THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Essays in Household Finance

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorization does not, to the best of my belief, infringe the rights of any third party.

I declare that my thesis consists of approximately 33,000 words.

Statement of conjoint work I confirm that Chapter 2 was jointly co-authored with Valentina Michelangeli. I contributed 50% of the work for Chapter 2. I confirm that Chapter 3 was jointly co-authored with Federica Ciocchetta, Valentina Michelangeli and Federico Maria Signoretti. I contributed 25% of the work for Chapter 3.

To my parents, for without them I would have never dared to dream of anything like this.

Per aspera ad astra.

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Abstract

In the first chapter, I exploit the rebranding of a mortgage lender, under a more salient name and in some Italian provinces, to empirically analyze households' choice behaviour in response to brand popularity. Loan-level data on both the universe of newly originated mortgages and the offer rates suggest that (1) brand awareness reduces the equilibrium price of residential mortgage contracts and (2) the reduction mainly reflects consumers' selection into cheaper products. Comparing contracted rates with concurrent market offers from the main online mortgage broker in Italy, I show that households' reallocation towards less expensive choices is unlikely to reflect pure substitution behaviours induced by brand persuasion. In fact, my findings support the informative view that brand awareness improves consumers' search and allows them to obtain more convenient deals, with an overall decrease in price dispersion.

In the second chapter, we back empirical findings with theoretical foundations, and quantify the impact of brand name on consumers' search costs and borrowers' transition across lenders within a life-cycle model. The model is well calibrated to replicate main features of the Italian household sector and to match the level of dispersion in the price of mortgage products encountered in the data. Model calibrations imply a 330 euro reduction in consumers' search costs due to brand popularity, and roughly a 10 percentage points increase in the share of households that move to cheaper lenders. The treatment effect of brand name on price dispersion is in line with the empirical evidence in chapter one.

In the third chapter, we use information on mortgage supply available from the online broker to assess trends in lending strategies of Italian banks. We document that (1) riskier mortgages (high loan-to-value, low borrower's income, and long maturity) are offered by fewer banks that charge higher rates; (2) keeping the level of risk constant, online banks offer better price conditions than traditional ones. We then use online offer rates to nowcast bank-level official rates (MIR). By relying on both regression analysis and machine learning algorithms (random forest), we show that online prices have a high predictive content for the equilibrium price of fixed-rate mortgages, and allow for a very timely assessment of changes in household financing conditions.

Contents

List of Tables

List of Figures

1. Information or persuasion in the mortgage market: the role of brand name

1.1 Introduction

How do consumers respond to brand name? The answer to this question is far from obvious. When shopping for a product, customers typically do not observe all options and have to find the one to their liking through search. They may first visit the seller whose name is more salient, and stop there if the deal they find is attractive enough to make searching not worthwhile to continue (Haan & Moraga-González 2011). Brand popularity might influence shopping behaviour in two ways. Either by increasing market knowledge, acting like a signaling device that reveals better alternatives to uninformed clients (Nelson 1970; Robert & Stahl 1993), or by creating spurious loyalty that persuades consumers into worse options (Braithwaite 1928; Robinson 1933).[1]

I address the dichotomy between brand persuasion and brand information in the Italian mortgage market and ask whether popularity of the brand causes borrowers to select high-price lenders (persuasive effect), or to switch to less expensive ones (informative effect). My main contribution is to provide empirical evidence in support of the informative role of brand name. I exploit the rebranding of a mortgage lender under a more salient name in some Italian provinces, and show that superior awareness of the brand induces households' reallocation to low-price lenders, with an overall decrease in price dispersion. Results set apart from previous empirical findings by Gurun et al. (2016), which document consumers' persuasion in the US subprime mortgage market, and instead are consistent with earlier works by Agarwal et al. (2017); Alexandrov & Koulayev (2017); Bhutta et al. (2018) and McManus & Yi (2018) for the US, and by Allen et al. (2014a) and Allen et al. (2019) for Canada, pre-

[1] The debate has centered on consumer goods, for which artificial product differentiation can be attained along many dimensions (Telser 1964; Nelson 1974; Comanor & Wilson 1975; Cubbin & Domberger 1988), while minor attention has been given to homogeneous goods characterized by few observable characteristics. With respect to the mortgage market, the only piece of empirical evidence relates to the US, and specifically refers to the persuasive role of advertising in leading borrowers towards more expensive choices (Agarwal & Ambrose 2008; Gurun et al. 2016).

senting evidence of wide dispersion in the mortgage rates that households pay on identical loans. This rate differential translates into substantial upfront costs for the borrower, an important component of which is attributable to knowledge and search.[2]

The Italian mortgage market has specific institutional features that differentiate it from others. In Italy, unlike Canada and the US, individual-based pricing and negotiation between the borrower and the lender are limited, thus all borrowers purchasing the same mortgage product pay close to the advertised rate (Gambacorta et al. 2019). Yet, this is not indicative of convergence towards the lowest price. Quite the opposite, price dispersion is material and overpayment concerns all borrower types (Carella et al. 2020).[3] Search costs, time constraints, brand loyalty, negotiation ability, they all offer a reasonable explanation for this (as in Allen et al. 2014a and in Allen et al. 2019), and they do even more so in a market, like the Italian one, dominated by traditional brick-and-mortar banks, where contracts are mainly settled at the physical branch.[4] It should also be noted that mortgages are complex products and some of their features might result obscure to households, or might require some degree of financial literacy which they lack (Hall & Woodward 2012; Gathergood & Weber 2017). This creates a demand for information and makes borrowers genuinely inclined to trust the intermediary with superior brand name. It also raises the question whether or not branding increases market knowledge and helps households choose the cheapest from a set of mortgage options.

Isolating the effect of brand name on consumers' behaviour is no easy task given the existence of several confounding factors (the macroeconomic scenario and the outlook of the financial sector, banks' policies and strategies, as well as borrowers' and lenders' characteristics). On top of that, individuals' choices over time are rarely observable, due to both confidentiality of this information and the absence of granular data. To tackle the first issue, I exploit variation

[2]Additional works include Iscenko (2018) for the UK, which illustrates that many borrowers choose mortgage products overpriced relative to other available alternatives; and Damen & Buyst (2017) for Belgium, according to which shopping allows mortgagors to save more.

[3]Price dispersion in Italy is mainly driven by contract characteristics (in particular, the loan-to-value, the rate type and the maturity) and figures are comparable to those recorded in other countries, including the US (Bhutta et al. 2018) and Canada (Allen et al. 2014a).

[4]In Italy, mortgages originated via MutuiOnline (the major online broker) amounted to about 6 per cent of the total in 2015, though this share is on the rise (Carella et al. 2020). In the same period, fintech lenders accounted for about 16 per cent of the US mortgage market (Buchak et al. 2018).

in brand name induced by the rebranding of a mortgage lender in some Italian provinces. My set-up closely resembles that of a natural experiment where nothing changes with the rebranding event, except for the name of the bank in those affected provinces. Parties involved are the subsidiary and the parent bank of a leading banking group in Italy. Importantly, they both follow the same pricing and offering policies, defined at the group headquarter level, and they each target specific Italian provinces, with no overlapping. The two banks belong to the group since January 2007, but have been operating with distinct brand names and identities until before August 2018 (rebranding event). At this time, the parent bank incorporates the subsidiary and replaces the brand with its own, more popular, one in all the provinces where the subsidiary is located (treated provinces). The event has no effect on the pricing and offering policies of the two banks (in fact, these are already in common), but it increases consumers' awareness of the brand in provinces (treated) where the name of the subsidiary changes into the one of the parent, and becomes more famous.[5] This rebranding constitutes my key source of exogenous variation in brand name across provinces, allowing me to identify the causal effect of brand popularity on households' choice of mortgage products. To overcome the second challenge, arising from limited information on individuals' mortgage choice, I count on the richness of my dataset, covering all new mortgage originations in Italy before and after the rebranding event. I take data from the Central Credit Register (CR) on mortgages originated in Italy over the period from 2018Q1 to 2018Q4.[6] To identify the treatment effect of brand name on the equilibrium price of mortgage contracts, I rely on a Difference-in-Differences design and compare the evolution of mortgage rates around the rebranding event (August 2018) in treated provinces versus remaining provinces not affected by the shock (control group). To make sure that findings are not artificially driven by underlying price trends, within the same group of treated provinces, I also look at what happens to the lender's main competitor, which is not experiencing any rebranding. My main result is that brand name reduces (by roughly 4 basis points)[7] the average equilibrium price of new mortgages issued by the

[5]I use Google Trends by region to measure brand awareness.

[6]Throughout the analysis I focus on indebted borrowers for which I observe a past lending relationship, and I either control for first-time borrowers or exclude them as they belong to a different sample.

[7]This reduction is quite relevant given an average annual percentage rate of about 2 per cent in Italy.

rebranding lender in treated provinces, while it has no effect on the competitor lender.[8] Noteworthy, as the offer rate does not change, the encountered price reduction mainly reflects consumers' selection into less expensive products.[9] Although interesting, the above result is compatible with two different households' behaviours: either a pure substitution pattern in favour of the lender whose name is more salient, and regardless of its expensiveness, or a more efficient search, which translates into borrowers' reallocation towards low-price intermediaries. To discriminate between the two, and corroborate my claim that branding improves consumers' ability to select the cheapest option (informative branding), I compare actual transactions with concurrent market offers. I match contracted rates with rates posted over the same period through Italy's main online broker, MutuiOnline, and come up with a very detailed, quarterly, loan-level dataset accounting for all the most important features of both the contract and the borrower (mortgage rate, amount, loan-to-value, maturity, rate type, borrower's income, job type, age and location). My merged dataset has fewer observations, but allows for significant improvements with respect to preceding works as I can exclude changes in the lenders' pricing and offering policies at the time of the event, and I can control for variables, previously not observable, that account for most of the variation in transacted rates (i.e. the mortgage maturity and the loan-to-value).[10] With such refinements at hand, I am able to track down households' response to brand name in all provinces, across all banks, and for any given mortgage product. Holding contract characteristics constant, I find that branding allows households at the top and middle of the transaction price distribution to obtain cheaper products. Most importantly, I show that households turn to the lender whose name is more popular only when the latter is also less expensive. That is, brand name allows to gather attention, but it does so only when combined with more competitive prices. I interpret this as evidence against brand persuasion: branding induces consumers to make more comparisons and, when there are lower prices, to choose the cheapest option.[11] I also find that brand popularity is mostly effec-

[8] This occurs because households switching to the rebranding lender come indistinguishably from all points of the transaction price distribution of its competitor, so that no aggregate effect emerges for the latter in equilibrium.

[9] Offer rates are observed from MutuiOnline and are not specific to online clients. Actually, they match those offered at the physical branch and listed on the bank's website.

[10] See also Carella et al. (2020); and for the UK Benetton (2018) and Robles-Garcia (2019).

[11] This is in line with the models of optimal consumer search behavior developed by Ozga (1960) and Stigler (1961), where brand awareness reduces consumers' search costs by

tive at switchers, that choose the rebranding bank for the first time, compared to old clients, that have an already established lending relationship with that bank. This further validates the thesis that an informative channel is at play. Intuitively, old clients already know the parent and for them the informative effect of branding is limited. Switchers, instead, are less informed and can fully enjoy the benefits of branding. The result is relevant because recourse to mortgage renegotiations (a proxy of households' switching behaviour) has become quite popular in Italy, reaching 17 per cent of the new loans origination in 2018 (Attinà & Michelangeli 2020).[12]

Understanding the relationships between brand name and the price of mortgages is important both because of the central role played by mortgage debt in households' credit landscape,[13] and because of trends that are currently shaping the Italian banking sector and that may, in turn, alter the intensity of local branding. In particular, my paper carries interesting policy implications with respect to ongoing bank consolidation strategies. It suggests that consolidation of small banks under a single name could have a positive impact on the lender's ability to reach potential clients similar to the one induced by an increase in consumers' incentive to seek information through the awareness mechanism. However, the informative effect only arises if consolidation also implies the simultaneous rebranding of the lender under a more popular name.

Related Literature. Although the literature acknowledges the important role of brand name on consumers' choice, the nature of this role is still not clear (Bagwell et al. 2007; Della Vigna 2009; Della Vigna & Gentzkow 2010). As economists struggle to reach consensus, there are three main views. According to the predominant one, branding is *persuasive*, for it creates spurious product differentiation and instills brand loyalty, which both distort competition and persuade consumers into bad choices (Braithwaite 1928; Kaldor 1950; Comanor & Wilson 1975; Thaler & Sunstein 2008; Gurun et al. 2016). In contrast to that, branding increases market knowledge and reduces search costs under the *informative* view, thereby allowing consumers to find better products (Ozga

conveying information on product's existence, price and quality.

[12]With the so called Bersani Law in 2008, households are allowed to modify their contract terms and, specifically, they can reduce their mortgage instalments without paying any additional extra costs. This lead to an acceleration in mortgage renegotiations, particularly pronounced since 2015.

[13]Mortgages represent the main liability for Italian households, accounting for over 50% of their financial debt.

1960; Stigler 1961; Telser 1964; Nelson 1974; Robert & Stahl 1993). The third possibility is that branding enters consumers' preferences in a way that is *complementary* to consumption and without changing consumers' preferences, but rather by influencing their behavior through both information and social prestige (Lancaster 1966; Stigler & Becker 1977; Nichols 1985). This paper adds to the debate on the role of brand name and provides empirical evidence in favour of the informative view. I bring together the literature on price dispersion for homogeneous goods (Allen et al. 2014a; Allen et al. 2014b; Allen et al. 2019) with the one on mortgage choices under imperfect consumers' information (Agarwal & Ambrose 2008; Gurun et al. 2016), and conclude that brand awareness leads to lower variation in the price of comparable mortgages. Finally, I complement existing approaches in household finance that study the determinants of mortgage choice under the assumption that the resulting contract reflects households' preferences (Mian & Sufi 2011; Hall & Woodward 2012; Fuster & Vickery 2013; Campbell & Cocco 2015; Foá et al. 2015; Hurst et al. 2016). In doing that, I am the first to exploit data on product offers from an online broker (the only source of information on the mortgage loan-to-value currently available in Italy) as to account for variability in the equilibrium mortgage price associated with the loan-to-value. More broadly, this work also relates to the emerging literature on how technology changes financial intermediation and price setting (Cavallo 2017; Basten et al. 2018; Fuster et al. 2018; Gorodnichenko et al. 2018; Hertzberg et al. 2018; Bartlett et al. 2019; Basten et al. 2019).

The rest of the paper proceeds as follows. Section 3.2 outlines some stylized facts about the Italian residential mortgage market, including anecdotal evidence on the rebranding event, and describes my main data sources. Section 3.3 provides supportive evidence to the argument that the rebranding exclusively affects consumers' awareness of the brand. Section 1.4 states the identification and estimation strategy, and discusses the main empirical findings. Section 3.4 concludes.

1.2 Rebranding Event and Data

1.2.1 The Rebranding Event

I look at variation in brand name induced by the rebranding of a leading banking group in Italy. The group owns several subsidiary banks active in different provinces, with no overlapping. The pricing and offering policies of each subsidiary are laid down by the parent and are common to all group components.[14] Actors taking part to the rebranding are the group parent bank and one group subsidiary. The latter joined the group in January 2007, as a result of a merger operation, but kept its own brand name (different from the parent's one). Few years later, in August 2018, the parent bank absorbs the subsidiary and replaces its brand. The brand of the subsidiary is decommissioned. This within-group incorporation only concerns provinces targeted by the subsidiary, whose name *de facto* becomes the one of the parent and inherits its much greater popularity. Nothing else changes as a result of the incorporation in terms of both policy implemented by parties involved, and resulting menu of product choices available to the consumer. Throughout the paper, I refer to this event as the rebranding event. I define as treated the provinces exposed to the subsidiary brand before the event and to the parent brand after, and as control the remaining provinces not affected by the within-group incorporation and thus exposed to the same brand before and after the event. The variation in brand awareness induced by the rebranding of the lender under a more famous name allows us to evaluate which of the informative or persuasive view on branding can best explain patterns in my data. I claim that brand awareness increases market knowledge and, in so doing, favours less expensive choices.

1.2.2 Data

My main data sources are confidential regulatory datasets collected by the Bank of Italy as part of its supervisory activities: the Central Credit Register

[14] I can exclude that bank-level policies change after the event. According to the group guidelines for managing the Fund Transfer Price System (FTP), the principles and guidelines set forth by the parent must be consistent at consolidated level and implemented by all group subsidiaries.

(CR) and the Analytical Survey of Lending Rates (TAXIA).[15] The CR contains information on loans, granted and utilized, and guarantees for each borrower whose aggregate exposure exceeds 30,000 euro. All financial intermediaries operating in Italy have to report this information to the Bank of Italy on a monthly basis in order to comply with Italian banking regulation. TAXIA is a subset of the CR and contains quarterly data on the interest rates that banks charge to individual households on each newly issued mortgage loan. I match the two datasets at the borrower level and get comprehensive information on the universe of residential mortgage originations in Italy from 2018Q1 to 2018Q4. Over this period, for each mortgage, I observe details on the lender's identity, the contract (annual percentage rate or APR, loan amount, rate type, maturity),[16] and the borrower (location, age, gender and nationality). Table 1.1 summarizes the data. I observe about 125 thousand mortgage contracts, of which more than 90% are FRM and the remaining ones are ARM. Other mortgage typologies, such as mixed-rate mortgages (characterized by a part of the mortgage rate which is fixed and a part which is adjustable), or adjustable rate mortgages with a cap, or those allowing to reset the interest rate (similarly to the five year-ARM in the US), are either very rare or they do not exists at all. The average APR is around 2%, with some regional variation; the average loan amount is around 130,000 euro; the average loan maturity is 22 years. The mean borrower is 38 years old; more than 50% of the mortgagors are located in the North, 25.33% in Central Italy and the remaining 23.73% in the South.

I complement this data with information at the contract level on mortgage offers available from the leading online broker in Italy, MutuiOnline (MO).[17] MO data are available on a monthly basis since March 2018.[18] Banks working with MO are 30 and they include the 10 largest banks in the country, accounting for about 70% of total mortgage originations.[19] House value is fixed at

[15]The CR is a confidential database managed by the Bank of Italy and TAXIA is a subset of the CR. Information of how to access these data is available here.

[16]The CR contains information on the residual maturity of the loan. To recover the original maturity, I use the French amortization method. A full description of the estimation methodology is provided in Appendix A.

[17]MO data are confidential and have been provided to the Bank of Italy free of charge by mutuionline.it for research purposes. Access to MO data for this thesis has been given by Valentina Michelangeli at the Bank of Italy.

[18]This information is adequate for a broad assessment of the Italian mortgage market because mortgages are almost entirely granted by banks and other financial intermediaries tend not to participate at all.

[19]These are the intermediaries I am left with as I keep the sample constant throughout my observation period.

200,000 euro, and mortgage amount varies with the LTV. Each month I observe the APR, if any, that participating banks are willing to offer to roughly 85,000 perspective profiles, constant over time. Each profile is defined by a combination of the following borrower and contract characteristics: borrower type (first-time home buyer or remortgager), location (borrower location is assumed to be the same as the one of the house), age (30 or 40 years), income (2000 or 4000 monthly net income), job type (fixed-term employee, employee with permanent contract or self-employed), mortgage LTV at origination (50, 60, 80 or 85 per cent), original maturity (10, 15, 20 or 30 years) and rate type (fixed or adjustable). Contract terms offered by banks via the platform are binding, provided that the information submitted by the borrower in the online application is accurate. Rates offered online are representative of the real market and have a high predictive power for the actual price of fixed-rate mortgages at the individual bank level (Carella et al. 2020). This alleviates potential concerns about the lender posting teaser rates through the broker, and reassure us on the reliability of my dataset. Tables 1.2 and 1.3 summarize these data. Although the Italian mortgage market is characterized by relatively homogeneous and plain-vanilla products, data from the online platform exhibit a significant degree of dispersion in the rate that lenders offer for identical loan and borrower types. Much of this dispersion (adjusted R-squared higher than 80 per cent) is explained by the mortgage LTV, maturity and rate type (Fig. A.1 in Appendix A).[20] Holding contract characteristics constant, the average price dispersion is 10 basis points according to MO; while the average differential from the minimum price that an identical borrower, in the same market and on the same day, obtains for a mortgage with the same characteristics (LTV, maturity and rate type) is 54 basis points, corresponding to 1,000 euro of extra interests, or 4 per cent of the total interests payments made over the entire duration of the loan.[21]

Finally, I include information on selected bank balance sheet items (total assets, marketing expenses, cost-to-income ratio, capital ratio, liquidity ratio, non-performing loans ratio, risk-weighted assets and return on assets) from

[20] This pattern holds across different countries, including the US and the UK (Michelangeli & Sette 2016; Benetton 2018; Robles-Garcia 2019).

[21] All estimates are based on 2018 data from MO and considering an average annual percentage rate from the Credit Register of about 2 per cent, a 20 year maturity mortgage with 60 per cent LTV and 200,000 euro house value, in line with the empirical evidence based on the Survey on Italian Household Income and Wealth (SHIW).

Supervisory Reports and banks' balance sheets; data on the distribution of physical branches by bank and province available from the Statistical Database of the Bank of Italy; and the brand popularity index from Google Trend. Overall, the combination of these five sources of information provides me with a very rich, loan-level dataset that is ideal for analyzing the effects of branding on households' choice behaviour. This paper is the first to exploit these combined datasets to address the role of brand name in the Italian residential mortgage market.

