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The supply side of household finance*

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Abstract

We propose a new, data-based test for the presence of biased financial advice when households choose between fixed and adjustable rate mortgages. If households are wary, the relative cost of the two types should be a sufficient statistic for a household contract choice: the attributes of the bank that makes the loan should play no role. If households rely on banks' advice to guide their choice, banks may be tempted to bias their counsel to their own advantage. In this case bank-specific supply characteristics will play a role in the household's choice above any role they play through relative prices. Testing this hypothesis on a sample of 1.6 million mortgages originated in Italy between 2004 and 2010, we find that the choice between adjustable and fixed rates is significantly affected by change in banks' supply factors, especially in periods during which banks do not change the relative price of the two mortgage types. This supports the view that banks are able to affect customers' mortgage choices not only by pricing but also through an advice channel.

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1 Introduction

The past decade has seen increasing interest in how good households are at making financial decisions, and in particular how well they do at picking the financial products that best fit their type. When households have limited knowledge about a financial product's suitability to their needs, they have a strong incentive to ask for experts' advice, and in fact they often rely on the supplier of the financial product itself to obtain counsel.[1] The problem is that advisors may in turn have an incentive to distort their recommendations in a way that serves their own needs rather than those of their customers, who often have little or no ability to detect this conflict of interest. A number of papers (see among others, Inderst, 2010; Inderst and Ottaviani, 2010, 2012a, 2012b; Carlin and Manso, 2011; Ottaviani and Squintani, 2006; Kartik, Ottaviani and Squintani, 2007) set forth the theoretical underpinnings of the literature on how advice affects unsophisticated households' financial choices when brokers and/or intermediaries, with their informational advantage, are in conflict of interest.

Several approaches have been taken to finding evidence for such distorted advice. One approach compares the investment performance of individuals who rely on advice with that of those who do not (e.g. Hackethal, Haliassos and Jappelli, 2012; Hackethal, Inderst and Mayer, 2010) or with some benchmark (Foerster, Linnainmaa, Meltzer and Previtero, 2014). This body of work has found that the accounts of those who rely on advice underperform those of non-advised individuals or the benchmark, both in terms of overall return and in terms of Sharpe ratios, if the costs of the advice are taken into account. This is consistent with the hypothesis of biased advice. However, because people choose to seek advice, the result is also consistent with the assumption that the less capable investors choose to get advice and are nevertheless unable to overcome the deficit in ability or to make proper use of the advice received. Indeed, there is some evidence that investors fail to heed advice even when it is free of charge and where it is, by construction,

[1] Hung et al. (2008) report that 73% of US investors rely on professional advice to conduct stock market or mutual fund transactions. About 60% of the investors in the 2007 Unicredit Clients Survey – a Survey on a sample of Italian investors - rely on the help of an advisor or intermediary when making financial decisions and only 12% decide without counsel. In the UK 91% of intermediary mortgage sales are "with advice" (Chater, Huck and Inderst, 2010) and according to a broad survey of German retail investors, 80% consult financial advisors.

unbiased (Battacharya et al., 2012). Moreover, even though advised investors do worse than the unadvised or the benchmark, they may nevertheless do better than they would have by choosing on their own. Advice may still help unsophisticated investors to avoid common investment mistakes or mitigate behavioral biases (Shapira and Venezia, 2001; Gennaioli, Shleifer and Vishny, 2015). This possible benefit cannot be detected by comparing investors who rely on advice with those who do not.

A second approach, which should deal with this problem, uses randomized field experiments, tracking the recommendations that trained auditors, posing as customers, receive from financial advisors with contrasting or aligned incentives. Mullainathan, Nöth, and Schoar (2012) find that if anything biases are augmented by professional advice, indicating potential suppliers' distortions in households' financial decisions. Anagol, Cole and Sarkar (2012), in an audit study of the Indian life insurance market in which it is possible to identify poor advice find that agents motivated by commissions recommend strictly dominated, expensive products, between 60 and 90 percent of the time. As usual with field experiments, the issue of external validity remains.

Most importantly in this context, one may doubt that the audited advisors would offer the same biased advice in the kind of long-term client relationships that one finds in the real world. Finally, common to both types of studies is the fact that only cases where advice is sought by the investors are observed. In practice, however, advice – especially distorted advice – may be offered even when it is not actually solicited by the customer: the intermediary or broker may emphasize a given financial product, or highlight some features while hiding others in order to steer the households' choice to the intermediary's advantage. If so, comparing customers who do and do not solicit advice may fail to detect supply-side distortions or produce and underestimate of their importance.

This paper proposes a data-based methodology to assess the presence of supplier-induced distortions in households' financial choices on mortgages. The mortgage market, in fact, can be taken as a typical example of transactions in which experts on one side may take advantage of costumers' lack of knowledge and experience. Woodward and Hall (2012) study the compensation that borrowers pay to mortgage brokers – for assistance through the entire process from loan application to closing – and find that confused borrowers overpay.

Our approach does not require explicit information on whether a household has asked for advice or even received it unilaterally, so we can detect its effects even when advice is not explicitly observed. Of course, this requires some identifying assumptions. But, as we will show, they are milder than those required by comparisons of advised and non-advised accounts. We look at the choice between fixed rate mortgages (FRM) and adjustable rate mortgages (ARM) using data on a sample of 1.6 million mortgages originated in Italy by 175 banks over the 7 year-period from 2004 through 2010. Besides information on the terms of the loans and characteristics of the households, the data identifies the bank originating the mortgage and shows its balance sheet and a rich set of characteristics.

The idea of the test is simple. On the hypothesis that banks have heterogeneous relative advantages in offering the two types of mortgage – some banks, say, will have access to cheaper long-term financing and will thus have a relative advantage in offering FRM rather than ARM – we suppose that they may influence households' mortgage choices in the direction that is more advantageous to them. If a household is wary, the only thing that should affect its choice is the relative cost of FRMs and ARMs. That is, the relative price of fixed and variable rate mortgages should be a sufficient statistic to influence a given household's mortgage choice. Thus, controlling for the relative price of the two types of mortgage, within banks variation over time in their cost characteristics should play no role. Differences in banks' efficiency in supplying FRMs and ARMs should be revealed in their relative prices and affect household's choice through this channel alone; otherwise these differences should play no role[2].

On the other hand, as in Inderst and Ottaviani (2010, 2012a, 2012b) and Ottaviani and Squintani (2006), if some households are naive, relative prices are in general no longer a sufficient statistic for mortgage contract choices. If banks exploit the conflict of interest by offering biased advice, the identity of the bank and its characteristics should affect households' choice, apart from any effect that differences in supply characteristics may exert via the relative prices of ARMs and FRMs. Our strategy is to test the null hypothesis that the mortgage choice is unaffected by price-relevant bank characteristics when households' characteristics and the relative prices of the two types of mortgage are controlled for.

We find, like Koijen, Van Hemert and Van Nieuwerburgh (2009), that

[2] The importance of bank-specific fixed effects in a mortgage choice equation may reflect market sorting. For this reason our test focuses on time-varying bank characteristics. These should be irrelevant for households' mortgage choices once prices are controlled for even in cases where fixed effects matter. We discuss this point more in detail below.

the choice between ARM and FRM is strongly affected by the relative prices of FRM and ARM. But we also find that bank time variation in bank specific measures of the relative advantage in originating FRM and ARM does predict mortgage type choices even when the relative price is controlled for. Importantly this result holds controlling for time-invariant bank characteristics captured by bank fixed effects which capture any sorting of customers into banks based on unobserved characteristics. Hence, identification of the presence of biased advice only relies on time-varying characteristics that measure changes over time in banks' incentives to recommend a particular type of mortgage. For example, time variation in the bank bond spread (the extra cost of financing by issuing fixed instead of variable rate bonds), which measures changes in the banks' relative cost to provide fixed rate mortgages, has a direct effect on household mortgage choices, in addition to the effect it has through the relative prices of FRM and ARM. A household borrowing from a bank in a quarter when the banks specific component of the bond spread has increased is more likely to choose an FRM than an otherwise equal household borrowing from the same bank in a quarter prior to the increase, in both cases controlling for any difference in relative prices. This is consistent with the hypothesis that banks with a relative disadvantage in providing FRMs try to influence households' decisions in favor of ARMs, not only by making the latter cheaper but also by distorting advice. Economically, the effect of these distortions is significant. For example, a 1-percentage-point increase in the bank bond spread lowers the probability of a household choosing a fixed rate mortgage by 2.8 percentage points. Yet, the magnitude of this effect, though important, is one tenth as great as that of a 1-percentage-point increase in the relative price of FRMs suggesting that there are limits to how much banks can distort choice through advice.

To validate our interpretation, we also exploit two implications of the biased advice model. First, the effect of distorted advice should be stronger among unsophisticated consumers; and second, as we show formally, supplier characteristics should distort choice more when there are frictions in adjusting prices. Consistent with these implications, we find that time-varying banks' incentives to offer distorted advice have a greater effect on the mortgage choices of unsophisticated consumers; further, these effects are stronger – particularly among unsophisticated consumers – during periods when relative prices do not change.

The rest of the paper proceeds as follows. In Section 2 we set up a model in which advice is a partial substitute for price setting and show that banks find it optimal to use advice to steer household choice. The model shows that if there are at least two supply-side factors that can affect banks' mortgage prices, observation of one or more of these factors can be used to detect the presence of unobserved distorted advice. In Section 3 we discuss our empirical strategy and specify our main equation of mortgage choice. Section 4 presents the data and Section 5 the estimation results. Section 6 concludes.

2 The Model

In a standard demand framework, prices are a sufficient statistic for the effect of supply factors on consumer choices. Households are uninterested in a firm's costs or technology; they care only insofar as these factors affect prices. Therefore, if prices are controlled for, supply variables should not have any predictive power on household choices. We use a simple model to refute this property where the lender can give biased advice and apply it to the choice between fixed rate and adjustable rate mortgages. If a consumer is unsure about which of several products best fits her needs, the firm can opportunistically bias her choice by giving advice. If the advice is followed, variables that are correlated with the bank's incentives predict consumer choices even controlling for prices: two households with identical characteristics facing the same prices may make different choices if they get different advice. Since *biased* advice is uniquely determined by lender profitability, supply factors will affect consumer choices regardless of prices. We show that this intuitive implication holds in a simple mortgage market model where some borrowers do not know which type of mortgage actually fits their needs. Our main result is that prices are a sufficient statistic for choices if there is no biased advice; but biased advice implies that observable supply factors have an *independent* role; this in turn means that the latter can be used to detect the presence of biased advice. Our model illustrates the conditions under which the independent role of supply factors can be interpreted as a test for the presence of (unobserved) biased advice.

2.1 Households

A continuum of households live for two periods, and they all need to finance a house purchase. Households have CARA utility and differ in risk aversion

γ. G denotes the distribution of risk aversion across households. Income is constant over time, nominal interest rates follow a random walk and inflation is unpredictable. Under these assumptions (as is shown by Koijen et al.), household γ chooses an adjustable rate mortgage (ARM) over a fixed rate mortgage (FRM) if and only if

$$\phi > \frac{\gamma H}{2}(\sigma_{\varepsilon}^{2} - \sigma_{\pi}^{2})$$

where ϕ is the FRM premium, H is the value of the house, σ_{ε}^{2} is the variance of interest rates and σ_{π}^{2} is the variance of inflation. In Annex A we illustrate the full derivation of the above decision rule.[3] We normalize $H = 2$ and $\sigma_{\varepsilon}^{2} - \sigma_{\pi}^{2} = 1$ so that the household decision rule is

$$\phi > \gamma$$

The normalization does not affect the results qualitatively. Under these assumptions, $G(\phi)$ households choose ARMs and $1 - G(\phi)$ choose FRMs.

2.2 Banks

There is a continuum of regions in the economy with one bank in each region. Customers cannot borrow from other regions and the distribution of risk aversion is G in every region. Under these assumptions each bank is a local monopolist[4]. Banks have fixed balance sheet size and fixed liabilities. They can only determine asset composition, choosing between long-term FRM and ARM. Every bank i is characterized by exposure to N supply factors $(\theta_1, ..., \theta_N)$. Banks are heterogeneous in their exposure to these factors. Supply factors include the cost of long-term finance, access to core deposit funding, access to securitization markets, and everything that affects the relative cost to the bank of the two mortgage types, hence the incentive to sell one rather than the other. Typically such factors affect supply costs

[3] Provided households make only one mortgage decision and under the same assumptions about the time profile of income, inflation and short-term nominal interest rate the household's decision rule would be the same if households lived for T periods and expected the variances they face to be larger because uncertainty is over T periods rather than one.

[4] Our results also hold under more general market structures, as long as banks have some market power. This is because what really matters for us is the bank's ability to choose both prices and advice: that is the absence of perfect competition is a sufficient condition for our result.

by affecting maturity mismatch and interest rate risk. For example, banks with higher access to securitization markets can tolerate more risk, giving them a comparative advantage in issuing FRMs (Fuster and Vickery, 2014). Similar reasoning holds for our other supply factors as well. The bank has a payoff function[5] $U(x, \phi, \theta)$ that depends on the share x of short term assets (i.e. adjustable rate mortgages), the FRM premium and supply factors. The bank takes θ as given and chooses x and ϕ.

2.3 No advice

Under these assumptions and in absence of advice, the problem of a bank choosing the fraction x of short term assets and the relative price ϕ can be written as

$$\max_{x,\phi} U(x, \phi, \theta)$$

s.t.

$$x = G(\phi)$$

Since the bank has market power, the objective function can be re-written as

$$v(\phi, \theta) \equiv U(G(\phi), \phi, \theta)$$

so that the optimal FRM premium $\phi(\theta)$ is determined by the first order condition:[6]

$$v_\phi(\phi(\theta), \theta) = 0$$

This simply leads us to our first result:

Proposition 1: In absence of advice, the household's mortgage choice is independent of bank supply factors conditional on the relative prices of ARM and FRM. In particular, $E(m|\phi) = E(m|\phi, \theta)$ where m denotes mortgage choice.

[5] We call it payoff rather than profits because banks' choices typically include adjustment for risk.

[6] Notice that we take interest rates as given and only allow the bank to set the relative price of FRM and ARM. Clearly, if we let banks choose the interest rate level they would charge an infinite rate since households here must choose one of two mortgages. This is done for simplicity and could be solved easily by adding an outside option, such as the possibility for households of renting at a certain rental rate instead of owing. The outside option would limit the interest rate that the monopolist bank can charge. Nothing relevant would change in our analysis if we add this feature.

