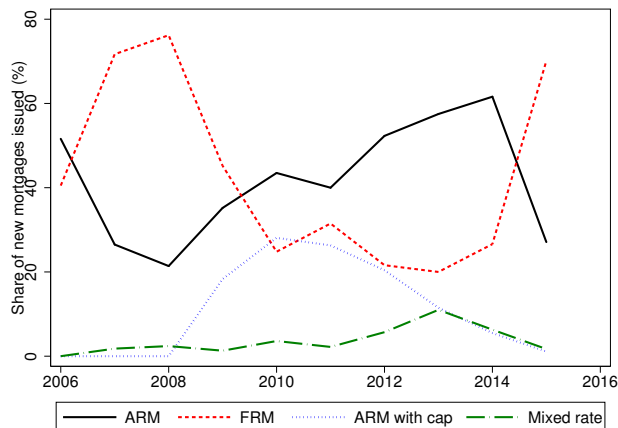
Figure 3: **Market Share by Type of Mortgage**

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

Exposure to interest rate risk   The US mortgage market is dominated by mortgage banks, which off-load mortgages from their balance sheets shortly after origination. Banks issuing mortgages in Europe are instead portfolio lenders: they fund loans with deposits and bond issuance and they keep mortgages on their balance sheets. In particular, Italian banks not only retain a large chunk of mortgages on their balance sheets, but also carry a substantial fraction of the associated interest rate risk as they appear not to hedge perfectly their position with derivatives. This distinction is important because it implies that Italian banks have the
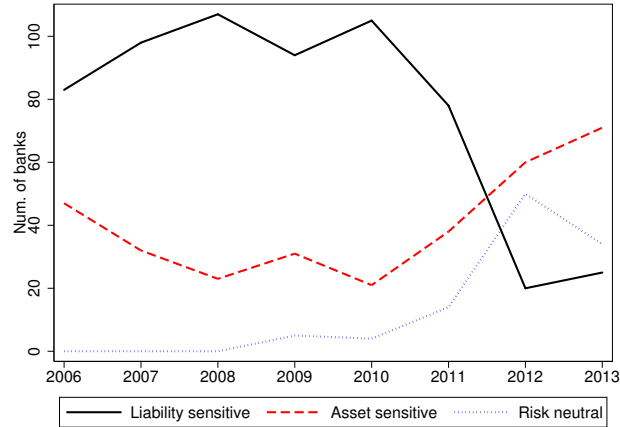
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Figure 4: **Exposure of Italian Banks to Interest Rate Risk**

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

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

In Figure 4, we plot the time series for the number of banks in the Italian system exposed to interest rate risk. The figure is based on the evidence provided in Cerrone et al. (2017) which implement a duration gap approach on data from the balance sheets of a representative sample of 130 Italian commercial banks. They offset assets and liabilities – on and off balance sheets – at each maturity to obtain a net position and assess the effect on the value of the bank of a 200 basis points parallel shift of the yield curve. Banks losing value in case of interest rate increase are defined "Asset sensitive"; banks losing value in case of an interest rate decrease are categorized as "Liability sensitive"; those hedged against interest rate risk are "Risk neutral". The picture shows that every bank in the sample analyzed by Cerrone et al. (2017) was exposed to interest risk for the full span of the time period that we analyze. In terms of the size of the exposure to interest rate, they report that over the period 2006-2013 the loss of value due to a 200 basis point parallel shift upward in the yield curve was 10.37% of the regulatory capital for "Asset sensitive" banks; whereas the average "Liability sensitive" bank would lose 6.62% of its regulatory capital from an equally sized downward shift. Hence, the exposure to interest rate risk, while below the 20% threshold set by Basel Committee on Bank Supervision, was significant throughout the period. Therefore, banks tend to have an overall mismatch between maturity of their assets and liabilities, which is not offset with the use of derivatives. Thus, they have incentives to skew their mortgage portfolios to mitigate this problem.

Other types of risk Our analysis focuses on the incentives to distort advice provided by the need to manage banks' exposure to interest rate risk. Default and refinancing risks are less important in Italy.

