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 1, 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 1: 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 incentive to steer customers towards ARM or FRM to manage their exposure to interest rate risk.

In Figure 2, we plot the time series for the number of banks in the Italian system exposed to interest rate risk. The figure is based on the evidence provided in Cerrone et al. (2017) which implement a duration gap approach on data from the balance sheets of a representative sample of 130 Italian commercial banks. They offset assets and liabilities—on and off balance sheets—at each maturity to obtain a net position and assess the effect on the value of the bank of a 200 basis points parallel shift of the yield curve. Banks losing value in case of interest rate increase are defined “Asset sensitive”; banks losing value in case of an interest rate decrease are categorized as “Liability sensitive”; those hedged against interest rate risk are “Risk neutral”. The picture shows that every bank in the sample analyzed by Cerrone et al. (2017) was exposed to interest risk for the full span of the time period that we analyze. In terms of the size of the exposure to interest rate, they report that over the period 2006-2013 the loss of value due to a 200 basis point parallel shift upward in the yield curve was 10.37% of the regulatory capital for “Asset sensitive” banks; whereas the average “Liability sensitive” bank would lose 6.62% of its regulatory capital from an
equally sized downward shift. Hence, the exposure to interest rate risk, while below the 20% threshold set by Basel Committee on Bank Supervision, was significant throughout the period. Therefore, banks tend to have an overall mismatch between maturity of their assets and liabilities, which is not offset with the use of derivatives. Thus, they have incentives to skew their mortgage portfolios to mitigate this problem.

**Other types of risk** Our discussion of the bank incentives to influence mortgages choice centered on interest rate risk. This is because in the Italian setting this appears to be a more prominent source of risk taken by banks when issuing mortgages compared to credit and pre-payment risks. Like in many other European countries, mortgages are full recourse in Italy: households cannot walk away if the value of the property falls short of the outstanding mortgage. Hence, the incidence of mortgage defaults is rather limited: the fraction of mortgages with late repayment or default is typically below 1% and surges only marginally to 1.5% during the 2009 financial crises. This also reflects banks’ tight screening policies with high rejection rates of risky loan applicants. Based on SHIW data, on average 13% of the households have had a rejected loan application in 2004; the figure rises to 27% in 2008. For this reason we do not include in our analysis the risk of default and also abstract from sophisticated pricing policies conditioning the mortgage rate offered on individual characteristics. In fact, banks submit applications to severe screening to minimize the default risk but then tend to ignore differences in accepted borrowers riskiness setting flat rates, with the exception of a recent attention to loan size or LTV (Liberati and Vacca (2016)).

Most Italian mortgages are held until maturity and it is relatively uncommon that households renegotiate the terms of the mortgage or transfer it to another bank. For most of the time span in our analysis, both prepayment and renegotiation were burdened by unregulated fees in the order of at least 3% of the remaining debt (Brunetti et al. (2020)). A reform enacted in April 2007 (the “Bersani law”) removed prepayment penalty fees for all new mortgages and capped them at a mandated level for existing ones. The reform bill also removed additional cost of renegotiation such as notary fees. Still, the effect of these changes on renegotiation has been modest (Bajo and Barbi (2018); Beltratti et al. (2017)). Based on Bank of Italy data, the share of refinanced mortgages is close to zero up until 2007 and consistently below 1% after. Refinanced mortgages represent between 10% and 15% of newly issued mortgages between 2005 and 2008; the same figure is between 40% and 50% for the US in the same period.

**Pricing of mortgages** Whereas Italian banks thoroughly screen mortgage applicants, the interest rate is set with much less sophistication. Income and other personal characteristics are not priced and until recently even loan to value did not significantly affect the interest rate charged. Further, the negotiation over rates with banks rarely impacts significantly the interest rate that the household pays.
To gauge the extent to which paid rates differ from posted rates in our sample, we rely on the microdata on 40% of all the mortgages issued between 2005 and 2008 which carry information on the rate set for each loan. We identify the modal interest rate paid by households for a branch-quarter-mortgage type combination as the posted rate for the type of mortgage in that market in that period. We then attribute to bargaining and pricing of individual characteristics 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 1 shows the results of this exercise. Over 50% of the mortgages of the same type issued by branches of the same bank in the same quarter and province are taken at the same interest rate, which points to both limited bargaining over rates and to little sophistication in the formulation of the price. For households taking mortgages at rates below the modal interest rate, we compute the size of the discount whose quartiles are 16, 38 and 76 basis points. These figures, especially the first two quartiles, are substantially lower than those reported by Allen et al. (2019) for the Canadian market where negotiation on mortgage rates is customary.

### Table 1: Mortgage Pricing

<table>
<thead>
<tr>
<th>% borrowing at posted rate</th>
<th>Discount (bps)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25th</td>
</tr>
<tr>
<td>Mortgages issued in the same quarter</td>
<td>56</td>
</tr>
<tr>
<td>Allen et al. (2019)</td>
<td>25</td>
</tr>
</tbody>
</table>

*Notes:* The table reports statistics on the fraction of households taking a mortgage at an interest rate lower than the modal rate emerging in a particular bank branch in a particular quarter for a particular type of mortgage. Conditional on the rate the household obtains being lower than the modal rate, we report descriptive statistics on the size of the gap. The last row reports comparable statistics for the Canadian market from Allen et al. (2019).

### B Evidence of Limited Sophistication

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

The evidence relies on the 2006 wave of SHIW. Half of the interviewees in 2006 (3,992 households) were administered a section of the questionnaire meant to elicit financial literacy using a set of standard questions in the literature (Van Rooij et al. [2011]; OECD [2016]). The section consists of six questions testing the ability to recognize the balance of a checking account statement, to compare the returns of two mutual funds, to understand the difference between real and nominal interest, the concept of compound interest, the wealth consequence 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.\footnote{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.}

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 3 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), yet, still less than 10% of them answered all questions correctly.

Figure 4 uses the second indicator of sophistication that provides information on people’s ability to understand the properties of FRMs and ARMs. It shows the distribution of the answers to the question: “Which of the following mortgage types allows you to know since the very beginning the maximum amount that you will be 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
**Figure 3: Distribution of the Sophistication Index**

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

**Figure 4: Understanding of Mortgage Characteristics**

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

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.

Table 2: Mortgage type and borrower sophistication

<table>
<thead>
<tr>
<th></th>
<th>Sophisticated</th>
<th>Naive</th>
<th>Clueless</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjustable rate</td>
<td>0.63</td>
<td>0.53</td>
<td>0.5</td>
</tr>
<tr>
<td>Fixed rate</td>
<td>0.37</td>
<td>0.47</td>
<td>0.5</td>
</tr>
</tbody>
</table>

C Household Choices absent Steering

The evidence above relies on mortgages mostly originated from banks. This means that the borrower already had some interaction with employees of the bank and the resulting mortgage choice could have been slanted by steering and does not reflect only the borrower’s preferences.

To address this problem and further enrich the evidence, we obtained a novel data set on Internet searches for mortgage deals provided by the leading Italian mortgage comparison website, MutuiOnline.it. The website only registers data on queries that result in the filing of an online application and our data consists of all such queries. The information collected includes both basic demographics of the potential borrower (city of residence, occupation, age, gender) and information on the characteristics of the type of contract the potential borrower was researching: the queried bank, the amount requested, the value of the house used as collateral, the type of mortgage and whether the applicant was looking for a new mortgage or to refinance. We observe the outcome of the search: the interest rate and the monthly instalment offered by the bank queried for the desired contract characteristics. Given that we know the province where the individual making the query lives, we can complement the demographic information with
weighted province-level averages of demographic variables. Most notably, we include variables measuring
the province-level share of individuals with education level below high school, that of those who attended
high school, and that of those who at least attended college. We take the province average of educational
attainment as a proxy of financial sophistication of a potential borrower, with the least educated agents
being more likely to be naive.