Prices depend on supply factors, but they do not affect household choice otherwise. Since bank supply factors are orthogonal to risk aversion,[7] they add no information, beyond relative mortgage prices, to household choices. In a model with no advice, prices encapsulate all the relevant supply characteristics. Proofs of this and the following characteristics are in Annex B.

2.4 Advice

We now show the solution when banks can affect customers' choices also by means of advice. To model advice we assume that a fraction μ of the banks' customers are naive. They do not know what their decision rule should be; in our context this can be interpreted as uncertainty over unknown parameters, such as the volatility of the interest rates and inflation. Thus, there is scope for well informed banks to provide counseling.[8] The rest of the population is sophisticated: they understand their decision rule. Naivete is independent of risk aversion and is private information, so that the bank cannot distinguish between naive and sophisticated borrowers. The bank can choose an optimal distortion α in the decision rule. This means that where biased advice has been given, the household's decision rule becomes:

$$\phi - \alpha > \gamma$$

so that a bank that tilts the decisions toward ARMs will choose $\alpha < 0$, and one distorting it toward FRMs will choose $\alpha > 0$. Since sophistication is unobservable, the bank gives the same advice to all the customers. Naive customers just follow the advice, while the sophisticated ignore it (they already know what is best for them). What is more, they realize that the bank has tried to mislead them, so that when it gives advice to a wary customer the bank suffers a reputation loss. We call this cost $c(\alpha, \mu, \theta)$. Under

[7]In the model orthogonality between supply factors and borrowers risk aversion is by construction; in reality, sorting can break this lack of correlation. We discuss how we deal with this in Section 3.

[8]If households don't know what is best for them, advice is valuable. We do not model "good advice". This is not a limit of this model or of our econometric test because, by definition, good advice should reflect household-specific factors (e.g. their level of financial knowledge or - as in Gennaioli et al , 2015 - of their "anxiety") and as such should not depend on bank characteristics. In our model advice should be interpreted as suggestions beyond (or short of) what would be needed to make up for the customer's ignorance. Put this way, in our model all advice is biased advice.

these assumptions, the share of customers effectively choosing ARMs is:

$$g(\phi, \mu, \alpha) = \mu G(\phi - \alpha) + (1 - \mu) G(\phi)$$

so the problem becomes:

$$\max_{\alpha,\phi} v(\phi, \alpha, \theta, \mu) \equiv \max_{\alpha,\phi} (U(g(\phi, \mu, \alpha), \phi, \theta) - c(\alpha, \mu, \theta))$$

Under this formulation, the bank's choices $\alpha(\theta)$ and $\phi(\theta)$ solve the pair of first order conditions:

$$v_\alpha(\phi(\theta), \alpha(\theta), \theta, \mu) = 0$$
$$v_\phi(\phi(\theta), \alpha(\theta), \theta, \mu) = 0$$

Here, the N bank specific factors θ affect both the optimal distortion and the mortgage price. Looking at the equations, we can see that in this case θ may have an independent role in determining mortgage choice even after the price ϕ has been controlled for. This is because choices are affected by an observed variable (prices) and a latent one (advice). Adding θ to a regression of mortgage choice on prices may add information on the unobserved value of α. This result does not always hold: if prices are a sufficient statistic for the effect of θ on α, they would capture everything that the econometrician needs to know about α to predict mortgage choice, so that θ would play no *detectable* independent role and the existence of distorted but unobserved advice would not be inferred. In particular we can give the following definition:

Definition: The above model satisfies the sufficient statistic property (SSP) if there exists a unidimensional sufficient statistic of the supply factors that fully determines α and ϕ. That is, if there exists a real-valued function $y = f(\theta)$ such that $\phi = h_1(y)$ and $\alpha = h_2(y)$.

If the model satisfies the SSP, knowing prices *and* advice gives the same information as knowing only prices or advice. Therefore θ has no additional predictive power on mortgage choice once ϕ is controlled for. The following proposition clarifies the conditions under which we can identify the presence of advice.

Proposition 2 : If the model does not satisfy SSP, household choices depend on the factors θ even after prices are controlled for. In other words, $E(m|\phi, \theta) \neq E(m|\phi)$ where $E(m|)$ is the conditional expectation of the household decision.

Under SSP, $E(m|\phi) = E(m|y) = E(m|\phi, \theta)$ so that the result in Proposition 2 fails. Notice that if $N = 1$ the SSP is mechanically satisfied with $f(\theta) = \theta$: with only one supply factor, the factor itself is the sufficient statistic. In short, for the econometrician advice is a latent choice variable. For this reason, whenever distortionary advice is unobserved, supply factors generally matter for consumer mortgage choice even conditioning on prices. But if there is a sufficient statistic of supply factors that determines banks' price and advice choices, the test fails, in that observing prices and advice gives exactly the same information.

We have presented conditions under which the presence of bank supply factors is a test for the presence of advice in the mortgage market. Our test is more general than that. In every situation where the bank has some control over prices and can give advice (unobserved), our test can in principle establish the presence of biased advice. Thus, the same logic can be applied to any financial choice involving a conflict of interest between the bank and the customer, such as investment or insurance product choices. Annex C provides an example that illustrates the importance of the SSP for the validity of our test.

2.5 Price rigidity

In the previous section we showed the conditions under which we can infer the existence of biased advice from the relation between banks' supply factors and customers' mortgage choices, once frictionless mortgage prices are controlled for. We now study the role of price rigidity, because advice is just a soft communication and so is extremely flexible. On the other side, prices are not. This is particularly true at large banks, where changes in pricing policy may entail significant coordination and other menu costs. Hence prices and advice may differ in responsiveness to supply factors. We show that if prices are less flexible than advice, one can infer the presence of biased advice from the correlation of mortgage choices with supply factors even when SSP holds. To see why, suppose there is a small menu cost of changing prices. If supply conditions change only modestly, banks find it optimal not to change prices, so that all movements in θ are reflected in movements in α and supply effects on consumer mortgages reveal biased advice. Moreover, the magnitude of the effect of θ on α may increase: if a bank cannot adjust prices, it is giving up the natural channel to twist demand toward the product it prefers. The alternative way to influence demand is to give advice, which thus under price rigidity, becomes a substitute for pricing activity. To see this, consider the model above and consider the case in which a bank, after a realization of supply factors θ, chooses to leave prices unchanged at ϕ_0 because of a menu cost[9]. The distortion chosen by the bank now satisfies:

$$v_\alpha(\phi_0, \alpha(\theta), \theta, \mu) = 0$$

so that θ has an effect on choices even if the model satisfies the SSP when prices are adjusted: since prices are not moving, the entire effect of θ on choices is due to advice. This can be summarized in the following proposition:

Proposition 3: Under price rigidity, $E(m|, \phi, \theta) \neq E(m|\phi)$.

Moreover, price rigidities may amplify the effects of supply factors since advice substitutes for pricing in distorting demand. Still, we are not able to establish this result formally, because the presence of rigidities changes the optimal choice of the bank, moving the position of the marginal borrower (i.e. the one who is indifferent between ARM and FRM) over the support of the distribution of risk aversion. This implies that the marginal effect of supply factors on advice depends on the distribution of risk aversion. To see this, note that the ARM share, in case of rigidities, is:

$$x = G(\phi_0 - \alpha(\theta))$$

so that

$$\frac{\partial x}{\partial \theta_i} = -g(\phi_0 - \alpha(\theta))\frac{\partial \alpha}{\partial \theta_i}$$

and the marginal effect depends on the shape of the distribution and the bank's payoff function. If there is some complementarity for the bank between prices and advice and if the distribution of risk aversion does not increase too rapidly in $\alpha - \phi$ the marginal effect is greater under price rigidity. For example, $v_{\alpha\phi} > 0$ and $g(\cdot)$ uniform are sufficient conditions for this result to be true. Generally, under $v_{\alpha\phi} > 0$, we need fixed costs that are high enough in order to argue that the marginal effect is not greater under price rigidity: if it is not, this means that the distortion under price rigidity differs very

[9] Here rigidity is implicitly modeled as a fixed cost $F > 0$ of changing the relative price. In this case for small movements in θ the optimal course is inaction. Note that the problem of choosing advice remains static conditional on prices.

substantially from that under price flexibility. When this is true, the marginal profitability of a change in prices must be higher, and high fixed costs are necessary for this to to happen[10].

In addition to these reasons, price rigidity helps in detecting the presence of distorted advice when the relative price of FRM and ARM ϕ is measured with error or if there are omitted price-relevant demand side variables. We discuss these issues in the next session.

3 Empirical strategy

In the model, we clarify the conditions under which it is possible to test for biased advice. In particular, we establish that if supply factors affect prices and advice differently enough, a regression of household choice on supply factors variables that affect banks' funding access and costs – controlling for prices – should find an important role not only for prices but also for biased advice. In this section, we illustrate our empirical strategy to test for the presence of biased advice and discuss the assumptions that enable us to determine the effect of advice. We run the following regression:

$$x_{ibt} = \beta_1 \phi_{ibt} + \beta_2 z_{ibt} + \beta_3 B_{bt} + f_b + f_t + u_{ibt} \tag{1}$$

where x_{ibt} denotes the mortgage choice of customer i at bank b at time t and ϕ_{ibt} is its relative price. z_{ibt} is a set of customer-specific covariates and B_{bt} a set of bank-specific supply factors (corresponding to the $\theta's$ in the model) ; f_b, f_t are bank and time fixed effects, and u_{ibt} is an error term. We denote the choice of FRM by $x_{ibt} = 1$ and ARM by $x_{ibt} = 0$. We include ϕ and z because they are natural determinants of choices, and B to test for advice. The presence of f_b and f_t helps us to identify the presence of advice, as explained below. Our test of advice relies on the economic and statistical importance of coefficients in β_3: biased advice makes these coefficients significant and their sign should be as predicted by the bank's incentives. Specification (1) makes it clear that the effect of advice on mortgage choice is identified only

[10] To see this, suppose there is only one supply factor and the optimal solution to the bank's problem is linear: $\alpha(\theta) = A_1\theta + A_2\phi$ and $\phi(\theta) = B_1\theta$. Under price flexibility, θ is insignificant and has zero coefficient for mortgage choice when ϕ is controlled for. Under rigidity, ϕ does not react to θ so that all the variation takes place through α and θ matters for choice. Therefore both the significance and the coefficient of θ for mortgage choice increase.

if household-specific unobserved heterogeneity is not correlated with time-varying bank supply factors. First, time-varying factors other than prices affect mortgage choices even in the absence of advice. For example, changes in interest rate volatility simultaneously affect choices and banks' balance sheets. These time-varying factors tend to be aggregate, not bank-specific, so that adding a time effect takes care of them.

Another potential problem is sorting: one might argue that more risk-averse consumers tend to be found at banks that are better able at managing interest rate risk, creating a correlation between choices and supply factors regardless of advice, unless individual risk aversion or banks' relevant characteristics are observed. To account for this, we include bank-specific fixed effects. The idea is that if there is any sorting this should take place through bank characteristics that are stable over time: while one could argue, for example, that larger banks attract more risk-averse customers, it is implausible that quarterly changes in securitization activity or the share of deposits in total funding at a given bank will alter the composition of the pool of borrowers. Therefore, the association of stable bank characteristics with different borrower pools is consistent with identification, in our model, as long as time-varying bank-specific supply factors do not affect the composition of such pools. Formally, identification requires that

$$E(u_{ibt}, B_{bt}|\phi_{ibt}, z_{ibt}, f_b, f_t) = 0 \tag{2}$$

In other words, the unobserved characteristics u_{ibt} of the consumers who borrow in quarter t from bank b, should bear no systematic relation with the variation from quarter to quarter in the bank specific component of supply factors, once we control for the relative price of the mortgages, fixed bank characteristics, common time effects and borrowers' observable characteristics. This requires that borrowers *not be sorted* into banks purely on the basis of quarterly change in some bank-specific supply factor, such as the cost of long-term funding. We regard this as a mild and reasonable assumption. We discuss this assumption further in Section 5.2 and provide supportive evidence.

The model in Section 2 carries two further implications about the observables. First, the correlation between bank supply factors and mortgage choice, controlling for prices, should be stronger where there is some price rigidity. As we show below, our data exhibit evidence of price adjustment inaction, so we can test for this implication by estimating

$$x_{ibt} = \beta_1 \phi_{ibt} + \beta_2 z_{ibt} + \beta_3 B_{bt} + \beta_4 D_{bt} \times B_{bt} + f_b + f_t + u_{ibt} \quad (3)$$

obtained adding the term $\beta_4 D_{bt} \times B_{bt}$ to the baseline model, where D_{bt} is a dummy for price inaction in bank b at time t. Based on the model, we expect the effect to be stronger during periods of inaction, so that β_4 should be significant and of the same sign as β_3, reinforcing the effect of bank-specific supply shocks. Second, the effect should be stronger for less sophisticated customers, as they rely more on advice. Furthermore the differential effect of bank supply factors between sophisticated and unsophisticated borrowers should be larger at times of price inaction. To test for this we estimate model (3) separately for the group of sophisticated and unsophisticated borrowers identified using a proxy S_{ibt} for the financial sophistication of customer i choosing his mortgage from bank b at time t. If the model is correct, we should find β_3 and β_4 to be larger (in absolute value) among unsophisticated borrowers.

Before leaving this section, we discuss two additional instances that may lead to a failure to identify condition (2). First, where there is measurement error in ϕ_{ibt}. If the the relative price of FRM and ARM is measured with error, because the true price is correlated with the bank supply factors, B_{bt} will capture part of the true variation in the relative price and show significance even when there is no biased advice. Second, where some price-relevant demand controls are omitted: in this case the price ϕ_{ibt} also captures the effect of these omitted factors on mortgage choice. This implies that ϕ_{ibt} is no longer sufficient to characterize bank supply conditions. Hence, supply factors B_{bt} may become significant because they are correlated with the true price even without distorted advice.

But under price inaction, these biases disappear. In fact, in both instances the bias arises because of the correlation between ϕ_{ibt} and B_{bt}. Price inaction breaks this correlation and allows one to identify the presence of distorted advice even if ϕ_{ibt} is measured with error or if there are omitted demand controls.