1.3 Descriptive Analysis

I hereby provide supporting evidence to the claim that the rebranding does not alter the choice set of the consumer, who keeps choosing among the exact same menu of mortgage products and prices. The rebranding group operates in several provinces through different individual banks, each of which follows the same offering and pricing policy defined at the headquarter level.[22] Figure 1.1 in relies on data from the online platform to illustrate the offering policy of banks belonging to the rebranding group. In particular, in each province, the map shows the number of products offered by the individual bank responsible for that province. I identify 32 products in total, where each product is a combination of the characteristics that account for the main source of variation in the offered APR: the mortgage LTV, the maturity and the rate type. Product differentiation is the same for each bank belonging to the group, and there is no geographical overlapping among them. To be precise, the parent brand targets dark blue provinces with 32 out of 32 potential products; the subsidiary brand targets bright blue provinces, with 32 out of 32 products as well; other subsidiary brands target the remaining light blue provinces and they offer the same 32 out of 32 products too. White provinces are those where the group does not make any online offer. As for the pricing policy, Figure 1.2 displays the APR offered by the rebranding group in treated provinces before and after the rebranding event for different combinations of rate type, maturity and LTV. Before the red line I observe the APR offered by the subsidiary brand, after the red line the subsidiary brand is replaced by the parent brand and I observe the APR offered by the latter. There is clearly no jump

[22] All group subsidiaries must follow the fund transfer pricing guidelines set by the parent bank and very minor misalignments are allowed.

between the APR offered by the two in treated provinces and, more in general, across all provinces: Figure 1.3 depicts minor or no misalignment at all between the average APR across provinces offered by the subsidiary brand (solid line, available until incorporation) and by the parent brand (dashed line), for different combinations of rate type, LTV and maturity level. A second set of supportive evidence comes from the distribution of physical branches by province. Table 1.4 documents the delta in both the number and the share of physical branches across provinces for the rebranding lender before and after the event. I find no evidence in the data that physical branches are increasing following the rebranding. In fact, the delta is zero for most provinces and, if anything, is negative, meaning that the parent is almost entirely replacing branches previously owned by the subsidiary, with no meaningful effect at the group level. Hence, data from the digital platform confirms that households in treated provinces after the rebranding face the same choices in term of listed products and prices from the parent brand after the event as from the subsidiary brand before the event.[23] At the same time, physical presence of the group on the territory is not strengthening, ruling out the possibility that the equilibrium outcome reflects changes in market power due to the rebranding strategy.

Actually, the main difference concerns consumers' knowledge of the bank, from small subsidiary to big parent, and her awareness of the associated brand, from low to high. Table 1.5 reports bank characteristics for the second quarter of 2018 (the last quarter preceding the event of study). Although the two belong to the same group, total assets endowment is much smaller for the subsidiary than for the parent brand; while marketing expenses (in absolute terms) and cost-to-income ratio suggest that the parent brand both invests more in advertising, and it is more efficient at doing so through a better management of operating costs. Capital, liquidity and profitability ratios also differ between parent and subsidiary. As for the lender's main competitor in treated provinces, bank characteristics are, instead, comparable to those of the parent bank. To proxy brand popularity, I extract the index of search volume by region from Google Trend. For given brand name, the index captures individual search behaviour within Google browsers and YouTube, excluding repeated search from same borrower over close periods of time. The index measures

[23]While I don't have data on cross-selling strategies, I observe no change with respect to products that are complementary to mortgages, such as insurances.

relative brand popularity compared to the highest point (a value of 100 is the peak popularity of the term, whilst a value of 50 means that the term is half as popular) and it is often used to monitor marketing and brand performances. More generally, it can be thought of as an indicator of relative ease with which consumers expect to find content online. Figure 1.4 compares the level of popularity in treated provinces for the parent and the subsidiary brand. As expected, the parent enjoys superior brand popularity (this is true both at the regional and the national level). In other words, although the pricing and offering policies do not change, when the rebranding occurs the consumer becomes more aware of the brand and she might so choose it. Interestingly, search volume for the subsidiary brand does not go to zero immediately after the event, possibly reflecting consumers' inertia or curiosity.

In the following section I address the main question of the paper, namely whether branding is effective at gathering consumers' attention, and whether it does so in a purely persuasive fashion (e.g., by creating deceptive brand loyalty), or rather by correcting for market inefficiencies due to imperfect households information.

1.4 Empirical Analysis

1.4.1 Estimation and Identification

I exploit variation in brand popularity across provinces induced by a within-group incorporation event to identify the causal effect of brand name on the equilibrium price of mortgage contract. I rely on a Difference-in-Differences (DID henceforth) methodology to compare the evolution of mortgage price around the rebranding event (August 2018) in provinces with different exposure to brand name. The rebranding is implemented through the incorporation into the parent bank of a wholly-owned group subsidiary, and the simultaneous rebranding of the subsidiary under the parent brand. As the parent enjoys superior popularity, brand awareness increases in provinces exposed to the subsidiary brand before the event and to the parent brand after. Crucially, the within-group incorporation does not imply any policy change, as parties involved already respond to the same headquarter, and it does not alter the choice set of the consumer, who still face the same menu of products and prices offered. Instead, it affects consumers' perception of the financial intermediary through awareness of the corresponding brand.

Before I formally exploit this variation, and derive the resulting impact on the equilibrium price of mortgage contracts, I look at how brand awareness affects market share. The regression I estimate is the following:

$$MarketShare_{jt} = \beta_0 + \beta_1 POST_t + \beta_2 Treated + \beta_3 (POST_t \times Treated) + \varepsilon_{jt} \quad (1.1)$$

where j indexes the lender and t the quarter. The dependent variable is the quarterly market share of the rebranding lender in each province, $Treated$ is a dummy for provinces affected by the rebranding event, $POST_t$ is a time dummy for the event, and the regression coefficient on the interaction between $POST_t$ and $Treated$ is the effect of interest.

Moving to the equilibrium mortgage price, I run my analysis using two different benchmark criteria. The first one is at the province level, and it compares the evolution of mortgage price in provinces where the brand becomes more salient after the event against provinces where brand awareness remains constant throughout the sample period. I estimate the following regression equation:

$$Y_{jimt} = \beta_0 + \beta_1 POST_t + \beta_2 Treated + \beta_3 (POST_t \times Treated) + X_i + Z_m + \varepsilon_{jimt} \quad (1.2)$$

where j indexes the lender, i the borrower, m the mortgage contract and t the quarter. The main outcome variable is the APR on newly originated mortgage contracts. The time dimension of the DID is the dummy $POST$, which is one starting from the third quarter of 2018 and zero before. The cross-sectional dimension, $Treated$, is a dummy equal to one for provinces directly affected by the rebranding and zero for remaining unaffected provinces. Identification of the effect of branding is achieved because the rebranding brings an exogenous source of variation in consumers' brand awareness across provinces, without altering the lenders' pricing policy. I control for contract and borrower characteristics to mitigate for potential selection bias: X_i is a vector of borrower characteristics (age, gender, nationality, a dummy for past default and one for first time borrowers), Z_m is a vector of contract characteristics (mortgage amount, maturity and rate type). The effect of interest is captured by the regression coefficient on the interaction between $POST$ and $Treated$. The second criterion is at the lender level in treated provinces. It evaluates the outcome for the rebranding lender against its main competitor, not changing name. The regression I estimate is:

$$\begin{aligned} Y_{jimt} = \beta_0 + \beta_1 POST_t + \beta_2 Treated + \beta_3(POST_t \times Treated) + \delta_1 Rebranding_j \\ + \delta_2(POST_t \times Rebranding_j) + \delta_3(Treated \times Rebranding_j) \\ + \gamma_1(POST_t \times Treated \times Rebranding_j) + X_i + Z_m + \varepsilon_{jimt} \end{aligned} \tag{1.3}$$

where j indexes the lender, i the borrower, m the mortgage contract and t the quarter. *Rebranding* is a dummy equal to one for the rebranding lender and zero for the competitor. Other variables are as previously defined. The coefficient of interest is γ_1 , which controls for the possibility that the treatment effect is driven by underlying price trends in treated provinces. If that were the case, trends should be affecting both the competitor and the rebranding lender equally, and the difference between the two should not be significant.

Then, to also confirm coherency of my results with standard prediction from economic theory, I run regressions 1.2 and 1.3 using the log amount of mortgage debt (at the contract level) as the main dependent variable, and look at the impact of rebranding on the equilibrium quantity of mortgage contracts.

Next, I look at household's choice behaviour as to shed lights on how branding attracts consumers. More precisely, whether it does so by lowering search costs and allowing them to find cheaper products (informative branding), or by creating spurious brand loyalty and persuading them into more expensive choices (persuasive branding). I combine data on originated mortgage contracts with data on mortgage offered from the digital platform and exploit full information on the composition of the consumer's choice set. I match the two datasets at the product level (lender, rate type, maturity, province, and APR). To address concerns about deceptive or unrealistic offers, I keep only quotes that are actually realized in equilibrium. This drastically reduces the number of observation at hands, but it also keeps the measurement error down to the minimum. Importantly, the matching with MO data allows to get information on the mortgage LTV, which would otherwise not be available.[24] I group homogeneous mortgages contracts into bins, where each bin is a combination of LTV, maturity and rate type, and there are 32 possible combinations in total (defined as before).[25] For each indebted borrower I observe the equilibrium product choice, which includes her choice of the current lender and the current contract, and I also observe the identity of the lender she borrowed from

[24] A full description of the LTV inference is provided in the Appendix A.

[25] The grouping reflects the characteristics that account for the main source of variation in the offered APR (Figure A.1).

within the past 20 years, together with the price offered today by that lender in the same province, at the same time and within the same bin. Next, I rank banks from higher to lower mortgage price within each bin, and study households' transition across lenders in response to the rebranding shock. I assume that cheaper mortgages are, all else equal, better products from the perspective of the consumer, and I expect households to switch to cheaper lenders if the brand is informative, and to be driven into more expensive choices if the brand is persuasive. I first estimate the following multivariate regression for the household's choice of high, medium or low-price lender:

$$\begin{cases} High_{jit} = \beta_0 + \beta_1 POST_t + \beta_2 Treated + \beta_3 (POST_t \times Treated) + \varepsilon_{jit} \\ Medium_{jit} = \beta_0 + \beta_1 POST_t + \beta_2 Treated + \beta_3 (POST_t \times Treated) + \varepsilon_{jit} \\ Low_{jit} = \beta_0 + \beta_1 POST_t + \beta_2 Treated + \beta_3 (POST_t \times Treated) + \varepsilon_{jit} \end{cases} \tag{1.4}$$

where j indexes the lender, i the borrower, and t the quarter. $High$, $Medium$ and Low are dummies reflecting the lender's ranking in terms of APR within bins. $POST$ and $Treated$ are defined as before. The three equations are estimated simultaneously and the regression coefficient β_3 captures the impact of brand name on the probability of choosing a lender with a given price ranking. Then, for each already indebted borrower, I exploit information on her previous lending relationship and estimate the treatment effect of rebranding on both the probability that she switches lender (1.5), and the probability that she switches from a more to a less expensive lender (1.6).

$$Switcher_{jit} = \beta_0 + \beta_1 POST_t + \beta_2 Treated + (POST_t \times Treated) + W_{jt} + X_i + \zeta_m + \varepsilon_{jit} \tag{1.5}$$

where j indexes the lender, i the borrower, m the mortgage contract and t the quarter. $Switcher_{jit}$ is the probability that borrowers originate a mortgage with a lender they have not borrowed from since 2000.[26] W_{jt} is a matrix of bank characteristics, which includes a measure of size (log total assets), capital ratio (tier 1 capital to total assets), liquidity ratio (cash plus deposits to the central bank and government bonds to total assets) and NPL ratio (net non-performing loans to total loans). X_i is a vector of borrower characteristics (age, gender, nationality, a dummy for past default and one for first time borrowers)

[26] For each already indebted borrower, I observe the identity of her previous lenders over the past 18 years. If none of these corresponds to her current lender, I set $Switcher_{jit}$ equal to one, zero otherwise.

and ζ_m are bin fixed-effects. $POST$ and $Treated$ are defined as before.

$$\begin{aligned}
Low_{jit} = \alpha_0 &+ \alpha_1 High_{j-1,i,t} + \alpha_2 Medium_{j-1,i,t} + \beta_1 POST_t + \beta_2 Treated \\
&+ \beta_3 POST_t \times Treated + \gamma_1 POST_t \times High_{j-1,i,t} + \gamma_2 Treated \times High_{j-1,i,t} \\
&+ \gamma_3 POST_t \times Treated \times High_{j-1,i,t} + \delta_1 POST_t \times Medium_{j-1,i,t} \\
&+ \delta_2 Treated \times Medium_{j-1,i,t} + \delta_3 POST_t \times Treated \times Medium_{j-1,i,t} \\
&+ W_{jt} + X_i + \zeta_m + \varepsilon_{jit}
\end{aligned} \tag{1.6}$$

where j indexes the lender, i the borrower, m the mortgage contract and t the quarter. High, Medium and Low are dummies defined according to the 2018 distribution of newly originated mortgage contracts, and reflect the current (j) and previous ($j-1$) lender's ranking in terms of APR within each bin.[27] $POST$, $Treated$, W_{jt}, X_i and ζ_m are as previously defined. The above specification, however, does not account for the possibility that branding is always attractive, and either an informative or a persuasive effect arises depending on whether the lender is low or high-price. To demonstrate that the relationship between branding and the expensiveness of mortgage contracts is not spurious, I exploit variation in the lender's ranking within bin and estimate the treatment effect of brand name on households' unconditional probability of choosing it:

$$\begin{aligned}
Rebranding_{jit} = \alpha_0 &+ \alpha_1 High_{jit} + \alpha_2 Medium_{jit} + \beta_1 POST_t + \beta_2 Treated \\
&+ \beta_3 POST_t \times Treated + \gamma_1 POST_t \times High_{jit} + \gamma_2 Treated \times High_{jit} \\
&+ \gamma_3 POST_t \times Treated \times High_{jit} + \delta_1 POST_t \times Medium_{jit} \\
&+ \delta_2 Treated \times Medium_{jit} + \delta_3 POST_t \times Treated \times Medium_{jit} \\
&+ W_{jt} + X_i + \zeta_m + \varepsilon_{jit}
\end{aligned} \tag{1.7}$$

where j indexes the lender, i the borrower, m the mortgage contract and t the quarter. $Rebranding_{jit}$ is a dummy equal to one for contracts originated by the rebranding lender and zero otherwise. All other variables are as before. The claim that the benefit of branding consists in the lowering of search costs for households that are not aware of each product's existence boils down to saying

[27] I divide the within-bin distribution of the APR at the bank-level into three equal segments. I then assign each current and previous lender a ranking reflecting their APR positioning within the bin (Low if the APR is smaller than or equal to the 33th percentile, Medium if the APR is between the 33rd and the 66th percentile, High if the APR is greater than or equal to the 66th percentile). On average 25% of the banks are high-price, 35% are medium-price, and 40% are low-price.

that a positive effect does not arise for borrowers that are already informed. To test this, I split the sample into old client, which are already indebted borrowers with a previous lending relationship with the parent brand, and switchers, which are already indebted borrowers that go to the parent brand for the first time since 2000, and I estimate regression 1.7 separately for the two sub-samples.

Lastly, I compute the quarterly standard deviation by province in the APR across all bins (between standard deviation) and within the same bin (within standard deviation), and run the following regression for the treatment effect of brand name on price dispersion:

$$PriceDispersion_{jit} = \beta_0+\beta_1 POST_t+\beta_2 Treated+\beta_3(POST_t\times Treated)+\varepsilon_{jit} \quad (1.8)$$

where $PriceDispersion$ is the average standard deviation in the mortgage rate by province across all bins and within the same bin. In all regressions, as standard in the literature, I cluster errors at the province level, allowing for the possibility that model errors in the same province (namely, some unobserved components within clusters) are correlated, while model errors in different provinces are assumed to be uncorrelated.

1.4.2 Estimation Results

Market Share. I start by illustrating results on the effect of rebranding on market share. First, graphical inspection of the quarterly market share for the rebranding and competitor lender, before and after the event (red line), shows that the former gains almost 20 per cent market share over its competitor in treated provinces (Figure 1.5). The market share is computed at the group level to account for the incorporation effect. Second, the regression analysis (Equation 1.1) points at a positive and significant treatment effect of brand awareness on market share: the rebranding lender increases market share following the event (Tables 1.6 and 1.7), and the effect is statistically significant for provinces where brand popularity increases because of the subsidiary's rebranding under the parent brand (Table 1.8). The result could reflect higher market power as well as greater competitiveness of the parent. If it is market power, I would expect the parent to enforce its dominant position and extract surplus by steering consumers into relatively more expensive products; if it is competitiveness, I would expect the parent to exploit its comparative advantage and attract consumers through more convenient deals. I look at the equilibrium mortgage price to address this question.

Equilibrium Mortgage Price. The DID identifying assumption is that the APR would have evolved according to a parallel trend in provinces with higher and lower brand awareness, had the rebranding not been implemented. While this assumption is not directly testable, Figure 1.6 provides visual inspection that, prior to the rebranding, the APR trends similarly across provinces with different levels of brand awareness. Figure 1.7 shows the average APR across all new mortgages issued by the rebranding and the competitor lender in treated provinces before and after the event (red line). I observe an average reduction in the equilibrium APR for mortgages originated by the rebranding lender after the event, while the APR on mortgages originated by the competitor lender continues on an increasing path ongoing from before. The DID estimator (Equation 1.2) shows that the rebranding strategy reduces the equilibrium APR on mortgages issued by the lender in treated provinces, and the effect survives after conditioning for loan and borrower characteristics (Table 1.9, columns 1 and 2). This, together with evidences presented in Section 3 (that the offering and pricing policies of the rebranding lender are not affected by the within-group incorporation), suggests that the rebranding shock induces consumers' selection into less expensive choices. As for the competitor lender (Equation 1.3), who is not experiencing any change in brand popularity, I find no effect on the price of mortgage contracts originated in treated provinces after the event (Table 1.9, column 3). Hence, households switching to the rebranding lender come indistinguishably from all points of the transaction price distribution of the competitor lender, so that no aggregate effect arises for the latter.[28] Also, the treatment effect is not driven by underlying price trends in treated provinces. If that were the case, trends should be affecting both the competitor and the rebranding lender equally and the difference between the two should not be significant. The coefficient for the interaction $POST$, *Treated* and *Rebranding* is significant, ruling out this possibility (Table 1.9, column 4). In fact, the treatment effect becomes stronger after netting out the evolution of price for the competitor lender, actually increasing in treated provinces (Figure 1.7).

[28] Table A.3 in Appendix A shows no statistically significant difference in the ranking of their previous intermediary for borrowers that switch to the rebranding lender.

Equilibrium Mortgage Quantity. I replicate the DID model (Equations 1.2 and 1.3) to also estimate the effect of brand name on the equilibrium amount of mortgage debt (outcome variable). Mortgage credit issued by the rebranding lender in treated provinces increases following the event, consistently with a downward sloping demand (Table 1.10). The effect survives after conditioning for loan and borrower characteristics (columns 1 and 2). The rebranding strategy does not affect the equilibrium amount of mortgage credit granted by the competitor lender in treated provinces, excluding the possibility that households entirely substitute products of the competitor with those of the rebranding lender (column 3). Also, the difference between the rebranding and the competitor lender is still significant, meaning that the effect is not spuriously driven by the evolution of mortgage demand in treated provinces (column 4). Given the observed reduction in the equilibrium mortgage price (Table 1.9), the effect on quantity is as expected and in line with classic microeconomics theory posing a negative relationship between the quantity demanded of a good and its price.

Household choice. Results presented so far already denote some kind of households' selection into cheaper products due to the rebranding. In what follows, I investigate patterns of such selection to show that this is unlikely to reflect pure substitution behaviours by the household in favour of the lender whose name is more salient, and instead it mirrors a better understanding of the most convenient option and a higher incentive to reallocate towards less expensive intermediaries. Unlike before, the matching with MO allows to effectively control for contract and borrower characteristics and confirms that, following the rebranding, households in treated provinces are, *ceteris paribus*, more likely to pick the lender with the lowest price (Equation 1.4 and Table 1.11). As previously argued, because the price offered does not change, this result is attributable to consumers' selection into less expensive contracts. To actually conclude that a selection outcome arises because the rebranding shock increases consumers' search for more convenient deals, I study households' choice among lenders with different price ranking. In Equation 1.5, I find a positive and significant treatment effect of rebranding on the probability that previously indebted borrowers switch to a new lender (Table 1.12) and, specifically in Equation 1.6, that they switch from a previous lender now offering a high or medium price to a current lender now offering a low price

(Table 1.13). Nevertheless, one could still argue that the informative effect of branding arises in this setting only because the lender whose brand is more salient also happens to be the one with the lowest price. If the lender were expensive, the result would be reversed and branding would be persuasive. To shut down this criticism, and validate the hypothesis that consumers' reallocation occurs because branding induces search for cheaper options, Equation 1.7 exploits variation in the lender's price ranking across offers.[29] The idea being the following: if brand is informative, households should select the rebranding lender only when the latter makes low-priced offers and abstain from doing so when it ranks high or medium. I estimate the treatment effect of brand name on the probability of choosing the rebranding lender and find that households do not fully substitute. In fact, they refrain from doing so for products where the rebranding lender is less competitive (the two triple interaction terms in Table 1.15 are both negative and significant). This result is inconsistent with the persuasive view that the brand alters consumer's preferences, leading them into expensive choices, and instead embraces the possibility that brand helps consumers taking more informed decision. Sample split between old clients and switchers[30] shows that the probability of choosing the rebranding lender increases only for the latter, who have never borrowed from the parent and are therefore likely to be less aware of its brand (Table 1.16). Old client, instead, already know the brand, and rebranding brings virtually no value to them.

Price Dispersion. I document a decrease in price dispersion by province across all bins (between standard deviation) and within the same bin (within standard deviation) (Tables 1.17-1.20) and find a negative 1 basis point and significant treatment effect of rebranding on price dispersion in treated provinces (Equation 1.8 and Table 1.22). As the searching process becomes more efficient, there might be less scope for discretionary price setting by the lender, and dispersion in the price of homogeneous products may go down, consistently with the law of one price and the hypothesis that branding ameliorates market inefficiencies due to imperfect consumers' information.

[29] Table 1.14 illustrates that the price ranking of the rebranding lender is not always constant, which makes it possible to disentangle households' response to brand name depending on the competitiveness of the offer.

[30] Old clients are already indebted borrowers that have a previous lending relationship with the parent brand. Switchers are already indebted borrowers that go to the parent brand for the first time since 2000.

1.5 Conclusions

Many markets are characterized by imperfect consumers' information with respect to product alternatives. My analysis focuses on the role that brand popularity plays in correcting distortions linked to this imperfection. Using a unique dataset that combines information on mortgage offers from the main Italian online broker, and mortgage originated from the Credit Register over the period 2018Q1 to 2018Q4, I study the relationship between brand name and the price of mortgage contracts obtained by households. I exploit variation in brand name across provinces induced by a within-group rebranding event that involves one of the leading mortgage lender in Italy. The set of evidence collected in this paper is inconsistent with brand persuasion, for which lenders exploit brand name to drive uninformed consumers into expensive choices, and instead supports the informative view that brand induces households' reallocation towards cheaper mortgages. It does so by increasing awareness of potential improvements in products offered, while also reducing the extent to which borrowers overpay relative to the rates available on the market. Yet, the limited time horizon does not exclude the possibility that lenders exploit the information effect and gain market share in the short term, to then steer consumers into expensive choices in the longer term.

My result well relates to today's policy issues and suggests that if bank consolidation brings better offers, under price competition, those improvements are best attained when consolidating banks rely on the more popular brand to reach less informed clients.