The sample we were able to obtain refers to the universe of searches on the website in two different
years: 2007 and 2014. The 2007 data fit right in the middle of the sample span we used for our main
analysis. However, the market for online mortgages was still in its infancy then and the sample of
borrowers looking for a mortgage online may be selected. The 2014 sample refers to a later period
than the one our estimates are based on, but it has the advantage that by then searching for mortgages
online had become a much more common activity. This is witnessed by the sheer number of searches
on the platform that rises from 32,486 in 2007 to 51,561 in 2014. Accordingly, we pool data from the
two years, thus, increasing the size and representativeness of the sample. Importantly, the availability
of searches at two points in time allows us to exploit the panel dimension introducing province fixed
effects when studying the effect of education on mortgage type preference. This way we take care of time
invariant heterogeneity across provinces that may confound the analysis. Because we observe the universe
of searches in two instances seven years apart, the amount of within-province variation in educational
attainment is substantial. Hence, we can obtain precise estimates of the effect of education on the
borrower preference for the type of mortgage.

Before showing the results of these estimates, we note that the average share of FRMs on the Mutu-
iOnline platform in the two years follows the same time pattern as that of the total originated mortgages.
Notably, the share of FRMs filed by consumers on MutuiOnline exceeds that chosen in the total popula-
tion in both years: it is 13 percentage points higher in 2007 and 5 percentage points higher in 2014 (the
population shares of FRMs in these years are 67% and 35%, respectively). This pattern is fully consistent
with our assumption that absent steering, naive households tend to prefer FRMs, while banks steer them
towards ARMs.

To further test this implication, we estimate a linear probability model where the dependent variable
is a dummy taking value 1 if the individual searched for an FRM, and 0 otherwise. As before, we restrict
the analysis to either pure ARMs or FRMs – which constitute over 95% of the searches in the data—and
consider only newly issued mortgages, dropping searches for refinancing. As explanatory variables, we use

39For the share of households with attainment below high school, the within province variation is 2/3 of the
variation across provinces. The same is true for the share of households with college education, whereas for the
share of households with a high school diploma the within province variation is over 3/4 of the cross province
variation.
### Table 3:

**Notes:** The dependent variable is a dummy for whether the individual searched for an FRM. The sample includes the universe of searches for new mortgages on MutuiOnline.it in 2007 and 2014. The variables on educational attainment are province level shares and the excluded group is that with education above high school diploma. The specification includes fixed effects for the year of the search, the occupation of the individual making the query, the bank whose offering are queried and the province where the individual lives.

Indicators of the level of education in the province where the individual lives excluding for comparison the share of the most sophisticated (those with college education); maturity and size of the mortgage; age, income, and household size of the individual making the search as well as whether she has relationships with a single bank. We include a dummy to control for the year in which the search was carried as well as controls for individual occupation, province and bank fixed effects. The latter capture systematic differences across banks in the interest rate spread between FRM and ARM.

Table 3 reports estimation results. First, compared to those with a college degree, the less sophisticated individuals tend to direct their searches more towards FRMs. Differences are economically significant: in a province with all borrowers having below college education the fraction of people voluntarily looking for a fixed rate mortgage would be more than 20 percentage points higher than in a
province with all borrowers having a college degree. Second, we find no significant difference between searches of households with just high school education attainment and those below high school. This suggests that acquiring financial sophistication may require a substantial investment in general education, and accordingly, that the share of unsophisticated borrowers in the population may be quite large. This evidence lends support to our structural estimates of a significant share of naive borrowers in population.

To summarize, we find evidence that supports our assumption that less sophisticated borrowers are more inclined to choose FRMs when acting on their own.

D 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%.
E Reduced Form Evidence of Steering

Foà et al. (2019) use data similar to ours to provide reduced form evidence that banks slant customers’ mortgage choices. Since establishing the presence of steering is a natural prerequisite for our goal to quantify its welfare implications, below we introduce the main findings by Foà et al. (2019) and show that they hold in our sample. We refer the reader to their paper for further details.

Foà et al. (2019) propose a test of the presence of a non-price channel through which banks influence customers’ mortgage choices. The basic idea is that if households are savvy, then the relative price of different financial products should be a sufficient statistic for their choice. However, if some households lack sophistication and the intermediary is able to steer their behavior to its own advantage, for given prices households’ choices could also be affected by characteristics of the bank (arguably, unobservable to the borrower) that affect the incentives of the bank to steer its customers towards a certain product. In this case, the direction of the effect should be consistent with the bank’s interest. Importantly, this methodology does not rely on a particular mechanism through which the customers were steered towards a certain product. Steering can be simply inferred from mortgage choices, relative prices, and balance sheet shocks to the bank originating the mortgage.

In Table 4, we use our data to replicate the main result in Foà et al. (2019). The choice between ARM and FRM is systematically correlated not only with the relative costs of two mortgage types (the Long Term Financial Premium or LTFP), but also with time varying characteristics of the bank that originates mortgages. We estimate a linear probability model where an indicator variable, which takes value 1 if the household chooses an FRM, is regressed on the Long Term Financial Premium (computed as the difference between the FRM rate and a moving average of ARM rates), household characteristics and the Bank Bond Spread, which measures the relative cost for the bank of securing funds at a fixed rate.

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 Long Term Financial Premium negatively affects the probability that the household picks an FRM. However, the negative and significant coefficient on the Bank Bond Spread implies that households borrowing from a given bank are less likely to choose an FRM in a given quarter if in that quarter the bank faces a higher cost of raising fixed-rate funding compared to households borrowing from

---

40The Bank Bond Spread is the difference between the rates of the fixed and adjustable rate bonds issued by the bank. We calculate it as a weighted average over all the bond maturities issued by the bank and consider only newly issued bonds to non-financial residents in Italy. See https://www.bancaditalia.it/pubblicazioni/moneta-banche/2010-moneta/index.html for further details on the construction and the sample of banks reporting it.
### Table 4: The Effect of Lenders’ Characteristics on Mortgage Choices

**Notes:** Each observation is a new mortgage contract between a household and a bank. The dependent variable is an indicator taking value 1 if the household chose an FRM. Long Term Financial Premium defined as in Foà et al. (2019) is the difference between the FRM rate and the expected ARM rate based on borrowers’ actual ARM rate and one year moving average of the one month interbank rate. The Bank Bond Spread is the average (across maturities) of the difference between the rates of fixed and adjustable rate bonds issued by the bank. Standard errors are in parentheses and are clustered at the bank level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long Term Financial Premium</td>
<td>$-0.0583^{***}$ (0.0129)</td>
<td>$-0.0590^{***}$ (0.0127)</td>
</tr>
<tr>
<td>Mortgage size (log)</td>
<td>$-0.0818^{***}$ (0.0109)</td>
<td>$-0.0826^{***}$ (0.0112)</td>
</tr>
<tr>
<td>Joint mortgage</td>
<td>$0.0270^{***}$ (0.0045)</td>
<td>$0.0274^{***}$ (0.0046)</td>
</tr>
<tr>
<td>Italian</td>
<td>$0.0411^{***}$ (0.0071)</td>
<td>$0.0393^{***}$ (0.0070)</td>
</tr>
<tr>
<td>Cohabitation</td>
<td>$-0.0029$ (0.0020)</td>
<td>$-0.0035^*$ (0.0020)</td>
</tr>
<tr>
<td>Age</td>
<td>$-0.0008^{***}$ (0.0002)</td>
<td>$-0.0009^{***}$ (0.0002)</td>
</tr>
<tr>
<td>Female</td>
<td>$0.0109^{***}$ (0.0015)</td>
<td>$0.0102^{***}$ (0.0014)</td>
</tr>
<tr>
<td>Bank bond spread</td>
<td>$-0.0831^{***}$ (0.0164)</td>
<td>$-0.0825^{***}$ (0.0163)</td>
</tr>
<tr>
<td>Bank f.e.</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year × Region f.e.</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Year × Province f.e.</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>631,993</td>
<td>631,993</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.3681</td>
<td>0.3721</td>
</tr>
</tbody>
</table>
the same bank in a quarter where the bank faces a lower costs of borrowing at fixed rate. The sign of the coefficient is consistent with the story that banks use steering (along with rate setting) in order to manage maturity of assets (in this case, issued mortgages) to that of their liabilities. The finding is confirmed in column (2) when we control for aggregate trends at a finer level of geography (a province). Thus, we establish that banks do steer customers’ choices through tools other than price.