4 The data

We use data from two main administrative sources: the Italian Credit Register (CR) and the Survey on Loan Interest Rates (SLIR). Both datasets are administered by the Bank of Italy. The first collects information on the loan exposures above the threshold of € 75,000 originated by all Italian banks. A subset of 175 banks participate in the SLIR and also report to the Credit Register data on their lending rates. We have obtained quarterly data on all the mortgages originated between 2004 and 2010 for all the 132 banks that participate in the SLIR and are active in the mortgage market. The dataset has complete records on around 1.9 million mortgages. Excluding contracts with a partially adjustable interest rates and length of less than 10 years (103,814 observations), mortgages granted on special terms or conditions (13,470 observations) and loans to sole proprietorships (160,574 observations) we were left with 1,662,429 observations on plain vanilla FRMs or ARMs (see Annex E for more details). The dataset contains detailed information on type of the loan (FRM or ARM), the contractual rate and original loan size, and a number of borrower characteristics. In addition, we have the identifier of each of the originating banks; and, most importantly, we can merge the mortgage dataset with detailed supervisory data on banks' characteristics and balance sheets. Finally, we complement the mortgage-originator data with information on the structure of the local market, the local market power of the bank and the distance between the bank's headquarters and the borrower residence. In the end, our dataset includes features of borrower, lender, the specific terms of the mortgage, and information on the local market.

4.1 Computing the relative price of FRM

There are two views on the best gauge of the long term finance premium (LTFP), the relative price of $FRMs$ and $ARMs$ in a household's mortgage choice. Campbell and Cocco (2003) posit that the choice of liquidity constrained households is driven by the current difference in funding costs, defined as the spread between FRM and ARM rates ($r^{FRM} - r^{ARM}$). Using panel data for nine countries, Badarinza et al (2014) support this view and find that the spread between FRM and ARM rates has a stronger explanatory power for the "ARM share" ($ARMs$ as a percentage of all mortgages) than other measures based on forecasts of ARM rates over a longer horizon. They therefore conclude that current cost minimization, not longer-term forecasts of ARM rates, is the primary driver in the choice.

Koijen et al (2009) propose an alternative measure of the LTFP. The mortgage's choice is driven by the time-varying FRM risk premium, defined as the difference between the fixed rate and expected future average values of the ARM rate ($r^{FRM} - E(r^{ARM})$). This spread is ordinarily positive, as borrowers pay a premium to be shielded from interest rate increases. Because they only have aggregate data, they proxy the FRM risk premium by the long-term bond risk premium, computed as the difference between the 10-year bond yield and the expected 1-year bond yield, proxying expectations about the latter with a moving average of past yields.

In our analysis we compute both measures at the borrower-bank level. In particular, we calculate: i) $Spread = r_{ibt}^{FRM} - r_{ibt}^{ARM}$; ii) FRM risk premium= $r_{ibt}^{FRM} - E(r_{ibt}^{ARM})$ for household i borrowing from bank b at time t.

Since we observe the interest rate on the chosen mortgage at time of origination, we can rely on both time series and individual specific variation in the relative cost of the two types of loans.[11] Obviously, while we observe the rate on the mortgage actually chosen by individual i and originated by bank b – say an FRM (ARM), we do not observe the rate on the alternative type of mortgage at the bank. We overcome this problem by imputing the rate that the customer would have been charged had they chosen an ARM (FMR). For this we group customers that chose FRM and ARM respectively, and then run a sequence of regressions, one for *each* bank, of the rate charged on each type of loan on loan characteristics, borrower characteristics and a full set of time dummies. We then use the estimated parameters to impute the interest rate to the specific household (for details on the imputation, see Annex D. There are three key points. First, because we run bank specific regressions any systematic interest rate difference across banks is reflected in the imputed interest rate. Second, because each regression includes a full set of time dummies, any effect on interest rates of any time varying bank-specific variable is also reflected in the imputed rate, in particular any variation in its supply factors. Thus the residual difference between the true rate the consumer would have faced on the alternative mortgage and the imputed rate reflects only unobserved borrower-specific characteristics. This measurement error may create attenuation bias in the estimated effect of the relative price of FRM on mortgage choice but is orthogonal to the time varying bank variables that we will use as proxies for the incentive to distort advice.

[11] For instance, the adjustable rate mortgage is given by the one-month interbank rate plus an individual specific credit spread. The first reflects time-varying market conditions and is common to the set of borrowers choosing ARM in a given quarter from a certain bank, but potentially can vary across banks; the second, reflects individual-specific credit-worthiness and differs in the cross section of borrowers that obtain an ARM in the same quarter.

Finally, to compute the FRM risk premium $(r^{FRM} - E(r^{ARM}))$ we follow Koijen et al (2009) and measure $E(r^{ARM}))$ using different lags and leads of the short terms ARM. Clearly, zero lag coincides with the current spread. Figure 1 shows that, as in Koijen et al. (2009), the one-year lag measure of the FRM risk premium has the greatest predictive power for the ARM share using either aggregate data (the light color bars) or individual data (the darker bars). Hence, we will use this as our reference measure. But notice the very close correlation of ARM share with the current spread. Figure 2 plots the aggregate ARM share (the share of new adjustable rate mortgages over total new mortgages) together with the FRM spread and the FRM risk premium using one-year lag to measure the latter; both correlate positively with the ARM share, but the fit of the FRM premium is somewhat better.

Table 1, Panel A reports summary statistics for the actual and imputed rates together with other information on the mortgage contract. The rest of the table reports summary statistics on the borrower (Panel B), the balance sheets of the lenders (Panel C) and the bank-borrower relationship (Panel D). More information is provided in Annex E.

4.2 Banks' supply factors

We use three measures for the bank supply factors that should affect the relative cost of FRM and ARM. The first is the bank bond spread - the premium the bank pays for raising long-term funding via fixed-rate over variable rate bonds. Banks that pay a higher premium face a higher cost of supplying FRM and should therefore have an incentive to distort advice towards ARM. For most of the banks in our sample we observe both rates; some small banks are not always active in both the fixed and variable rate bond markets. For those quarters in which these banks were inactive in a specific segment we impute the rate using the bank-specific spread (with respect to the market rate) the last time they were active in that segment. We show that results do not depend on this imputation.

The second measure is a proxy for banks' access to securitization. Fuster and Vickery (2014) show that the share of fixed-rate mortgages is positively related to access to securitization. By allowing banks to dispose of some of their assets, securitization enhances asset allocation flexibility and so makes long-term investments more palatable. These banks should have a relative advantage in originating $FRMs$ vs $ARMs$ and should accordingly, bias their advice towards the former. We proxy access to securitization with a dummy variable equal to 1 if the bank (or the group to which the bank belongs to) has sold securitised loans on the market in the last two years.

The third measure is the share of deposits in total funding. Because individual depositors face higher switching costs than institutional investors, banks that can count on core deposits can be slower and less complete in adjusting their funding to changing market conditions than banks whose liabilities consist mainly of variable rate bonds, which respond rapidly and fully to market movements (Berlin and Mester, 1999). Hence, the former are less exposed to market risk and so are better able to stand greater maturity mismatching. Being less subject to interest rate risk, banks with a relatively large deposit base should have a relative advantage over banks with a low deposit share in issuing $FRMs$ vs $ARMs$ and may be expected to bias their advice accordingly. This is consistent with Berlin and Mester (1999) and Ivashina and Scharfstein (2010), who found that banks with better access to rate-inelastic core deposits more commonly engage in loan rate smoothing (i.e. relationship lending).

In sum, when estimating equations 1 and 3 we expect β_3 and β_4 both to be negative if the bank supply factor considered is the bank fixed bond spread and both to be positive if it is securitization activity or the deposit ratio.

Table 1, Panel C, shows summary statistics of our supply factors.

4.3 Identifying price inaction

To identify periods of inaction in setting the relative price of $FRMs$ and $AMRs$ we look at the quarter to quarter changes in spread , $r_{bt}^{FRM} - r_{bt}^{ARM}$. This is the price that banks control. For each bank, we compute it by first taking averages across borrowers of the rates charged on the two types of mortgages originated by the bank in each quarter covered by the sample. The first column of Figure 3 shows the cross-sectional distribution of $\Delta Spread = \Delta(r_{bt}^{FRM} - r_{bt}^{ARM})$ over the whole sample (2004-2010), both before the financial crisis (2004-2007) and during it (2008-2010). In all periods the distribution has a spike around zero, consistent with infrequent adjustments of relative mortgage prices.[12] The distribution tends to be symmetric around

[12] Because we are considering the average spread over quarters, the change may differ slightly from zero due to time aggregation. For instance, if adjustment takes place in the last ten days of the quarter, the change in that quarter will not be exactly zero. Accordingly, we define inaction as a change in the spread within a small interval around

zero except during the financial crisis, when it shows a fat tail to the right: that is because following the Lehman Brothers' default Italian banks had trouble issuing fixed rate bonds, which resulted in a higher costs of $FRMs$ (Levy and Zaghini, 2010). Therefore, part of the adjustment of the spread reflects changes in the slope of the yield curve that modify the relative cost of FRM. The second column of Figure 3 shows the distribution of changes in the spread net of the adjustment in the slope of the yield curve $(\Delta(r_{bt}^{FRM} - r_{bt}^{ARM}) - \Delta Slope_t)$.[13] When these are filtered out, the distribution of the changes in the relative price of FRM and ARM becomes symmetric around zero. This disconfirms the hypothesis that most of the changes during the crisis reflects an increase in the cost of fixed-term borrowing common to all banks.

Our main indicator of price inaction for bank b in quarter t is a dummy equal to 1 if $\Delta(r_{bt}^{FRM} - r_{bt}^{ARM})$ is comprised between $\pm\frac{sd}{3}$, where sd is the standard deviation of the spread of bank b. For robustness we also compute alternative measures. First, we define inaction using a tighter threshold, namely $\pm\frac{sd}{4}$. Second, we define inaction if the change in the spread of bank b in a given quarter falls within $\pm\frac{1}{3}$ of the standard deviation of the change in the spread in the pooled data.

Using our main definition, banks are inactive about 40 percent of the time with considerable heterogeneity in the number of price adjustments (Figure 4). Figure 5 shows that this finding is robust to changes in the inaction measure, while Figures 6 shows that hazard rates are decreasing over time, consistently with the baseline menu cost models.

4.4 Other controls

In estimating (1) and (3) we control for characteristics of the mortgage (amount, whether it is a joint mortgage), borrower specific variables (age, sex, dummies for Italian nationality and cohabitation) that capture part of the heterogeneity in consumer preferences; characteristics of the local market (provincial lending concentration measured by the market share of the top lender, GDP per capita), and a measure of borrower-lender relationship (the distance between borrower's residence and lender's headquarter). We also consider a dummy for the "Bersani Law" (Law 40/2007) which abolished

zero.

[13]The slope of the yield curve is obtained by taking the difference between the 15-year swap rate and the 1-month interbank rate.

early-prepayment fees and a dummy for those banks that joined the "Patti Chiari" (Clear Deals) initiative launched in 2003 by the Italian Banking Association to simplify bank-borrower relation. Summary statistics for these variables are reported in Table 1 panel B and D.

5 The results

Before estimating our baseline model (1), in Table 2 we report OLS estimates of various specifications of households mortgage contract choice. Because Probit estimates are known to be biased when there are a large number of fixed effects (Lancaster, 2000) and because in Probit regressions interaction effects are not readily interpreted, given the importance of both fixed and interaction effects to our identification strategy, in the rest of the paper we estimate linear probability models. The left hand side is a dummy variable equal to 1 for FRM and 0 otherwise. The first column controls only for bank fixed effects. Systematic differences across banks can explain about 9.8 percent of the variance and bank fixed effects are highly significant jointly. The second column adds the long-term financial premium measured using the FRM risk premium. As expected this variable has a negative effect on mortgage choice, and it is highly significant (p-value $< 1\%$). Interestingly, while the bank fixed effects continue to be statistically significant, when the relative price is added the explanatory power increases considerably: the model can explain about 47.6 percent of the variance. This is consistent with the role that theory attributes to relative prices. Economically, a one percentage point increase in the relative cost of $FRMs$, lowers the probability of choosing this type of contract by as much as 31 percent. The correlation in column II between mortgage choice and relative price captures both variation over time in the relative cost of $FRMs$ common to all banks as well as variation over time specific to the bank (systematic differences in relative prices across banks are picked up by the bank fixed effects). Column III includes a full set of time dummies so that the variation in the relative price of $FRMs$ is now strictly bank specific. Notice that since the expectations about future short term rates used to compute the average expected ARM rate are common to all individuals, they are absorbed by the time fixed effects; thus the variation in the FRM risk premium reflects that in the current spread. When we rely only on this source of variation, the marginal effect on the relative price is negative and significant, and also somewhat larger (a one percentage point increase in the spread lowers the probability of choosing a FRM by 35 percent). Adding time fixed effects also improves the fit (R^2=0.59) suggesting that there are relevant time varying common variables, apart from the FRM risk premium, such as changes in the relative riskiness of the two types of mortgage contract captured by the time effects. Adding borrower specific controls (Column IV) and then a set of province fixed effects and a measure of local market concentration (Column V) adds little explanatory power and leaves the marginal effect of the relative price unchanged. Columns VI replicates the estimates in Column II using the current spread as a measure of the $LTFP$. The results are very similar to those using the FRM risk premium although the latter yields a marginally better fit. Hence, in the rest of the paper we simply take the FRM risk premium as our gauge of the $LTFP$.

Overall, this evidence assigns a key role to the relative price as a driver of mortgage contract choice - a point made by Koijen et al (2009). But it also reveals some systematic effects of fixed characteristics of the mortgage originator. This may simply reflect sorting or it may reflect lenders' systematic ability to shift consumer choices not via prices but via biased advice. To shed some light on the importance of sorting we retrieve the bank fixed effects from the estimates in Table 2, Column V, whose distribution is shown in Figure 7. The figure suggests some heterogeneity in the pattern of banks specialization: some banks mainly originate $FRMs$, others mainly $ARMs$. The vast majority, however tend to originate both. We then compute the means of the observable borrower characteristics for banks that tend to originate mostly $FRMs$ (the top decile of the distribution of the bank fixed effects), mostly $ARMs$ (the bottom decile of the distribution of the bank fixed effects) and of those that tend to originate both. Means and variances are reported for the whole sample and for our two subperiods (2004-2007 and 2008-2010). As can be seen from Table 3, there is no difference in the distribution (summarized by mean and standard deviation) of any observable borrower characteristic neither across the three types of banks nor over time for a given type of bank. Although sorting could of course occur as a result of unobservables, the fact that the distributions of observable borrower characteristics are so similar across banks and over time makes this a fairly remote possibility **(Section 5.2 discusses this issue in greater detail)**. Even so, in our tests we always include bank fixed effects and identify biased advice only out of bank-specific time variation in supply factors.