1.6 Tables

Descriptive Statistics

Table 1.1: Summary Statistics: originated mortgage contracts (All Sample)

VARIABLES	Obs	Mean	Std. Dev.	Min	Max
Mortgage amount (€)	125,916	131,155	43,022	80,000	300,000
Fixed-rate (%)	115,573	2.12	0.61	0.36	6.84
Adjustable-rate (%)	10,343	1.75	0.77	0.28	6.24
Mortgage maturity	125,916	22	5.51	10	30
Borrower age	125,916	38	6.44	18	50
Mortgage rate by location					
North-West	42,220	2.07	0.64	0.28	6.43
North-East	24,588	2.02	0.63	0.32	6.84
Center	28,605	2.11	0.60	0.44	6.72
South	30,503	2.16	0.63	0.40	6.37
	Percentage share				
Rate type	Fixed-rate		91.79		
	Adjustable-rate		8.21		
Borrower sex	Male		61.96		
	Female		38.04		
Borrower nationality	UE		96.73		
	Extra-UE		3.27		
Borrower location	North-West		31.55		
	North-East		19.39		
	Center		25.33		
	South		23.73		

Note: The table reports summary statistics for new mortgage contracts originated in Italy in the period from 2018Q1 to 2018Q4. *Source:* CR and TAXIA.

Table 1.2: Probability of mortgage offer

	Share of profiles with an offer (%)
All sample	25.24
Contract characteristics	
FRM	25.11
ARM	25.36
10 years maturity	23.75
15 years maturity	24.91
20 years maturity	26.06
30 years maturity	26.22
50% LTV	33.38
60% LTV	33.34
80% LTV	31.61
85% LTV	2.62
Borrower characteristics	
30 years old	25.24
40 years old	25.24
€2000 net monthly income	24.15
€4000 net monthly income	26.32
Fixed-term job	7.91
Permanent job	33.90
Self-employed	33.90
North-West	29.64
North-East	27.20
Center	26.84
South	20.63

Note: The table reports information on the probability of observing on online mortgage offer by one of the 30 partner banks in the period from March to December 2018 for selected profiles, defined by combinations of the following contract and borrower characteristics: mortgage rate type (fixed or adjustable), original maturity (10, 15, 20 or 30 years), LTV at origination (50, 60, 80 or 85 per cent); borrower age (30 or 40 years), income (2000 or 4000 monthly net income), job type (fixed-term employee, employee with permanent contract or self-employed) and location (North-West, North-East, Center, South). *Source:* MutuiOnline.

Table 1.3: Characteristics of mortgage offers

VARIABLES	Obs	Mean	Std. Dev.	Min	Max
Mortgage amount (€)	6,182,580	120,000	0	120,000	120,000
Mortgage instalment (€)	6,182,580	577	197	291	1015
FRM (%)	3,075,676	2.04	0.55	0.94	4.72
ARM (%)	3,106,904	1.19	0.56	0.43	3.80
Mortgage maturity	6,182,580	19	7.40	10	30
Mortgage LTV	6,182,580	63.60	12.70	50	85
Mortgage rate by maturity					
10 years	1,454,824	1.43	0.62	0.43	4.43
15 years	1,525,560	1.55	0.66	0.43	4.41
20 years	1,596,132	1.60	0.70	0.54	4.41
30 years	1,606,064	1.85	0.76	0.54	4.72
Mortgage rate by LTV					
50 per cent	2,044,188	1.48	0.65	0.43	4.52
60 per cent	2,042,020	1.57	0.62	0.57	4.72
80 per cent	1,936,116	1.67	0.64	0.56	4.70
85 per cent	160,256	3.27	0.94	2.00	4.43
Mortgage rate by location					
North-West	1,650,588	1.61	0.68	0.43	4.72
North-East	1,332,576	1.63	0.69	0.44	4.72
Center	1,315,328	1.62	0.74	0.44	4.72
South	1,884,088	1.62	0.71	0.44	4.72
Mortgage rate by borrower age					
30 years old	3,091,290	1.61	0.70	0.43	4.72
40 years old	3,091,290	1.61	0.70	0.43	4.72
Mortgage rate by borrower income					
€2000 (monthly net)	2,957,948	1.62	0.70	0.43	4.72
€4000 (monthly net)	3,224,632	1.60	0.70	0.43	4.72
Mortgage rate by employment status					
Fixed-term contract	645,984	1.54	0.76	0.43	4.43
Permanent contract	2,768,298	1.62	0.69	0.43	4.72
Self-employed	2,768,298	1.62	0.69	0.43	4.72

Note: The table reports summary statistics for online mortgage offers by the 30 partner banks in the period from March to December 2018. *Source:* MutuiOnline.

Table 1.4: Distribution of physical branches of the rebranding lender by province

	Provinces	Treated	Number of Physical Branches			% Share of Physical Branches		
			Pre-Rebranding	Post-Rebranding	Delta	Pre-Rebranding	Post-Rebranding	Delta
1	Gorizia	Y	85	85	0	13	13	0
2	Pordenone	Y	32	31	-1	12	12	0
3	Trieste	Y	165	163	-2	19	19	0
4	Udine	Y	15	11	-4	15	12	-4
5	Verona	N	18	18	0	21	21	0
6	Vicena	N	43	43	0	11	11	0
7	Belluno	N	233	232	-1	15	15	0
8	Padova	N	27	27	0	6	6	0
9	Rovigo	N	79	78	-1	20	21	1
10	Torino	N	106	105	-1	20	20	0
11	Aosta	N	65	65	0	19	19	0
12	Genova	N	194	195	1	12	12	0
13	Milano	N	159	159	0	24	25	0
14	Trento	N	12	12	0	9	9	0
15	Venezia	N	11	11	0	12	12	0
16	Bologna	N	66	66	0	16	16	0
17	Ancona	N	14	14	0	9	9	0
18	Firenze	N	13	13	0	15	15	0
19	Perugia	N	42	35	-7	13	11	-2
20	Roma	N	25	25	0	21	21	0
21	Napoli	N	10	10	0	9	9	0
22	L'Aquila	N	42	40	-2	25	24	-1
23	Campobasso	N	25	24	-1	6	5	0
24	Bari	N	17	17	0	12	12	0
25	Potenza	N	27	23	-4	12	11	-2
26	Catanzaro	N	15	15	0	17	17	0
27	Palermo	N	15	15	0	10	11	0
28	Cagliari	N	3	3	0	3	3	0
29	Vercelli	N	61	61	0	17	17	0
30	Novara	N	58	58	0	18	18	0
31	Cuneo	N	6	6	0	5	5	0
32	Asti	N	78	78	0	13	13	0
33	Alessandria	N	61	61	0	8	8	0
34	Imperia	N	53	53	0	19	19	0
35	Savona	N	24	24	0	10	10	0
36	La Spezia	N	25	25	0	9	9	0
37	Varese	N	21	21	0	6	6	0
38	Como	N	74	61	-13	13	11	-2
39	Sondrio	N	136	114	-22	27	24	-3
40	Bergamo	N	36	28	-8	26	21	-4
41	Brescia	N	135	119	-16	29	26	-2
42	Pavia	N	148	122	-26	29	25	-3
43	Cremona	N	47	39	-8	35	31	-4
44	Mantova	N	79	68	-11	20	17	-2
45	Bolzano	N	20	15	-5	24	20	-4
46	Treviso	N	37	28	-9	21	17	-4
47	Piacenza	N	12	12	0	7	7	0
48	Parma	N	54	54	0	19	19	0
49	Reggio Emilia	N	16	16	0	5	5	0
50	Modena	N	31	31	0	8	8	0

	Provinces	Treated	Number of Physical Branches			% Share of Physical Branches		
			Pre-Rebranding	Post-Rebranding	Delta	Pre-Rebranding	Post-Rebranding	Delta
51	Ferrara	N	12	12	0	7	7	0
52	Ravenna	N	21	21	0	8	8	0
53	Forli'	N	43	43	0	16	16	0
54	Pesaro Urbino	N	26	26	0	12	12	0
55	Macerata	N	17	17	0	9	9	0
56	Ascoli Piceno	N	26	26	0	21	21	0
57	Massa Carrara	N	9	9	0	10	10	0
58	Lucca	N	27	27	0	13	13	0
59	Pistoia	N	39	39	0	28	28	0
60	Livorno	N	17	17	0	9	10	1
61	Pisa	N	26	26	0	10	10	0
62	Arezzo	N	39	39	0	19	20	0
63	Siena	N	23	23	0	13	13	0
64	Grosseto	N	23	23	0	16	17	0
65	Terni	N	23	23	0	22	22	0
66	Viterbo	N	33	33	0	19	19	0
67	Rieti	N	27	26	-1	40	39	-1
68	Latina	N	14	14	0	9	9	0
69	Frosinone	N	17	17	0	10	10	0
70	Caserta	N	41	41	0	25	25	0
71	Benevento	N	10	10	0	12	13	0
72	Avellino	N	19	19	0	17	17	0
73	Salerno	N	49	49	0	15	15	0
74	Teramo	N	27	27	0	18	18	0
75	Pescara	N	14	14	0	10	11	0
76	Chieti	N	15	15	0	10	10	0
77	Isernia	N	4	4	0	17	17	0
78	Foggia	N	28	28	0	15	15	0
79	Taranto	N	19	19	0	14	14	0
80	Brindisi	N	21	21	0	20	20	0
81	Lecce	N	33	33	0	14	14	0
82	Matera	N	9	9	0	12	12	0
83	Cosenza	N	22	22	0	13	13	0
84	Reggio Calabria	N	22	22	0	22	22	0
85	Trapani	N	28	26	-2	22	21	-1
86	Messina	N	25	24	-1	15	15	0
87	Agrigento	N	14	13	-1	11	11	-1
88	Caltanissetta	N	11	9	-2	14	12	-2
89	Enna	N	10	9	-1	18	17	-2
90	Catania	N	17	17	0	7	7	0
91	Ragusa	N	10	10	0	11	11	0
92	Siracusa	N	10	10	0	10	10	0
93	Sassari	N	28	28	0	16	16	0
94	Nuoro	N	8	8	0	10	10	0
95	Oristano	N	4	4	0	6	6	0
96	Lodi	N	16	16	0	12	12	0
97	Monza	N	45	45	0	12	12	0
98	Fermo	N	10	10	0	11	12	0
99	BAT	N	17	17	0	16	17	0
100	Barletta Andria Trani	N	32	32	0	33	33	1
101	Crotone	N	2	2	0	6	6	0
102	Biella	N	7	7	0	6	6	0
103	Verbania	N	21	21	0	31	32	1
104	Lecco	N	23	23	0	10	11	0
105	Rimini	N	20	20	0	9	9	0
106	Vibo Valentia	N	6	6	0	20	20	0

Note: The table lists the average number and share of physical branches by province of the rebranding lender (at the group level) in the two quarters preceding and following the rebranding event, and computes the delta between the two periods. Treated provinces are those exposed to the subsidiary brand before the event and to the parent brand after. *Source:* Bank of Italy Statistical Database and authors' calculation.

Table 1.5: Bank characteristics before rebranding (2018 Q2)

VARIABLES	Units	Subsidiary Brand	Parent Brand	Competitor Brand
Total Assets	billions Euro	5.98	536	437
Marketing Expenes	millions Euro	0.08	81	77
CTI	% of Net Income	68.9	41.2	43.6
T1 ratio	% of Total Assets	14.5	15.3	25.1
NPL ratio	% of Total Loans	17.0	14.0	13.3
Liquidity Ratio	% of Total Assets	0.80	3.60	10.4
RWA	% of Total Assets	29.3	49.1	46.1
ROA	% of Total Assets	0.00	0.52	0.68

Note: The table compares selected bank's balance sheet items for the subsidiary, parent and competitor brands at the latest available date before the rebranding event. For marketing expenditure the latest values available from the subsidiary bank's balance sheet is as of December 2017. All other items are as of 2018 Q2. *Source:* Supervisory Reports and banks' balance sheets.

Market share

Table 1.6: All sample

VARIABLES	Obs	Mean	Std. Dev.	Min	Max
Pre-Rebranding	215	49.30	24.72	3.95	87.37
Post-Rebranding	214	52.60	20.31	1.90	84.37

Table 1.7: Treated Provinces

VARIABLES	Obs	Mean	Std. Dev.	Min	Max
Pre-Rebranding	8	36.62	19.97	8.51	64.93
Post-Rebranding	8	54.31	12.93	34.48	77.59

Note: The tables report the quarterly market share of the rebranding group for new mortgage originations in my entire sample and in treated provinces only, for the two quarters preceding and following the rebranding event. Treated provinces are those exposed to the subsidiary brand before the event and to the parent brand after. Pre and post periods are the two quarters preceding and following the rebranding event. *Source:* TAXIA

Table 1.8: Brand name on market share

	(1)	(2)
VARIABLES	Market Share	Market Share
POST	1.987	0.209
	(2.272)	(2.342)
Treated	-13.83**	-16.12***
	(5.544)	(5.510)
POST × Treated	15.70**	17.41**
	(7.842)	(7.774)
Branches		0.106**
		(0.0502)
Observations	429	397
R-squared	0.020	0.035

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The dependent variable is the quarterly market share of the rebranding group for new mortgage originations in each province. Pre and post periods are the two quarters preceding and following the rebranding event. All values are in percentage points. *Source:* TAXIA

Equilibrium Mortgage Price

Table 1.9: Brand name on the equilibrium mortgage APR

	Rebranding Lender		Competitor Lender	All Contracts
	(1)	(2)	(3)	(4)
VARIABLES	Mortgage APR	Mortgage APR	Mortgage APR	Mortgage APR
POST	0.0293***	0.0423***	0.0163***	0.0241***
	(0.00495)	(0.00352)	(0.00465)	(0.00498)
Treated	0.0862**	0.00890	-0.105***	-0.119***
	(0.0338)	(0.0239)	(0.0186)	(0.0219)
POST × Treated	-0.0373*	-0.0356**	0.0102	0.0136
	(0.0199)	(0.0144)	(0.00915)	(0.0108)
Branches		0.0452	-0.147	-0.0351
		(0.126)	(0.156)	(0.114)
Rebranding				-0.116***
				(0.0158)
POST × Rebranding				0.0180***
				(0.00594)
Treated × Rebranding				0.148***
				(0.0381)
POST × Treated × Rebranding				-0.0529**
				(0.0235)
Contract characteristics	N	Y	Y	Y
Borrower characteristics	N	Y	Y	Y
Observations	65,107	63,665	60,068	123,723
R-squared	0.001	0.625	0.684	0.628

Standard errors clustered at the province level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: in columns (1) and (2) the dependent variable is the percentage interest rate on mortgage contracts originated by the rebranding group. In column (3) the dependent variable is the percentage interest rate on mortgage contracts originated by the competitor group. In column (4) the dependent variable is the percentage interest rate on both mortgage contracts originated by the rebranding and the competitor lenders (both at the group level). Rebranding is a dummy equal to one for the lender implementing a rebranding strategy and zero for the competitor lender. Contract characteristics include mortgage amount, rate type and maturity. Borrower characteristics include age, gender, nationality, a dummy for past default and one for first-time borrowers. Data are quarterly.

Equilibrium Mortgage Quantity

Table 1.10: Brand name on equilibrium mortgage debt

	Rebranding Lender		Competitor Lender	All Contracts
	(1)	(2)	(3)	(4)
VARIABLES	log Mortgage debt	log Mortgage debt	log Mortgage debt	log Mortgage debt
POST	0.0242***	0.0178***	0.00496***	0.00511***
	(0.00338)	(0.00243)	(0.00162)	(0.00157)
Treated	-0.0481*	-0.0402*	-0.00247	-0.00325
	(0.0247)	(0.0222)	(0.00730)	(0.00768)
POST × Treated	0.0345**	0.0284**	-0.00203	-0.00200
	(0.0158)	(0.0134)	(0.00471)	(0.00496)
Branches		-0.00223	0.00216	-0.00635
		(0.0416)	(0.0186)	(0.0206)
Rebranding				-0.0124***
				(0.00362)
POST × Rebranding				0.0137***
				(0.00235)
POST × Treated				-0.0338
				(0.0243)
POST × Rebranding × Treated				0.0295*
				(0.0153)
Contract characteristics	N	Y	Y	Y
Borrower characteristics	N	Y	Y	Y
Observations	65,107	63,665	60,068	123,723
R-squared	0.002	0.890	0.918	0.901

Standard errors clustered at the province level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: in columns (1) and (2) the dependent variable is the log amount of mortgage debt on contracts originated by the rebranding group. In column (3) the dependent variable is the is the log amount of mortgage debt on contracts originated by the competitor group. In column (4) the dependent variable is the log amount of mortgage debt on mortgage contracts originated by the competitor and the rebranding lender (both at the group level). Rebranding is a dummy equal to one for the lender implementing a rebranding strategy and zero for the competitor lender. $POST$ is a time dummy equal to one starting from the third quarter of 2018 and zero before. $Treated$ is a dummy variable equal to one for provinces provinces directly affected by the rebranding and zero for remaining unaffected provinces. Contract characteristics include mortgage amount, rate type and maturity. Borrower characteristics include age, gender, nationality, a dummy for past default and one for first-time borrowers. Data are quarterly.

Household Choice

Table 1.11: Multivariate regression: Household's choice of lender

VARIABLES	(1) High	(2) Medium	(3) Low	(4) High	(5) Medium	(6) Low
POST	-0.0769***	0.186***	-0.109***	-0.0815***	0.187***	-0.105***
	(0.0116)	(0.0169)	(0.0168)	(0.0116)	(0.0170)	(0.0169)
Treated	0.157***	-0.0185	-0.139**	0.155***	-0.0122	-0.143**
	(0.0391)	(0.0570)	(0.0566)	(0.0390)	(0.0572)	(0.0567)
POST × Treated	-0.117**	-0.154**	0.271***	-0.128**	-0.151**	0.279***
	(0.0523)	(0.0762)	(0.0758)	(0.0522)	(0.0766)	(0.0760)
Bin FE	Y	Y	Y	N	N	N
Observations	3,718	3,718	3,718	3,718	3,718	3,718
R-squared	0.041	0.066	0.041	0.021	0.034	0.012

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: High, Medium and Low are dummies defined according to the 2018 distribution of newly originated mortgage contracts, and reflect the current lender's ranking in terms of APR within bin. Bins are combinations of mortgage LTV, maturity and rate type. $POST$ is a time dummy equal to one starting from the third quarter of 2018 and zero before. $Treated$ is a dummy variable equal to one for provinces provinces directly affected by the rebranding and zero for remaining unaffected provinces. Data are quarterly.

Table 1.12: Household's probability of switching lender

VARIABLES	(1) Switching	(2) Switching	(3) Switching
POST	-0.0860***	-0.0633***	-0.0616***
	(0.0160)	(0.0164)	(0.0162)
Treated	-0.206***	-0.260***	-0.301***
	(0.0445)	(0.0538)	(0.0514)
POST × Treated	0.238***	0.243***	0.267***
	(0.0604)	(0.0604)	(0.0650)
Branches		-0.236	-0.220
		(0.147)	(0.138)
Bin FE	Y	Y	N
Bank characteristics	N	Y	Y
Borrower characteristics	N	Y	Y
Observations	3,236	3,145	3,145
R-squared	0.053	0.211	0.187

Standard errors clustered at the province level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The dependent variable is a dummy for indebted borrowers that originate a mortgage with a lender they have not borrowed from in the past 20 years. $POST$ is a time dummy equal to one starting from the third quarter of 2018 and zero before. $Treated$ is a dummy variable equal to one for provinces directly affected by the rebranding and zero for remaining unaffected provinces. $Branches$ is the lender's share of physical branches by province. Bins are combinations of mortgage LTV, maturity and rate type. Bank characteristics include size, capital ratio, liquidity ratio and NPL ratio. Borrower characteristics include age, gender, nationality, and a dummy for past default. Data are quarterly.

Table 1.13: Household's transition to cheaper lenders

VARIABLES	(1) Current Low	(2) Current Low	(3) Current Low	(4) Current Low	(5) Current Low	(6) Current Low
Previous High	-0.264**	-0.273**	-0.250**	-0.281**	-0.290**	-0.253**
	(0.0463)	(0.0481)	(0.0693)	(0.0542)	(0.0552)	(0.0618)
Previous Medium	-0.289***	-0.288***	-0.193*	-0.311***	-0.309***	-0.196*
	(0.0285)	(0.0233)	(0.0611)	(0.0322)	(0.0285)	(0.0634)
Branches	-0.170*	-0.0573	-0.0726	-0.154	-0.0510	-0.0689
	(0.0684)	(0.0635)	(0.0922)	(0.108)	(0.0726)	(0.0937)
POST		-0.0376	0.0209		-0.0251	0.0509
		(0.0401)	(0.0559)		(0.0406)	(0.0467)
Treated		-0.181*	0.0268		-0.200	0.00934
		(0.0769)	(0.0969)		(0.0963)	(0.122)
POST × Treated		0.172**	-0.0962		0.187**	-0.0901
		(0.0353)	(0.0888)		(0.0528)	(0.107)
Previous High × POST			-0.0219			-0.0444
			(0.0600)			(0.0466)
Previous High × Treated			-0.250*			-0.243*
			(0.103)			(0.0896)
Previous High × POST × Treated			0.215*			0.203*
			(0.0843)			(0.0781)
Previous Medium × POST			-0.145			-0.174
			(0.114)			(0.0998)
Previous Medium × Treated			-0.347*			-0.364*
			(0.123)			(0.133)
Previous Medium × POST × Treated			0.548**			0.586**
			(0.166)			(0.152)
Bin FE	Y	Y	Y	N	N	N
Bank chacacteristics	Y	Y	Y	Y	Y	Y
Borrower chacacteristics	Y	Y	Y	Y	Y	Y
Observations	3,145	3,145	3,145	3,145	3,145	3,145
R-squared	0.262	0.228	0.233	0.245	0.210	0.217

Standard errors clustered at the province level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The dependent variable is a dummy equal to one if the current lender is low-price and zero otherwise. High, Medium and Low are dummies defined according to the 2018 distribution of newly originated mortgage contracts, and reflect the current and previous lender's ranking in terms of APR within bin. Bins are combinations of mortgage LTV, maturity and rate type. $POST$ is a time dummy equal to one starting from the third quarter of 2018 and zero before. $Treated$ is a dummy variable equal to one for provinces directly affected by the rebranding and zero for remaining unaffected provinces. $Branches$ is the lender's share of physical branches by province. Bank characteristics include size, capital ratio, liquidity ratio and NPL ratio. Borrower characteristics include age, gender, nationality, and a dummy for past default. First-time borrowers are excluded. Category excluded is the previous lender with Low price ranking. Data are quarterly.