[1] Foà et al. (2019) strengthen their analysis by 1) extending the evidence to other supply shocks; 2) documenting stronger responses to supply shocks among less sophisticated households; 3) showing stronger effects of supply shocks when banks face price adjustment costs; 4) estimating the model on a subsample of households taking multiple mortgages so that they can include household fixed effects in the specification to control for any source of time-invariant household unobserved heterogeneity. Below, we report additional results from [2] Foà et al. (2019), which show the robustness of their findings and pinpoint more precisely the channel through which the steering occurs.

Banks can steer their customers by using advice (i.e., providing selected information in one-on-one interaction), advertising (selecting the pool of applicants through messages to the general public) or rationing (systematically denying loan requests not aligned with their needs). [3] Foà et al. (2019) claim that in the Italian data the first mechanism is prevalent. They reason that both advertising and rationing would generate sorting of customers across banks and provide evidence (reported in our Table 5) that there is no dynamic sorting of households, i.e., the characteristics of the customer pool of a bank does not correlate with the bank bond spread which is the balance sheet variable affecting the convenience for the bank of selling ARM vs FRM.

42 Sorting may not only occur on observable but also on unobservable characteristics. Therefore, [4] Foà et al. (2019) deepen their analysis to rule out sorting on unobservables. First, they use data from mortgage-takers included in SHIW to assess whether we observe sorting based on risk aversion, the most critical unobserved variable affecting the mortgage choice. In SHIW, households reporting that they took a mortgage provide an identifier of the bank extending the loan and also answer questions allowing to elicit their risk aversion. The first two columns of Table 6 report the results of an ordered logit run by [5] Foà et al. (2019), where the dependent variable is a categorical index corresponding to the investment strategy that best describes the household attitude: high return with high risk; good return with fair

41 Our empirical strategy requires within bank variability in the spread between the rate on their fixed and adjustable rate bonds. Such variation can arise from several sources. For instance, since corporate bonds are often privately placed rather than publicly issued on the open market, idiosyncratic shocks to the risk absorption capacity of institutional investors that a particular bank can reach will affect its spread between fixed and adjustable bonds, even at quarterly frequency.

42 Static sorting is not a plausible explanation of the correlations presented in Table 4 since it would be taken care of by the bank fixed effects.
capital protection; fair return with good capital protection; low return with no risk. It emerges that there is no correlation between the balance sheets of a bank and the degree of risk aversion of the customers taking a mortgage there in a particular period. The last two columns of Table 6 show instead a different exercise which Foà et al. (2019) use to rule out that rationing is used as a steering tool. They obtained extra data from the Italian Credit Registry that include the fraction of rejected mortgage applications for each bank-quarter and use it to show that banks do not respond to fluctuations in their cost of long term funding by adjusting their rejection rate, even in periods where the bank does not adjust pricing.

A final exercise performed in Foà et al. (2019) to address the issue of selection on unobservables is to replicate the baseline specification on the subsample of households who take more than one mortgage during the sample period considered. These estimates are based on a smaller sample (13.7% of the households take two mortgages; 1.7% take three) but allow Foà et al. (2019) to include households fixed effects in the specification, absorbing all the unobserved time-invariant household characteristics. The results are robust to the introduction of the household fixed effects (see Table 7) and the fixed effects are not correlated with the supply factors of the bank.

---

Table 5: **Dynamic sorting on observables**

<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>Mortgage size (log)</th>
<th>Italian Cohabitation</th>
<th>Age</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bank bond spread</td>
<td>0.0005 (0.0040)</td>
<td>-0.0079 (0.0025)</td>
<td>0.0034 (0.0056)</td>
<td>-0.1227 (0.0074)</td>
</tr>
<tr>
<td>Bank f.e.</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Region-time f.e.</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>F-test joint significance (p-value)</td>
<td>0.6901</td>
<td>0.2414</td>
<td>0.4817</td>
<td>0.4556</td>
</tr>
</tbody>
</table>

**Source**: Table 6 in Foà et al. (2019). In the original tables, the coefficients for Deposit ratio and Securitization activity (other two potential shifters of the maturity mismatch) are also reported: neither is significant. The test of joint significance of bank characteristics row reports the p-value of an F-test testing the null that the coefficients on Bank Bond Spread, Deposit ratio and Securitization activity are jointly equal to 0.

---

43 The price inaction dummy $D_{ib}$ is defined as equal to 1 if the change in the FRM-ARM spread was within one-third of its bank-specific standard deviation. See Foà et al. (2019) for more details.
<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>Dependent variable is individual risk aversion</th>
<th>Dependent variable is bank rejection rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Baseline</td>
<td>baseline with interaction</td>
<td></td>
</tr>
<tr>
<td>adding bank time fixed effects terms</td>
<td>baseline with interaction</td>
<td></td>
</tr>
<tr>
<td>Bank bond spread</td>
<td>0.0243 (0.0692)</td>
<td>−0.0413 (0.797)</td>
</tr>
<tr>
<td>$D_{ih}$ (price inaction dummy)</td>
<td>0.0520 (0.5758)</td>
<td></td>
</tr>
<tr>
<td>Bank bond spread* $D_{ih}$</td>
<td>0.0673 (0.2288)</td>
<td></td>
</tr>
<tr>
<td>Bank fixed effects (BFE)</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Time fixed effects (TFE)</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>F-test on joint significance of bank-specific characteristics (P-value)</td>
<td>0.9269</td>
<td>0.3723</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Estimator</th>
<th>ML-Ordered logit</th>
<th>ML-Ordered logit</th>
<th>OLS</th>
<th>OLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>3,023</td>
<td>3,023</td>
<td>3,023</td>
<td>3,023</td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>0.0010</td>
<td>0.0596</td>
<td>0.461</td>
<td>0.460</td>
</tr>
</tbody>
</table>

Table 6: Sorting on unobservables and rationing

Source: Table 9 in Foa et al. (2019). In the original tables, the coefficients for Deposit ratio and Securitization activity (other two potential shifters of the maturity mismatch) and their interactions with the price inaction dummy (for the specification in column (4)) are also reported. The test of joint significance of bank characteristics row reports the p-value of an F-test testing the null that the coefficients on Bank Bond Spread, Deposit ratio and Securitization activity are jointly equal to 0.
Dependent variable is a dummy=1
Dep. variable:

if a FRM is chosen

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline model</td>
<td>With borrowers' fixed effects</td>
<td>Test for correlation of BOFE on supply factors</td>
</tr>
</tbody>
</table>

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Long Term Financial Premium</td>
<td>$-0.0519^{**}$</td>
<td>$-0.0528^{**}$</td>
</tr>
<tr>
<td></td>
<td>$(0.0052)$</td>
<td>$(0.0103)$</td>
</tr>
<tr>
<td>Bank bond spread</td>
<td>$-0.0569^{***}$</td>
<td>$-0.0635^{***}$</td>
</tr>
<tr>
<td></td>
<td>$(0.0097)$</td>
<td>$(0.0087)$</td>
</tr>
</tbody>
</table>

| | yes | yes | yes |
| Bank Fixed effects (BFE) | | | |
| Region-Time fixed effects | yes | yes | yes |
| Borrowers’ characteristics | yes | yes | no |
| Borrowers’ fixed effects (BOFE) | yes | yes | no |
| Other controls | yes | yes | no |

Test of joint significance of . 0.000 .