5.1 Baseline model estimates

Table 4 shows the estimates of our baseline model (1). The first column uses the complete specification of Table 2 (Column V) and adds the fixed rate bank bond spread, the securitization activity dummy and the deposit ratio as measures of time-varying banks supply factors. Not only are these variables statistically significant (the fixed rate bank bond spread at 10% and the other two with p-values $< 1\%$), their sign too is consistent with the nature of the banks' incentives that they are intended to reflect, as discussed in Section 4.2. A high fixed-rate bond spread lowers the chances that the borrower will opt for a fixed rate mortgage, while the bank's ready access to loan securitization and its ability to rely on core deposits for funding both increases the likelihood of the borrower's taking an FRM. Because the estimates control for the relative price of FRM and ARM, these effects are additional to any effect of lender supply factors on the spread. In fact, a regression (unreported) of the spread on bank fixed effects, time dummies and our three bank supply factors shows that these variables do affect the spread. Taken together this evidence is consistent with the hypothesis that banks respond to changes in funding conditions both by adjusting prices and by giving biased advice.[14] The fact that costumers' choice is correlated with these bank variables is also consistent with models of naive consumers, as in Ottaviani and Squintani (2006) and Kartik et al (2007), while it tells against models of uninformed but smart costumers which predict that advice will not distort choice (as in Crawford and Sobel, 1982). Our results suggest that the mortgage market is more likely to be populated by genuinely naive costumers than by uninformed borrowers who rationally anticipate that their bank will be offering biased advice. If that were the case, the biased advice would not be credibly transmitted and it would therefore not distort behavior.

Compared with the response to changes in relative mortgage prices the effect of biased advice is smaller, as one would expect, but far from negligible.

[14] The correlation could reflect reverse causality: that is banks faced with a stronger demand for $FRMs$ securitize more and try to attract more deposits. We have two answers to this observation. First, a current shift in the relative demand for $FRMs$ is unlikely to be able to cause a response in securitizaton and in the deposit base in the same quarter; second, and most importantly, reverse causality cannot explain the effect of the bank bond spread. An increase in the relative demand for $FRMs$ would trigger an increase in the issues of fixed rate bonds (to match maturities) and presumably an increase in the bond spread - giving rise to a *positive* correlation between FRM share and bond spread. This is the opposite of what we find.

A 100 basis point increase in the fixed-rate bank bond spread lowers the probability of the borrower opting for a FRM (through the biased advice channel) by 2.6 percentage points, which is 1/13 of the effect of an increase in the $LTFP$ of that size. A one standard deviation increase in the quarter-to-quarter variation in securitization activity increases the probability of a borrower choosing an FRM in that quarter by 3.1 percentage points; it increases by a similar amount (3.2 percentage points) if the quarter-to-quarter specific variation in the bank deposit ratio increases by one sample standard deviation.

In Column II we run the estimates using only the banks for which we actually observe the fixed rate bank bond spread in all relevant quarters, thus avoiding imputations. The results are unchanged. One problem is that the banks' supply factors might be capturing non-linear effects of the relative price of $FRMs$ versus $ARMs$ in the household's decision problem. To address this concern, Column III adds a quadratic and a cubic term in the $LTFP$. The results do not warrant the concern: although there is some evidence of non-linearity in the effect of $LTFP$ on contract choice, the effect of the bank supply factors is unchanged, both statistically and economically. Finally, Column IV assesses possible distortions due to local shifts in the demand for different mortgage types by adding time-province fixed effects; and in Column V we run the model only for the banks that are present in all provinces, in order to assess possible biases due to sorting (see next Section). The results are unchanged, qualitatively and quantitatively.

It is worth emphasizing the thought experiment that underlies the identification of biased advice in our estimates. Take the effect of the fixed rate bank bond spread. The estimate of this coefficient results from comparing the choices of customers at a given bank in a given quarter facing a given (customer specific) FRM spread with the choices of the customers of the *same* bank in a different quarter, possibly facing a different (customer specific) FRM spread and observing that customers that choose the contract in a quarter in which the bank faces a higher cost to attract long-term funding tend (once the component of the costs common to all banks is filtered out) to opt for fixed rate mortgages. In making this comparison, we take into account the fact that the pools of customers in different quarters may have different observable characteristics, and we interpret the result of the comparison as evidence that banks use biased advice to distort the mortgage contract choices of their customers to their own advantage. That is when the cost of long term funding increases relative to short term, the bank tends to recommend $ARMs$ so as to reduce exposure to interest rate risk. This interpretation rests on the identifying assumption that the variation in the unobservable characteristics of the pools of borrowers from one quarter to the next is not correlated with the quarterly change in the fixed rate bank bond spread. A similar argument applies to the deposit ratio and to securitization activity. That is borrowers do not sort into banks according to time-varying supply factors.[15] As this is the key identification assumption in our empirical model, we discuss it further in the next Section.

5.2 Sorting

Unobserved heterogeneity due to sorting of customers by *time invariant* bank characteristics is inconsequential for the estimates, since this is accounted for by the bank fixed effects. Furthermore, as shown in Table 3, when we split banks according to pattern of specialization in $FRMs$ or $ARMs$, we find that the mean and variance of our six household-specific variables do not vary across subsamples, which suggests that even sorting by stable characteristics is unlikely to play a role.

However, there could be sorting by the *time varying* component of the bank supply factors, a possibility that we have excluded by imposing it as our identifying assumption. For this assumption to fail and for our results accordingly to be driven by sorting depending on time-varying supply factors, the distribution of risk aversion (or other borrowers characteristics that affect mortgage choice) would have to react to quarterly changes in supply factors. This does not seem like a plausible mechanism, if only because customers have limited access to banks' balance sheet data. In other words, our key identification assumption is that the composition of borrowers at a given bank does not vary with its balance sheet. To further strengthen this assumption, we look for evidence of this kind of sorting in our sample. Table 5 seeks to explain household-specific observable characteristics at a given bank using our three time-varying supply factors (while controlling for bank fixed effects). No coefficient is significant.

One possible critique of our check is that some sorting may be due not to observables but to unobserved heterogeneity, in particular differences in risk aversion. We conclude that there is not much evidence that this mechanism

[15] Note that the theoretical model does not allow for sorting, since all banks face the same pool of borrowers.

drives the result. First, our observables contain proxies of risk aversion, such as the mortgage size (proxying for wealth) and the cohabitation dummy (proxying for informal insurance). Second, we run a specification of the model only for banks that are present in all provinces: sorting is more likely in smaller banks, as the large ones have bigger customers base (Table 5, Column V). The supply factors remain statistically and economically significant in this specification; if anything their effect becomes stronger (the coefficients for securitization and the deposit ratio display a moderate increase), which is inconsistent with sorting at local level.

Taken together, the evidence in Tables 3 and 5 suggests that different banks face a similar pool of borrowers that does not change with balance-sheet variables. As we discuss in Section 5.5 this helps to address two potential alternative explanations of our findings.

5.3 The results with price inaction

Table 6 reports the estimates of model (3) which adds to the baseline model (1) interaction terms between the three bank supply factors and a dummy equal to 1 if in a given quarter the bank kept the FRM/ARM spread unchanged. The model predicts greater reliance on advice - hence greater bias in household contract choice - in periods of price inaction. In Panel A, we use our reference measure to define price inaction. In all specifications the interaction with the price inaction dummy has the same sign as that of the specific supply factor - thus reinforcing its effect - and is statistically significant. The effect is particularly strong for the fixed rate bank bond spread: in quarters in which the bank does not adjust the FRM spread, an increase of 100 basis point in the cost of long-term funding lowers the probability that a household will choose an FRM through the advice channel by about almost 8 percentage points - against an average effects over all periods of 2.6 percentage points (using the estimates of Column I, Table 5 and Column I, Table 6). In periods of price adjustment, changes in the bond spread translate mostly into changes in relative mortgage prices, leaving little room for the advice channel. For the other two factors the differences in marginal effects between times of price inaction and the overall average for all quarters are more limited, but they are positive, as the biased advice model implies, and they are statistically significant.

As was observed in Section 3, studying the effect of bank supply factors under price inaction not only permits a valid test of a unique implication of the biased advice model even when only one supply factor is available but overcomes two potential objections. The first objection is that supply factors may become significant only because the relative mortgage price is measured with error. Because the rate on the mortgage not chosen is imputed, this may be a concern. Since the bias arises because supply factors are correlated with the relative mortgage price (measured with error), price constancy breaks this correlation and allows a neat identification of the advice channel. The second objection is that this procedure might omit demand controls that also affect relative mortgage prices. Because the omitted controls end up in the error term, they will bias the coefficient of relative price; and because the relative price and supply factors are correlated, the latter's effect may become significant, independently of distorted advice. Though the time-province fixed effects in Column V should capture these factors for demand shift, it is still questionable whether they capture them all.[16] Under price inaction this source of bias is eliminated so if supply factors nevertheless still affect mortgage choice, this is clearly due to biased advice.

These results are confirmed if we use the more stringent definition of price inaction, as is shown in panel B, Table 6.

Hence, on this ground too we conclude that the evidence consistently indicates a significant role for biased advice when households choose between $FRMs$ and $ARMs$.

5.4 Financial sophistication

The model in Section 2 predicts that banks supply factors bias the mortgage choice of unsophisticated customers more than those of sophisticated borrowers. To test this implication we estimate model (3) separately for samples of sophisticated and unsophisticated customers. We proxy sophistication with the size of the loan and distinguish between experienced borrowers (who have borrowed from some banks in the past) and inexperienced borrowers (who are applying for a loan for the first time). Wealthier households tend to be more financially sophisticated (Calvet, Campbell and Sodini, 2009); in turn, wealth is positively correlated with the size of the house purchased and thus with that of the loan. Relying on this argument, we define "unsophisticated" households as those taking out a mortgage for the first time

[16] Inserting time-province fixed effects leaves the effects of the relative price and of the interaction terms unchanged, suggesting that omitted demand shifters are unlikely to be an issue.

and for an amount less than € 80,000, not far above the Credit Register reporting threshold. This group accounts for about 2 percent of our sample observations. We than select 2% of the observations from the top tail of the distribution of mortgage size (above € 320,000) among borrowers who have already borrowed in the past: this defines the group of "sophisticated" borrowers. Table 7 shows the estimates on the two samples using the benchmark measure of price inaction. Results (unreported) are the same using the tighter definition of inaction. Two broad features emerge. First, unsophisticated borrowers display a stronger negative response to increases in the fixed-rate bond spread, and particularly so at times of price inaction. In periods of price inaction, a 100-basis-point-increase in this spread lowers the probability of choosing an FRM by 8.5 percentage points among unsophisticated households and 3.6 points among the sophisticated ones and the difference is statistically significant (the test for the difference in shown in the last column). Second, the overall response of mortgage choice to the securitization activity indicator and to the core deposit ratio is positive for both groups but larger overall among unsophisticated and again particularly so in times of price constancy. For instance, a one standard deviation increase in the quarter to quarter bank specific variation in the deposit ratio increases the probability of opting for a FRM by 4.2 percentage points among the unsophisticated and by 3.0 percentage points among the sophisticated in normal times and by 4.9 and 3.0 points respectively during quarters of price inaction. Securitization activity has similar effects, and they too are stronger at times of price inaction.[17]

Overall, we take the results in Table 7 as additional evidence for the importance of biased advice.

[17]Though this evidence is consistent with the differential effects of biased advice on wary and naive borrowers predicted by the model, there is a problem with our proxy for sophistication: we may be confounding the effect of sophistication with the pure effect of the size of the loan. From Section 2.1, a larger loan leads to larger portfolio risk, shifting household choices toward $FRMs$. We solve this problem by noting that, in the case of pure size effects, the effect of the loan size on prices and advice should be proportional, whereas our estimates suggests that in the data it is not. From Section 2, the fraction of households choosing $ARMs$ is

$$x = G\left(\frac{\phi + \alpha}{H\sigma^2}\right)$$

where G is the distribution of risk aversion (with density g), ϕ is the FRM premium, α is the advice bias, σ^2 is the variance of real interest rates and H is the size of the loan. ϕ and α are choices for the bank so that they depend on supply factors. The effect of a

5.5 Alternative explanations

A first possible alternative explanation of our findings is that they reflect rationing rather than advice. Suppose banks target a desired FRM share $\overline{s}$ that depends on supply factors (and so is higher for banks with larger core deposits, easier access to securitization and a smaller bond spread). If the actual share is below target the bank turns down applicants who opt for ARM and grant mortgages only to those who choose FRM; and conversely if the share is above target. This could explain our findings. Supply factors will affect the probability of observing a given mortgage choice. Rationing, and thus the effects of supply factors, will be more severe at times of price inaction and these effects may be stronger for unsophisticated borrowers if they face higher search costs, so that they are more likely to take the contract offered rather than move to another bank and keep searching. However, rationing implies sorting which should be visible even on observable features, but in our data this does not occur as discussed in Section 5.2.

A second concern turns on the difference between advice (a signal sent to a group of customers at the banks premises) and advertising (a signal sent to the general public, being clients or not). If some banks invest in advertising a particular financial product, they will tend to sell more of it, even in the absence of advice (Gurun, Matvos and Seru, 2015). If the difference in advertisement levels is correlated with balance sheets, then our results could not be interpreted as advice. While some advertising might be present in our sample, if this is to be the key driver of the result we would have to observe at least some sorting. By definition advertisement affects a vast pool of potential borrowers *before* they self-select into a given bank. A bank heavily pushing $ARMs$ over $FRMs$ would end up with a certain type of customers. But as we have seen, the data display little evidence of sorting, so we see

change in the supply factor θ_k is then:

$$\frac{\partial x}{\partial \theta_k} = g\left(\frac{\phi+\alpha}{H\sigma^2}\right)\frac{1}{H\sigma^2}\left[\frac{\partial \phi}{\partial \theta_k} + \frac{\partial \alpha}{\partial \theta_k}\right]$$

If changes in H are pure size effects, distortion and prices are affected proportionally by θ_k. Therefore the change in the regression coefficients of prices ϕ and supply factor θ should be proportional as well. Now suppose that H is related to the fraction of sophisticated borrowers μ. In this case a change in H leads to a change in μ, leading in turn to a change in $\partial\phi/\partial\theta_k$, $\partial\alpha/\partial\theta_k$. In this sense, the fact that size has an effect on choices that is not proportional between ϕ and α signals that the effect works through sophistication rather than pure size.

advertisement as an implausible explanation for our results.