Table 1.14: Share of low-priced offers by the rebranding lender in treated provinces by bin

Bins	10 years maturity	15 years maturity	20 years maturity	30 years maturity
ARM with 50% LTV	100%	100%	80%	100%
FRM with 50% LTV	0%	0%	0%	20%
ARM with 60% LTV	100%	100%	80%	0%
FRM with 60% LTV	0%	0%	0%	0%
ARM with 80% LTV	100%	100%	80%	100%
FRM with 80% LTV	0%	0%	0%	20%
ARM with 85% LTV	100%	100%	100%	100%
FRM with 85% LTV	100%	100%	100%	100%

Note: Green cells are bins where the lender's price ranking is not constant across all offers. Blue cells are bins where the lender always makes low-price offers. Grey cells are bins where the lender is the only one making an offer. This are loans with LTV above 80 % are fairly uncommon because they are penalized by regulation, as banks that offer those kind of loans need to hold extra capital. *Source:* MutuiOnline.

Table 1.15: Household's choice of rebranding vs competitor lender (unconditional probability)

VARIABLES	(1) Rebranding	(2) Rebranding	(3) Rebranding	(4) Rebranding	(5) Rebranding	(6) Rebranding
High	-0.364***	-0.661***	-0.445*	-0.444***	-0.741***	-0.448
	(0.0336)	(0.0285)	(0.183)	(0.0345)	(0.0174)	(0.216)
Medium	0.183***	-0.429**	-0.319	0.152***	-0.441*	-0.277
	(0.0321)	(0.127)	(0.201)	(0.0316)	(0.150)	(0.209)
Treated	-0.309***	-0.620***	-0.237**	-0.396***	-0.709***	-0.237**
	(0.0585)	(0.0683)	(0.0470)	(0.0605)	(0.0496)	(0.0525)
POST	0.0250	-0.715***	-0.321**	0.0462*	-0.698***	-0.261**
	(0.0230)	(0.0469)	(0.0788)	(0.0246)	(0.0419)	(0.0639)
POST × Treated	0.119*	0.620***	0.252**	0.128*	0.666***	0.226*
	(0.0659)	(0.0757)	(0.0675)	(0.0734)	(0.0651)	(0.0751)
High × POST		0.766***	0.477**		0.791***	0.500**
		(0.0684)	(0.108)		(0.0519)	(0.128)
High × Treated		0.665***	0.407**		0.709***	0.406**
		(0.0688)	(0.0904)		(0.0496)	(0.114)
High × POST× Treated		-0.653***	-0.525**		-0.760***	-0.591*
		(0.0786)	(0.136)		(0.0682)	(0.201)
Medium × POST		1.203***	0.574*		1.195***	0.506
		(0.146)	(0.234)		(0.172)	(0.248)
Medium × Treated		0.608***	0.305**		0.632***	0.276**
		(0.0628)	(0.0613)		(0.0518)	(0.0794)
Medium × POST× Treated		-0.805***	-0.427**		-0.869***	-0.397**
		(0.0965)	(0.107)		(0.0611)	(0.121)
Branches			0.0711*			0.0764*
			(0.0297)			(0.0323)
Bin FE	Y	Y	Y	N	N	N
Bank chacacteristics	N	N	Y	N	N	Y
Borrower chacacteristics	N	N	Y	N	N	Y
Observations	3,718	3,718	3,718	3,718	3,718	3,718
R-squared	0.197	0.428	0.689	0.120	0.359	0.672

Standard errors clustered at the province level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The dependent variable is a dummy equal to one for mortgage contracts originated with the rebranding group and zero otherwise. High, Medium and Low are dummies defined according to the 2018 distribution of newly originated mortgage contracts, and reflect the current lender's ranking in terms of APR within bin. Bins are combinations of mortgage LTV, maturity and rate type. *POST* is a time dummy equal to one starting from the third quarter of 2018 and zero before. *Treated* is a dummy variable equal to one for provinces affected by the rebranding and zero otherwise. *Branches* is the lender's share of physical branches by province. Bank characteristics include size, capital ratio, liquidity ratio and NPL ratio. Borrower characteristics include age, gender, nationality, and a dummy for past default. First-time borrowers are excluded. Category excluded is the lender with Low price ranking. Data are quarterly.

Table 1.16: Household's choice of rebranding vs competitor lender (conditional probability)

	Old clients		Switchers	
	(1)	(2)	(3)	(4)
VARIABLES	Rebranding	Rebranding	Rebranding	Rebranding
High	-0.267***	-0.240***	0.0502	0.0264
	(0.0681)	(0.0714)	(0.0989)	(0.104)
Medium	-0.0576	-0.0597	0.0910**	0.0864**
	(0.0493)	(0.0456)	(0.0348)	(0.0354)
Time	0.122***	0.121***	-0.119***	-0.111***
	(0.0310)	(0.0299)	(0.0271)	(0.0259)
Treated	-0.181***	-0.204***	-0.338***	-0.329***
	(0.0456)	(0.0468)	(0.108)	(0.104)
POST × Treated	-0.0739	-0.0830	0.281***	0.276***
	(0.117)	(0.121)	(0.0976)	(0.0966)
Branches	0.0467***	0.0512***	0.0890***	0.0933***
	(0.0134)	(0.0139)	(0.0166)	(0.0169)
Bin FE	Y	N	Y	N
Bank chacacteristics	Y	Y	Y	Y
Borrower chacacteristics	Y	Y	Y	Y
Observations	2,164	2,164	1,554	1,554
R-squared	0.481	0.466	0.296	0.283

Standard errors clustered at the province level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The dependent variable is a dummy equal to one for mortgage contracts originated with the group implementing a rebranding strategy. Old clients are indebted borrowers with a previous lending relationship with the parent brand. Switchers are indebted borrowers that go to the parent brand for the first time since 2000. High, Medium and Low are dummies defined according to the 2018 distribution of newly originated mortgage contracts, and reflect the current lender's ranking in terms of APR within bin. Bins are combinations of mortgage LTV, maturity and rate type. $POST$ is a time dummy equal to one starting from the third quarter of 2018 and zero before. $Treated$ is a dummy variable equal to one for provinces directly affected by the rebranding and zero for remaining unaffected provinces. $Branches$ is the lender's share of physical branches by province. Bank characteristics include size, capital ratio, liquidity ratio and NPL ratio. Borrower characteristics include age, gender, nationality, and a dummy for past default. First-time borrowers are excluded. Category excluded is the lender with Low price ranking. Data are quarterly.

Price Dispersion

Across bins

Table 1.17: All sample

VARIABLES	Obs	Mean	Std. Dev.	Min	Max
Pre-Rebranding	169	.336	.019	0	1.04
Post-Rebranding	183	.324	.018	0	1.13

Table 1.18: Treated Provinces

VARIABLES	Obs	Mean	Std. Dev.	Min	Max
Pre-Rebranding	8	.470	.017	0.20	0.71
Post-Rebranding	8	.342	.206	0	0.661

Note: The tables summarize the quarterly standard deviation in the mortgage rate by province across all bins. Bins are combinations of mortgage LTV, maturity and rate type. Pre and post periods are the two quarters preceding and following the rebranding event. Treated provinces are those exposed to the subsidiary brand before the event and to the parent brand after. *Source*: TAXIA, CR and MutuiOnline.

Within bin

Table 1.19: All sample

VARIABLES	Obs	Mean	Std. Dev.	Min	Max
Pre-Rebranding	135	.096	.139	0	.562
Post-Rebranding	153	.076	.079	0	.415

Table 1.20: Treated Provinces

VARIABLES	Obs	Mean	Std. Dev.	Min	Max
Pre-Rebranding	8	.086	.141	0	.357
Post-Rebranding	8	.056	.083	0	.293

Note: The tables summarize the quarterly standard deviation in the mortgage rate by province holding bins constant. Bins are combinations of mortgage LTV, maturity and rate type. Pre and post periods are the two quarters preceding and following the rebranding event. Treated provinces are those exposed to the subsidiary brand before the event and to the parent brand after. *Source*: TAXIA, CR and MutuiOnline.

Table 1.21: Price Dispersion

VARIABLES	Obs	Mean	Std. Dev.	Min	Max
Between St. Dev.	352	.33	.18	0	1.13
Within St. Dev.	288	.09	.11	0	.56

Note: The table summarizes the quarterly dispersion in the mortgage rate by province across all bins (between standard deviation) and within the same bin (within standard deviation). Bins are combinations of mortgage LTV, maturity and rate type. Data refer to contracts originated in the period from 2018Q1 to 2018Q4. *Source*: TAXIA, CR and MutuiOnline. Note: The dependent variable is the average standard deviation in the

Table 1.22: Quarterly price dispersion by province

	(1)	(2)
VARIABLES	Between St. Dev.	Within St. Dev.
POST	-0.00259	-0.0187
	(0.0173)	(0.0193)
Treated	0.144**	-0.0102
	(0.0303)	(0.00826)
POST × Treated	-0.125**	-0.0110*
	(0.0278)	(0.00431)
Observations	352	288
R-squared	0.023	0.010

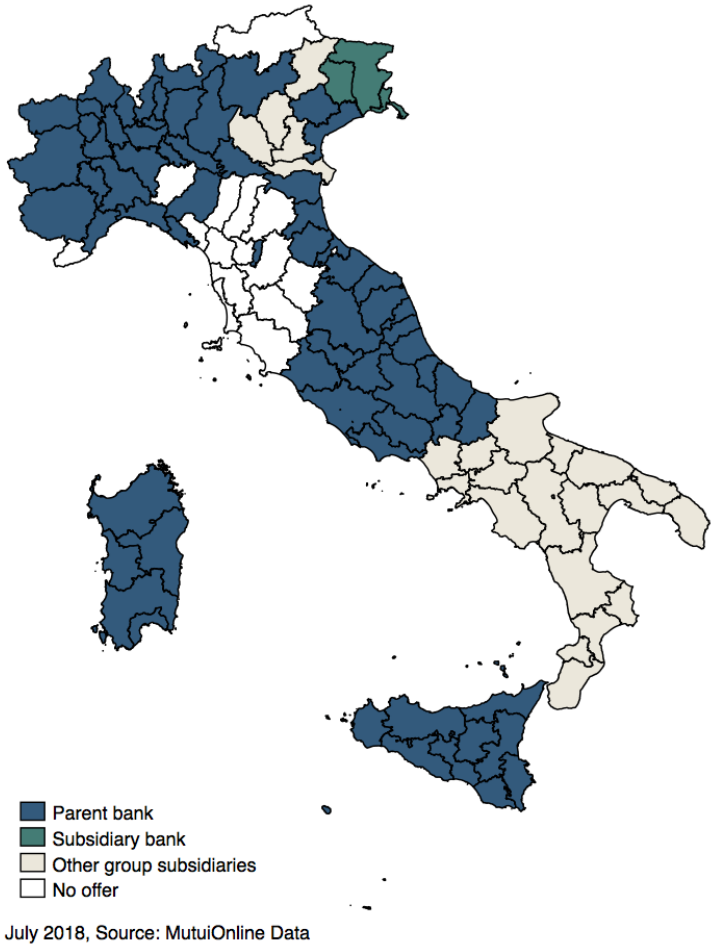
Standard errors clustered at the province level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

mortgage rate by province across all bins (column 1) and within the same bin (column 2). Bins are combinations of mortgage LTV, maturity and rate type. *POST* is a time dummy equal to one starting from the third quarter of 2018 and zero before. *Treated* is a dummy variable equal to one for provinces directly affected by the rebranding and zero for remaining unaffected provinces. *Branches* is the lender's share of physical branches by province. Data are quarterly.

1.7 Figures

Offering Policy

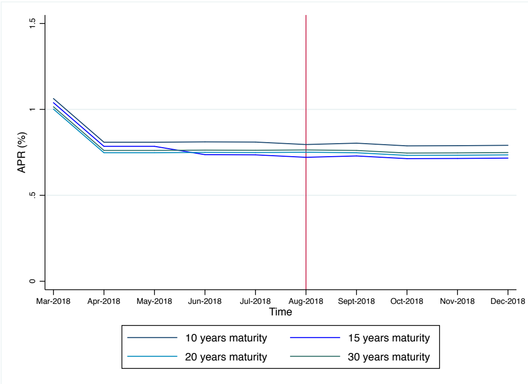
Figure 1.1: Product offers by banks belonging to the rebranding group



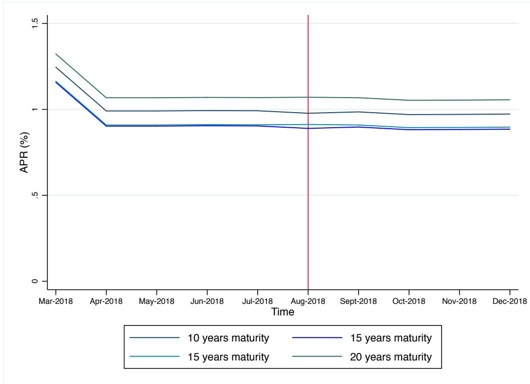
Note: The map shows product offered by individual banks belonging to the rebranding group in each province as of July 2018. A product is a combination of mortgage LTV, maturity and rate type, and there are 32 possible combinations in total. Each bank targets specific provinces with the same products and there is no geographical overlapping among them. Blue provinces are served by the parent bank with 32 out of 32 product offers. Green (treated) provinces are served by the subsidiary bank with 32 out of 32 product offers. Grey provinces are served by other subsidiaries of the group with 32 out of 32 product offers. White provinces are those with no online offer by the group (offers through the branch are still possible). *Source:* MutuiOnline.

Pricing Policy

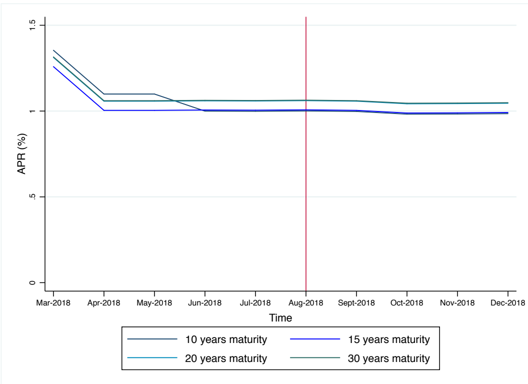
Figure 1.2: Pricing policy of the rebranding group: treated provinces



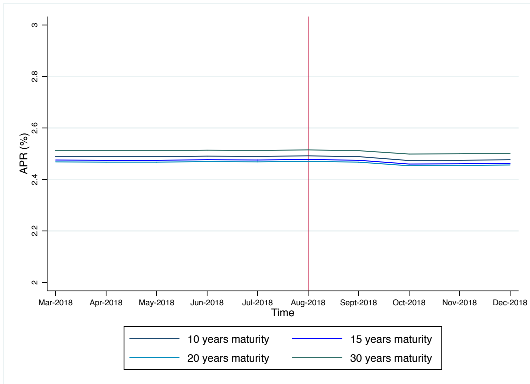
(a) ARM with 50% LTV



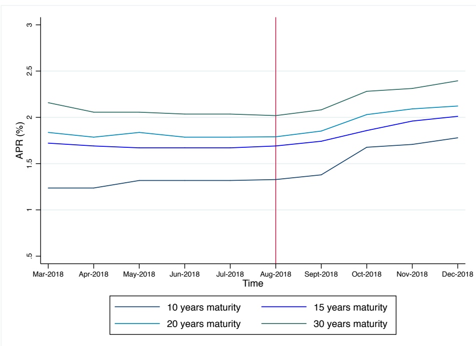
(b) ARM with 60% LTV



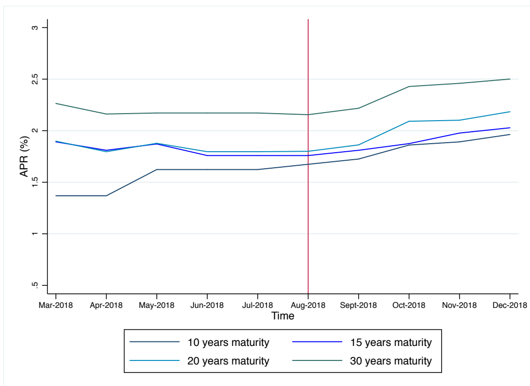
(c) ARM with 80% LTV



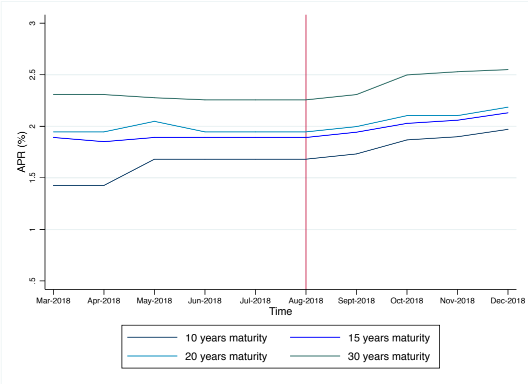
(d) ARM with 85% LTV



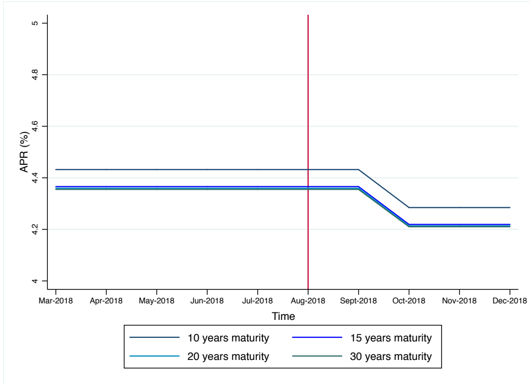
(e) FRM with 50% LTV



(f) FRM with 60% LTV



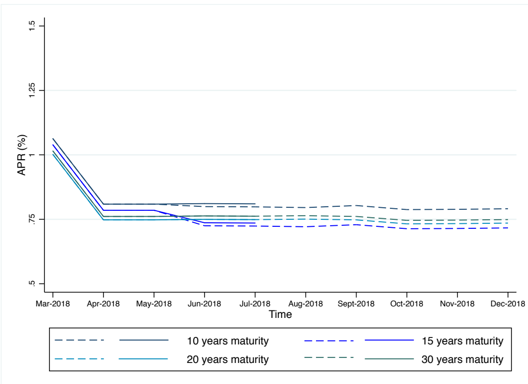
(g) FRM with 80% LTV



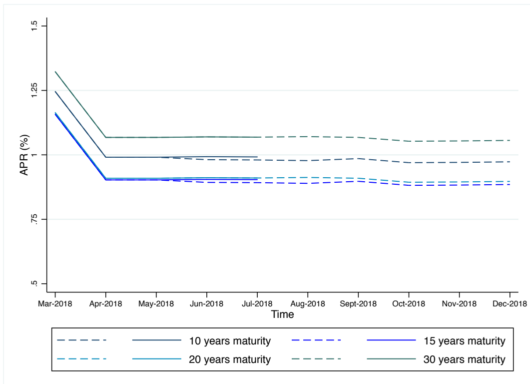
(h) FRM with 85% LTV

Note: The charts plot the APR offered by the rebranding group in treated provinces for different combinations of mortgage maturity, LTV and rate type. The red line denotes the month of the rebranding event. Treated provinces are those exposed to the subsidiary brand before the event and to the parent brand after. To the left of the red line, the chart displays the APR offered by the subsidiary brand. To the right, the APR offered by the parent brand. *Source:* MutuiOnline.

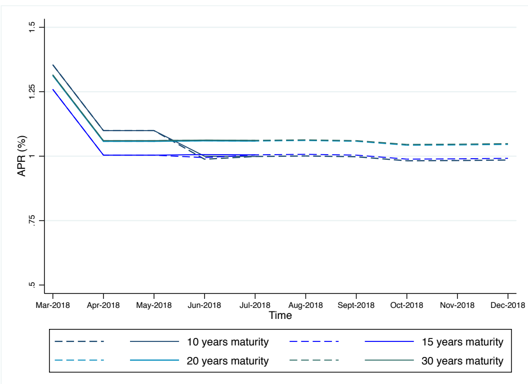
Figure 1.3: Pricing policy of the rebranding group: average across all provinces



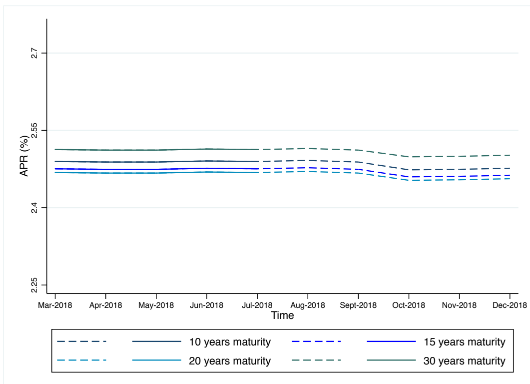
(a) ARM with 50% LTV



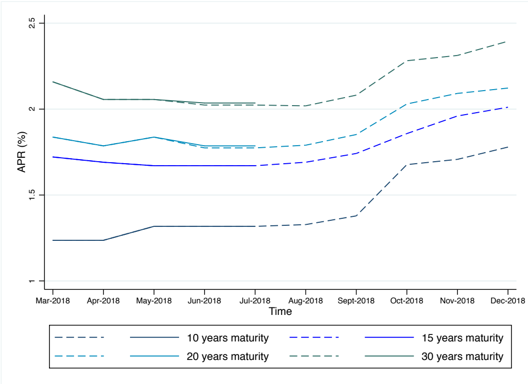
(b) ARM with 60% LTV



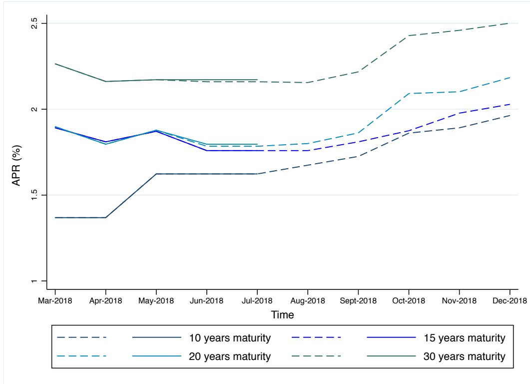
(c) ARM with 80% LTV



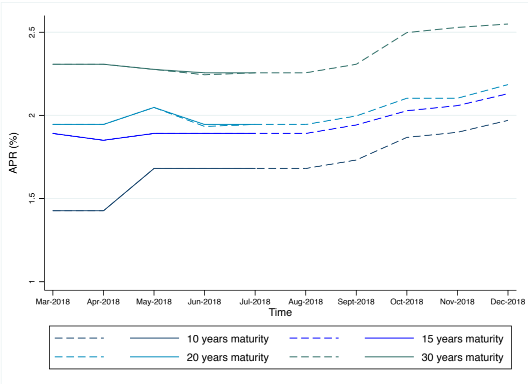
(d) ARM with 85% LTV



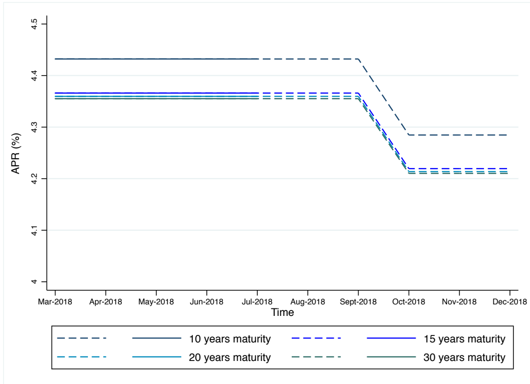
(e) FRM with 50% LTV



(f) FRM with 60% LTV



(g) FRM with 80% LTV

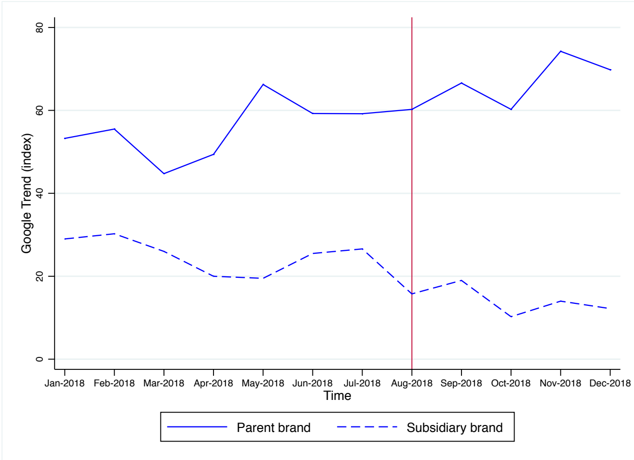


(h) FRM with 85% LTV

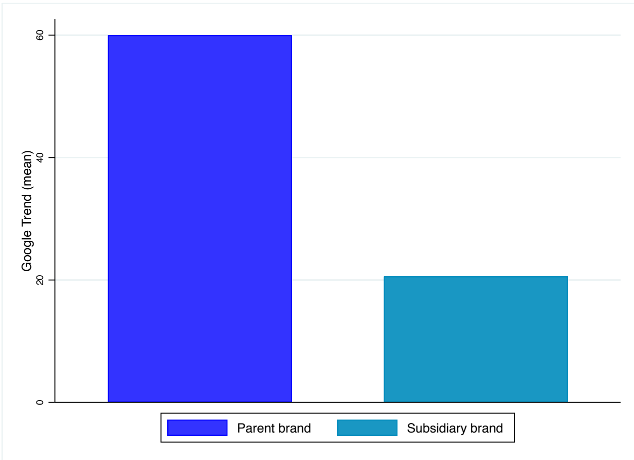
Note: The charts plot the average APR offered by the rebranding group across all provinces for different combinations of of mortgage maturity, LTV and rate type. The solid line is the average APR offered by the subsidiary brand, available until incorporation. The dashed line is the average APR offered by the parent brand, available throughout my observation sample. *Source:* MutuiOnline.