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

Based on Bank of Italy data, the share of existing mortgages which are refinanced is consistently below 1% during the time span we analyze. Refinanced mortgages represent between 10% and 15% of newly issued mortgages between 2005 and 2008; the same figure is between 40% and 50% for the US in the same period. Further, default rates are also low, typically below 1% and surging only marginally to 1.5% during the 2009 financial crises.

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

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

Table 8 shows the results of this exercise. Over 50% of the mortgages of the same type issued by branches of the same bank in the same quarter and province are taken at the same interest rate, which points to both limited bargaining over rates and to little sophistication in the formulation of the price. For households taking mortgages at rates below the modal interest rate, we compute the size of the discount whose quartiles are 16, 38 and 76 basis points. These figures, especially the first two quartiles, are substantially lower than those reported by Allen et al. (2014) for the Canadian market where negotiation on mortgage rates is customary.

	% borrowing at posted rate	Discount (bps)		
		25th pctile	50th pctile	75th pctile
Mortgages issued in the same quarter	56	16	38	76
Allen et al. (2014)	25	50	75	95

Table 8: **Mortgage Pricing**

Notes: The table reports statistics on the fraction of households taking a mortgage at an interest rate lower than the modal rate emerging in a particular bank branch in a particular quarter for a particular type of mortgage. Conditional on the rate the household obtains being lower than the modal rate, we report descriptive statistics on the size of the gap. The last row reports comparable statistics for the Canadian market from Allen et al. (2014).

A.2 Sample Construction

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

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

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

A.3 Microfoundation for Naive Households' Behavior

In this appendix, we use the "money doctors" framework introduced in Gennaioli et al. (2015) to microfound the behavior of naive households. Suppose that naive households are uncertain about $\nu_\pi, \sigma_\pi^2, \nu_\varepsilon$, and σ_ε^2, and have some full-support beliefs F about their joint distribution. Conditional on $\nu_\pi, \sigma_\pi^2, \nu_\varepsilon$, and σ_ε^2, the utility of naive households from taking FRM is the same as of sophisticated households and is given by $\mathbb{E}[y-(1+r_t^f(h)-\pi)H]-\gamma\mathbb{V}[y-(1+r_t^f(h)-\pi)H]$.[31] However, conditional on $\nu_\pi, \sigma_\pi^2, \nu_\varepsilon$, and σ_ε^2, their utility from ARM is given by

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

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

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

A.4 Evidence of Limited Sophistication

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

The evidence relies on the 2006 wave of SHIW. Half of the interviewees in 2006 (3,992 households) were administered a section of the questionnaire meant to elicit financial literacy using a set of standard questions in the literature (e.g., Van Rooij et al. (2011); OECD (2016)).

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[31]Thus, their unconditional utility equals

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

where the outside expectation is with respect to household's beliefs about $\nu_\pi, \sigma_\pi^2, \nu_\varepsilon$, and σ_ε^2.
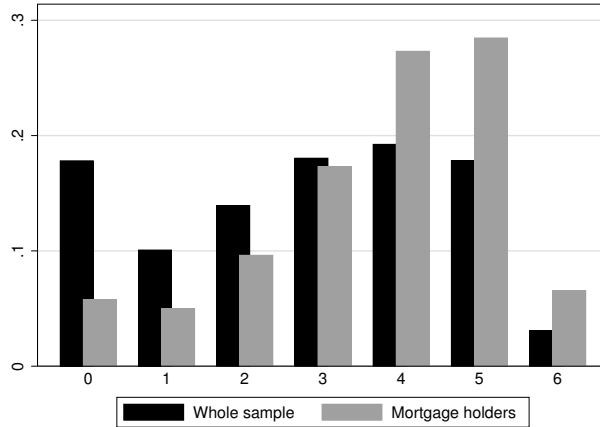
Figure 5: **Distribution of the Sophistication Index**

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.