6 Conclusion

In this paper we use a novel methodology to detect the presence of biased financial advice from banks to households choosing a mortgage. We show that in a simple model of mortgage choice where the lender can set the price and also give the customer advice, the relative price of fixed rate and adjustable rate mortgages is generally not a sufficient statistic for the choice. Banks that face a mixed pool of sophisticated and unsophisticated borrowers will respond to changes in the cost and availability of funding by adjusting prices and by providing advice to steer borrowers toward the choices most advantageous to the bank. Hence, supply shocks affect borrowers' mortgage choices not only through prices but also directly, insofar as they proxy for unobservable advice; and thus they actually reveal the existence of such advice.

We find evidence that is consistent with this prediction and thus with the hypothesis that intermediaries offer biased advice to customers. Time varying measures of the bank's incentive to steer households towards adjustable rate mortgages - such as its access to long-term funding - affect household choice even when controlling for the relative cost at origination of the two types of mortgage. As the model predicts, the effect of this distortion is stronger in periods when banks do not adjust the relatives price of their mortgages. In addition, and again consistent with the model, non-price supply side effects on borrowers' choice are stronger in the case of unsophisticated borrowers, who should theoretically be more responsive to the bank's advice. Further research is needed to assess the effects of financial advice on the performance of mortgages and to seek to determine whether bank advice is beneficial or harmful to consumers.

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Annex A. Mortgage decision rule

In Section 2 we refer to the Koijen rule (Koijen et al., 2009) for mortgage choice. Here we show that in our setting this rule governs mortgage choice. Consider a household with CARA utility and absolute risk aversion γ. Income is y in every period and we abstract from saving behavior. The household needs to finance the purchase of a house worth H with a 100% mortgage. The house is purchased before the first period and sold after the second. Utility from housing is separable from utility from consumption. Under these assumptions, consumption in each period equals income minus interest payments. The household must choose between FRM and ARM. Under ARM, the household pays the nominal interest rate $r + \pi + \varepsilon$ where r is known, $\varepsilon \sim N(0, \sigma_r^2)$ is an unpredictable component, and $\pi \sim N(0, \sigma_\pi^2)$ is inflation. ε and π are uncorrelated. Under FRM, she needs to pay interest $r + \phi$ with $\phi > 0$ known. Under these assumptions, choosing ARM is optimal if and only if

$$-\frac{1}{\gamma}E\left(e^{-\gamma(y-(r+\varepsilon)H)}\right) \geq -\frac{1}{\gamma}\left(Ee^{-\gamma(y-(r+\phi-\pi)H)}\right)$$

Using the MGF of the normal distribution the above inequality reduces to

$$\phi > \frac{\gamma H}{2}(\sigma_\varepsilon^2 - \sigma_\pi^2)$$

so that in our setting the Koijen rule is optimal. In the data $\sigma_\varepsilon^2 > \sigma_\pi^2$ and $\phi > 0$, so that the rule correctly predicts that a positive fraction of customers will choose both types of contract. This simple model posits just two periods but the results are the same in a *multi* period model, adjusting once parameters such as income and variances appropriately.

Annex B. Proofs

In this annex we prove the propositions that characterize the model solution. In what follows we adopt the convention $m = 1$ if the choice is ARM and $m = 0$ if the choice is FRM.

Proposition 1: In the absence of advice, households' mortgage choice is independent of bank supply factors conditional on the relative prices of ARM and FRM. In particular, $E(m|\phi) = E(m|\phi, \theta)$ where m denotes mortgage choice.

Proof If there is no advice the equilibrium household decision rule as a function of risk aversion and supply factors is:

$$m(\gamma) = \begin{cases} 1 & \text{if } \phi(\theta) > \gamma \\ 0 & \text{if } \phi(\theta) \leq \gamma \end{cases}$$

so that $E(m|\phi) = G(\phi)E(m|\gamma > \phi) + (1 - G(\phi))E(m|\gamma \leq \phi) = G(\phi) = E(m|\phi, \theta)$.

Proposition 2: If the model does not satisfy the SSP, household choices depend on the factors θ even controlling for prices. In other words, $E(m|\phi, \theta) \neq E(m|\phi)$.

Proof With advice, the household decision rule becomes:

$$m(\gamma) = \begin{cases} 1 & \text{if } \phi(\theta) - \alpha(\theta) > \gamma \\ 0 & \text{if } \phi(\theta) - \alpha(\theta) \leq \gamma \end{cases}$$

Now $E(m|\phi) = E_\theta \left\{ G(\phi - \alpha(\theta))E(m|\gamma > \phi) + (1 - G(\phi - \alpha(\theta)))E(m|\gamma \leq \phi) \right\} = E_\theta \left\{ G(\phi - \alpha(\theta)) \right\}$. By a similar calculation, $E(m|\phi, \theta) = G(\phi - \alpha(\theta))$. If the two coincide, it must be that $\alpha(\theta)$ is deterministic given ϕ, otherwise it is not possible for the expectation of $\alpha(\theta)$ to coincide with each of its realizations. Hence there must be a deterministic function linking ϕ to α, so that the SSP must be satisfied.

Proposition 3 Under price rigidity, $E(m|, \phi, \theta) \neq E(m|\phi)$.

Proof If the SSP does not hold, the result is proved by the last proposition which holds for general degrees of flexibility. Now suppose SSP holds. Under price rigidity, there exists a subset of the supply factor space Θ such that the bank does not adjust the price. Call this subset Θ^I. Now if a bank starts with price ϕ and gets two draws of supply factors $\theta_1, \theta_2 \in \Theta^I$ with $\theta_1 \neq \theta_2$, it must be that $E(m|\phi, \theta_1) = G(\phi - \alpha(\theta_1)) \neq G(\phi - \alpha(\theta_2)) = E(m|\phi, \theta_2)$. Since $E(m|\phi) = E_\theta \left(E(m|\phi, \theta) \right)$ and the same expectation cannot be associated with two different realizations, we must have $E(m|\phi) \neq E(m|\phi, \theta)$.

Annex C. An example

The following example produces a closed form solution for mortgage choice in the presence of biased advice and further illustrates the conditions under which an observer can infer biased advice from the correlation between customers' mortgage choice and banks' supply factors. Assume the following form for the bank's payoff function:

$$v = \phi + \alpha - \frac{1}{2}\sum_{i=1}^{N} k_i(\phi - \theta_i)^2 - \frac{\mu}{2}\sum_{i=1}^{N} q_i(\alpha - \theta_i)^2$$

This formulation captures the idea that the FRM premium and the biased advice positively affect profits but that each carries a cost in terms of maturity risk (captured by the term $\frac{1}{2}\sum_{i=1}^{N} k_i(\phi - \theta_i)^2$) or reputation loss (the term $\frac{\mu}{2}\sum_{i=1}^{N} q_i(\alpha - \theta_i)^2$). For tractability such costs are assumed to be quadratic and are allowed to depend on supply factors in a different way for prices and advice through the sets of coefficients $\{k_i\}, \{q_i\}$. The reputation loss due to giving biased advice also depends on the proportion of sophisticated customers μ. The solution to the bank's problem in this case is:

$$\phi(\theta) = \frac{1}{k^s} + \frac{1}{k^s}\sum_{i=1}^{N} k_i\theta_i$$

$$\alpha(\theta) = \frac{1}{\mu q^s} + \frac{1}{q^s}\sum_{i=1}^{N} q_i\theta_i$$

where $k^s \equiv \sum_{i=1}^{N} k_i$ and $q^s \equiv \sum_{i=1}^{N} q_i$. We can see clearly why a regression of mortgage choice on prices gains from adding supply factor θ's: they inform the regression by proxying for advice. Note that this result fails if the two sets of coefficients are linearly related. For example, if $k_i = k$ and $q_i = q$ for all i then $\alpha(\theta)$ is linear in $\phi(\theta)$ so that θ's have no independent effect on demand: in this case the sample average of the factors is a sufficient statistic for bank choices, and the price control is sufficient to capture it.

Annex D. Interest rate imputation

To impute the interest rate on the mortgage type that has not been chosen, we divide the sample into two groups: households choosing FRM and ARM. For each bank b we estimate two interest rate models:

$$r_{ibt}^{FRM} = \varpi_1 Z_{ibt} + \chi_1 T_t + u_{ibt} \qquad i \in (FRM\ group) \tag{4}$$

$$r_{ibt}^{ARM} = \varpi_2 Z_{ibt} + \chi_2 T_t + u_{ibt} \qquad i \in (ARM\ group) \tag{5}$$

where r_{ibt}^{FRM} (r_{ibt}^{ARM}) is the actual rate on the mortgage granted by bank b to individual i who has chosen an FRM (or ARM) mortgage at time of origination t; Z_{ibt} is a vector of mortgage and borrower specific characteristic, T_t is a vector of time dummies and u_{ibt} a regression residual.

We then use the estimated coefficients $\widehat{\varpi}_1$, $\widehat{\varpi}_2$, $\widehat{\chi}_1$ and $\widehat{\chi}_2$ to impute the FRM rate for clients who have chosen an ARM and conversely

$$\widehat{r}_{ibt}^{FRM} = \widehat{\varpi}_1 Z_{ibt} + \widehat{\chi}_1 T_t \qquad i \in (ARM\ group) \tag{6}$$

$$\widehat{r}_{ibt}^{ARM} = \widehat{\varpi}_2 Z_{ibt} + \widehat{\chi}_2 T_t \qquad i \in (FRM\ group) \tag{7}$$

where $\widehat{r}_{ibt}^{FRM}$ ($\widehat{r}_{ibt}^{ARM}$) is the imputed rate charged by bank b to client i who has chosen an ARM (FRM) at time of origination t.

Annex E. Details on the data

The initial dataset obtained from the Italian Credit Register (CR) and the Survey on Loan Interest Rates (SLIR) includes around 1.9 million observations from 175 banks. For comparability we exclude: i) mortgages to sole proprietorships (160,574 observations); ii) mortgage shorter than ten years (20,802 observations); iii) contracts in which the interest rate is only partially adjustable (83,012 observations); iv) mortgages granted on special terms or conditions (13,470 observations). This reduces the initial sample by 14%. To have enough observations on both ARM and FRM rates for each bank to apply our procedure for computing the relative prices of the two mortgage types, we exclude banks whose home mortgage business is limited (those that originate less than 1,000 mortgages over the sample period, 10,685 observations). Finally we eliminate outliers by dropping observations with interest rates above the 99th and below the 1st percentile (17,011 observations). The final dataset has 1,662,429 observations on mortgages originated by 132 banks.

E.1 Mortgage contract information

The Survey on Loan Interest Rates reports the date of origination of the mortgage, the amount in euros, the type of mortgage (FRM or ARM) and the interest rate at origination. Thus if the mortgage chosen is an FRM, the rate reported fully measures the cost of the mortgage. In case of ARM the initial rate is reported along with the spread over the benchmark – typically one-month Euribor - to which the mortgage rate is indexed. Summary statistics for mortgage contract information, including the imputed values of the rates on the mortgage not chosen, are reported in Panel A of Table 1.

E.2 Borrower variables

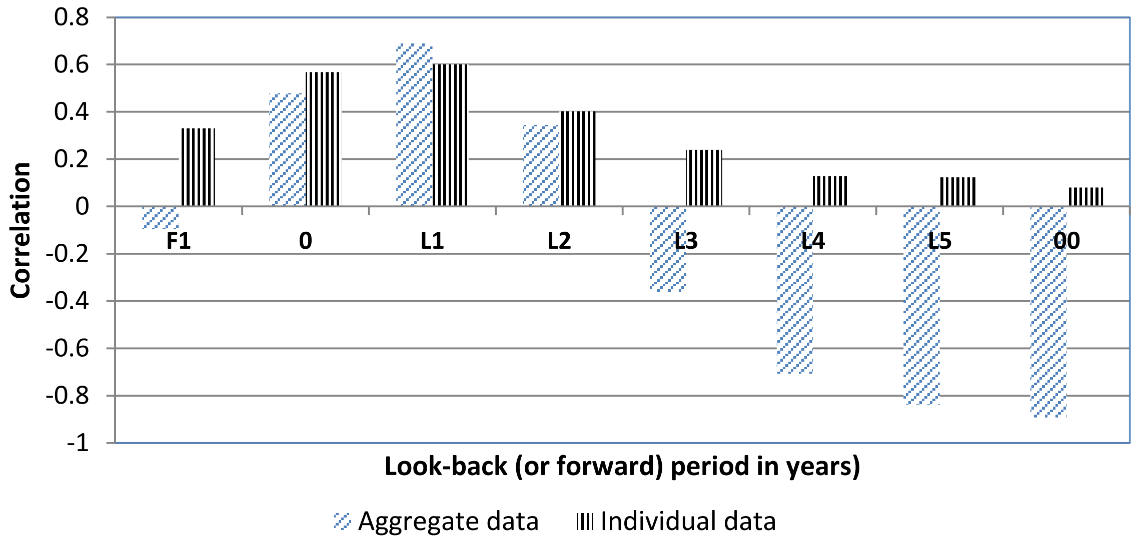
As is often the case, administrative records are rich in the data they were meant to collect but commonly lack information on the unit of observation (in our case the household) when it is not essential for the purpose of the administrative database. We observe some demographic variables, in particular the age, gender, residence and nationality of the borrower and whether the mortgage is taken jointly with the spouse. Some of these variables, in particular gender (together with mortgage size) are reasonable proxies for borrowers' risk attitude (Guiso and Sodini, 2012). But we lack data on households' labor income (and its variance), liquidity constraints and the probability of moving, all of which are included in extended models of mortgage choice (Campbell and Cocco, 2003). Nationality proxies for mobility (Italians are less likely to move), while the cohabitation indicator and provincial residence dummies are likely to capture differences in income risk and local credit market development, hence in the severity of liquidity constraints. Guiso, Pistaferri and Schivardi (2012) show that background risk and local market efficiency differ systematically across Italian provinces. Regional GDP per capita proxies for income and wealth effects. Table 1, Panel B shows summary statistics for these variables.

E.3 Lender variables

The Survey on Loan Interest rates and the Credit Register record the identity of the lenders so we can match the mortgage data with information on their balance sheets. We include three bank-specific supply factors that affect banks' preferences between $FRMs$ vs $ARMs:$ a) the ratio of core-deposits to total funding; b) a securitization dummy equals to 1 if the bank (or the group to which the bank belongs to) has sold securitised loans on the market in the last two years; c) the bank bond spread defined as the difference between fixed and variable rate bonds issued by the bank. From the balance sheet and lender data we also get bank size (log of total assets); leverage (TIER1/Total Assets); delinquency rate (Bad Loans/Total Loans), and dummies for institutional characteristics (mutual bank, banks belonging to a group, foreign banks). Summary statistics for bank specific characteristics are summarized in Panel C of Table 1.