Google Trend Index

Figure 1.4: Treated Provinces



(a) Brand popularity over time

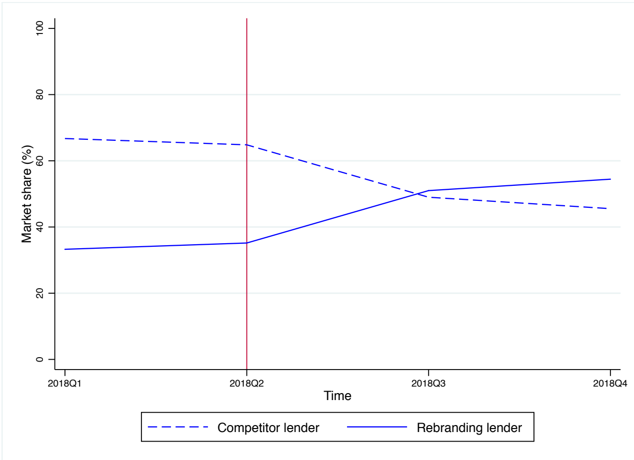


(b) 2018 average brand popularity

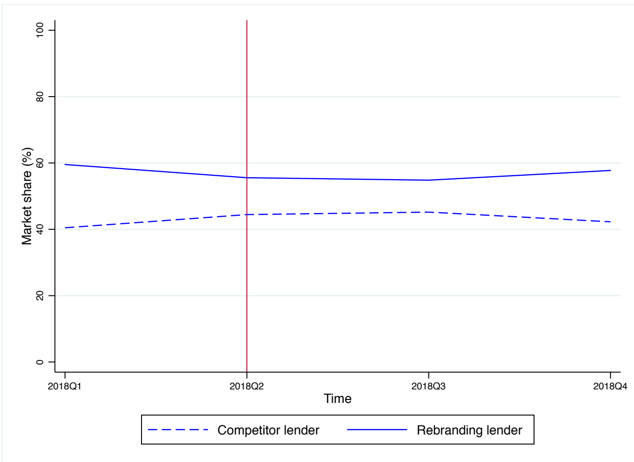
Note: The charts plot the index of individual search behaviour (Google Trend index) within Google browsers and YouTube for the parent and subsidiary brands in treated provinces, excluding repeated search from the same individual over close periods of time. The index measures relative brand popularity compared to the highest point: a value of 100 is the peak popularity of the term, a value of 50 means that the term is half as popular. Treated provinces are those exposed to the subsidiary brand before the event and to the parent brand after. Panel (a) shows the time series of the index from January 2018 to December 2018 in treated provinces. The red line denotes the month of the rebranding event. Panel (b) shows the 2018 average index value in treated provinces. *Source:* Google.

Market Share

Figure 1.5: Market share by lender and province



(a) Treated provinces

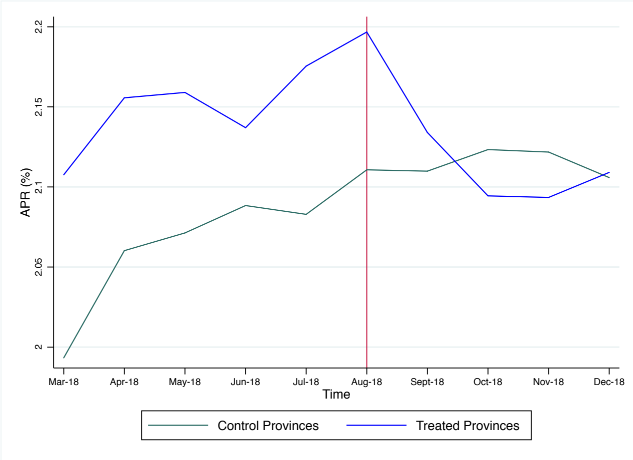


(b) Control provinces

Note: The chart plots the quarterly market share of the rebranding and the competitor lenders (both at the group level) in 2018. The red line denotes the quarter of the rebranding event. Treated provinces are those exposed to the subsidiary brand before the event and to the parent brand after. Control provinces are remaining unaffected provinces, exposed to the same brand before and after the event. Panel (a) shows the average market share of the two banking groups in treated provinces in each quarter of 2018. Panel (b) shows the groups' average market share in control provinces in each quarter of 2018. *Source:* TAXIA.

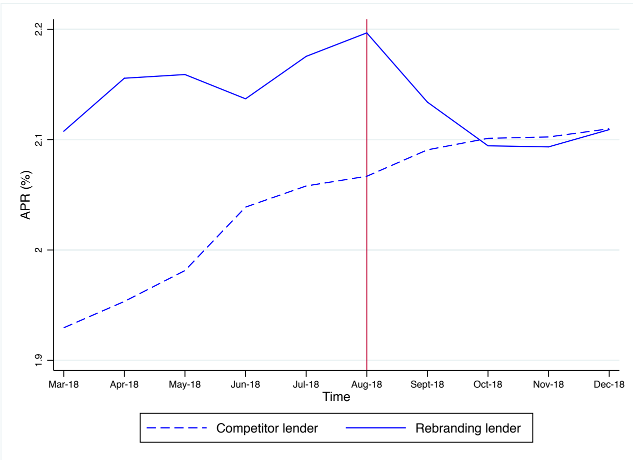
Equilibrium Mortgage Price

Figure 1.6: Visual inspection of parallel trend assumption



Note: The chart plots the APR on all new mortgage contracts originated by the rebranding group in treated and control provinces in the period from March 2018 to December 2018. The red line denotes the month of the rebranding event. The blue line denotes treated provinces, exposed to the subsidiary brand before the event and to the parent brand after. The green line denotes control provinces, exposed to the same brand before and after the event. *Source:* TAXIA and CR.

Figure 1.7: APR on originated mortgage contracts in treated provinces



Note: The chart plots the average APR on all new mortgage contracts originated in treated provinces by the rebranding and by the competitor lender (both at the group level) in the period from March 2018 to December 2018. The red line denotes the month of the rebranding event. Treated provinces are those exposed to the subsidiary brand before the event and to the parent brand after. *Source:* TAXIA and CR.

2. Households' choice of financial intermediary within a life-cycle model

2.1 Introduction

With the empirical evidence from the previous chapter in mind, we develop a theoretical framework to evaluate the value added of informative brands. We quantify the effect of brand name on consumers' search costs and households' transition across lenders within a life-cycle model. Our model is well calibrated to replicate main features of the Italian household sector and to match the level of dispersion in the price of mortgage products encountered in the data. We focus on previously indebted borrowers and their choice of either remaining with the current financial intermediary, or moving to a different one with a lower price.[1] Moving requires some initial searching effort and determines all the future streams of mortgage payments to be made by the borrower. More precisely, if the household puts zero effort (say, because time constraints or search costs are too high), she ends up paying mortgage instalments at a premium for the entire duration of the loan.[2] In each period, the household also makes consumption and portfolio choices under uncertainty about survival probabilities, income realizations and capital returns.[3] We compare two different scenarios. In the first one (no rebranding), households are exposed to the same brand before and after the event. In the second one (rebranding), households are exposed to the subsidiary brand before the event, and to the parent brand after. We rank intermediaries in terms of price (high, medium and low) and derive the transition matrices of borrowers across lenders with different rankings. Then, we let households reallocate from one intermediary to the

[1] Recourse to mortgage renegotiations has been recently increasing in Italy, after the introduction of regulatory incentives in 2008, and is about 17 per cent of new loans origination in 2018 (Attinà & Michelangeli 2020).

[2] The premium could reflect consumer's inertia, inattention, loyalty, lack of information or other search frictions (Delgado-Ballester & Munuera-Alemán 2001; Banerjee & Bandyopadhyay 2003; White & Yanamandram 2004; Lewis & Soureli 2006; Su 2009; De Clippel et al. 2014; Ericson 2014; Miravete & Palacios-Huerta 2014; Andersen et al. 2015; Matějka & McKay 2015; Seenivasan et al. 2016; Ho et al. 2017; Ozdemir et al. 2020).

[3] Including these sources of uncertainty is necessary to replicate within the model the limited share of households investing in risky assets that we observe in the data.

other according to the transition probabilities observed in affected provinces before (control scenario) and after (treatment scenario) the lender takes on a more popular name. Our calibration delivers initial values for borrowers' overpayments and search costs that match those of related studies for other countries.[4]

Following the event, the share of households that move to an intermediary with a lower price increases by more than 9 percentage points (from 16 per cent to roughly 26 per cent). For our model to replicate this figure, the corresponding decline in consumers' search costs amounts to 330 euro (or 0.3 per cent of the average Italian loan).[5] This lump-sum reduction captures the direct benefit for the household, namely time saved in searching for information and other monetary costs not incurred to visit the physical branch or to contact the bank's representative (say, by phone or mail). To get a comprehensive estimate of the total value added for the borrower, one should also include savings in the monthly instalments attained by moving to a cheaper lender and collected throughout the duration of the mortgage. Taking those into account, the household gains more than 6 per cent of the initial loan amount, equivalent to 7,200 euro for an average Italian mortgage contract. Moreover, price dispersion goes down more in treated than in untreated provinces, and the difference (1 basis point) is consistent with the treatment effect documented in the data.

Finally, our model delivers interesting results in terms of optimal investment choice. We find that, for a given level of consumption, investment in risky assets decreases as the search cost goes down. Hence, the rebranding has an impact on households' exposure to risk in the financial market too. This directly relies on the assumption that households are risk-averse and choose consumption as to limit tail-risk exposure.

[4]Bhutta et al. (2018) estimate a gap between the 10th and 90th percentile mortgage rate that US borrowers with the same characteristics obtain for identical loans equal to 54 bps, of which 26 bps (1.2% of the average US loan) are attributable to knowledge and shopping (search costs account for 0.9% of the average Italian loan in our model and they also lead to overpayment by the borrower). Allen et al. (2019) find that search frictions reduce consumers' surplus by 12 dollars a month in the Canadian mortgage market, and are for 50% attributable to search costs (this percentage is at least 30% according to our calibration).

[5]The average mortgage in Italy has 120,000 euro amount, 20-year maturity, 60% LTV and 200,000 euro house value.

Related literature. This paper contributes the theoretical literature on housing and portfolio choice within a life-cycle model (Campbell & Cocco 2015; Cocco 2005; Gomes & Michaelides 2005; Cocco et al. 2005). We study households' choice of financial intermediary, while accounting for their contemporaneous choice over consumption and risky assets. To model households' uncertainty about future income and asset returns, we build on Barro (2006) analysis of rare disasters during the 20th century, and Alan (2012) and Liu et al. (2003) solution of the asset allocation problem in the presence of tail risks. We complement existing approaches in household finance that study the determinants of mortgage choice under the assumption that the resulting contract reflects households' preferences (Mian & Sufi 2011; Hall & Woodward 2012; Fuster & Vickery 2013; Campbell & Cocco 2015; Foá et al. 2015; Hurst et al. 2016). In doing that, we are the first to exploit data on product offers from an online broker (the only source of information on the mortgage loan-to-value currently available in Italy) as to account for variability in the equilibrium mortgage price associated with the loan-to-value. This paper relates to the literature on price dispersion too. Among other papers, Allen et al. (2019) develop a search and negotiation model to quantify the role of search costs and brand loyalty for market power; Allen et al. (2014a) show that price dispersion in the credit market reflects consumer bargaining leverage; while Allen et al. (2014b) relies on reduced-form techniques to argue that mergers reduce price dispersion in the Canadian mortgage market.

The rest of the paper is organized as follows. Section 2.2 summarizes some stylized facts of the italian mortgage market. Section 2.3 outlines the model. Section 2.4 describes the solution method and illustrates the parameterization. Section 2.5 presents the results. Section 2.6 concludes.

2.2 The Italian Mortgage Market

Mortgages represent the main source of liability of Italian households, accounting for over 50 per cent of their financial debt. They are almost entirely granted by banks, for a total amount of about 385 billion euros in 2018, while other financial intermediaries tend not to participate to this market at all. Default on mortgage contracts are not very common in Italy. Following the financial and sovereign debt crises, the share of new mortgages granted to borrowers at higher risk of default decreased significantly, reflecting both demand and supply factors. On one side, banks selectivity in granting mortgages increased; on the other, demand from high-income households broadened. Based on latest available data from the Center of Risks in Financial Intermediation (CRIF), the share of risky borrowers is equal to 3 per cent, about 8 percentage points less than in 2012. The mean loan-to-value (LTV) is around 65 per cent according to the Regional Banking Lending Survey (RBLS), slightly higher than the average value (less than 60 per cent) recorded in the period 2012-16. New loans with LTV above 80 per cent account for less than 10 per cent of the total; these loans are penalized by regulation as banks must detain extra capital in order to grant them. Average mortgage length is 22 years and around 20 per cent of new loans have duration above 30 years. Adjustable-rate mortgages (ARM) account for the majority of outstanding loans (around 60 per cent), although they are less common now than in the past. The share of new fixed-rate mortgages (FRM) has significantly increased in recent years, also thanks to the low-rate environment, and has reached about 70 per cent in 2018 (25 per cent in 2012). Other mortgage typologies (mixed-rate mortgages, adjustable rate mortgages with a cap, mortgages allowing to reset the interest rate) are very rare or unavailable. One notable fact about the Italian mortgage market is that since 2008, with the so called Bersani Law, households are allowed to modify their contract terms and, specifically, they can reduce their mortgage instalments without paying any additional extra costs. This lead to an acceleration, particularly pronounced since 2015, in the recourse to mortgage renegotiations, which reached 17 per cent of the new loans origination in 2018. (Attinà & Michelangeli 2020).

2.3 The Model

2.3.1 Model assumptions

We model households' choice of financial intermediary upon taking a new mortgage to quantify the impact of brand name on consumers' search costs. We restrict the analysis to indebted households with an already established relationship with a lender, and we exclude first-time borrowers. The former are the ones facing the highest costs of switching to a new intermediary, and are naturally more inclined to accept higher mortgage rates. When taking a mortgage (which could be a refinancing of a previous loan, as well as a new loan for house purchase), the household can either remain with the current lender, or put effort to find a cheaper one. This effort choice entails some initial search costs and affects the household's life-time savings accumulation and consumption levels.

The timing of the events is as follows. The household enters at period $t = 40$, observing her cash-on-hand and her current period financial intermediary, and makes her effort choice. In the initial period, she can decide to take a new mortgage from her current financial intermediary, or to exert positive effort in looking for a new one that offers a cheaper price. In all the subsequent periods, for the entire duration of the mortgage, the household pays a mortgage instalment that depends on her initial choice of the financial intermediary. In each period, the household also chooses consumption C_t and the fraction of the remaining cash-on-hand to invest in the risky asset α_t. After those decisions are made, shocks to risky assets' return, labor income and survival probability are realized, and next period wealth is determined.

In the baseline model, we assume that the house value is fixed at 200.000 euro, the LTV equals 60%, the maturity is 20 years (which capture the median values in Italy), and the mortgage rate type is fixed (around 80% of new Italian mortgages are fixed-rate).

Household's Preferences. Let $S_{it} = \{X_{it}, H_{it-1}\}$ denote the household vector of state variables, where $t = 40, ..., T$ is household's age and T is set to 100; $X_{it} = W_{it} + Y_{it}$ is cash-on-hand, which includes wealth at the beginning of period t and labor income; H_{it} is the household's financial intermediary. Households' preferences are described by a standard CRRA utility function in consumption and the household maximizes her expected lifetime utility:

$$U(C_it) = \frac{C_{it}^{1-\gamma}}{1-\gamma} \tag{2.1}$$

where γ is the coefficient of relative risk aversion. In the final period, the household consumes all her wealth and does not receive any utility from leaving a bequest to her heirs.

Household's Income. We follow the labor income process in Cocco, Gomes, and Maenhout (2005). Before retirement, household i's labor income, Y_{it}, is exogenously given by:

$$log(Y_{it}) = f(t) + v_{it} + \epsilon_{it} \tag{2.2}$$

where t indexes the household's age, $f(t)$ is a deterministic function of age, ϵ_{it} is an idiosyncratic temporary shock distributed as $N(0, \sigma_{\epsilon}^2)$, and v_{it} is given by:

$$v_{it} = v_{it-1} + u_{it} \tag{2.3}$$

where u_{it} is distributed as $N(0, \sigma_u^2)$ and it is uncorrelated with ϵ_{it}. Hence, log labor income is the sum of a deterministic component, which is calibrated to replicate hump-shaped earnings over the lifecycle, and two random components, one transitory and one persistent. Retirement income is a constant fraction of permanent labor income in the last working-year.

Financial assets. There are two financial assets. The first one is a riskless asset with gross real return $R_F = 1 + r_F$. The second one is a risky asset with gross real return $R_t = 1 + r_t$. As in Cocco, Gomes, and Maenhout (2005), the excess premium, namely the difference between the gross real return on the risky asset and the gross real return on the safe asset, is:

$$R_{t+1} - R_F = \mu_r + \iota_{t+1} \tag{2.4}$$

where μ_r is the mean excess premium and ι_{t+1} is the innovation to the excess premium distributed as $N(0, \sigma_{\iota}^2)$. B_t and S_t denote the amount of safe and risky assets held by the household at time t, such that:

$$S_t \geq 0, B_t \geq 0, \forall t. \tag{2.5}$$

Equation 2.5 implies that the household cannot short-sell any of these assets.

2.3.2 The Household's Optimization Problem

In the first period, the household takes the effort choice decision. If she exerts positive effort ($e > 0$), the Bellman equation is:

$$V(S_{it}, e > 0) = \max_{C_{it},\alpha_{it}} U(C_{it}) + \beta sp(it+1)E_t V(S_{it+1}) \tag{2.6}$$

where next period wealth is given by:

$$W_{it+1} = R_{t+1}(W_{it} + Y_{it} - C_{it} - M(H_{it}) - Q) \tag{2.7}$$

$M(H_{it})$ is the mortgage instalment that depends on the financial intermediary, which here is the one offering the lowest price; Q reflects the search costs that are paid only in the initial period, including those to get information on the lender; β is the discount factor; and $sp(it+1)$ the survival probability at age t. If she exerts zero effort ($e = 0$), she remains with the previous financial intermediary, the search costs are equal to zero and the Bellman equation boils down to:

$$V(S_{it}, e = 0) = \max_{C_{it},\alpha_{it}} U(C_{it}) + \beta sp(it+1)E_t V(S_{it+1}) \tag{2.8}$$

where next period wealth is given by:

$$W_{it+1} = R_{t+1}(W_{it} + Y_{it} - C_{it} - M(H_{it})) \tag{2.9}$$

Moreover, the following conditions always hold:

$$C_{it} \geq C_{min}, 0 \leq \alpha_{it} \leq 1 \tag{2.10}$$

meaning that household's consumption must be positive and above a minimum level, and the share invested in risky assets must be in between 0 and 1. In the initial period, the households chooses the effort level that delivers the maximum between $V(S_{it}, e > 0)$ and $V(S_{it}, e = 0)$. In the following periods until maturity, the household chooses consumption and the share of portfolio to invest in the risky asset, subject to uncertainty over survival, income and returns on financial assets.