BOFE (p-value)

Test of joint significance of bank characteristics (p-value) 0.000 0.000 0.677

Observations 253,763 253,763 253,763

Adjusted R-squared 0.332 0.342 0.142

Table 7: Households with multiple mortgages

Source: Table 10 in [Foà et al. (2019)](Foà et al. 2019). In the original tables, the coefficients for Deposit ratio and Securitization activity (other two potential shifters of the maturity mismatch) are also reported. The test of joint significance of BOFE row reports the p-value of an F-test testing the null that all the borrowers fixed effects are jointly equal to 0. The test of joint significance of bank characteristics row reports the p-value of an F-test testing the null that the coefficients on Bank Bond Spread, Deposit ratio and Securitization activity are jointly equal to 0.
E.1 Additional Evidence of Steering

We complement the evidence in Foà et al. (2019) with two additional pieces of evidence that steering is driven by banks’ incentives to manage maturity mismatch and it is potentially associated with distortions. First, if the significance of the Bank Bond Spread in Table 4 indicates that banks are steering their customers’ decisions to manage their maturity mismatch, then banks with larger maturity mismatch should have higher incentives to steer and, therefore, banks balance sheets should be even more significant in explaining households mortgage decisions. To test this prediction, we obtained from the Bank of Italy Supervisory Reports detailed data on maturity buckets (in months) for all banks’ assets and liabilities. We have then computed each bank’s duration mismatch as the difference between the average maturity of assets and that of liabilities for the bank, which is the standard measure of exposure to interest rate risk (see, e.g., Drechsler et al. (forthcoming)). Overall, the measure captures the real costs each bank in our sample would incur in case of an increase in interest rates. In order to limit endogeneity problems, we use the maturity mismatch in 2003, the last year before the start of our sample span.

We divide banks into two groups: those with a low duration mismatch (below median) and those with a high duration mismatch (above median). We then repeat for each group the baseline regression whose results we reported in Table 8. The Bank Bond Spread affects negatively the probability that a household chooses an FRM both in banks with an above and a below median maturity mismatch. However, for banks with a higher maturity transformation cost the coefficient is almost twice as large. A one-tailed test rejects at 10% the null of equality of the two coefficients against the alternative of a larger effect for banks with above the median mismatch.

Second, in order to show that banks’ steering sometimes distorts household choices, we exploit data on customers’ complaints on mortgage contracts raised to the Arbitro Bancario Finanziario (henceforth, ABF). Specifically, we construct an indicator of the distortionary steering as follows. We use the estimates from the model in Table 4 and generate predicted values excluding supply factors from the specification. These predicted values identify what the undistorted choice of a household (with certain characteristics and facing a certain Long Term Financial Premium) should be. We compare it to the actual mortgage choice of that household and count as an instance of distortion cases where the predicted and the actual choice do not coincide. We confront this measure of alleged distortion obtained through our methodology with data on actual complaints of wrongdoing in mortgage contracts filed by customers to the ABF. In

For assets and liabilities that are not fixed rate, we substitute the average time to adjust interest rates for the average maturity. The duration mismatch is also corrected for the use of derivatives.

We exploit data on the complaints to the ABF from 2011 to 2015. This time span is later than our sample period, because it normally takes time for the household to realize potential misconduct and to file the complaint. Cases referring to mortgages issued in the 2005-2008 period could have reached the ABF only years later.
### Table 8: Effect of Lender Characteristics, by severity of maturity mismatch

**Notes:** The table reports results from the specification in column (1) of Table 4 for two separate subsamples. In column (1), we consider only mortgages originated by banks whose duration mismatch was below the median in the quarter. In column (2), we consider only mortgages originated by banks whose duration mismatch was above the median in the quarter. The duration mismatch is calculated based on data from the Bank of Italy Supervisory Report that details all assets and liabilities for each bank by “buckets” of maturity (in months). The *borrowers’ characteristics* included in the specifications for both columns are the same as in Table 4: (log of) mortgage size, dummy for mortgages jointly taken by two individuals, dummy for mortgages given to Italian households, dummy for mortgages given to cohabitants, age of the mortgage taker and a gender dummy.

<table>
<thead>
<tr>
<th></th>
<th>(1) Dependent variable</th>
<th>(2) Dependent variable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FRM=1</td>
<td>FRM=1</td>
</tr>
<tr>
<td>Banks with</td>
<td></td>
<td></td>
</tr>
<tr>
<td>below median duration</td>
<td></td>
<td></td>
</tr>
<tr>
<td>mismatch</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Long Term Financial Premium</td>
<td>$-0.0551^{***}$</td>
<td>$-0.0575^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.0146)</td>
<td>(0.0188)</td>
</tr>
<tr>
<td>Bank Bond Spread</td>
<td>$-0.0575^{***}$</td>
<td>$-0.1008^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.0148)</td>
<td>(0.0180)</td>
</tr>
<tr>
<td>Bank f.e.</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year×Region f.e.</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Borrowers’ characteristics</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>291,138</td>
<td>340,855</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.3300</td>
<td>0.4295</td>
</tr>
</tbody>
</table>


Figure 5: Distortionary Steering is behind Borrowers’ Complaints

Notes: The figure plots on the horizontal axis the number of instances of distortionary steering inferred based on our methodology, for each bank scaled by the number of mortgages issued by the bank. On the vertical axis we have the number of actual complaints about mortgages received by the Arbitro Bancario Finanziario for each bank, also scaled by the total number mortgages issued by the bank.

Figure 5, each dot represents a bank. For each bank, we plot the share of ABF complaints against the constructed indicator of distortionary steering, both scaled by the number of mortgages issued by the bank. There is a positive and significant correlation between the incidence of distortion obtained through our methodology and a more factual measure based on lawsuits that customers are bringing against their banks.

F Omitted Analytical Details

F.1 Optimality of the Spread Rule

We present a simple version of Koijen et al. (2009) that shows that the spread rule is optimal when households have mean-variance utility function. By the same argument, the spread rule is also optimal in the CARA-normal model. Households have several dimensions of heterogeneity: the size of their mortgage $L$, the degree of risk aversion $\gamma$, the future (stochastic) real income $y$, and their beliefs about the distribution of shocks. Each household believes that the mean and the volatility of real interest rate shock $\varepsilon$ are $\nu_\varepsilon$ and $\sigma_\varepsilon^2$, respectively; that the mean and the volatility of inflation shock $\pi$ are $\nu_\pi$ and $\sigma_\pi^2$, respectively; and that the correlation between $y$ and $\varepsilon$, and $y$ and $\pi$ are $\sigma_{y\varepsilon}$ and $\sigma_{y\pi}$, respectively. For ease of notation, we omit indexing these characteristics by $h$, although the reader should keep in mind
that they do vary across households.

Households take a mortgage of size $L$ whose principal and interest are fully repaid after $\Delta$ quarters without intermediate payments. Thus, if $r_{t+\Delta}^{curbr}$ is the 1-month Euribor benchmark rate at date $t$, then $r_{t+\Delta}^{curbr} = r_t^{curbr} + \pi + \varepsilon$ is the 1-month Euribor at date $t + \Delta$, where $\pi$ and $\varepsilon$ are inflation and real interest rate shocks at time $t + \Delta$. Let $r_t^f$ 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 $(1 + r_t^f)L$ when it takes the FRM, and to $(1 + r_{it}^a + \pi + \varepsilon)L$ when it takes the ARM, where $r_{it}^a = s_{it}^a + r_{t}^{curbr}$. Adjusted for inflation, the payments are $(1 + r_t^f \neq \pi)L$ and $(1 + r_{it}^a + \varepsilon)L$, respectively.