The section consists of six questions testing the ability to recognize the balance of a checking account statement, to compare the returns of two mutual funds, to understand the difference between real and nominal interest, the concept of compound interest, the wealth consequence of stock prices fluctuations, and the properties of fixed and adjustable rates. For each question, four options are offered: one of them is correct; two incorrect and a fourth option allows the interviewee to profess his cluelessness about the topic.[32]

We construct a summary index of sophistication by counting the number of correct answers given by an individual. The index ranges from zero (least financially literate households) to six (most sophisticated). In Figure 5, we show the distribution of this sophistication index among the whole sample and for the subset of those who have a mortgage outstanding (information about mortgages and other forms of debt is collected in another section of SHIW). Only 3% of the households interviewed answers correctly all the questions, 18% do not get a single one right and 42% do not do better than two correct answers out of six. Compared to the distribution of the index for the whole sample, mortgage holders show higher sophistication (80% of them answer at least two questions correctly).

Figure 6 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*

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[32]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`.
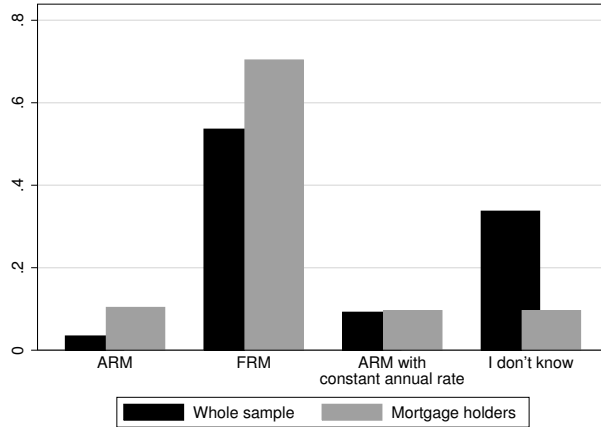
Figure 6: **Understanding of Mortgage Characteristics**

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.

very beginning the maximum amount that you will paying annually and for how many years before you extinguish the mortgage?" The answers offered are: 1) Adjustable rate mortgage; 2) Fixed rate mortgage; 3) Adjustable rate mortgage with constant annual payment; and 4) I do not know. Only 50% of the interviewees provide the right answer. Even among mortgage holders, nearly one third of the interviewees are either clueless or provide a wrong answer.

Further, we provide support to our assumption that unsophisticated borrowers tend to opt for fixed rate mortgages by exploiting a question meant to elicit people's ability to understand the link between interest rates and inflation. Specifically, they are asked: *"Suppose you have 1000 Euros in an account that yields a 1% interest and carries no cost (e.g management fees). If inflation is going to be 2% do you think that in one year time you could be able to buy the same goods that you could by today spending your 1000 euros?"* The answers are: 1) Yes, I would be able; 2) No, I could only buy a lower amount; 3) No, I could buy a higher amount; 4) I do not know. We define *Sophisticated* all those who provide the correct answer (answer 2); *Naive* those who provide either of the wrong answers (answer 1 or 3); and *Clueless* those who cannot answer (answer 4). We tabulate the type of mortgage that households in these different groups:

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

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

A.5   Optimal Spread Setting

We derive an explicit formula for (4.7) that we use in the estimation. We distinguish two cases depending on whether bank i has the lowest ARM-Euribor spread on the market $(s_{it}^a < \underline{s}_{-it}^a)$ or not $(s_{it}^a > \underline{s}_{-it}^a)$.[33] We use super-index a for the former case and super-index A for the latter. After banks post FRM-ARM spreads, bank i has either the lowest FRM rate $(s_{it}^f < \underline{s}_{-it}^f)$ or not $(s_{it}^f > \underline{s}_{-it}^f)$. We use super-index f for the former case and super-index F for the latter.

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

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

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

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

Then ϕ_{it} is determined by maximizing either $(A.1)$ or $(A.2)$ depending on whether $s_{it}^a > \underline{s}_{-it}^a$ or $s_{it}^a < \underline{s}_{-it}^a$, respectively. To complete the characterization of the optimal rate setting, we determine functions $m_{it}, \underline{x}_{it}$, and $\overline{x}_{it}$ for different cases. Let

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

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

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

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

   (b) If $s_{it}^f < \underline{s}_{-it}^f$, then bank i in addition to its attached customers attracts all naive un-attached households and sophisticated un-attached households that prefer to take FRM in the market. The mass of the former is $\psi\mu$, the mass of the latter is $\psi(1 -$

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

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$\mu)\kappa(\phi_t)$. Thus, the total mass of bank i's customers equals