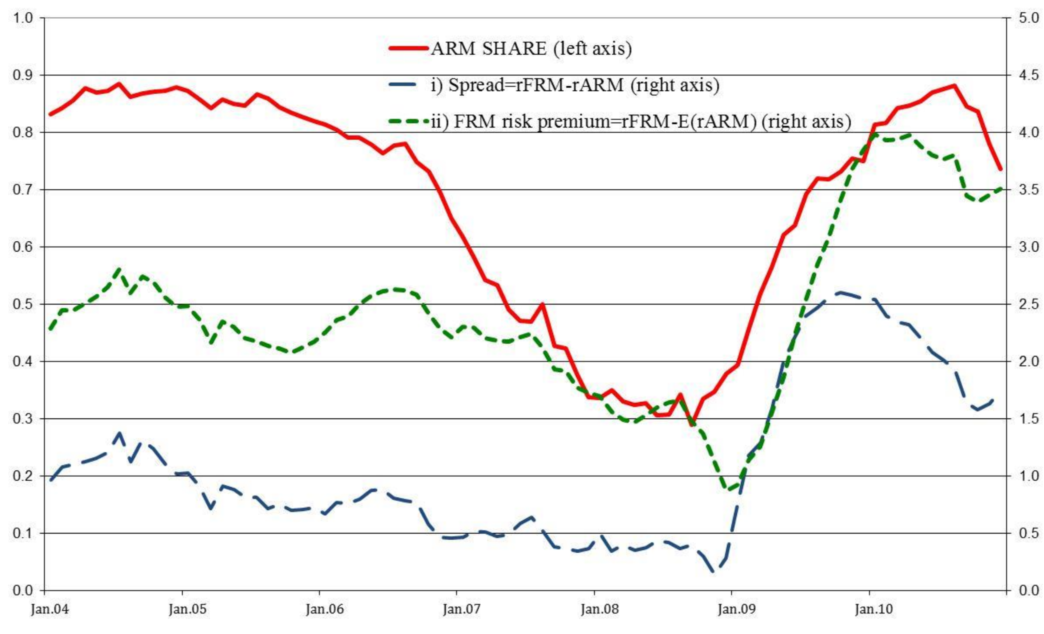
Using the matched data, we compute indicators of the bank-borrower relationship and the bank's market power vis-à-vis the borrower. Market power is gauged by the market share of the largest 5 banks in the borrower's province (assumed to be the relevant local market). As for bank-borrower relations we compute the distance between the bank's headquarters and the household's residence as a proxy for informational distance. Summary statistics for bank-borrower relationship variables are reported in Panel D of Table 1.

Figure 1. Correlation between the ARM share and alternative measures of the “FRM risk premium”



Note: The figure shows the correlation between alternative measures of the FRM risk premium and the ARM share. The blue bars are correlations computed on aggregate data; black bars using data at the bank-client level. The FRM risk premium is given by the difference between the FRM rate and the expected value of the interbank rate. This is calculated under various assumptions about the horizon: a forward-looking horizon of 1 year (F1), the actual value (0), a backward-looking horizon of 1, 2, 3, 4, and 5 years (L1 to L5) and an infinite horizon (∞) approximated using the whole sample. The correlation at 0 is the correlation with the current FRM/AMR. Correlations are calculated over the period January 2004 through Dec. 2010.

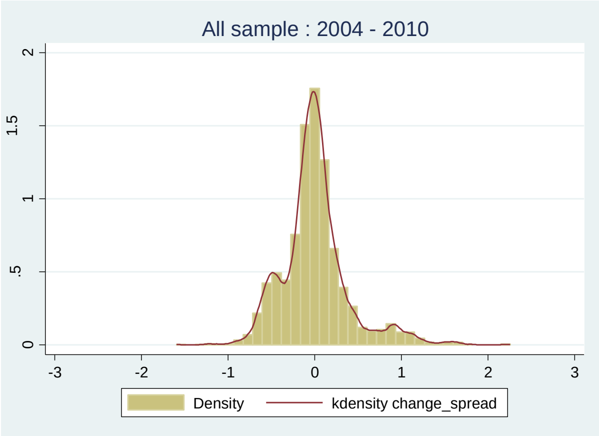
Figure 2. Aggregate share of ARM and alternative “Long term financial premium” measures



Note: The red solid line shows the Adjustable Rate Mortgage (ARM) share in Italy (values on the left axis). The blue dashed line is the spread between the FRM and the ARM interest rates (values on the right axis); the dashed green line shows the FRM risk premium computed as the difference between the FRM rate and the one year moving average of the one month interbank rate (a proxy for the expected value of the ARM rate). Data are monthly from January 2004 to December 2010.

Figure 3 Distribution of the change of the spread between FRM and ARM

<table>
<tr><th>$\Delta(r_{bt}^{FRM} - r_{bt}^{ARM})$</th><th>$\Delta(r_{bt}^{FRM} - r_{bt}^{ARM}) - \Delta Slope_t$</th></tr>
<tr><td>



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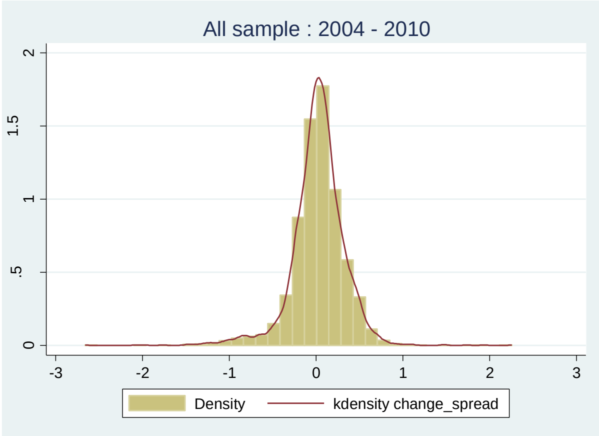
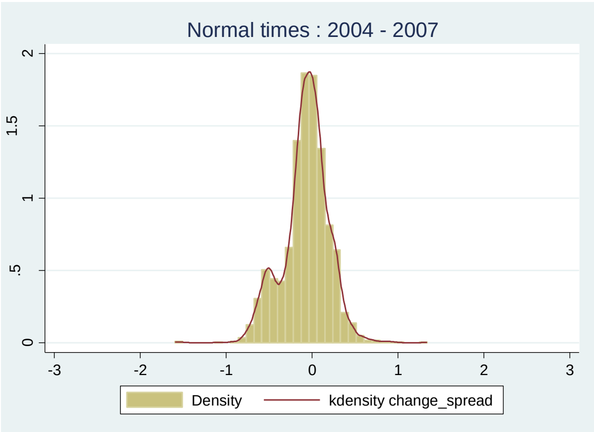


</td></tr>
<tr><td>Mean: 0.01 Std: .40 Min:-1.85 Max:2.62</td><td>Mean: 0.02 Std: 0.31 Min:-2.66 Max:2.25</td></tr>
<tr><td>



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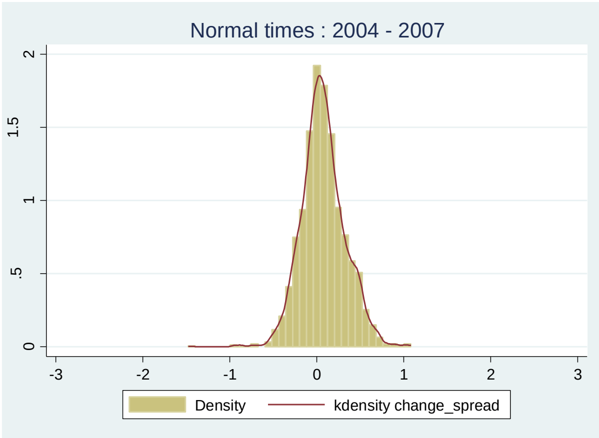
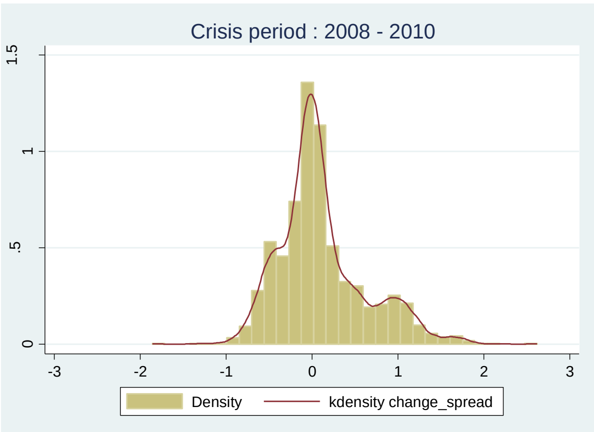


</td></tr>
<tr><td>Mean: -0.07 Std: 0.27 Min:-1.59 Max:1.34</td><td>Mean: 0.07 Std: 0.25 Min:-1.47 Max: 1.08</td></tr>
<tr><td>



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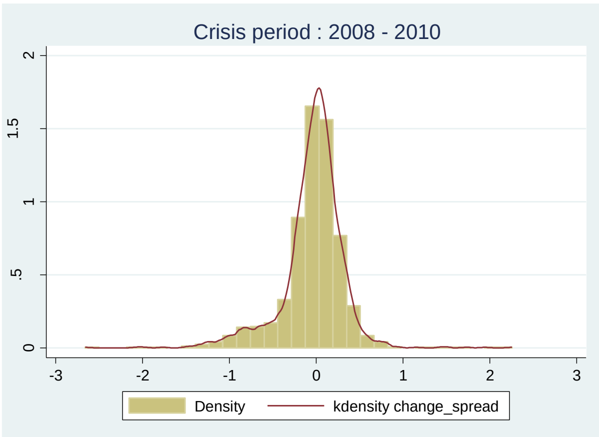
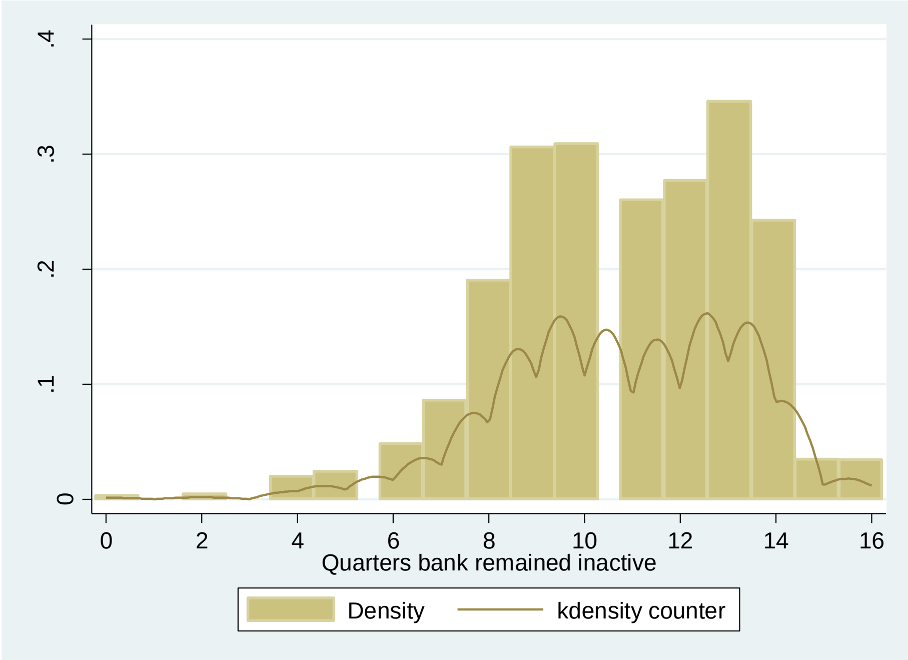


</td></tr>
<tr><td>Mean: 0.10 Std: 0.51 Min:-1.85 Max:2.62</td><td>Mean: -0.04 Std: 0.36 Min:-2.66 Max:2.25</td></tr>
<tr><td colspan="2">Note: The figure shows the distribution of the quarterly changes in the FRM/ARM spread in the cross section of banks for the whole sample and two sub-periods. The second column shows the distribution net of the change in the slope of the yield curve (Slope), computed as the difference between the 15-year swap rate and the one month interbank rate.</td></tr>
</table>

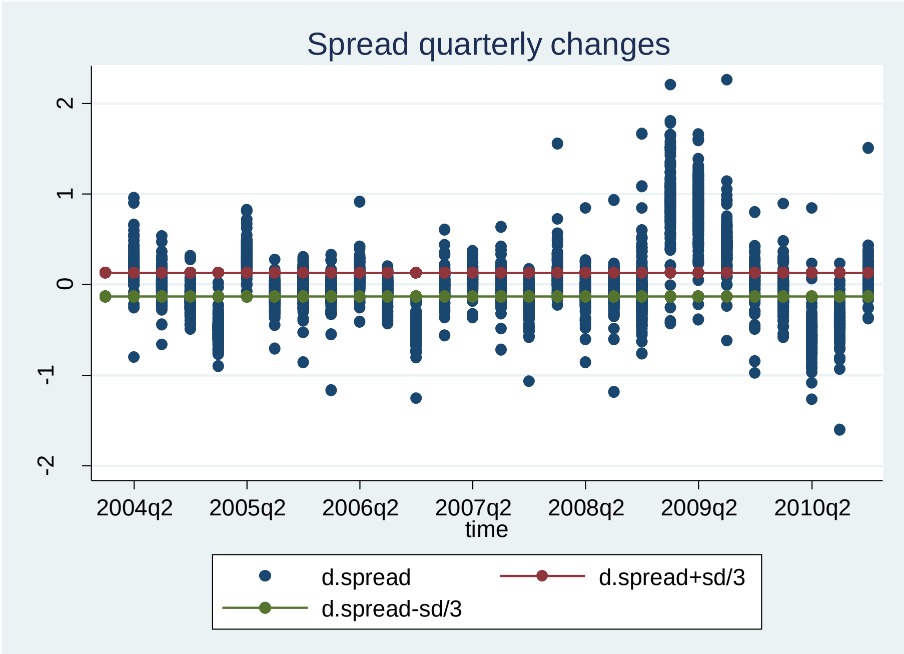
Figure 4 Cross sectional distribution of the number of quarters of banks price inaction



Mean: 10.8 Std: 2.49 Min: 0 Max:16

Note: The figure shows the cross sectional distribution of the number of quarters of price inaction (spread unchanged between two quarters). In principle the distribution ranges between 0 (no inaction) and 28 (no spread adjustment over the samples). Inaction at bank *b* is an indicator set to 1 if the absolute value of the quarterly change of the spread ($\Delta\left(r_{bt}^{FRM} - r_{bt}^{ARM}\right)$) is lower that 1/3 of the standard deviation of the change (i.e. the change falls between $\pm\frac{sd_b}{3}$), where the standard deviation is specific to each bank.