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

$$
E[y - (1 + r_{it}^a(h) + \varepsilon)L] - \gamma V[y - (1 + r_{it}^f(h) + \varepsilon)L] \\
\geq E[y - (1 + r_{it}^f(h) - \pi)L] - \gamma V[y - (1 + r_{it}^f(h) - \pi)L]. \quad (F.1)
$$

Simplifying,

$$
\nu_t + \nu_\varepsilon + \gamma L(\sigma_{\varepsilon}^2 - \sigma_{\pi}^2) - 2\gamma(\sigma_{\gammat} + \sigma_{\gamma\varepsilon}), \quad (F.2)
$$

which gives us the spread rule (4.1) with

$$
\delta(h) = \nu_t + \nu_\varepsilon + \gamma L(\sigma_{\varepsilon}^2 - \sigma_{\pi}^2) - 2\gamma(\sigma_{\gammat} + \sigma_{\gamma\varepsilon}). \quad (F.3)
$$

ARM is preferred when the household believes that inflation is more volatile compared to real interest rates, expects lower nominal interest rates, or when the household income tends to co-move with the nominal interest rates (e.g., because the European Central Bank tends to lower interest rates during the crisis). The effect of risk aversion and mortgage size depends on the household’s beliefs about the volatility of different shocks. If the households believes that inflation is less volatile than real interest
rates, then lower risk aversion and smaller mortgage size make the ARM more attractive. However, if the households believes that inflation is more volatile than real interest rates, then higher risk aversion and larger mortgage size make the FRM more attractive. Because sophisticated households are able to make the optimal mortgage choice based on mortgage rates and their knowledge of two products, steering by the bank that issues the mortgage does not affect them.

F.2 The Adjusted Spread Rule in the CRRA Model

In this section, we provide a model of the mortgage size choice in which the bank’s profit per customer can be decomposed into the product of the net profit margin and the average mortgage size justifying the form of the profit function in (4.2). To do so, it is sufficient to show that the distribution of the mortgage type choices is independent of the distribution of the mortgage size.

We suppose that each household has current wealth $W_0$ and its future wealth equals $W_0(1 + y)$, where $y$ is the wealth shock. Households are heterogeneous in $W_0$ and $y$. We suppose that each household spends a fraction $\alpha$ of its current wealth on the downpayment and takes a mortgage at the LTV $l$. Thus, the mortgage size $L = \xi W_0$, where $\xi \equiv \frac{\alpha l}{1 - l}$.

The naive households’ choices of the mortgage type are shaped by the banks’ steering policies, hence, their mortgage type choice is indeed independent of the mortgage size choice. Sophisticated households choose the mortgage type optimally. We suppose that sophisticated households have CRRA utility function with (heterogeneous) degree of risk aversion $\gamma$, that is, the household’s utility from the stochastic future wealth $W$ equals $U(W) \equiv W^{1-\gamma}/(1 - \gamma)$. Household’s beliefs about the distribution of shocks are as in the previous section. Then, the households expected utility from taking FRM equals

$$\mathbb{E} \left[ U \left( W_0(1 + y) - (1 + r_f^h(h) - \pi)\xi W_0 \right) \right] = W_0^{1-\gamma} \mathbb{E} \left[ U \left( 1 + y - (1 + r_f^h(h) - \pi)\xi \right) \right]$$

and its expected utility from taking ARM equals

$$\mathbb{E} \left[ U \left( W_0(1 + y) - (1 + r_a^h(h) - \pi)\xi W_0 \right) \right] = W_0^{1-\gamma} \mathbb{E} \left[ U \left( 1 + y - (1 + r_a^h(h) + \varepsilon)\xi \right) \right].$$

Thus, the household prefers ARM if and only if

$$\mathbb{E} \left[ U \left( 1 + y - (1 + r_f^h(h) - \pi)\xi \right) \right] \geq \mathbb{E} \left[ U \left( 1 + y - (1 + r_a^h(h) + \varepsilon)\xi \right) \right].$$

Note that the current wealth does not enter into this decision rule. Thus, if $\xi$ is constant across households,
the mortgage choice by sophisticated households is indeed independent of the mortgage sizes that they choose.

We next show that this rule can be simplified to yield an adjusted spread rule. First, the normalized (by $W_0^{1-\gamma}$) expected utility from taking FRM equals

$$
E \left[ U \left( 1 + y - (1 + r_f^I(h) - \pi)\xi \right) \right] = \frac{1 - \gamma}{(1 + \nu_y - \xi)^\gamma} \approx U (1 + \nu_y - \xi) + \frac{\gamma E \left[ U \left[ y - \nu_y - (r_f^I(h) - \pi)\xi \right] \right]}{(1 + \nu_y - \xi)^\gamma} - \frac{\gamma E \left[ (y - \nu_y - (r_f^I(h) - \pi)\xi)^2 \right]}{2(1 + \nu_y - \xi)^{\gamma+1}} 
$$

$$
= U (1 + \nu_y - \xi) - \frac{(r_f^I(h) - \nu_y)\xi}{(1 + \nu_y - \xi)^\gamma} + \frac{\gamma E \left[ (y - \nu_y)^2 - 2(y - \nu_y)(r_f^I(h) - \pi)\xi + (r_f^I(h) - \pi)^2\xi^2 \right]}{2(1 + \nu_y - \xi)^{\gamma+1}} 
$$

$$
= U (1 + \nu_y - \xi) - \frac{(r_f^I(h) - \nu_y)\xi}{(1 + \nu_y - \xi)^\gamma} + \frac{\gamma \left[ \sigma_y^2 + 2\sigma_y\xi + \sigma_x^2\xi^2 + (r_f^I(h) - \nu_y)^2\xi^2 \right]}{2(1 + \nu_y - \xi)^{\gamma+1}},
$$

where we used second-order approximation in the third line. Similarly, the normalized (by $W_0^{1-\gamma}$) expected utility from taking ARM equals

$$
E \left[ U \left( 1 + y - (1 + r_f^A(h) + \varepsilon)\xi \right) \right] = \frac{1 - \gamma}{(1 + \nu_y - \xi)^\gamma} \approx U (1 + \nu_y - \xi) + \frac{\gamma E \left[ U \left[ y - \nu_y - (r_f^A(h) + \varepsilon)\xi \right] \right]}{(1 + \nu_y - \xi)^\gamma} - \frac{\gamma E \left[ (y - \nu_y - (r_f^A(h) + \varepsilon)\xi)^2 \right]}{2(1 + \nu_y - \xi)^{\gamma+1}} 
$$

$$
= U (1 + \nu_y - \xi) - \frac{(r_f^A(h) + \nu_x)\xi}{(1 + \nu_y - \xi)^\gamma} + \frac{\gamma E \left[ (y - \nu_y)^2 - 2(y - \nu_y)(r_f^A(h) + \varepsilon)\xi + (r_f^A(h) + \varepsilon)^2\xi^2 \right]}{2(1 + \nu_y - \xi)^{\gamma+1}} 
$$

$$
= U (1 + \nu_y - \xi) - \frac{(r_f^A(h) + \nu_x)\xi}{(1 + \nu_y - \xi)^\gamma} + \frac{\gamma \left[ \sigma_y^2 + 2\sigma_y\xi + \sigma_x^2\xi^2 + (r_f^A(h) + \nu_x)^2\xi^2 \right]}{2(1 + \nu_y - \xi)^{\gamma+1}}.
$$

Thus, the sophisticated household prefers an ARM if and only if

$$
r_f^I(h) - r_f^A(h) \geq \nu_x + \nu_x + \frac{(\sigma_x^2 - \sigma_y^2)\xi - 2(\sigma_y\nu + \sigma_y\nu + \sigma_x\xi) + \xi \left( r_f^A(h) + r_f^I(h) \right)}{(1 + \nu_y - \xi)^1 / \gamma + \xi (\nu_x - \nu_x) + \xi \left( r_f^A(h) + r_f^I(h) \right)}.
$$

Thus, the spread rule [4.4] should be adjusted to account for the fact that the level of rates (quantity $r_f^A(h) + r_f^I(h)$) also matters for the optimal mortgage choice of the household with CRRA utility function. Observe that the spread rule is a good approximation whenever $\xi$ is close to zero (e.g., when the
downpayment constitutes a small fraction of the household’s wealth) or the risk aversion $\gamma$ is low.