2.4 Solution Method

The model is solved using numerical techniques (Judd 1998). Specifically, we rely on value function iterations starting from the final life period and moving backward until age 40. In the last period, a terminal value function is obtained for each combination of the state variables. That function acts as a continuation value function. In each previous period and for each vector of state variable, the household chooses her consumption and share of risky assets. As consumption and portfolio choices are continuous variables, we use cubic spline interpolation to evaluate the function outside the grid. Mortgage instalments are fixed for the mortgage duration and depend on the price ranking of the bank. In the initial period, the household makes a discrete choice over effort: she can exert positive effort and choose the financial intermediary that offers the lowest price, or she can exert zero effort and remain with the current financial intermediary. This effort decision depends on the maximum value of the value function associated with each grid point of the vector of state variables in the initial period. We implement grid search to select over the possible choices and rely on the quadrature based method (Tauchen & Hussey 1991) to approximate the return on risky assets. We also include a small probability for the event risk. Once the model is solved and the policy functions are obtained, we simulate 3,000 households of age 40 and we use the computed policy functions to obtain households' choices over time.

2.4.1 Parameterization

We draw from several data sources to select parameter values used in the model (see Table 2.1). We use the Survey on Household Income and Wealth (SHIW) from the Bank of Italy for mortgage characteristics and income;[6] ISTAT for survival probabilities and minimum consumption;[7] OECD for replacement rates and for computing equivalent consumption; Mediobanca for return on risky assets;[8] Credit Register and MutuiOnline (CR-MO) data for mortgage rate offered by banks with different price ranking.[9] We exclude first-time borrow-

[6]See bancaditalia.it
[7]See ISTAT.it
[8]See Mediobanca.com
[9]CR-MO is obtained from CR data merged with MO data. Access to CR and MO databases is described in chapter 1, Section 1.2.2.

ers and restrict the sample to individuals older than 40 years as to capture indebted households looking for a new mortgage. As mortgage choices and subsequent payment of the instalments typically occur during the household's working age, we abstract from considerations about retirement medical costs, moving costs, and bequest preferences. The final SHIW sample consists of about 2,500 households, which we combine with the matched CR-MO dataset to compare empirical evidences with our model predictions.

Preference and demographic parameters. Following standard values in the literature of portfolio choice, we fix the risk aversion parameter γ to 5 and the discount factor to 0.96. The bequest parameter θ is set to zero, and households are assumed to consume all their wealth before dying. Survival probabilities are based on ISTAT data and refer to the average values for the Italian population in each year.

Income. We use SHIW data to estimate Equation 2.2, according to which household labor income is given by a function of age and income shocks. Labor income includes working income, workers compensation and transfers, but not capital income. We carry our estimation on the sample of indebted households aged 40 to 65, without distinguishing them based on their education level or marital status. This because around 80% of households in our sample have high school degree and are married, thus if we were to split by education or marital status the estimation would count on a very limited number of observations. We estimate the parameters for the variance of the persistent and the transitory shock using the approach described in Blundell et al. (2008). Households retire at age 65. The replacement rate is taken from OECD data and equals 91.8%.[10]

Financial markets. We define as safe assets the sum of deposits and short-term government bonds, and as risky assets other bonds, stocks, managed assets, foreign bonds, and residual assets. For the return on the risky assets, we use Mediobanca data since 1950. We compute the real stock return starting from the index of total stock return deflated by the consumer price index, while the return on safe assets is computed using the nominal return on Italian

[10]This implies that after retirement households receive a constant annual income equal to 91.8% of their income in the last working period.

one-period bonds (BOT) deflated by the consumer price index to obtain real returns. The excess premium is given by the difference between the real return on risky assets and the real return on safe assets in each period. The mean return on safe assets is $r_F = 0.012$, the mean excess premium μ is 0.049, and the standard deviation of the innovation to excess premium σ_ι is 0.26. We define as event risk a rare event that has a low probability of happening, but to which is associated a significant reduction in the return of risky assets. We assume that when the event risk occurs, the stock return equals its mean minus two-standard-deviation, which corresponds to a stock return lower than -40%. To assess the validity of this assumption, we consider two datasets covering the years between 1950 and 2010: *"Indice Annuale dei corsi della Borsa Italiana"* by Mediobanca, and the "Milan Comit Global - DS Total Return Inde" (DSRI). The probability of an event risk is assumed to be equal to 0.05.

Consumption floor. According to ISTAT data, the level of absolute poverty varies according to both the number of household's components and the geographic area. Among households aged 18 to 59, it ranges from a minimum of about 600 euro per month for a single household living in the South, and a maximum of about 1,150 euro per month for a married couple living in the North.[11]. To capture this heterogeneity, we assume a minimum consumption floor C_{min} of about 850 euro per month

Financial intermediaries and price of mortgages. We focus on characteristics of the average mortgage in Italy. Based on SHIW data, the average LTV is 60% and the average mortgage amount is 120,000 euro (which implies a house value of 200,000 euro). We consider three types of financial intermediaries classified according to their price ranking: Low, Medium and High, to which the model imputes their respective offered mortgage rate as taken from the CR-MO dataset. We consider the average rate for fixed-term contracts with LTV less than or equal to 60% and 20 years maturity, which reflects a safe profile. Within this bin (or combination of LTV, maturity and rate-type), we observe some degree of price dispersion: the low rate equals 1.87%, the middle rate equals 2.03%, the high rate equals 2.37%. We exploit the French amortization formula, quite standard in Italy, to compute the mortgage instalments associated to each of the three types of lender over the duration of the

[11] Data from "La misura della povertá assoluta," ISTAT 2018, adjusted for inflation.

mortgage. Households are not allowed to change bank after the first period, which is a reasonable assumption to make as we are not considering changes in the interest rates at the macro level. Households at age 40 have all the necessary information to make a choice that would affect their future lifetime.

2.5 Model results

We evaluate predictions of our model against real data, and we quantify the search costs paid by the households before and after the rebranding event.

The main statistics for the Italian economy are reported in Table 2.2. As initial condition, we assign households to three types of financial intermediaries (High, Medium or Low offered price) according to their pre-rebranding distribution from the CR-MO dataset: almost 33% of households have a low-price lender, 45% of them have a medium-price one, and the remaining 22% have a high-price one. For statistics on labor income, annual consumption and portfolio choices we rely on SHIW data. The model is able to deliver median values for annual income and annual consumption that closely mirror those observed in the real data: annual labor income is just above 30 thousand euro, annual consumption is around 28 thousand euro. To mirror true data on the share of households with risky assets, we account for tail risks in their return. This makes risk-averse households less inclined to take on risky investments and delivers a share of around 20 percent, in line with the one observed in the data. A model without tail risks would convey a much higher share because the average return on the risky asset exceeds the one on the safe asset.

We use the model to predict our two main variables of interest: the degree of dispersion in the price of homogeneous mortgage contracts (measured as the standard deviation in the mortgage rates) and the search costs faced by the household when choosing a financial intermediary. We exploit borrowers' transition matrices across lenders derived from our combined CR-MO dataset, which reflect the household's probability to either remain with her time $t = 0$ lender, or to move to a better one at time $t = 1$. One obvious difficulty is to identify better and worse lenders. In fact, some households might value more non-financial conditions (such as speediness) than financial ones; while some others might be rationed by all banks but the chosen one. In this paper, we abstract from reasons that could induce households to move to a more expensive intermediary, and we assume that less expensive products are, all else equal, better products from a rational consumer in an economy without frictions. Hence, households with a low-price intermediary never switch.[12] Our model delivers a standard deviation of 23 bps, which is consistent with the value observed in the data before any rebranding event occurs (24 bps). Table 2.3 presents our main results.

We consider two different scenarios. The first one ("no rebranding") captures what happens in untreated provinces, under the assumption that they are comparable with treated ones before the rebranding.[13] To calibrate search costs, we let households reallocate according to the transition matrices observed in treated provinces before the event: about 50% of them does not move; while almost 17% switches to a low-price lender. The initial amount of search cost consistent with this reallocation is 1080 euro (0.9% of the average loan amount), similar to the estimates provided by Bhutta et al. 2018 for the US.[14] Price dispersion decreases to 19 bps. The second scenario ("rebranding") captures what happens in provinces affected by the shift in brand popularity, where households reallocate from one intermediary to the other according to the transition matrices observed in treated provinces after the event. Price dispersion decreases from 23 bps (initial value at time $t = 0$) to 18 bps (post-treatment value at time $t = 1$). Both values very much replicate the ones observed in the data (price dispersion in treated provinces is about 24 bps before the rebranding, and 19 bps after). The share of households that do not move shrinks to 40%, and the share of those moving to a cheaper lender exceeds 25%. The search cost consistent with this reallocation drops by 30 per cent, to 750 euro, which conforms to previous findings by Allen et al. (2019).[15] By comparing the above two scenarios, we can also quantify the treatment effect in consumers' search costs and price dispersion due to the rebranding. According to the model, branding leads to a 330 euro decrease in search costs paid by the household at the beginning of the period. This accounts for potential transportation costs to visit a branch, other financial outlays sustained to get information on a new lender (for example, phone calls or interned), non-

[12] This is not a very strong assumption: according to CR-MO data, only a minor share of households move to a lender offering a higher price than their current one.

[13] This is the closest possible to a parallel trend assumption and allows for homogeneity within our model.

[14] They estimate upfront costs for the borrower attributable to shopping or knowledge equal to about 1.2% of an average loan.

[15] They find that 50% of search frictions are specifically due to search costs.

monetary costs (search effort, time devoted to shopping around, inconvenience experienced to avail a product, and psychology costs like the fear of rejection), while it does not include savings accrued from lower monthly payments also attained when shifting to a cheaper lender. Counting them in would lead to a total benefit for the household of 6% of the initial loan amount, corresponding to more than 7200 euro.[16] Moreover, the standard deviation in the APR goes down both in treated and untreated provinces, but the decrease is more pronounced (precisely by 1%) in treated ones, consistently with our previous empirical findings on the treatment effect of brand name on price dispersion.

As a corollary of our model, we show that households choosing low-price intermediaries have, on average, higher income (in line with what emerges from the the SHIW). Among households that switch to a lower price-ranking lender, we record a 9% reduction in the share of those investing in risky assets. This happens because households are risk-averse, and prefer to attain their target level of consumption by limiting tail-risk exposure, which implies a reduction in investor's riskiness at the aggregate level.

2.6 Conclusion

We derive a life-cycle model that accounts for households' choice of financial intermediary. Our model is well calibrated on Italian data and quantifies a decline in consumers' search costs following the rebranding equal to 330 euro, which does not contradict previous results. Adding in the savings from lower mortgage instalments for borrowers that move to cheaper lenders, whose share after the rebranding increases by roughly 10 per cent, the total gain for the household amounts to 6 per cent of the average Italian loan. Also, the rebranding event affects households' portfolio choice by limiting risk exposure in the financial market. We conclude that brand awareness brings new clients to lenders that are more price competitive, and reduces the extent to which borrowers overpay relative to the rates available on the market.

[16] Estimates are obtained considering moving from a High to a Low price, i.e. from 2.36% to 1.87%, for a 20 year maturity mortgage with 60% LTV and 200,000 house value, in line with empirical evidence from the SHIW.

2.7 Tables

Table 2.1: Parameterization

Description		Parameter value	Source
Coefficient of relative risk aversion	γ	5	Gomes & Michaelides (2005)
Discount factor	β	0.98	Campbell & Cocco (2015)
Bequest factor	θ	0	Cocco et al. (2005)
Retirement age	K	65	Cocco et al. (2005)
Labor income - Age polynomial	Constant	5.0039	SHIW
	Age	-0.13743	SHIW
	$\text{Age}^2/10$	0.03486	SHIW
	$\text{Age}^3/100$	-0.00271	SHIW
Variance permanent labor income shock	σ_e	0.0166	SHIW
Variance transitory labor income shock	σ_u	0.0220	SHIW
Replacement rate (%)		91.8	OCSE
Return on risk free asset	r_f	1.012	Mediobanca
Excess return	μ	0.049	Mediobanca
Std. dev. return on risky assets	σ_r	0.0784	Mediobanca
Tail risk		- 2 σ_r	Mediobanca
Pr(tail risk)		0.05	Mediobanca
Rate on consumer credit	r	1.08	ECB
House value (median, euro)		200,000	SHIW
LTV (median, %)		60	SHIW
Mortgage maturity (median, years)		20	SHIW
Mortgage rate (%)	Low	1.87	CR-MO
Mortgage rate (%)	Medium	2.03	CR-MO
Mortgage rate (%)	High	2.37	CR-MO

Note: The table reports the parameter values assumed in the model and their source.

Table 2.2: Main statistics for the economy

	Data	Model	Data Source
Initial conditions:			
Share of HHs by type of lender (%)			
Low price	32.4	32.4	CR-MO
Medium price	45.1	45.1	CR-MO
High price	22.4	22.4	CR-MO
Price dispersion (%)	0.24	0.23	CR-MO
Labor income (median, thousands euro)	31.9	30.1	SHIW
Annual consumption (median, thousands euro)	27.6	28.2	SHIW
Share of HHs with risky assets (%)	18.4	18.7	SHIW

Note: The SHIW sample consists of indebted households in their working period (40-65 years old). SHIW data include the 2002-2016 waves.

Table 2.3: Model results

	Data	Model	Data Source
No rebranding (untreated provinces)			
Transition matrixes			
- HHs that remain with previous lender (%)	49.6	50.9	CR-MO
- HHs that move to cheaper lender (%)	16.0	16.7	CR-MO
Search costs (euro)		1080	
Price dispersion (%)		0.19	
Rebranding (treated provinces)			
Transition matrixes			
- HHs that remain with previous lender (%)	40.4	39.7	CR-MO
- HHs that move to cheaper lender (%)	25.4	27.8	CR-MO
Search costs (euro)		750	
Price dispersion (%)		0.18	
Delta (*Rebranding* − *No rebranding*)			
Search costs (euro)		330	
Price Dispersion (%)	-0.01	-0.01	CR-MO

Note: The Table reports the model results for transition matrices, price dispersion and search costs. The last two rows (Delta) capture the treatment effect of rebranding, that is the differences in price dispersion and search costs between the “no-rebranding" and “rebranding" scenario.

3. What can we learn about mortgage supply from online data?

3.1 Introduction

Over the past years, a new type of information brought about by digitalization, the so-called *Big Data*,[1] has become available in large amount to support policymaking (Edelman 2012; Einav & Levin 2013). A key advantage of datasets obtained from digital sources, as compared to traditional ones, is that they are often very timely and very granular. This makes them extremely useful for up-to-date assessments of the impact of economic policies.

We exploit data on mortgage supply from the major online broker in Italy, MutuiOnline, to analyse the evolution of mortgage supply by risk-profile.[2] From a financial stability perspective, this allows to monitor banks' risk taking behaviour over time, and to evaluate changes in their incentive to engage in risky lending following the implementation of regulatory policies. It also uncovers systematic differences between the supply policy of online versus traditional banks. Furthermore, we present the first application of online data to nowcast mortgage rates. By relying on both standard regression analysis and machine learning algorithms, we asses the extent to which online prices improve short-term prediction of the realized interest rate. The nowcasting exercise is particularly informative for monetary policy. It provides policymakers with an estimate of the actual rate months before before this becomes available, thus allowing for a timelier assessment of the transmission of changes in policy rates to lending supply conditions. Previous papers have used information from web to nowcast, and forecast at longer horizons, other economic indicators, including unemployment (Fondeur & Karamé 2013; Vicente et al.

[1]The term Big Data refers to "the massive volume of data generated by the increasing use of digital tools and information systems" (FSB, 2017; Tissot 2017). They are "unstructured data resulting from non-statistical activity or structured data that create operational challenges owing to their size or complexity" (Cœuré 2017; Nymand-Andersen 2015).

[2]Data have been provided free of charge by MutuiOnline.it for research purposes at the Bank of Italy. They refer to fictitious customer profiles and contain no personal confidential information. Use of privately own data for research purposes does not imply the endorsement of the owner, its products or services.

2015; D'Amuri & Marcucci 2017), housing demand (Pangallo & Loberto 2018) and local economic activity (Glaeser et al. 2017).

Our database covers over 30 lenders (including the largest banks in the country) and about 85,000 borrower profiles. The 85,000 profiles are fixed over time and adjustments in the offer rates entirely reflect the bank's lending choice. Differently from studies based on the equilibrium rate, our analysis is immune from demand side biases and the associated endogeneity problems arising either from borrowers' self-selection into specific banks, or from discouraged borrowers that choose not to apply (Michelangeli & Sette 2016). In fact, by holding the demand constant, we can fully isolate changes in the supply. Moreover, compared to traditional statistics accessible for the Italian mortgage market, MutuiOnline data (MO) are more attractive in terms of both granularity and frequency of the information provided: they represent the only source of information on the mortgage loan-to-value (LTV) currently available in Italy, and they are available about 50 days before the release of official bank-level interest rate statistics (MIR).[3] Data are collected on a monthly basis within the 10th day of each reference month, in line with the timing of mortgage pricing decisions (typically taken at the beginning of each month).

Our main results are the following. First, risky profiles (characterized by higher LTV, longer maturity and lower borrower's income) face both systematically higher offer rates and fewer contract offers compared to other, less risky, profiles. This could mean that banks' actually price risk correctly. By comparison, online banks charge lower prices and serve a larger share of profiles than traditional ones. Second, online data are powerful in nowcasting official fixed mortgage rates contracts (the currently most used contract in Italy), also controlling for time-varying demand conditions (lagged values of the consumer confidence index), the market reference rate (10-year interest rate swap, IRS), and unobserved time-invariant bank characteristics. Using a machine learning algorithm we show that the main predictor for the delta in the realized fixed rate is the contemporaneous change in the online offer rate attached to a low-risk profile. This suggests that fixed-rate mortgages are typically chosen by safer borrowers and, more broadly, that online mortgage data are important for a prompt assessment of changes in household financing conditions.

[3]MFI Interest Rate (MIR) are euro area harmonized statistics.

Related Literature This paper relates to the growing body of research that uses unconventional data to back traditional statistics and get a better understanding of economic phenomena (Granello & Wheaton 2004; Ettredge & Karuga 2005; Cavallo 2017; Basten et al. 2018; Bhutta et al. 2018; Fuster et al. 2018; Glaeser et al. 2018; Gorodnichenko et al. 2018; Hertzberg et al. 2018; Bartlett et al. 2019; Basten et al. 2019). In particular, our analysis builds on the recent literature that uses machine learning techniques to predict consumers' default (Fuster et al. 2018; Albanesi 2019) and to forecast bankruptcy (Barboza2017; Moscatelli et al. 2019. Among the machine learning approaches, we rely on the random forest algorithm (Breiman 2001), only recently applied in economic contexts for forecasting (Glaeser et al. 2017) and variable selection (De Moor, Lieven and Luitel, Prabesh and Sercu, Piet and Vanpée, Rosanne 2018). The random forest algorithm has a high predictive performance, generally outperforms other traditional approaches, and delivers a ranking of the indicators used to predict the target variable that allows for identification of the most relevant one.

The rest of the paper is organized as follows. Section 3.2 describes the data. Section 3.3 presents descriptive statistics and provides empirical evidence on the evolution of mortgage supply conditions by borrowers' risk-profile. Section 3.4 highlights the main differences between online and traditional banks. Section 3.5 illustrates the nowcasting exercise. Section 3.6 concludes.

3.2 The Data

Mutuionline (MO) is an online mortgage broker that lists mortgage rates offered by affiliated banks, including all the major Italian banks, and puts prospective borrowers in touch with the bank making the preferred offer.[4] Upon submitting an application through MO, borrowers have to specify several characteristics, which the broker then uses to identify the applicant risk-profile, the list of banks willing to make an offer, and the terms of the contracts offered (e.g., net interest rate, additional fees, monthly instalments).

Figure C.1 illustrates a screenshot of the main characteristics that the borrower has to specify in order to submit the online application (age, job

[4] In 2015 MutuiOnline intermediated about 2.5 billion euro of mortgages, which corresponds to about 6 per cent of the total amount of new loans for home purchase in Italy. Since then, this share has been on the rise.

type, income, mortgage type, rate type, house value, mortgage amount, and house location). A profile is a combination of these characteristics. Once the borrower provides this information, the broker lists the sample of banks willing to grant her a loan and the financial conditions they apply (Figure C.2). This represents the pre-approval stage of the application process. Our data allow us to observe up to this point, with no information on subsequent stages leading to actual conclusion of the contract.

We observe mortgage offers by banks for roughly 85,000 prospective borrower profiles, each one defined by a combination of: mortgage category (first home vs subrogation), rate type (fixed vs adjustable), loan-to-value (LTV), maturity, applicant's age, income, job type, and location. The number and terms of contracts offered vary across profiles and over time, depending on banks' willingness to grant a loan through the broker. The contract terms offered are binding, conditional on the accuracy of the information provided by the applicant. We consider applications for first house purchase and for renegotiations of the contract terms only. House value is fixed at 200,000 euro and mortgage amount varies with the LTV. In the next stage (which we don't observe), the household selects the preferred offer and provides the broker with additional personal information (full name, date and municipality of birth, current address of residence, marital status, tax identification number, job position, etc.). The broker forwards this information to the bank, which then reaches out the borrower. Finalization of the contract occurs at the bank's branch, or online if the bank does not have any. At this point, the offer rate cannot be modified, unless information provided by the household turns out to be incorrect. Banks active on the platform have a commitment to the broker not to modify the terms of the contract posted online and, for reputational concerns, they have very low incentive not to respect such a commitment. According to MO reports, mortgage applications and mortgages actually settled exhibit strong similarities (Figure C.4 Appendix C).

Data are collected on a monthly basis, from March 2018 to August 2019, and within the 10th day of each reference month.[5] The sample of institutions working with MO consists of all the major Italian banking groups and other leading mortgage lenders in the country, accounting for more than 80 percent of residential mortgages granted in 2018. Our data include information on the characteristics of the borrower and the contract, as well as the contract

[5]Mortgage pricing decisions are mostly taken by banks at the beginning of the month.

terms offered (Table 3.1). By comparison, official interest rate statistics (MIR) are available about 50 days later than MO data and are aggregated at the bank level, thus not providing any information on the characteristics of the borrower or the contract.[6] Other traditional data sources, such as the Interest Rate Reporting (TAXIA) and the Bank Lending Survey (BLS), are available only quarterly and also do not include variables (such as the mortgage loan-to-value and maturity, and the borrowers' income) that account for most of the variation in the transacted rates.

We construct a matrix where, for each of the 85,000 profiles, we record the conditions offered (if any) by each bank in each month (Figure C.3). Among contract terms, we mostly focus on interest rates, always distinguishing between fixed and adjustable rates. For a given profile, we also report information on the share of banks that offer a product. The complement to 1 of this indicator (the "no offer rate") is correlated with the probability that a bank denies credit to a given profile and, thus, is informative on the actual loan rejection rate.