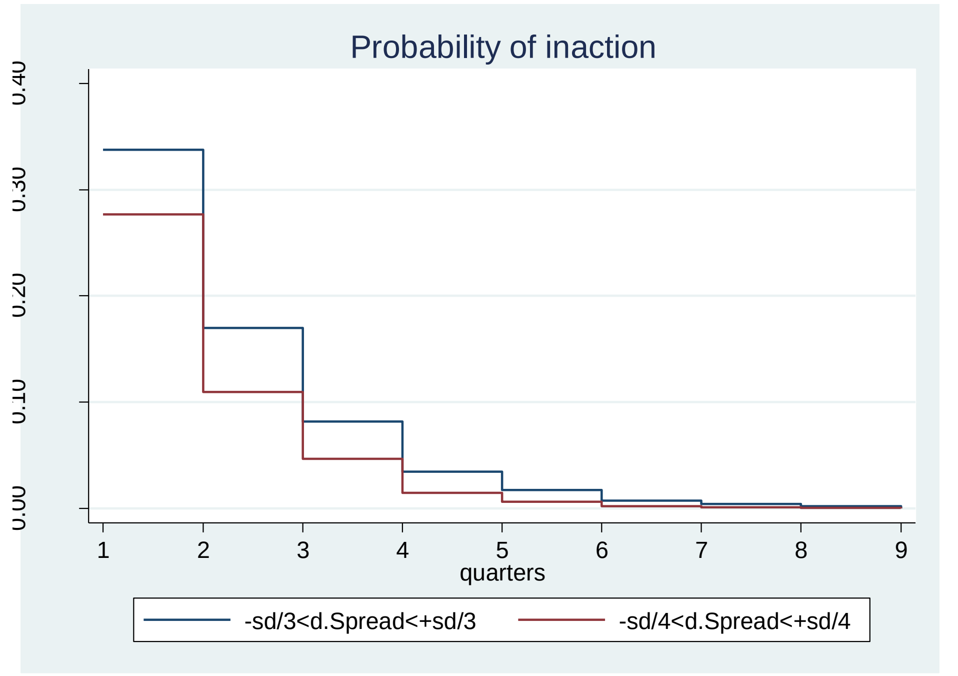
Figure 5 Scatter plot of the quarterly changes of the spread



Mean: 0.01 Std: 0.39 Min:-1.59 Max:2.25

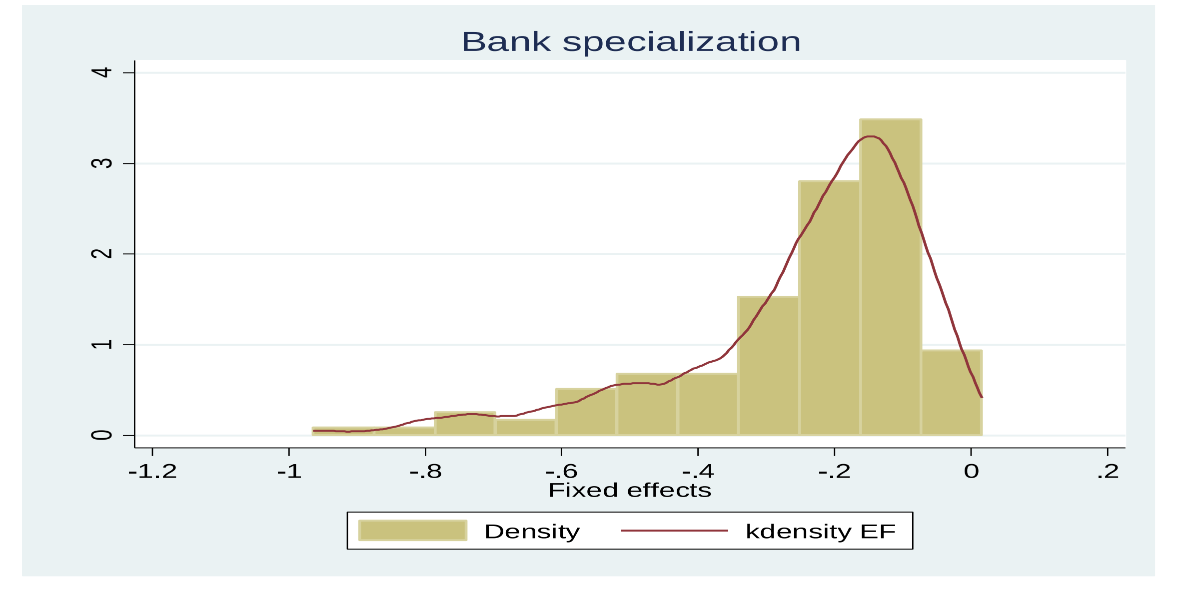
Note: The dots represent the quarterly change of the FRM/AMR spread (ΔSpread= $\Delta(r_{bt}^{FRM} - r_{bt}^{ARM})$). The two horizontal lines (green and red) delimit a band of price inaction an area for inaction, defined as $|\Delta\text{Spread}| < \left(\frac{sd}{3}\right)$ and the standard deviation is defined over the whole sample. The band's rage is in the interval [0.13, -0.13] points.

Figure 6. Probability of price inaction: Kaplan and Meier survival estimates



Note: Figure shows the Kaplan and Meier's survival probability of keeping the price invariant, for the baseline measure of price inaction (blue line) and when using the tighter threshold (red line).. The Kaplan–Meier estimator is the nonparametric maximum likelihood estimate of the probability that a bank does not change the FRM/ARM spread in a quarter exceeding t.

Figure 7. Pattern of bank specialization in the mortgage market



Note: The figure shows the distribution of the bank fixed effects obtained from the regression in Table 3 column (V). Banks in the bottom decile of the distribution (13 banks, 9.6% of the market) are defined as specialized in ARM mortgages; banks in the top decile of the distribution (13 banks accounting for 14.1% of the market) are defined as specialized in FRM.

Table 1. Descriptive statistics of the main variables used in the estimation

Variables	Obs.	Mean	Std. Dev.	Median	P10	P90
(A) Contracts' characteristics						
Fixed Rate Mortgage contract	1662429	0.303	0.460	0.000	0.000	1.000
Mortgage size (log)	1662429	11.734	0.441	11.733	11.280	12.206
Joint Mortgage	1662429	0.509	0.500	1.000	0.000	1.000
Interest rate actual:						
- FRM rate	504407	5.545	0.834	5.713	4.606	6.376
- ARM rate	1158022	3.829	1.181	3.775	2.227	5.530
Interest rate fitted:						
- FRM rate	1158022	5.106	0.482	5.133	4.403	5.959
- ARM rate	504407	4.706	1.107	5.270	2.670	5.670
Spread (1)	1662429	0.915	1.004	0.725	0.000	2.300
FRM risk premium (2)	1662429	0.897	1.074	0.938	-0.360	2.226
(B) Borrowers' characteristics (3)						
Italian	1662429	0.893	0.294	1.000	0.500	1.000
Cohabitation (4)	1662429	0.206	0.405	0.000	0.000	1.000
Age (in years)	1662429	38.165	9.302	37.000	27.500	51.000
Female	1662429	0.435	0.356	0.500	0.000	1.000
(C) Banks' characteristics						
Supply shift factors:						
Deposit funding % (5)	1662429	44.441	20.444	46.124	10.494	67.448
Securitization dummy (6)	1662429	0.783	0.321	1.000	0.000	1.000
Bank bond spread (7)	1662429	0.283	0.496	0.267	-0.390	0.960
Other characteristics:						
Leverage ratio % (7)	1600446	6.449	2.524	6.238	3.582	10.578
Mutual bank dummy	1662429	0.005	0.072	0.000	0.000	0.000
Delinquency ratio %(8)	1662410	3.489	2.278	3.140	0.957	8.301
Bank size (log)	1662429	10.215	1.436	10.144	8.230	12.174
Group dummy	1662429	0.918	0.275	1.000	1.000	1.000
Foreign subsidiary dummy	1662429	0.051	0.219	0.000	0.000	0.000
Patti Chiari (9)	1662429	0.632	0.482	1.000	0.000	1.000
(D) Bank-Borrower relationship (10)						
Distance 1 (province)	1662429	0.152	0.359	0.000	0.000	1.000
Distance 2 (region)	1662429	0.264	0.441	0.000	0.000	1.000
Distance 3 (same area)	1662429	0.185	0.388	0.000	0.000	1.000
Distance 4 (elsewhere)	1662429	0.400	0.490	0.000	0.000	1.000
Concentration Index (11)	1662389	60.152	7.386	59.294	50.169	68.127
GDP per capita (12)	1662429	10.190	0.236	10.273	9.745	10.387

Notes. (1) Difference between the FRM rate and the ARM rate. (2) Difference between the FRM rate and expectation of the ARM rate. The latter is based on the one year moving average of the one month interbank rate. (3) Average across individuals in the case of joint mortgages. (4) In case of joint mortgage. (6) Deposits over total liabilities. (6) Dummy that takes the value of 1 if the bank is active in the securitization market in a given quarter. (7) Tier1 capital over total assets. (8) Bad loans over total loans. (9) Dummy that takes the value of 1 if the bank takes part to the "Patti Chiari" initiative, whose main objective is to simplify bank-borrower relationship. (10) We control for the distance between the lending bank headquarters and household residence by four dummy variables: DIST1 is equal to 1 if borrower k has his residence in the same province where bank j has its headquarters; DIST2 is equal to 1 if: a) DIST1=0 and b) firm k is resident in the same region where bank j has its headquarters; DIST3 is equal to 1 if: a) DIST2=0 and b) borrower k is resident in the same geographical area where bank j has its headquarters; DIST4 is equal to 1 if DIST3=0. (11) Market share of the first 5 banking groups in each province. Not reported Dummy banks, dummy provinces. (12) At the regional level; in thousands euros.

Table 2. Do lender characteristics affect mortgage choice?

	(I) only Bank Fixed Effects (BFE)	(II) BFE and Long Term Financial Premium (LTFP)	(III) BFE+ LTFP + Time Fixed Effects (TFE)	(IV) BFE+TFE+ Borrowers' Characteristics (BC)	(V) Complete model	(VI) BFE and Long Term Financial Premium (LTFP)
		LTFP= FRM risk premium (1)				LTFP= Spread (2)
Long Term Financial Premium (LTFP)		-0.307***	-0.348***	-0.346***	-0.342***	-0.269***
		(0.029)	(0.027)	(0.027)	(0.026)	(0.023)
Mortgage size (log)				-0.044***	-0.044***	
				(0.007)	(0.007)	
Joint Mortgage				0.006*	0.007**	
				(0.003)	(0.003)	
Italian				0.065***	0.050***	
				(0.009)	(0.009)	
Cohabitation				0.004***	-0.001	
				(0.002)	(0.001)	
Age (in years)				-0.0001	-0.0004*	
				(0.0002)	(0.0002)	
Female				0.012***	0.011***	
				(0.002)	(0.002)	
Bank fixed effects (BFE)	yes	yes	yes	yes	yes	yes
Time fixed effects (TFE)	no	no	yes	yes	yes	no
Province fixed effects (PFE)	no	no	no	no	yes	no
Other controls (3)	no	no	no	no	yes	no
Test of BFE joint significance (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
Test of TFE joint significance (p-value)	-	-	0.000	0.000	0.000	-
Test of PFE joint significance (p-value)	-	-	-	-	0.000	-
Observations	1662429	1662429	1662429	1662429	1662429	1662429
Pseudo R-squared	0.0984	0.4760	0.5919	0.5954	0.6000	0.4395
Sample period	2004:Q1-2010:Q4	2004:Q1-2010:Q4	2004:Q1-2010:Q4	2004:Q1-2010:Q4	2004:Q1-2010:Q4	2004:Q1-2010:Q4

Notes: The table shows the parameter estimates of a linear probability model of mortgage type choice;. The left hand side variable is a dummy =1 if the borrower chooses a FRM, zero otherwise. Robust standard errors clustered at bank level are reported in brackets. *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. Coefficients for dummies and fixed effects are not reported. (1) In columns II-V the LTFP is the difference between the FRM rate and the expected ARM rate based on borrower's actual ARM rate and one year moving average of the one month interbank rate (2) In column 5 the LTFP is the difference between the FRM rate and current the ARM rate. (3) Include: i) GDP per capita at the regional level; ii) a Bersani Law dummy= 1 from the second quarter of 2007 onwards; iii) a dummy if the bank participates in the "Patti Chiari" initiative; iv) dummies to control for the distance between the lending bank headquarters and household residence.

Table 3. Borrowers' characteristics for specialized and non-specialized banks

	Observations	Mortgage size (log)		Joint mortgage (%)		Italian (%)		Cohabitation (%)		Age (in years)		Female (%)	
		Mean	*Variance*	*Mean*	*Variance*	*Mean*	*Variance*	*Mean*	*Variance*	*Mean*	*Variance*	*Mean*	*Variance*
All sample													
a) Banks specialized in ARM	169,135	11.737	0.200	0.534	0.249	0.908	0.074	0.222	0.173	38.054	84.471	0.441	0.121
b) Non-specialized banks	1,341,323	11.738	0.188	0.506	0.250	0.897	0.084	0.204	0.162	38.259	87.305	0.435	0.127
c) Banks specialized in FRM	247,509	11.719	0.194	0.539	0.248	0.876	0.099	0.226	0.175	37.960	82.274	0.434	0.119
Ho: Mean (a) = Mean (c) (p-value)		(0.977)		(0.993)		(0.934)		(0.994)		(0.994)		(0.988)	
Ho: Var (a) = Var (c) (p-value)			(0.773)		(0.762)		(0.633)		(0.756)		(0.772)		(0.765)
2004-2007													
a) Banks specialized in ARM	70,617	11.691	0.202	0.551	0.247	0.894	0.086	0.234	0.179	37.684	88.621	0.437	0.116
b) Non-specialized banks	759,241	11.714	0.186	0.514	0.250	0.881	0.097	0.211	0.166	37.899	88.508	0.431	0.126
c) Banks specialized in FRM	198,768	11.708	0.193	0.540	0.248	0.867	0.106	0.228	0.176	37.574	79.944	0.432	0.119
Ho: Mean (a) = Mean (c) (p-value)		(0.986)		(0.991)		(0.975)		(0.995)		(0.991)		(0.995)	
Ho: Var (a) = Var (c) (p-value)			(0.781)		(0.760)		(0.669)		(0.769)		(0.803)		(0.750)
2008-2010													
a) Banks specialized in ARM	98,518	11.770	0.195	0.522	0.250	0.919	0.066	0.214	0.168	38.319	81.328	0.444	0.124
b) Non-specialized banks	582,082	11.770	0.189	0.495	0.250	0.919	0.066	0.194	0.157	38.729	85.346	0.441	0.130
c) Banks specialized in FRM	48,741	11.764	0.196	0.535	0.249	0.913	0.070	0.219	0.171	39.535	88.690	0.444	0.120
Ho: Mean (a) = Mean (c) (p-value)		(0.995)		(0.989)		(0.994)		(0.995)		(0.895)		(0.999)	
Ho: Var (a) = Var (c) (p-value)			(0.759)		(0.762)		(0.734)		(0.754)		(0.724)		(0.774)

Note: The table shows the first and second moment of borrowers observable characteristics for three types of banks. a) Banks specialized in ARM; b) non-specialised banks; c) banks specialised in FRM. The three groups have been identified based on the method described in Figure 7. Banks in the first decile of the distribution (13 banks, 9.6% of the market) are defined as specialized in ARM mortgages; banks in the last decile of the distribution (13 banks accounting for 14.1% of the market) are defined as specialized in FRM. The others are non-specialized. P-values of the test that the mean (or the variance) in group (a) is equal to that in group (c) are reported in parenthesis.