### F.3 Microfoundation for Naive Households’ Behavior

Next, 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 $\nu_e, \sigma_e^2, \nu_c$, and $\sigma_c^2$, and have some full-support beliefs $F$ about their joint distribution. Conditional on $\nu_e, \sigma_e^2, \nu_c$, and $\sigma_c^2$, the utility of naive households from taking FRM is the same as of sophisticated households and is given by

$$E[y - (1 + r_f^t(h) - \pi)H] - \gamma \nu [y - (1 + r_f^t(h) - \pi)H]$$

However, conditional on $\nu_e, \sigma_e^2, \nu_c$, and $\sigma_c^2$, their utility from ARM is given by

$$E\left[y - (1 + \frac{\nu}{s_a} + r_{Euribor} - \pi)H\right] - \alpha \nu [y - (1 + \frac{\nu}{s_a} + r_{Euribor} - \pi)H].$$

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 unattached, 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 $\nu_e, \sigma_e^2, \nu_c$, and $\sigma_c^2$ (that can differ across households), which naive households believe to be undistorted and perfectly informative. Thus, if the bank’s signal is such that $\sigma_c^2 - \sigma_e^2$ and/or $\nu_e + \nu_c$ 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.

### F.4 Optimal Spread Setting

We derive an explicit formula for (4.6) that we use in the estimation. We distinguish two cases depending on whether bank $i$ has the lowest ARM-Euribor spread on the market ($s_a^i < s_a^{i',t}$) or not ($s_a^i > s_a^{i',t}$).

We use super-index $a$ for the former case and super-index $A$ for the latter. After banks post FRM-ARM

46Thus, their unconditional utility equals

$$E_{\nu_e, \sigma_e^2, \nu_c, \sigma_c^2} \left[ E[y - (1 + r_f^t(h) - \pi)H] - \gamma \nu [y - (1 + r_f^t(h) - \pi)H] \right],$$

where the outside expectation is with respect to household’s beliefs about $\nu_e, \sigma_e^2, \nu_c$, and $\sigma_c^2$.

47We abstract from ties as they are not observed in our data.
spreads, bank $i$ has either the lowest FRM rate ($s_{it}^a < z_{it}^a$) or not ($s_{it}^a > z_{it}^a$). We use super-index $f$ for the former case and super-index $F$ for the latter.

When $s_{it}^a > z_{it}^a$, we can rewrite the expected profit as

$$m_{it}^{AF} V^{AF} (\phi_{it} | \theta_{it}) G \left( s_{it}^f \left| s_{it} \right. \right) + m_{it}^{AF} V^{AF} (\phi_{it} | \theta_{it}) \left( 1 - G \left( s_{it}^f \left| s_{it} \right. \right) \right), \quad \text{(F.4)}$$

and similarly, when $s_{it}^a < z_{it}^a$, we can rewrite the expected profit as

$$m_{it}^{AF} V^{AF} (\phi_{it} | \theta_{it}) G \left( s_{it}^f \left| s_{it} \right. \right) + m_{it}^{AF} V^{AF} (\phi_{it} | \theta_{it}) \left( 1 - G \left( s_{it}^f \left| s_{it} \right. \right) \right). \quad \text{(F.5)}$$

Then $\phi_{it}$ is determined by maximizing either (F.4) or (F.5) depending on whether $s_{it}^a > z_{it}^a$ or $s_{it}^a < z_{it}^a$, respectively. To complete the characterization of the optimal rate setting, we determine functions $m_{it}^{AF}, z_{it}^{AF}$, and $\pi_{it}$ for different cases. Let

$$\kappa(\phi) \equiv 1 - \Phi \left( \frac{\phi - \mu}{\sigma} \right),$$

and $\psi_t \equiv \frac{1}{2} \left( s_{it}^f + r^{s_{it}^{\text{FRM}}} - (s_{it}^a + r^{t^{\text{EURIBOR}}} \right)$ 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 ($s_{it}^a > z_{it}^a$)

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

   (b) If $s_{it}^f < z_{it}^a$, then bank $i$, in addition to its attached customers, attracts all naive unattached households and sophisticated unattached households that prefer to take FRM in the market. The mass of the former is $\psi \mu_a$, the mass of the latter is $\psi (1-\mu_a) \kappa(\phi_{it})$. Thus, the total mass of bank $i$’s customers equals

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

Sophisticated attached households take FRM with probability $\kappa(\phi_{it})$, while all sophisticated unattached households that bank $i$ attracts take FRM. Thus,

$$z_{it}^{Af} = \frac{(1-\psi) p_{it} (1-\mu_a) \kappa(\phi_{it}) + \psi (1-\mu_a) \kappa(\phi_{it})}{(1-\psi) p_{it} + \psi \mu_a + \psi (1-\mu_a) \kappa(\phi_{it})}.$$
The fraction of naive households is given by

\[ \mu_{it}^{Af} = \frac{(1 - \psi)\mu_a + \psi\mu_u}{(1 - \psi)\mu_a + \psi(1 - \mu_u)\kappa(\phi_t) + \psi\mu_u} \]

and so,

\[ x_{it}^{Af} = \mu_{it}^{Af} + \frac{(1 - \psi)\mu_a + \psi\mu_u}{(1 - \psi)\mu_a + \psi(1 - \mu_u)\kappa(\phi_t) + \psi\mu_u}. \]

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

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

\[ m_{it}^{AF} = (1 - \psi)\mu_a + (1 - \mu_u)\psi(1 - \kappa(\phi_t)) \]

Among those, there is a fraction

\[ \mu_{it}^{AF} = \frac{\mu_a(1 - \psi)\mu_a}{(1 - \psi)\mu_a + (1 - \mu_u)\psi(1 - \kappa(\phi_t))} \]

of naive households. Further,

\[ x_{it}^{AF} = \frac{(1 - \mu_u)(1 - \psi)\mu_a\kappa(\phi_t)}{(1 - \psi)\mu_a + (1 - \mu_u)\psi(1 - \kappa(\phi_t))}, \]

\[ \bar{x}_{it}^{AF} = \frac{1 - \mu_u)(1 - \psi)\mu_a\kappa(\phi_t) + \mu_u(1 - \psi)\mu_a}{(1 - \psi)\mu_a + (1 - \mu_u)\psi(1 - \kappa(\phi_t))}. \]

(b) If \( s_{it}^d < s_{it}^a \), then bank i in addition to its attached customers attracts all unattached households. Thus, the total mass of bank i’s customers is \( m_{it}^{AF} = (1 - \psi)\mu_a + \psi \); and

\[ x_{it}^{AF} = ((1 - \psi)(1 - \mu_u) + \psi(1 - \mu_u))\kappa(\phi_t) \] and

\[ \bar{x}_{it}^{AF} = ((1 - \psi)(1 - \mu_u) + \psi(1 - \mu_u))\kappa(\phi_t) + ((1 - \psi)\mu_u + \psi\mu_u). \]
F.5 Likelihood Function for Distribution of \( \theta \)s

The likelihood for distribution of \( \theta \)s is given by

\[
\sum_{t,k} \left[ \sum_{x_{ikt} \in (\mathcal{E}_{ikt}, \mathcal{F}_{ikt})} \ln \left( \frac{1}{\sigma} \phi \left( \frac{x_{ikt} - \frac{1}{2\pi} (\phi_{ikt} - r^\text{swap25}_t + r^\text{curbe}_t) - \mu}{\sigma} \right) \right) - N^*_t \ln \left( \Phi \left( \frac{1 - \mu}{\sigma} \right) - \Phi \left( \frac{-\mu}{\sigma} \right) \right) \right] + \sum_{x_{ikt} \in \mathcal{E}_{ikt}} \ln \left( \Phi \left( \frac{x_{ikt} - \frac{1}{2\pi} (\phi_{ikt} - r^\text{swap25}_t + r^\text{curbe}_t) - \mu}{\sigma} \right) - \Phi \left( \frac{-\mu}{\sigma} \right) \right) + \sum_{x_{ikt} \in \mathcal{F}_{ikt}} \ln \left( \Phi \left( \frac{1 - \mu}{\sigma} \right) - \Phi \left( \frac{r^\text{swap25}_t - \phi_{ikt} + \mu}{\sigma} \right) \right) \right].
\]

We maximize it over \( \mu \) and \( \sigma \) to obtain estimates of these parameters.