3.3 Descriptive Statistics

Table 3.2 provides summary statistics for the month-to-month change in the mortgage rate offered through MutuiOnline. We analyse fixed (FRM) and adjustable-rate mortgages (ARM) separately, to account for the possibility that intermediaries specialize in one of the two mortgage type, associated with specific risk levels. Figure 3.1 shows the distribution over time (average, median, 10th, 25th, 75th and 90th percentiles) of mortgage rates offered by banks through MO, distinguishing between fixed and adjustable. Fixed rates are generally higher than adjustable, with some heterogeneity across banks and profiles. We further breakdown mortgage rates by borrower and contract characteristics, as to evaluate heterogeneity in pricing due to different risk profiles. Such a breakdown would not be possible with alternative

[6] MIR statistics include information on interest rates applied by monetary financial institutions in the euro area to loans and deposits vis- á-vis households and non-financial corporations. The financial institutions involved in the data collection are legally obliged to report monthly information to their National Central Banks, which in turn report to the ECB. Data are collected on a sample basis; in Italy the sample consists of banks representing about 85 per cent of total outstanding loans and deposits to households and firms. MIR data can be downloaded here.

traditional databases, for they lack several pricing-relevant information (such as the mortgage LTV and maturity and the borrower's income). Figure 3.2 plots the evolution of fixed and adjustable interest rates by mortgage LTV and maturity, and by borrower's income and job type. Additional summary statistics are reported in Table C.1 of Appendix C. Riskier contracts, namely those with high LTV (above 80 per cent), long maturity (30 years), or fixed rate, are associated with higher average interest rates and greater dispersion. As for borrower characteristics (income level and job type), rates exhibit little variation.[7] Geographic characteristics of the province where the property is located do not explain variation in mortgage prices, possibly reflecting the fact that local differences in house prices, employment and economic growth are captured by other product characteristics (notably the LTV). The no-offer rate shows variability across both borrower and contract characteristics too (see Table C.2 in Appendix C). In particular, riskier contracts have a higher probability of not being offered: for instance, the probability of not facing an offer exceeds 80 per cent for borrowers without a permanent job and is above 90 per cent for loans with LTV greater than 80 per cent.

We also look at the distribution of interest rates for different banks' categories: the largest five banking groups, other significant groups (subsidiaries of foreign banking groups included), less significant groups, and online banks (Figure 3.3). Overall, there is significant heterogeneity across banks' category (see also Tables C.3, C.4 and Figure C.5 in Appendix C for more detail and a comparison of the mean across groups). For fixed-rate mortgages, the top five largest groups offer the most expensive rates and exhibit the highest degree of dispersion; for adjustable-rate mortgages, subsidiaries banks offer the highest rates and features the largest dispersion.

Next, we define two profiles characterized by different risk levels:[8]

1. Low-risk profile: mortgage LTV equal to 60 per cent and mortgage maturity equal to 15 years; borrower with a permanent employment contract and net monthly income equal to 4000 euro;

2. High-risk profile: mortgage LTV equal to 80 per cent and mortgage maturity equal to 20 years; borrower with a permanent employment contract

[7] Differences in interest rates by borrower characteristics are statistically significant.

[8] We do not present results for the very risk profile (LTV above 80 per cent and fixed-term job) because very few banks are willing to accept these applications and, therefore, results are very sensitive to changes made by just one lender.

and net monthly income equal to 2000 euro.

For both profiles, the age is fixed at 30 years, all mortgages are for first house purchase and we distinguish between fixed and adjustable rates. We analyse each profile with respect to four indicators: rate level, month-to-month change and volatility (standard deviation), and no-offer rate. Figure 3.4 shows that the average interest rate associated with the high-risk profile is significantly higher than the one associated with the low risk profile. The difference is, on average, equal to 20 basis points and it is higher for FRM (25 b.p. versus 14 b.p. for ARM). Differences have become more pronounced over time, reaching 36 b.p. for FRM and 18 b.p. for ARM in August 2019. For both profiles, rates have decreased over the past years, with the reduction being more marked for the low-risk profile. As for the month-to-month change, fixed rates have been on a decreasing trend lately, while adjustable-rate mortgages have been more stable. The only exception was October 2018, when rates increased for fixed-rate mortgages and decreased for adjustable ones. The standard deviation is quite high for all profiles and mortgage types, and averaged to about 30 basis points (or 20 per cent of the average mortgage rate). The average no-offer rate is below 10 per cent for the low risk profile. After increasing slightly in January 2019, the rate decreased and flattened at around 0 per cent since April 2019, meaning that all banks in the sample were willing to offer a mortgage to safe borrowers. This is not true for the high risk profile: the no-offer rate is on average equal to 20 per cent, although it has also been declining since January 2019.

3.4 Online versus traditional banks

Our dataset allows to disentangle differences in mortgage policies adopted by online banks from those chosen by traditional brick-and-mortar banks. This provides preliminary insights on the impact of digital technology and the benefits for final consumers stemming from Fintech. Figure 3.5 shows that online banks always offer lower average mortgage rates and are characterized by lower no-offer rates, for both fixed- and adjustable-rate mortgages. The difference between the interest rate offered by traditional and online banks is larger for fixed-rate than for adjustable-rate mortgages. Specifically, between March 2018 and August 2019, the average offer rate was about 17 and

9 p.p. lower, respectively for fixed-rate and adjustable-rate mortgages, for online banks compared to traditional ones. Online banks also exhibit a lower dispersion, on average equal to 0.36 p.p. for fixed-rate mortgage and 0.22 p.p. for adjustable-rate mortgages (it is 0.65 and 0.51 p.p. for traditional banks). This could mean that lower costs sustained by online banks in the provision of financial services, thanks to their use of advanced technologies, are at least to some extent passed-through to customers in terms of lower rates. It could also reflect superior skills of online banks in risk pricing.[9] Differences between online and traditional banks are confirmed also conditional on the riskiness of the borrowers: online banks offer the lowest possible price for given segments of clients based on their riskiness (in some cases the rate could be equal to that offered by traditional banks, Figure 3.6). Finally, we check for differences between online and traditional banks that belong to the same banking group. In our sample, we have four banking groups that include both online and traditional banks. For these, on average over the entire period, online banks charge lower rates than traditional banks belonging the same banking group. However, there is some heterogeneity within risk profile, over time, and across banks (Table 3.3). This implies that the banking group changes its mortgage policy across the different channels (online vs traditional) every month, allowing also for changes across profiles. A closer look indicates that, for those profiles for which there is an offer from both traditional and online banks, the interest rate is quite similar within the banking group.[10]

3.5 Nowcasting exercise

We use standard a regression analysis and a random forest algorithm to test whether MO data help predicting official loan rates, and to evaluate their nowcasting power. The regression we estimate is the following:

$$\begin{aligned}\Delta FRM_{bt} = {} & \beta_0 + \beta_1 \Delta IRS10_t + \beta_2 \Delta IRS10_{t-1} + \beta_3 \Delta IRS10_{t-2} + \beta_4 \Delta IRS10_{t-3} \\ & + \beta_5 \Delta MO_{bt} + \beta_6 \Delta MO_{bt-1} + \beta_7 \Delta MO_{bt-2} + \beta_8 \Delta MO_{bt-3} \\ & + \beta_8 Conficence_{bt-1} + \beta_9 Confidence_{bt-2} + \varepsilon_{bt} \end{aligned} \tag{3.1}$$

[9]A more throughout assessment of the issue is beyond the scope of this paper and would require additional analyses.

[10]There are several profiles for which we observe an offer only from the online banks; these profiles mostly include first home mortgages, from applicants with a fixed term contract, and characterized by low LTV.

where b indexes the bank and t the month. $IRS10$ is the 10-year IRS, MO is the average online offer rate from MutuiOnline, and $Confidence$ is the consumer confidence index from ISTAT.

We first regress the monthly change in the realized MIR fixed rate, at the bank level, on the MO offered rate, averaged across all contracts offered by the bank in a given month, and several other covariates (Table 3.4, Columns 1-3). The regression with MO variables (Column 2) considerably improves the estimation and nowcasting ability as compared to a specification including only the market reference rate (10-year IRS; Column 1). The Adjusted R-squared increases to 31 percent (from 6 percent) and the share of correct out-of-sample predictions increases to 72 percent (from 67).[11] The coefficients on the MO rate remain unchanged upon inclusion of monthly, time-varying, demand controls (the two lagged values of the consumer confidence index), which also increases accuracy of the out-of-sample prediction (the RMSE decreases and the share of correct predictions increases to 83 percent, Column 3).

Then, we run a random forest algorithm, which fully exploits the information on all the borrower-contract profiles included in our dataset[12] and further improves predictive capacity: the out-of-sample RMSE decreases to 7.6 percent and the share of correctly predicted cases increases to 89 percent (Column 4). Considering the latest month in our sample (June 2019), the variable that plays the largest role in driving the total variation is the contemporaneous change in the MO rate for the profile with 80 percent LTV, 10-year maturity, age of 40, monthly net income of 4,000 euro and permanent job (Figure 3.7, panel A). The second and the third profiles in order of importance exhibit similar low-risk characteristics (60 percent LTV, short maturity and permanent employment status), suggesting that FRM are typically chosen by safe borrowers. The same analysis carried out for the previous four months displays low time variability in the profiles ranking, suggesting that banks only marginally adjust their pricing model over time (Figure 3.7, panel B). Overall, the most important profiles are those with high LTV, short maturity, and low-income volatility.

[11] This is calculated as the number of banks for which the predicted rate lies within one standard deviation from the actual value on the last date of the sample (June 2019).

[12] We consider 128 profiles defined by combinations of LTV, maturity, age, income and job type. Each profile captures a different risk-level.

3.6 Conclusions

Online platforms provide researchers and policymakers with crowdsourced data at the granular level, months before official statistics become available. This paper describes data from the major online mortgage broker in Italy (MutuiOnline) and shows how these can be exploited for policy analysis. Our dataset is extremely valuable for it provides very timely information and accounts for different sources of heterogeneity in the mortgage product (at both the borrower and contract level). Traditional databases are available with some time lag and do not provide such granular and detailed information on product characteristics. Also, they reflect an equilibrium between demand and supply, which makes it hard to control for the endogenous matching between banks, borrowers and contracts. Conversely, MO data allow to fully isolate mortgage supply choices of the main Italian banks (conditional on demand characteristics).

Our analysis indicates that, on average, riskier contracts are characterized by higher mortgage rates and are generally offered by fewer intermediaries. Moreover, online banks tend to charge lower rates than traditional ones. We also provide evidence that online price data can improve short-term predictions and forecasting models, allowing for a timelier appraisal of changes in banks' lending strategies. In particular, offer rates from MO contain policy-relevant information on realized banks' rates (which also depend on loan demand conditions and unobserved time-invariant bank characteristics). Such information can be extremely useful for nowcasting purposes.

3.7 Tables

Table 3.1: Borrower and contract characteristics

Characteristics of the borrower	
Age	30 or 40 years old
Job type	Self-employed, permanent contract, fixed-term contract
Monthly net income	2000 or 4000 euro
Characteristics of the loan	
Purpose of the contract	First-time homebuyer, renegotiations
Loan-to-value (LTV)	50, 60, 80 or 85 per cent
Rate type	Fixed or adjustable
Maturity	10, 15, 20 or 30 years
Characteristics of the property	
Location	110 Provinces
Characteristics of the offer	
Monthly installment	
Interest rate and APR	
Contract name	

Source: MutuiOnline.

Table 3.2: Summary statistics for the month-to-month change in the offer rate

	Mean	Std.Dev.	Min	Max
Fixed rate	-0.03	0.02	-0.14	0.06
Adjustable rate	-0,01	-0.02	-0.14	0.03

Note: Data are in percentage points The offer rate refers to the simple average across all profiles of rates offered through Mutuionline. *Source:* MutuiOnline.

Table 3.3: Within group rate differential between traditional and online banks

	Panel A. Low risk profile							
	Fixed rate				Variable rate			
	Group 1	Group 2	Group 3	Group 4	Group 1	Group 2	Group 3	Group 4
Mar-18	0	0	-0.14	0.32	2.22	0.68	0	-0.2
Apr-18	0	0	0.04	0.35	2.27	0.63	0	-0.2
May-18	0	0	0.07	0.7	2.27	0.63	0	-0.2
Jun-18	0	0	0.02	0.66	2.27	0.63	0	-0.2
Jul-18	0	0	0.12	0.68	2.27	0.63	0	-0.2
Aug-18	0	0	0.48	0.74	2.27	0.63	0	0.05
Sep-18	0	0	0.45	0.8	2.27	0.63	0	0.05
Oct-18	0	0	0.48	-0.11	0	0	0	-0.1
Nov-18	0	0	0.36	-0.14	0	0	0	-0.1
Dec-18	0	0	0.38	-0.27	0	0	0	-0.1
Jan-19	0	0	1.57	0.1	0	0	0	1
Feb-19	0	0	0.1	-0.16	0	0	0	0.05
Mar-19	0	-0.01	0.25	-0.03	0	0	0	0.05
Apr-19	0	-0.01	-0.01	0.02	0	0	0	0.05
May-19	0	-0.01	0.17	-0.01	0	0	0	0.05
Jun-19	0	-0.01	0.12	-0.17	0	0	0	0.06
Jul-19	0	-0.01	0.99	-0.06	0	0	0	0.1
Aug-19	0	-0.01	0.91	-0.25	0	0	0	0.79
	Panel B. High risk profile							
	Fixed rate				Variable rate			
	Group 1	Group 2	Group 3	Group 4	Group 1	Group 2	Group 3	Group 4
Mar-18	0	0	0	-0.14	2.07	0.83	-0.2	0.1
Apr-18	0	0	0	0.16	2.07	0.83	-0.2	0.1
May-18	0	0	0	0.18	2.07	0.83	-0.2	0.1
Jun-18	0.23	0	0	0.13	2.07	0.83	-0.2	0.23
Jul-18	0.23	0	0	0.22	2.07	0.83	-0.2	0.23
Aug-18	0.22	0	0	0.55	2.07	0.83	0.05	0.22
Sep-18	0.22	0	0	0.54	2.07	0.83	0.05	0.22
Oct-18	-0.05	0	1.9	0.57	0	0	0	-0.05
Nov-18	-0.05	0	1.95	0.46	0	0	0	-0.05
Dec-18	-0.05	0	1.9	0.48	0	0	0	-0.05
Jan-19	0.05	0	0	1.72	0	0	1	0.05
Feb-19	0	0	0	-0.01	0	0	-0.11	-0.1
Mar-19	0	0	-0.01	0.16	0	0	-0.11	-0.1
Apr-19	0	0	-0.01	-0.12	0	0	-0.11	-0.1
May-19	0	0	-0.01	0.08	0	0	-0.11	-0.1
Jun-19	0	0	-0.01	0.03	0	0	-0.1	-0.1
Jul-19	0	0	-0.01	0.89	0	0	-0.06	-0.1
Aug-19	0	0	-0.01	2.16	0	0	0.68	-0.1

Note: Data are in percentage points are refer to average values for the period averages March 2018 to August 2019. Low risk are profiles with mortgage LTV equal to 60 per cent,mortgage maturity equal to 15 years and a permanent employment contract with net monthly income equal to 4000 euro. High risk are profiles with mortgage LTV equal to 80 per cent, mortgage maturity equal to 20 years and a permanent employment contract with net monthly income equal to 2000 euro. *Source:* MutuiOnline.

Table 3.4: Predicting interest rates using OLS and machine learning: FRM

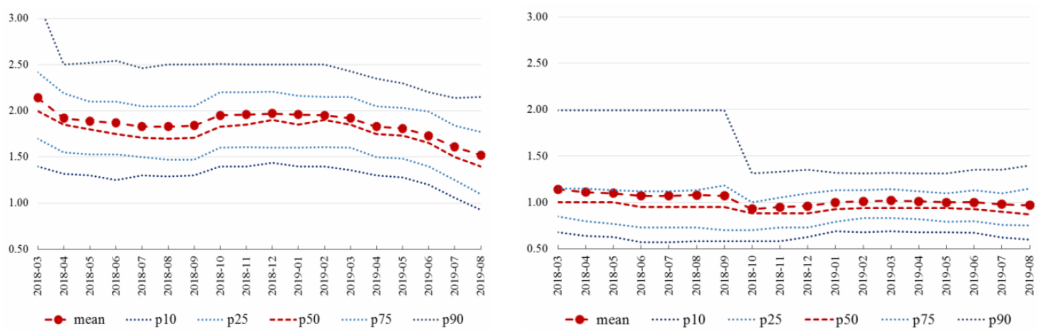
	Monthly change in official fixed rate			
	Only reference rate	+ MutuiOnline average	+ demand controls	Random Forest
	(1)	(2)	(3)	(4)
Delta IRS-10y (t)	0.203***	0.154	0.257***	
	(0.112)	(0.095)	(0.150)	
L.Delta IRS-10y (t)	0.174	0.113	0.107	
	(0.110)	(0.076)	(0.074)	
L2.Delta IRS-10y (t)	-0.089	0.031	0.068	
	(0.114)	(0.085)	(0.087)	
L3.Delta IRS-10y (t)	0.120	-0.141	0.023	
	(0.109)	(0.098)	(0.179)	
MO delta rate (b, t)		0.394***	0.388***	
		(0.073)	(0.074)	
L.MO delta rate (b, t)		0.107***	0.112***	
		(0.045)	(0.046)	
L2.MO delta rate (b, t)		0.197***	0.192***	
		(0.048)	(0.046)	
L3.MO delta rate (b, t)		0.253***	0.256***	
		(0.064)	(0.067)	
L.Consumer confidence			0.000	
			(0.002)	
L2.Consumer confidence			-0.009	
			(0.007)	
Bank FE	Y	Y	Y	Y
Observations	234	234	234	329
Adjusted R-squared	0.061	0.310	0.307	
Out of sample RMSE	0,1106	0,1109	0,0974	0,0759
Out of sample correct predictions	0.67	0.72	0.83	0.89

Standard errors clustered at the bank level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The dependent variable is the monthly change in official interest rate on fixed-rate mortgage, at the bank level. MO delta rate is the monthly change in MO offered rate (net of fees and commissions) on fixed-rate mortgages in the Mutuionline dataset; IRS-10y is the 10-year interest rate swap in euro; consumer confidence is a measure of how optimistic or pessimistic households are regarding their expected financial situation. Note: b stands for banks and t for months. Ln is the n-months lag. Columns 1 to 3 show the results from standard OLS regressions; Column 4 those from a random forest algorithm. Out-of-sample correct predictions are those within one standard deviation from the true value, with reference to the June 2019. All models specifications include bank fixed effects). *Source:* Mutuionline, MIR, and ISTAT.

3.8 Figures

Figure 3.1: Online offer rates

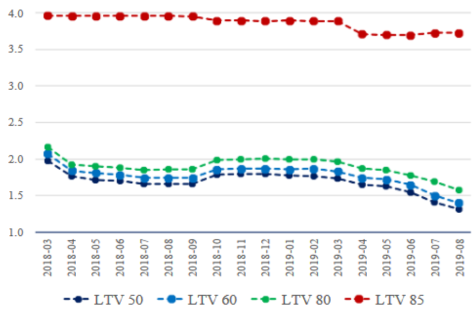


(a) Fixed-rate mortgages (FRM)

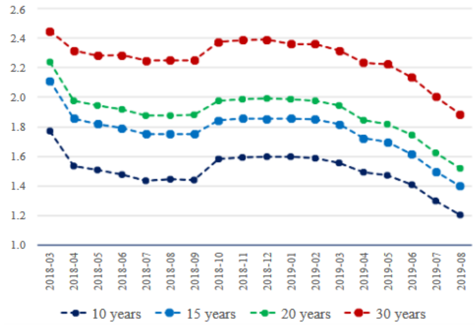
(b) Adjustable-rate mortgages (ARM)

Note: Data are in percentage points. *Source:* MutuiOnline.