Table 4. Time-varying bank characteristics and mortgage choice

Dependent variable is the linear probability that the borrower chooses a FRM	(I) Baseline model including bank supply factors	(II) Sample of banks with bond spread always observed	(III) Adding non- linear terms for LTFP	(IV) Including time*province fixed effects	(V) Banks operating in all provinces
LTFP (1)	-0.354***	-0.354***	-0.477***	-0.280***	-0.404***
	(0.024)	(0.026)	(0.040)	(0.021)	(0.026)
$LTFP^2$			-0.012		
			(0.010)		
$LTFP^3$			0.027***		
			(0.005)		
Bank bond spread (2)	-0.026*	-0.028*	-0.028*	-0.027*	-0.026*
	(0.015)	(0.017)	(0.017)	(0.015)	(0.017)
Securitization activity (3)	0.140***	0.151***	0.126***	0.132***	0.223***
	(0.027)	(0.038)	(0.024)	(0.030)	(0.038)
Deposit ratio % (4)	0.006***	0.007***	0.006***	0.005***	0.009***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Bank fixed effects (BFE)	yes	yes	yes	yes	yes
Time fixed effects (TFE)	yes	yes	yes	no	yes
Borrowers' Charact. (BC)	yes	yes	yes	yes	yes
Province fixed effects (PFE) and control for bank competition (5)	yes	yes	yes	no	yes
Other controls (6)	yes	yes	yes	yes	yes
Time*Province fixed effects	no	no	no	yes	no
Test on BFE joint significance (p-value)	0.000	0.000	0.000	0.000	0.000
Test on TFE joint significance (p-value)	0.000	0.000	0.000	0.000	0.000
Test on BC joint significance (p-value)	0.000	0.000	0.000	0.000	0.000
Observations	1,662,389	1,261,404	1,662,389	1,662,389	957,961
Adjusted R-squared	0.6080	0.6217	0.6283	0.5801	0.6615
Sample period	2004:Q1-2010:Q4	2004:Q1-2010:Q4	2004:Q1-2010:Q4	2004:Q1-2010:Q4	2004:Q1-2010:Q4

Notes: The table shows linear probability estimates of mortgage choice. The left hand side variable is a dummy=1 if a FRM is chosen; zero otherwise. Robust standard errors (clustered at bank level) are reported in brackets. *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. Coefficients for borrowers' characteristics and fixed effects are not reported. (1) The Long Term Financial Premium (LTFP) 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. (2) Difference between the cost of fixed rate bank bonds and variable rate bonds. (3) Dummy equal to one if the bank is active in the securitization market, 0 elsewhere. (4) Deposits over total liabilities. (5) The bank concentration index is equal to the market share of the first 5 banking groups in each province. (6) Include: i) GDP per capita at the regional level; ii) a Bersani Law dummy= 1 from the second quarter of 2007 onwards; iii) a dummy if the bank participates in the "Patti Chiari" initiative; iv) dummies to control for the distance between the lending bank headquarters and household residence.

Table 5. A test for the presence of "dynamic" sorting

Explanatory variables	Dependent variables					
	Mortgage size (log)	Joint mortgage	Italian	Cohabitation	Age	Female
Bank bond spread	0.0014	0.0022	0.0020	0.0005	-0.0151	-0.0018
	(0.0041)	(0.0025)	(0.0040)	(0.0022)	(0.0745)	(0.0013)
Deposit ratio	0.0004	-0.0001	-0.0003	-0.0000	-0.0025	-0.0000
	(0.0003)	(0.0002)	(0.0005)	(0.0004)	(0.0130)	(0.0001)
Securitization activity	0.0082	0.0058	-0.0001	0.0030	-0.3217	0.0025
	(0.0121)	(0.0062)	(0.0027)	(0.0039)	(0.3259)	(0.0030)
Bank fixed effects	yes	yes	yes	yes	yes	yes
Time effects	yes	yes	yes	yes	yes	yes
Province fixed effects	yes	yes	yes	yes	yes	yes
F-test on joint significance of bank-specific characteristics (p-value)	0.4020	0.4367	0.9166	0.8890	0.7853	0.2684
Observations	1,662,429	1,662,429	1,662,429	1,662,429	1,662,429	1,662,429
R-squared	0.0518	0.0217	0.0597	0.0175	0.0342	0.0031

Note: The table reports the results of regressions of customers' observable characteristics on time-varying bank specific characteristics, controlling for bank, time and province fixed effects.

Table 6. The role of price inaction

A. Main definition of price inaction (threshold ($\pm \frac{sd_b}{3}$)

	(I) Baseline linear probability model	(II) Sample of banks for which we observe the bond spread	(III) Adding non-linear terms for LTP	(IV) Baseline model without time dummies
LTFP (1)	-0.3499***	-0.3495***	-0.4742***	-0.2400***
	(0.0241)	(0.0269)	(0.0407)	(0.0156)
$LTFP^2$			-0.0122	
			(0.0096)	
$LTFP^3$			0.0276***	
			(0.0048)	
Bank bond spread (2)	-0.0140	-0.0112	-0.0023	-0.0047
	(0.0157)	(0.0168)	(0.0183)	(0.0161)
Securitization activity (3)	0.1370***	0.1480***	0.1243***	0.1485***
	(0.0252)	(0.0346)	(0.0217)	(0.0352)
Deposit ratio % (4)	0.0053***	0.0062***	0.0053***	0.0038***
	(0.0021)	(0.0021)	(0.0023)	(0.0015)
D_{ib} (5)	0.0518*	0.0486	0.0456	0.1494***
	(0.0311)	(0.0414)	(0.0319)	(0.0510)
Bank bond spread * D_{ib}	-0.0621***	-0.0716***	-0.0682***	-0.0860***
	(0.0129)	(0.0132)	(0.0147)	(0.0189)
Securitization Activity * D_{ib}	0.0166*	0.0182*	0.0119*	0.0119*
	(0.0096)	(0.0104)	(0.0071)	(0.0071)
Deposit ratio % * D_{ib}	0.0008*	0.0008*	0.0006*	0.0012*
	(0.0005)	(0.0005)	(0.0003)	(0.0007)
Bank fixed effects (BFE)	yes	yes	yes	Yes
Time fixed effects (TFE)	yes	yes	yes	No
Borrowers' Characteristics (BC)	yes	yes	Yes	Yes
Province fixed effects (PFE) and control for bank competition (6)	yes	yes	Yes	Yes
Other controls (7)	yes	yes	Yes	Yes
Observations	1,662,389	1,261,404	1,662,389	1,662,389
Adjusted R-squared	0.6128	0.6263	0.6327	0.5295
Sample period	2004:Q1-2010:Q4	2004:Q1-2010:Q4	2004:Q1-2010:Q4	2004:Q1-2010:Q4

B. Tighter definition of price inaction (threshold ($\pm\frac{sd_b}{4}$)

	(I) Adding non-linear terms for LTP	(II) Sample of banks for which we observe the bond spread	(III) Adding non-linear terms for LTP	(IV) Baseline model without time dummies
LTFP (1)	-0.3493***	-0.3489***	-0.4741***	-0.2379***
	(0.0238)	(0.0266)	(0.0404)	(0.0150)
LTFP^2			-0.0122	
			(0.0096)	
LTFP^3			0.0277***	
			(0.0048)	
Bank bond spread (2)	-0.0195	-0.0163	-0.0078	-0.0177
	(0.0146)	(0.0159)	(0.0168)	(0.0136)
Securitization activity (3)	0.1422***	0.1546***	0.1269***	0.1530***
	(0.0253)	(0.0349)	(0.0214)	(0.0340)
Deposit ratio % (4)	0.0061***	0.0069***	0.0060***	0.0043***
	(0.0020)	(0.0019)	(0.0022)	(0.0013)
D_{ib} (5)	0.0369	0.0290	0.0319	0.1333***
	(0.0242)	(0.0309)	(0.0280)	(0.0494)
Bank bond spread * D_{ib}	-0.0430**	-0.0504***	-0.0483***	-0.0603***
	(0.0165)	(0.0177)	(0.0182)	(0.0153)
Securitization Activity * D_{ib}	0.0160*	0.0174*	0.0116*	0.0110
	(0.0096)	(0.0104)	(0.0071)	(0.0071)
Deposit ratio % * D_{ib}	0.0007*	0.0007*	0.0007*	0.0008
	(0.0004)	(0.0004)	(0.0004)	(0.0009)
Bank fixed effects (BFE)	yes	yes	yes	Yes
Time fixed effects (TFE)	yes	yes	yes	No
Borrowers' Characteristics (BC)	yes	yes	Yes	Yes
Province fixed effects (PFE) and control for bank competition (6)	yes	yes	Yes	Yes
Other controls (7)	yes	yes	Yes	Yes
Observations	1,662,389	1,261,404	1,662,389	1,662,389
Adjusted R-squared	0.6118	0.6253	0.6320	0.5285
Sample period	2004:Q1-2010:Q4	2004:Q1-2010:Q4	2004:Q1-2010:Q4	2004:Q1-2010:Q4

Notes: The table shows linear probability estimates of mortgage choice. The left hand side variable is a dummy=1 if a FRM is chosen; zero otherwise. Robust standard errors (clustered at bank level) are reported in brackets. *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. Coefficients for borrowers' characteristics and fixed effects are not reported. (1) The Long Term Financial Premium (LTFP) 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. (2) Difference between the cost of fixed rate bank bonds and variable rate bonds. (3) Dummy equal to one if the bank is active in the securitization market, 0 elsewhere. (4) Deposits over total liabilities. (5) Price inaction: in panel A, dummy D_{ib} =1 in quarters where bank b the change in the FRM/ ARM spread fall in the rage $\pm\frac{sd_b}{3}$ where the standard deviation is specific to each bank.; in panel B if change I the spread fall in the rage $\pm\frac{sd_b}{4}$ (6) The bank concentration index is equal to the market share of the first 5 banking groups in each province. (7) Include: i) GDP per capita at the regional level; ii) a Bersani Law dummy= 1 from the second quarter of 2007 onwards; iii) a dummy if the bank participates in the "Patti Chiari" initiative; iv) dummies to control for the distance between the lending bank headquarters and household residence.

Table 7. A test based on borrowers' degree of sophistication

Main definition of price inaction (threshold ($\pm \frac{sd_b}{3}$)

Dependent variable is the probability that the borrower chooses a FRM	(a) Sophisticated borrowers: old clients with mortgages>320.000 euros	(b) Unsophisticated borrowers: new clients with mortgages<80.000 euros	Difference |b-a| H0: |b-a|>0	
Long Term Financial Premium (*LTFP*) (1)	-0.3148***	-0.3972***	0.082	**
	(0.0254)	(0.0291)	(0.039)	
Bank bond spread (2)	-0.0131	0.0074	0.021	
	(0.0187)	(0.0236)	(0.030)	
Securitization activity (3)	0.1085***	0.1747***	0.066	**
	(0.0239)	(0.0190)	(0.031)	
Deposit ratio % (4)	0.0054***	0.0074***	0.002	*
	(0.0010)	(0.0011)	(0.001)	
D_{ib} (5)	0.0604	0.0464	0.014	
	(0.0390)	(0.0280)	(0.048)	
Bank bond spread * D_{ib}	-0.0364**	-0.0847***	0.048	**
	(0.0152)	(0.0245)	(0.029)	
Securitization Activity * D_{ib}	-0.0173	0.0272*	0.045	**
	(0.0213)	(0.0150)	(0.026)	
Deposit ratio % * D_{ib}	-0.0012	0.0012**	0.003	**
	(0.0016)	(0.0004)	(0.002)	
Bank fixed effects (BFE)	yes	yes		
Time fixed effects (TFE)	yes	yes		
Borrowers' Characteristics (BC)	yes	yes		
Province fixed effects (PFE) and control for bank competition (6)	yes	yes		
Other controls (7)	yes	yes		
Bank fixed effects (BFE)	yes	yes		
Observations	29,527	27,158		
Adjusted R-squared	0.4938	0.6677		
Sample period	2004:Q1-2010:Q4	2004:Q1-2010:Q4		

Notes: The table shows linear probability estimates of mortgage choice. The left hand side variable is a dummy=1 if a FRM is chosen; zero otherwise. Robust standard errors (clustered at bank level) are reported in brackets. *, **, and *** represent significance levels of 10%, 5%, and 1% respectively. Coefficients for borrowers' characteristics and fixed effects are not reported. (1) The Long Term Financial Premium (LTFP) 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. (2) Difference between the cost of fixed rate bank bonds and variable rate bonds. (3) Dummy equal to one if the bank is active in the securitization market, 0 elsewhere. (4) Deposits over total liabilities. (5) Price inaction: dummy D_{ib} =1 in quarters where bank *b* the change in the FRM/ ARM spread fall in the rage $\pm \frac{sd_b}{3}$ where the standard deviation is specific to each bank. (6) The bank concentration index is equal to the market share of the first 5 banking groups in each province. (7) Include: i) GDP per capita at the regional level; ii) a Bersani Law dummy= 1 from the second quarter of 2007 onwards; iii) a dummy if the bank participates in the "Patti Chiari" initiative; iv) dummies to control for the distance between the lending bank headquarters and household residence.