F.6 Computing Changes in Certainty Equivalent

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 due to the policy intervention. This measure reflects the variation in yearly mortgage payment for the average household due to the policy. The certainty equivalent of an FRM with rate \( r^f_t(h) \) equals

\[
CE \left( r^f_t(h) \right) = E[y] - \gamma V[y] - H \left( 1 + r^f_t(h) - \nu_a + \gamma H \sigma^2 \right).
\] (F.6)

The certainty equivalent of an ARM with ARM-EURIBOR spread \( s^a_t(h) \) equals

\[
CE \left( s^a_t(h) \right) = E[y] - \gamma V[y] - H \left( 1 + s^a_t(h) + r^\text{curbe}_t + \nu_e + \gamma H \sigma^2 \right).
\] (F.7)

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 \( s^a_t(h) \) to ARM with \( s^a_t(h) \), or from FRM with \( r^f_t(h) \) to FRM with \( r^f_t(h) \), then the change in the certainty equivalent equals \( H \left( s^a_t(h) - s^a_t(h) \right) + H \left( r^f_t(h) - r^f_t(h) \right), \) respectively. If the household switches from ARM with \( s^a_t(h) \) to FRM with \( r^f_t(h) \) or from FRM with \( r^f_t(h) \) to ARM with \( s^a_t(h) \), then the change in the certainty equivalent equals \( H \left( s^a_t(h) + r^\text{curbe}_t + \delta - r^f_t(h) \right) \) and \( H \left( r^f_t(h) - s^a_t(h) - r^\text{curbe}_t - \delta \right), \) respectively.
Frictions in the Italian mortgage market

On January 31st, 2007 the Italian government issued Legislative Decree n.7, which came to be known as Bersani law named after the minister who drafted it. The decree included provisions meant to liberalize several sectors of the economy. For instances, it prohibited surcharges on purchases of credit for prepaid mobile phones and voided penalty fees for changes of telecom provider. Most relevant for our study, it also banned prepayment and renegotiation fees for newly issued mortgages (and drastically reduced them for existing ones).

The chief moment driving identification of $\psi$, the parameter picking up the degree of frictions in the mortgage market, is computed using data from the 2006 wave of SHIW. This raises a potential concern to the extent that we believe that the Bersani law altered the ability of borrowers to shop around for mortgages and their expectations on their chances to be able to renegotiate their contracts with a bank other than the one that originated it.

It is important to notice that the effects of the Bersani law can threaten our demand estimates but not our supply parameters. The estimate of bank’s cost efficient fraction of FRMs, $\theta_{kt}$, is the residual that makes the first-order condition for steering hold for each bank-market-quarter. This means that, if there is a change in banks’ preferences over mortgage types due to the Bersani reform, it will be picked up by our estimates of $\theta_{kt}$’s, as we allow them to vary across banks and quarters. Therefore, any potential impact of the Bersani reform on the supply side would be fully accounted for in our model (banks choose their spread conditional on the realized $\theta_{kt}$).

The Bersani reform had the full force of law immediately after it had been issued. Therefore, the reform had the potential to influence mortgage transactions in the second half of our sample. However, we show below that according to several auxiliary measures of household mobility the reform did not have an immediate substantial impact on the mortgage market. If there were obstacles in the initial implementation of the reform, as press reports suggest, the option of refinancing would be less salient and would not affect much the decisions of households at the stage of mortgage origination in our sample span.

In the paper, we identify households able to take a mortgage outside their home bank ("switchers") as those who declare they have obtained a mortgage in the year and whose relationship with their main bank started recently (less than two years before the survey was administered). The fraction of switchers is then given by the ratio between the number of such households over the total number of mortgage-takers, computed using the sampling weights provided by SHIW. The survey is administered to a representative sample of Italian households every two years. The two questions that we use to define switchers are
present in the waves collected in 1995, 1998, 2000, 2002, 2004, 2006, 2010 and 2012. In 2008, the question asking whether the household had taken a mortgage is present but the one about the length of the relationship with the main bank is not. This is the reason why we only used 2006 SHIW data in our estimation procedure.

In order to check if there was a spike in switchers caused by Bersani reform, we impute the fraction of switchers in 2008 indirectly using SHIW2008 and SHIW2010 as follows. We consider a subsample of households who are interviewed both in the 2008 and in the 2010 wave of SHIW. Households reporting in 2010 that the relationship with their main bank was between two and four years old, would have had a relationship shorter than 2 years in 2008. This way we can impute the desired length of relationship with the main bank for a subsample of surveyed households in 2008, and compute the fraction of switchers in year 2008. To compare the procedure relying on current SHIW data with those exploiting imputation, we repeat the imputation procedure even for years where we have the information on the length of the relationship available in the survey. In Figure 6, we present both the fraction of switchers constructed using the original SHIW (red dots) and the fraction of switchers obtained using the imputation from the subsequent SHIW (blue dots).

The figure delivers several insights. First, both actual and imputed fractions of switchers stay on average around 8-9% in years before 2012, which is in line with our structural estimate 8.8% of the fraction of unattached households.

Second, the variation in the fraction of switchers is larger for the imputed series than the actual series, which is explained by the fact that the imputed series is based on a smaller subsample of households who are present in two consecutive waves of SHIW. We cannot say that the imputed series is systematically biased in one direction relative to the actual series, which is the reason why we decided not to use the imputed fraction of switchers in 2008 in our estimation.

Third, the imputed fraction of switchers in 2008 is around 5%, which points that there was no significant jump in the fraction of switchers right after Bersani reform was introduced. In fact, even if we were to assume that in 2008 the imputed fraction underestimates the true figure by 10 percentage points (which is the largest observed gap between the actual and the imputed series), this would put the actual fraction of switcher in 2008 at about 15 percent. This is higher than the 11% from the 2006 SHIW but it hardly suggests that we would be completely off using it to inform our estimation procedure. Further, in years 2010 and 2012 –when arguably the awareness of the Bersani reform is higher than right after the announcement – the actual fraction of switchers does not spike considerably either and is below 14%.
Figure 6: Fraction of Borrowers Switching Bank
To confirm the conclusion that the Bersani reform is unlikely to have changed dramatically the fraction of unattached households during our sample period, we also look at the evidence on mortgage renegotiations during this period. We find indications that the effect of Bersani law on the mortgage market materialized with a significant lag. Some anecdotal evidence is provided, for instance, in an article published by Il Sole 24 Ore on the 10 years anniversary of the reform\textsuperscript{48} In this article, it is recounted how in the Spring of 2007 and, in part, even in the following year “mortgage-takers trying to switch bank at no cost lamented issues in obtaining the enforcing of the new rules” and how “... the very first surge [in renegotiations]... was only in 2009 and subsequent years”. The same article contains data on renegotiations based on elaboration by MutuiSupermarket.it, a mortgage comparison website. We use them to create the plot in Figure 7.