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

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

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

The fraction of naive households is given by

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

and so,

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

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

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

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

   Among those, there is a fraction

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

   of naive households. Further,

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

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

A.6 Stationarity of Households Characteristics

Here, we show that the distribution of risk aversion and mortgage size experienced negligible changes in the period that we analyze. Figure 7 plots the cumulative distribution of a proxy of risk aversion and of the mortgage size for the beginning and the end of the time span covered by our data. Since they represent the main elements determining the optimal spread cutoff, this evidence should reassure on the stationarity of the distribution of δ which underlies our identification of the supply side estimation.
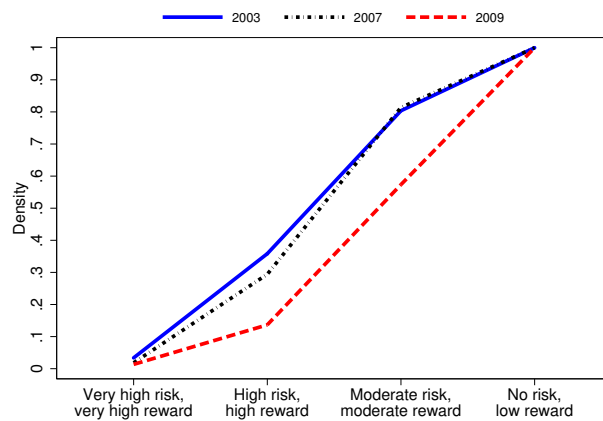
(a) Distribution of Risk Aversion
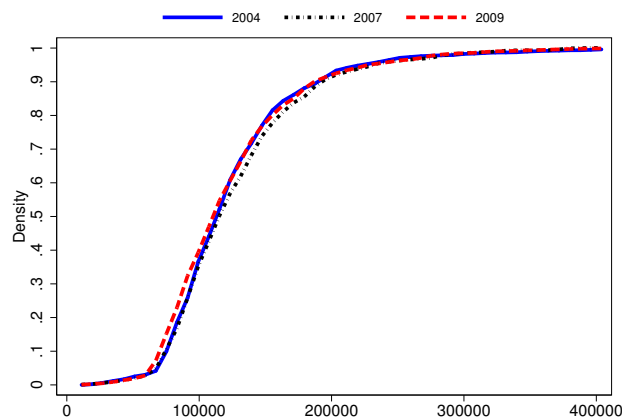
(b) Distribution of Mortgage Size

Figure 7: **Cumulative Distribution of Households Characteristics**
Notes: The top panel plots the cumulative distribution of the responses to a question asking a sample of retail investors of a major Italian banking group to indicate the investment strategy that best characterizes their behavior. The bottom panel plots the cumulative distribution of granted mortgage size using a random sample of Credit Registry microdata representing 40% of the mortgages originated in Italy between 2004 and 2010.

Figure 7a plots the cumulative distribution of the answer to a question meant to elicit risk aversion. The data come from a survey conducted by a major Italian bank on its retail customers. The question we are focusing on asks respondents about the investment strategy that best identifies their approach. The four options offered span a profile consistent with high risk tolerance (households pursuing "very high reward" and willing to be exposed to "very high risk" to achieve it) to extreme risk aversion (households content to obtain "low reward" as long as it entails "no risk" at all). The survey counts several waves and is a repeated cross section. The distribution of answers in 2003 (before the beginning of our sample) and 2007 (the next to last year we consider) is nearly identical. The risk aversion of Italian investors seems instead profoundly affected by the explosion of the financial crisis which dates to the second semester of 2009 in Italy. The investors surveyed in 2009 report a much more risk averse attitude than measured before. This evidence motivates the choice to limit our analysis to the years prior to the financial crisis in Italy.

Figure 7b depicts the distribution of the real mortgages size (in 2004 euros) exploiting microdata on a random subsample covering 40% of the mortgages issued between 2004 and 2009. Conditional on the mortgage being issued, the distribution of mortgage size does not change through our sample. Interestingly, this variable does not seem to be affected even by the intervention of the financial crisis: the distribution in 2009 is nearly identical to the 2004 and 2007 ones.