The plot features two measures of the relevance of renegotiations in the Italian mortgage market since the Bersani reform. Both in terms of amount of money lent (left axis) and fraction of new mortgages issued (right axis) renegotiations in 2007 and 2008 were at levels not comparable to those reached in

\textsuperscript{48}“Mutui, la surroga compie 10 anni. Conviene ancora cambiare?”, published on June 22, 2017.
the years since 2009. The explosion in renegotiations, which has in part created the perception that the Bersani reform had a seismic shift in the Italian mortgage market, materializes only in 2009 and 2010 and, after a drop due to a sharp rise in spreads, from 2015 on. In short, we have reason to believe that the Bersani reform would not have significantly affected transactions in our sample span. This evidence is not necessarily inconsistent with the findings in Beltratti et al. (2017). Their estimates are based on two cross sections of mortgage-takers: one in 2005, well before the reform, and one in 2009 when, as we have shown, the take up in renegotiations had already ramped up. The fact that they document that there was some effect on pricing in 2009 does not conflict with our claim that the reform had a slow start.

The fraction of renegotiated mortgages computed by MutuiSupermarket.it is depicted in Figure 7 with green crosses. This series tracks pretty closely our other two measures of household mobility, hence, validating them. It also indicates that in 2007 and 2008 (years in our sample), the Bersani reform did not lead to a significant increase in renegotiations: Renegotiated mortgages constitute merely 5% of total mortgages issued. This points again to limited mobility of households across banks during our sample period. Even when households have a very low cost option to renegotiate their mortgages, not many ended up using this option. This is consistent with Andersen et al. (2020) who document long delays in mortgage refinancing and, more generally, with the pervasive finding in studies of household financial decision-making that individuals respond slowly to changing financial incentives.

To summarize, we argued above that our model is flexible enough to incorporate the effect of Bersani reform on the supply side, while additional evidence indicates that its effect on the demand side was limited during our sample period.

H Stationarity of Households Characteristics

Here, we show that the distribution of risk aversion and mortgage size experienced negligible changes in the period that we analyze. Figure 8 plots the cumulative distribution of a proxy of risk aversion and of the mortgage size for the beginning and the end of the time span covered by our data. Since they represent the main elements determining the optimal spread cutoff, this evidence should reassure on the stationarity of the distribution of δ which underlies our identification of the supply side estimation.

Figure 8a plots the cumulative distribution of the answer to a question meant to elicit risk aversion. The data come from a survey conducted by a major Italian bank on its retail customers. The question we are focusing on asks respondents about the investment strategy that best identifies their approach. The

---

49 See for example Choi et al. (2002), and Madrian and Shea (2001) on retirement savings plans and Anagol et al. (2018) and Calvet et al. (2009) on portfolio rebalancing.
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.
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 8b depicts the distribution of the real mortgages size (in 2004 euros) exploiting microdata on a random subsample covering 40% of the mortgages issued between 2004 and 2009. Conditional on the mortgage being issued, the distribution of mortgage size does not change through our sample. Interestingly, this variable does not seem to be affected even by the intervention of the financial crisis: the distribution in 2009 is nearly identical to the 2004 and 2007 ones.

I Correlation between attachment and naivete

Our estimation strategy for the correlation between naivete and attachment relies on the restrictions implied by the model and does not require external data to proxy these measures. This give us the opportunity to validate our findings using survey data that contain proxies for naivete and attachment. For this purpose, we turn to a survey administered by a major Italian bank to a representative sample of 1,686 of its customers in the summer of 2007. The survey records detailed demographic information and includes several questions on customers preferences and attitudes towards investment management and usage of financial services. We use the survey to construct two different proxies for lack of attachment and six different proxies for sophistication.

- Proxies for lack of attachment
  1. Dummy variable for whether the customer is considering product and services offered by banks other than the one running the survey. This indicator signals that the customer is willing to entertain the idea of shopping around for financial services.

We entertained the idea of using these proxies directly in the estimation. Our main concern was that these measures come from the clientele of a single bank, though large. Hence, our preferred strategy was to rely on the main data from the Credit Registry for the identification of the parameters of the model and to resort to this survey only to provide a sanity check of our findings.
2. Dummy variable for whether the customer had a bank account with banks other than the one running the survey. This indicator identifies customers who have a relationship with multiple banks and, therefore, a clear opportunity to move around them looking for the best conditions.

• Proxies for sophistication

1. Dummy for whether the customer has ever invested in stocks. We assume that those who have familiarity with the mechanics of the stock market will have a level of financial literacy higher than those who stuck to more simple financial assets (bonds, saving accounts,...).

2. Age of first investment in stocks (only for the subsample of those who ever did). The assumption is that more sophisticated customers will have entered the stock market earlier.

3. Correct answer to a financial literacy question. The survey includes a question meant to measure customers’ understanding of the working of financial instruments. The question asks the interviewee whether it is optimal to purchased asset yielding a fixed interest rate if one expects interest rates to rise. We construct a dummy identifying as sophisticated those who answer correctly.

4. Frequency at which the customer checks his/her investments. The survey asks to report the frequency at which the customer checks the status of his/her investment. The possible answers range from “I have no investment” to “I check my investments daily”. We assume that subject controlling their investments more frequently display a higher degree of sophistication. In particular, we construct an indicator that signals as sophisticated all the customers reporting that they check their investment at a frequency higher than the median (i.e. at least once per month).

5. Frequency at which the customer adjusts his/her investments. This proxies is akin to the previous one but relies on the frequencies at which customers actually reallocate their investment portfolio. Interviewees that re-optimize more frequently can be thought of as more sophisticated. We consider as sophisticated all the customers reporting that they reallocate their investment at a frequency higher than the median (i.e. about once per year).

6. Time spent collecting financial information. The survey asks each interviewee how much time do they spend gathering information useful to make investment decisions. The answers can range from “No time at all” to “Over 7 hours per week”. We define as sophisticated the
subjects that report spending more time gathering financial information than the median person in the sample (i.e. more than 30 minutes per week).

We estimate correlations between these two set of proxies conditional on a series of demographic controls: geographical area of residence, wealth, age, gender, education, employment status and household size. The table below reports in each cell the result of a different regression where the proxy for lack of attachment listed in the column header is the dependent variable run on the proxy for naivete listed in the row, accounting for all the controls just mentioned.

This simple set of regressions delivers a positive correlation between sophistication and lack of attachment which confirms the finding of our structural estimation that more naive customers are more likely to be attached to their home bank.

<table>
<thead>
<tr>
<th></th>
<th>Considers other banks</th>
<th>Has other bank accounts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Has ever held stocks</td>
<td>0.057***</td>
<td>0.136***</td>
</tr>
<tr>
<td>Age of first stock investment</td>
<td>-0.003**</td>
<td>-0.004**</td>
</tr>
<tr>
<td>Correct answer to finlit question</td>
<td>0.033**</td>
<td>0.027</td>
</tr>
<tr>
<td>Frequency of investments check</td>
<td>0.052***</td>
<td>0.096***</td>
</tr>
<tr>
<td>Frequency of investment reallocation</td>
<td>0.042**</td>
<td>0.037</td>
</tr>
<tr>
<td>Time spent gathering information</td>
<td>0.11***</td>
<td>0.11***</td>
</tr>
</tbody>
</table>
Figure 9: Dispersion of Rates

Notes: The figures display the bank fixed effects (in rate percentage points) estimated from regressing adjustable rates (top figure) and fixed rates (bottom figure) on bank, province and quarter dummies.
Figure 10: Rate Spreads on a 25-year Mortgage Set by a Major Italian Bank
Figure 11: Benchmark Rates for adjustable and fixed rate mortgages

Notes: The figure portrays the evolution of adjustable and fixed rates posted by a large bank during the sample span we analyze. We compare them with the rate of the instrument we assume banks use as benchmark for the pricing of their mortgages. In the top panel, we display the ARM rate posted by the bank and the Euribor 1 month rate; in the bottom panel, the rate on a 25 years FRM is portrayed alongside the rate of a 25 years interest rate swap.
Figure 12: Estimated Distribution of $\delta$ and Kernel Density of $\phi_{11}$