A.7 Heterogeneity in Demand Parameters

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

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

$$\mu_r = \frac{exp(a_0 + a_1 Education_r)}{1 + exp(a_0 + a_1 Education_r)},$$
$$\psi_r = \frac{exp(b_0 + b_1 RelationLength_r)}{1 + exp(b_0 + b_1 RelationLength_r)},$$

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

Table 9: **Demand with Regional Heterogeneity**

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

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

The maximum likelihood estimates are displayed in Table 9 and line up with intuition. A larger share of highly educated is associated with fewer naive households. Further, regions where the relationships between customers and banks are tighter have a lower fraction of un-attached households. In quantitative terms, the dispersion estimated in the fraction of un-attached is minimal: the estimates of ψ across regions range between 8.5% and 9.3%. Dispersion in the fraction of naive is also moderate: the share ranges from 45% to 52%.
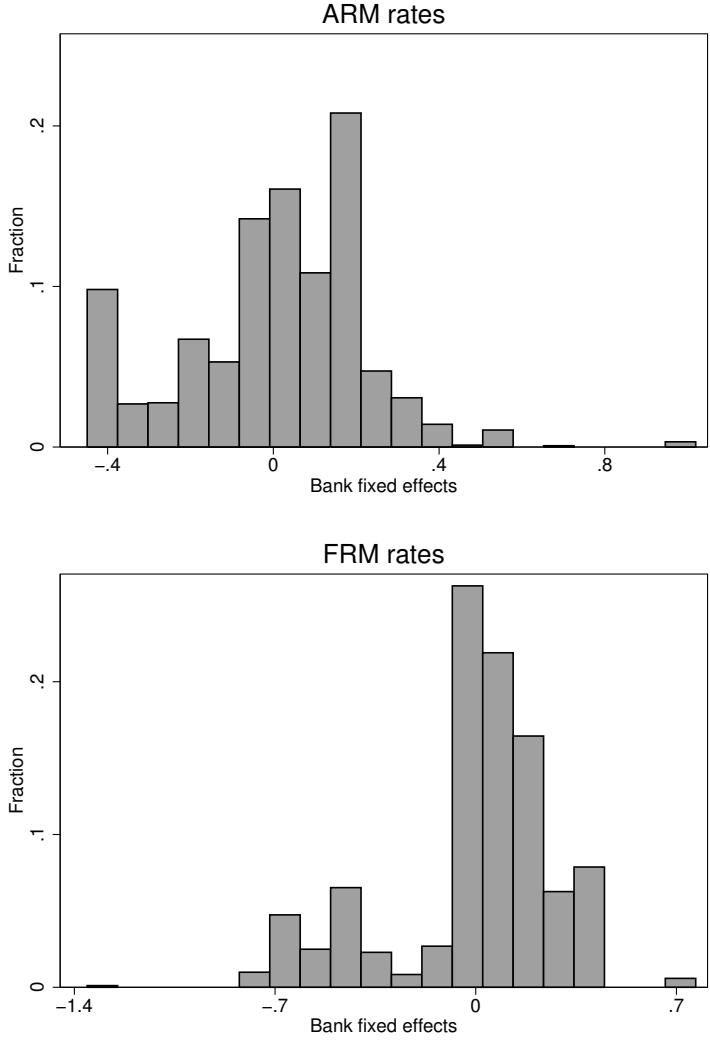
A.8   Additional Figures

Figure 8: **Dispersion of Rates**

Notes: The figures display the bank fixed effects (in rate percentage points) estimated from regressing adjustable rates (top figure) and fixed rates (bottom figure) on bank, province and quarter dummies.
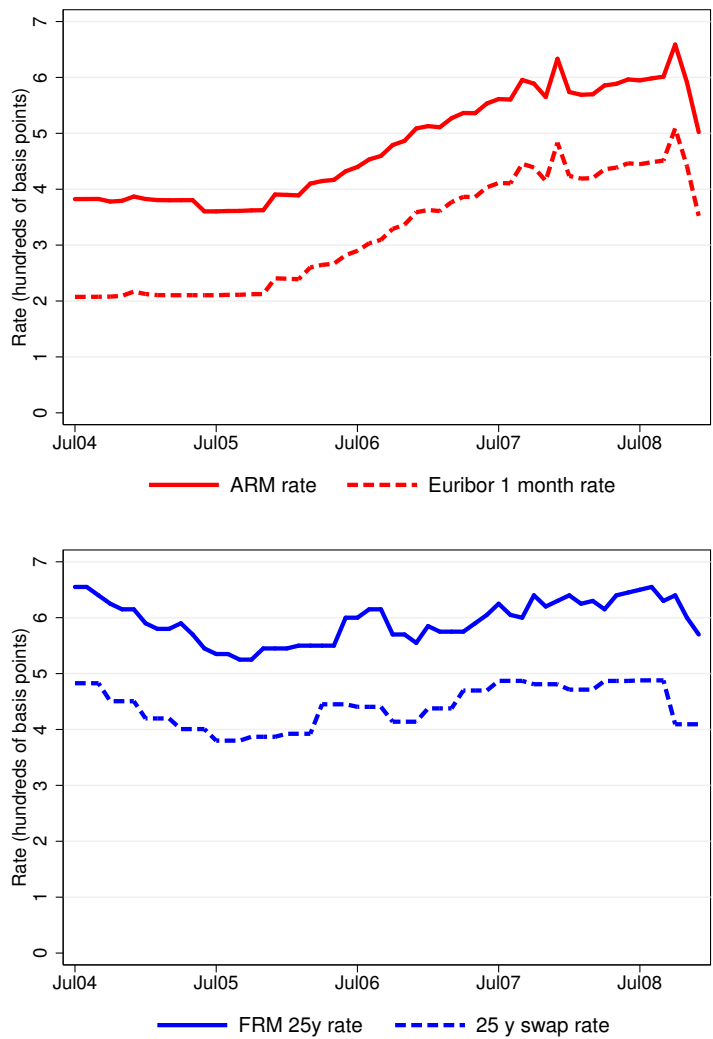
Figure 9: **Benchmark Rates for adjustable and fixed rate mortgages**

Notes: The figure portrays the evolution of adjustable and fixed rates posted by a large bank during the sample span we analyze. We compare them with the rate of the instrument we assume banks use as benchmark for the pricing of their mortgages. In the top panel, we display the ARM rate posted by the bank and the Euribor 1 month rate; in the bottom panel, the rate on a 25 years FRM is porttrayed alongside the rate of a 25 years interest rate swap.
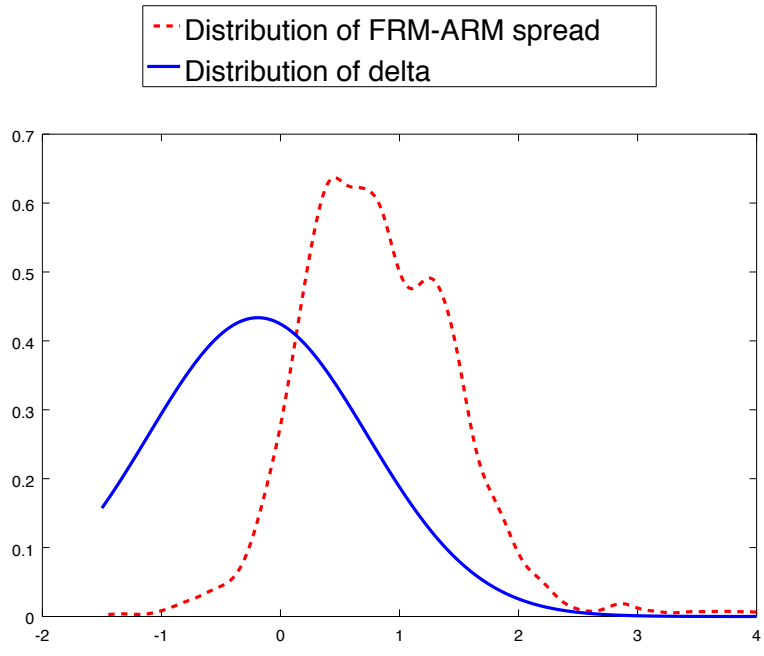
Figure 10: **Estimated Distribution of δ and Kernel Density of ϕ_{it}**