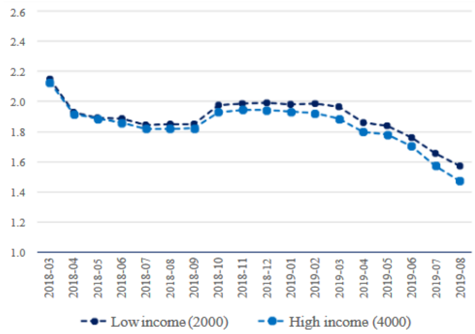
Figure 3.2: Online offer rates by loan and borrower's characteristics



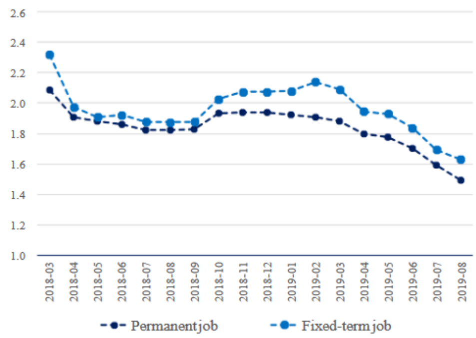
(a) FRM by LTV



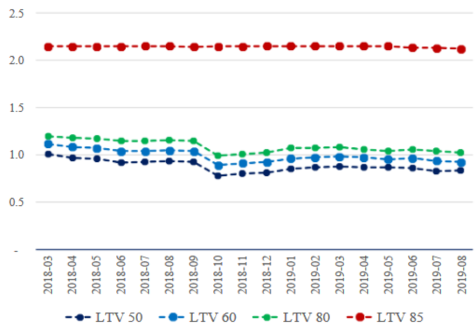
(b) FRM by maturity



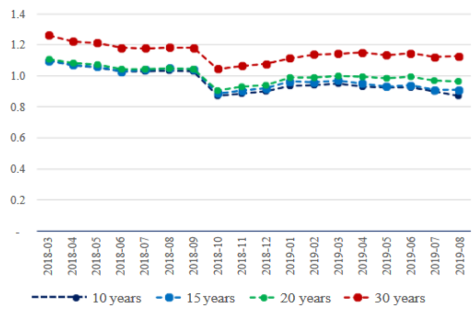
(c) FRM by income level



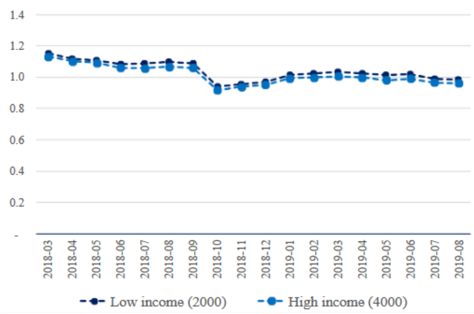
(d) FRM by job type



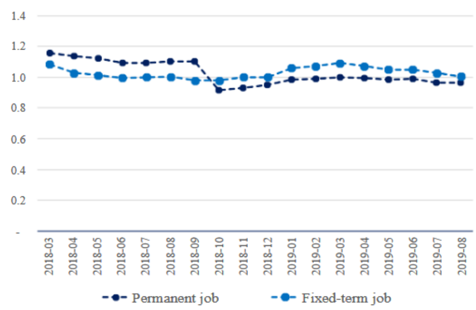
(e) ARM by LTV



(f) ARM by maturity



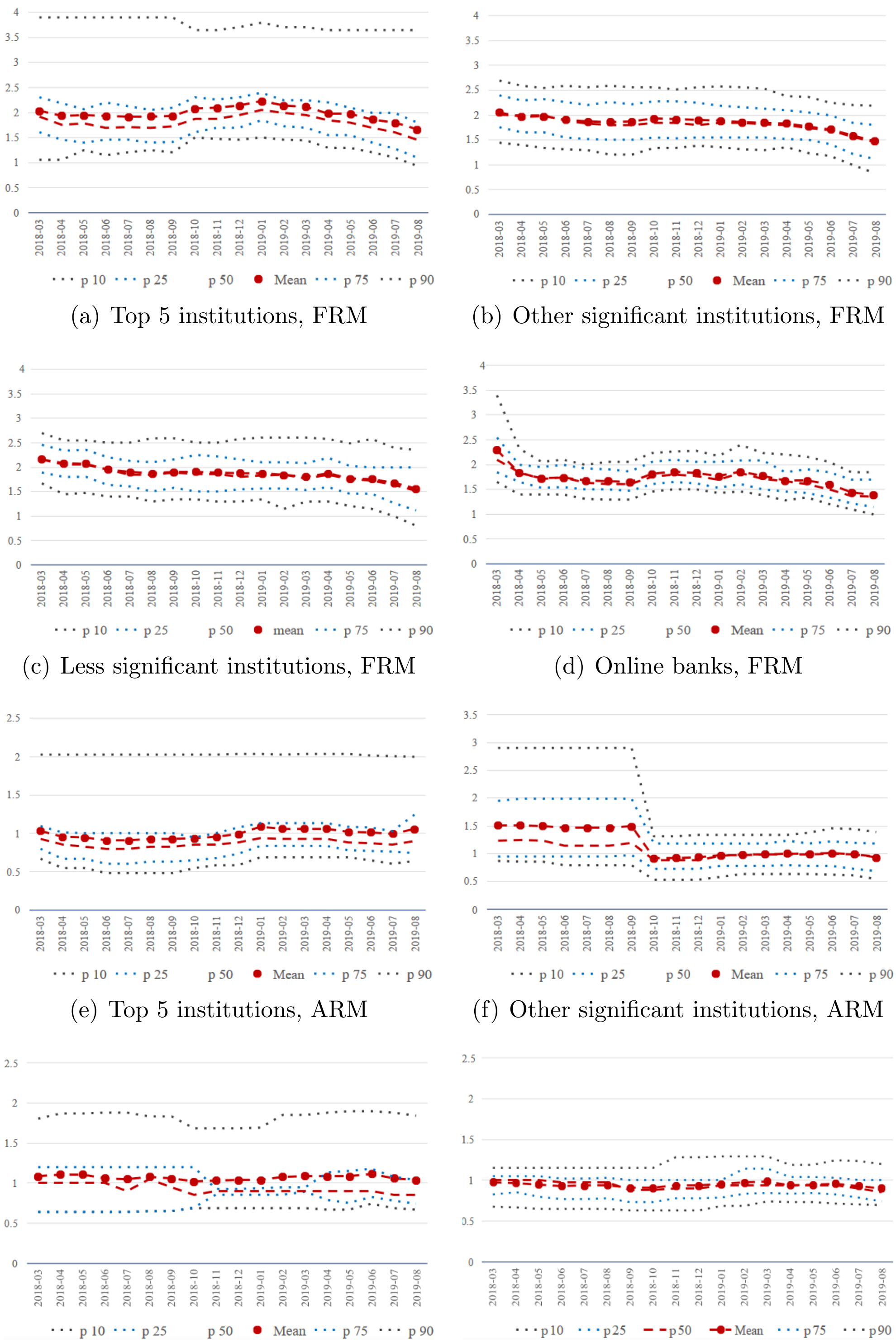
(g) ARM by income level



(h) ARM by job type

Note: Data are in percentage points. *Source:* MutuiOnline.

Figure 3.3: Online offer rates by bank category



(a) Top 5 institutions, FRM (b) Other significant institutions, FRM

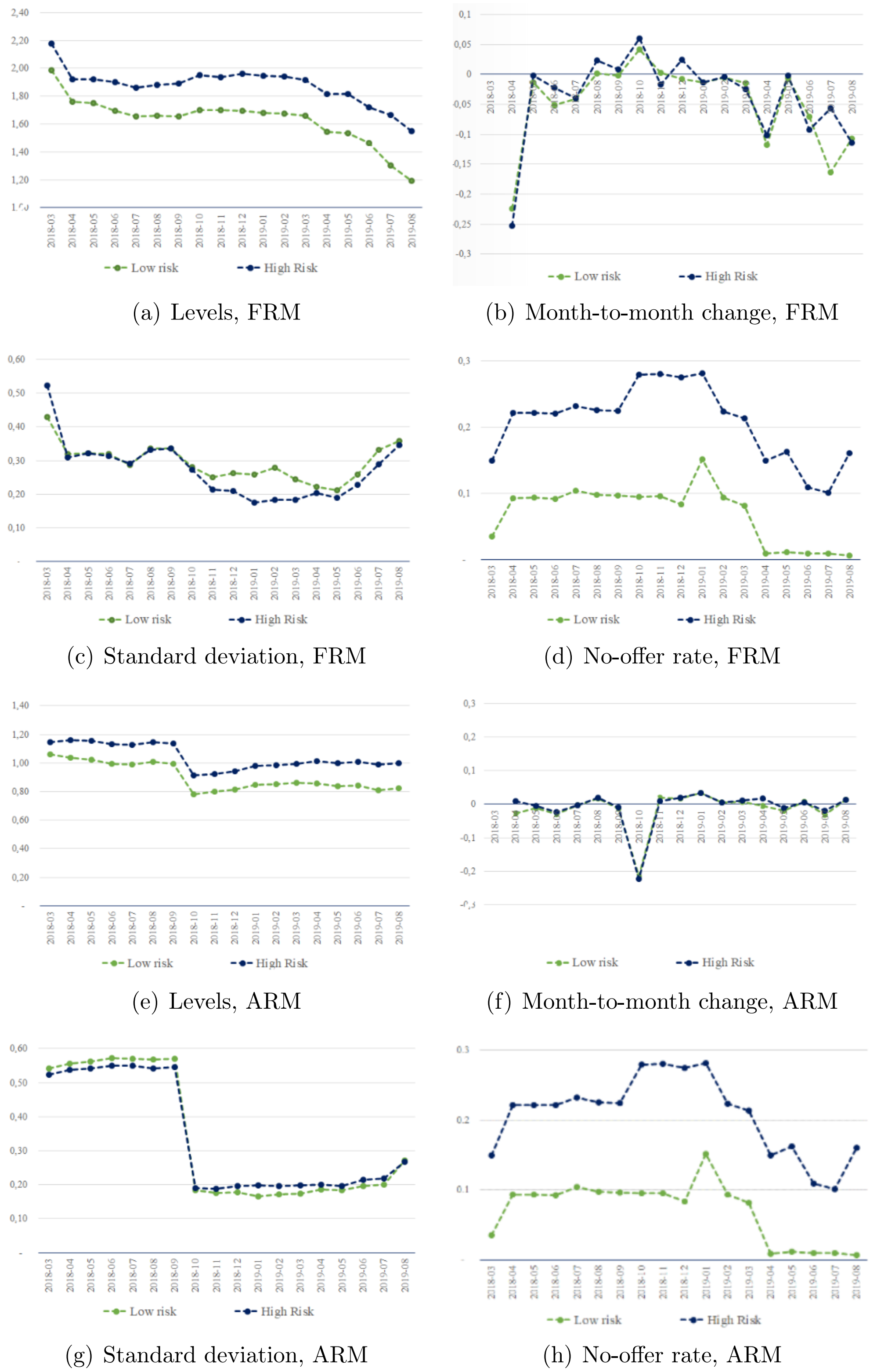
(c) Less significant institutions, FRM (d) Online banks, FRM

(e) Top 5 institutions, ARM (f) Other significant institutions, ARM

(g) Less significant institutions, ARM (h) Online banks, ARM

Note: Data are in percentage points. *Source:* MutuiOnline.

Figure 3.4: Online offer rates by risk profile



(a) Levels, FRM

(b) Month-to-month change, FRM

(c) Standard deviation, FRM

(d) No-offer rate, FRM

(e) Levels, ARM

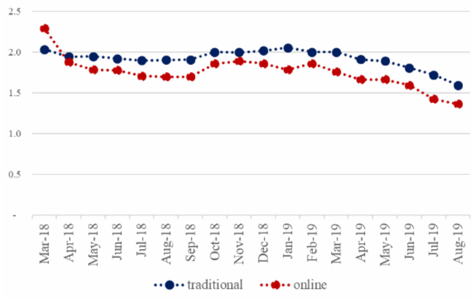
(f) Month-to-month change, ARM

(g) Standard deviation, ARM

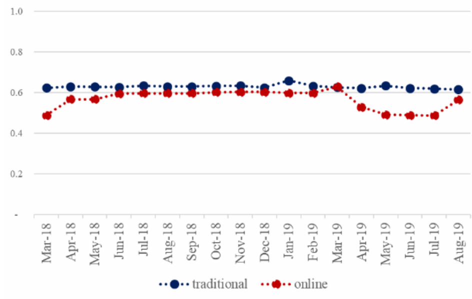
(h) No-offer rate, ARM

Note: Data are in percentage points. *Source:* MutuiOnline and authors' elaborations.

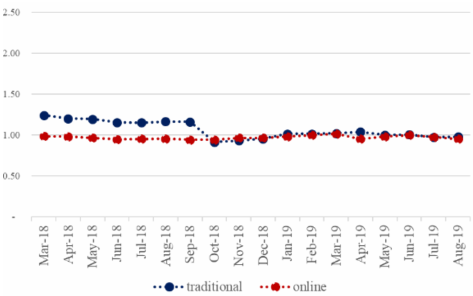
Figure 3.5: Traditional versus online banks



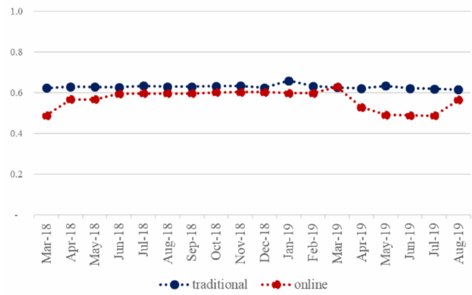
(a) Fixed-rate mortgage



(b) No-offer rate, FRM



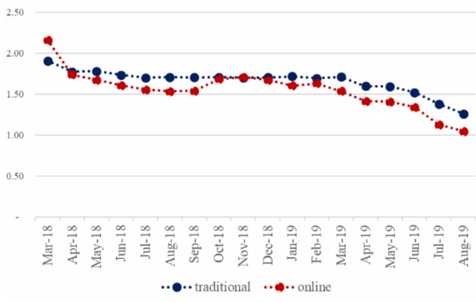
(c) Adjustable-rate mortgage



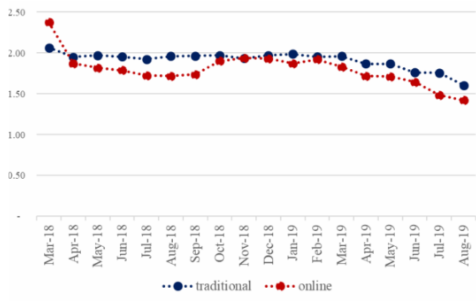
(d) No-offer rate, ARM

Note: Data are in percentage points. *Source:* MutuiOnline.

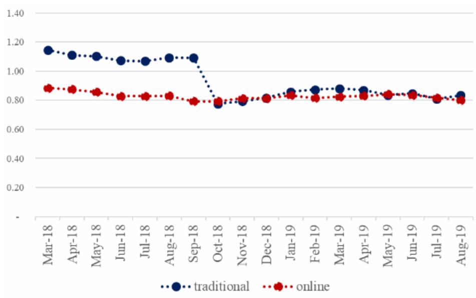
Figure 3.6: Traditional versus online banks by risk profile



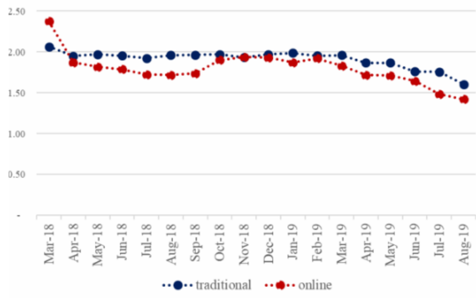
(a) Low risk, FRM



(b) High risk, FRM



(c) Low risk, ARM

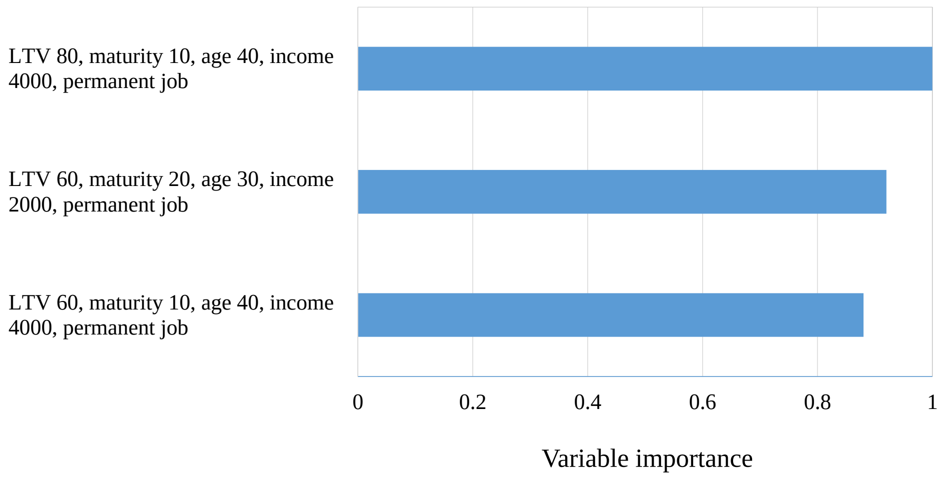


(d) High risk, ARM

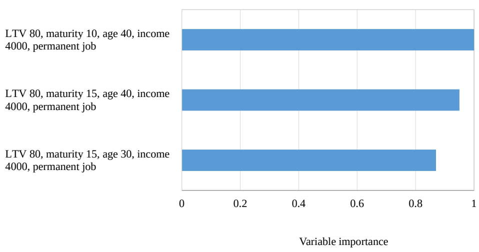
Note: Data are in percentage points. *Source:* MutuiOnline and authors' elaborations.

Figure 3.7: Random Forest, fixed rate

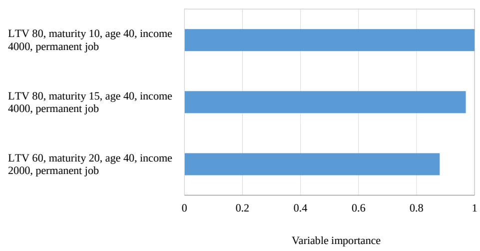
Panel A: Profile importance, June 2019



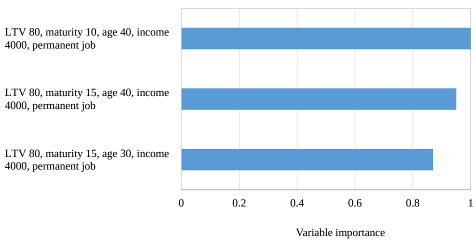
Panel B: Profile importance over time



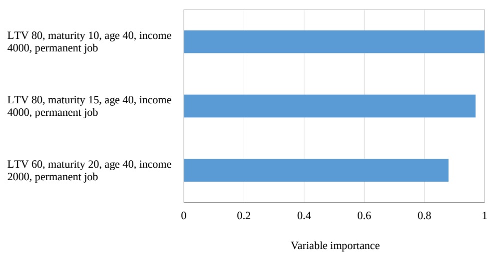
(a) May 2019



(b) April 2019



(c) March 2019



(d) February 2019

Note: The importance score indicates how useful each indicator is in predicting the target variable using the random forest. The score varies between 0 and 1, with 1 being the most informative variable. *Source:* MutuiOnline, MIR and ISTAT.

Bibliography

Agarwal, S. & Ambrose, B. W. (2008). "Does it pay to read your junk mail? evidence of the effect of advertising on home equity credit choices".

Agarwal, S., Amromin, G., Chomsisengphet, S., Landvoigt, T., T. Piskorski, A. S., & Yao, V. (2017). "Mortgage Refinancing, Consumer Spending, and Competition: Evidence From the Home Affordable Refinance Progra". *NBER Working Paper*, (21512).

Alan, S. (2012). "Do disaster expectations explain household portfolios?". *Quantitative Economics*, 3(1), 1–28.

Albanesi, S., a. D. V. (2019). "Predicting Consumer Default: A Deep LearningApproach". *NBER Working Paper*, (26165).

Alexandrov, A. & Koulayev, S. (2017). "No Shopping in the U.S. Mortgage Market: Direct and Strategic Effects of Providing Information".

Allen, J., Clark, R., & Houde, J. (2014a). "Price dispersion in mortgage markets". *The Journal of Industrial Economics*, 62(3), 377–416.

Allen, J., Clark, R., & Houde, J. (2014b). "The Effect of Mergers in Search Markets: Evidence from the Canadian Mortgage Industry". *American Economic Review*, 104(10), 3365–96.

Allen, J., Clark, R., & Houde, J. (2019). "Search Frictions and Market Power in Negotiated-Price Markets". *Journal of Political Economy*, 127(4), 1550–98.

Andersen, S., Campbell, J. Y., Nielsen, K., Kasper, M., & Ramadorai, T. (2015). "Inattention and inertia in household finance: Evidence from the Danish mortgage market".

Attinà, C. A., F. F. & Michelangeli, V. (2020). "Modelling households' financial vulnerability with consumer credit and mortgage renegotiations". *International Journal of Microsimulation*, 13(1), 67–91.

Bagwell, K., Armstrong, M., & Porter, R. (2007). "The Economic Analysis of Advertising". *Handbook of Industrial Organization*, 3, 1701–1844.

Banerjee, B. & Bandyopadhyay, S. (2003). "Advertising Competition Under Consumer Inertia". *Marketing Science*, 22(1), 131–144.

Barro, R. J. (2006). "Rare disasters and asset markets in the twentieth century". *The Quarterly Journal of Economics*, 121(3), 823–866.

Bartlett, R., Morse, A., Stanton, R., & Wallace, N. (2019). "Consumer-Lending Discrimination in the FinTech Era". (25943).

Basten, C., Guin, B., & Koch, C. (2018). "How do banks and households manage interest rate risk? Evidence from mortgage applications and banks' responses". *Bank of England Staff WP*, (733).

Basten, C., Guin, B., & Koch, C. (2019). "The Geography of Mortgage Lending in Times of FinTech". *Swiss Finance Institute Research Paper*, (39).

Benetton, M. (2018). "Leverage Regulation and Market Structure: An Empirical Model of the UK Mortgage Market".

Bhutta, N., Fuster, A., & Hizmoy, A. (2018). "Paying Too Much? Price Dispersion in the US Mortgage Market". *FEDS Working Paper*, (pp. 2020–062).

Blundell, R., Pistaferri, L., & Preston, I. (2008). "Consumption Inequality and Partial Insurance". *American Economic Review*, 98(5).

Braithwaite, D. (1928). "The Economic Effects of Advertisement". *Economic Journal*, 38(149), 16–37.

Breiman, L. (2001). "Random Forests". *Machine Learning)*, 45, 5–32.

Buchak, G., Matvos, G., Piskorski, T., & Seru, A. (2018). "Fintech, regulatory arbitrage, and the rise of shadow banks". *Journal of Financial Economics*, 130(3), 453–483.

Campbell, J. Y. & Cocco, J. (2015). "A model of mortgage default". *The Journal of Finance*, 70(4), 1495–1554.

Carella, A., Ciocchetta, F., Michelangeli, V., & Signoretti, F. (2020). "What can we learn about mortgage supply from online data?". *Questioni di Economia e Finanza (Occasional Papers) 583, Bank of Italy, Economic Research and International Relations Area*.

Cavallo, A. (2017). "Are Online and Offline Prices Similar? Evidence from Large Multi-Channel Retailers". *The American Economic Review*, 107(1), 283–303.

Cocco, J. F. (2005). "Portfolio choice in the presence of housing". *The Review of Financial Studies*, 18(2), 535–567.

Cocco, J. F., Gomes, F., & Maenhout, P. (2005). "Consumption and portfolio choice over the life cycle". *The Review of Financial Studies*, 18(2), 491–533.

Comanor, W. S. & Wilson, T. A. (1975). "Advertising and Market Power". *Journal of Behavioral Economics*, 4(1), 201–204.

Cubbin, J. S. & Domberger, S. (1988). "Advertising and Post-entry Oligopoly Behaviour". *Journal of Industrial Economics*, 37(2).

Cœuré, B. (2017). Speech at the conference on "Economic and Financial Regulation in the Era of Big Data". *Banque de France*. `https://www.ecb.europa.eu/press/key/date/2017/html/ecb.sp171124.en.html`.

Damen, S. & Buyst, E. (2017). "Mortgage Shoppers: How Much Do They Save?". *Real Estate Economics*, 45(4), 898–929.

De Clippel, G., Eliaz, K., & Rozen, K. (2014). "Competing for consumer inattention". *Journal of Political Economy*, 122(6), 1203–1234.

De Moor, Lieven and Luitel, Prabesh and Sercu, Piet and Vanpée, Rosanne (2018). "Subjectivity in sovereign credit ratings". *Journal of Banking & Finance*, 88(C), 366–392.

Delgado-Ballester, E. & Munuera-Alemán, J. L. (2001). "Brand trust in the context of consumer loyalty". *European Journal of marketing*.

Della Vigna, S. (2009). "Psychology and Economics: Evidence from the Field". *Journal of Economic Literature*, 47(2), 315–72.

Della Vigna, S. & Gentzkow, M. (2010). "Persuasion: Empirical Evidence". *Annual Review of Economics*, 2(1), 643–669.

D'Amuri, F. & Marcucci, J. (2017). "The predictive power of Google searches in forecasting US unemployment". *International Journal of Forecasting*, 33(4), 801–816.

Edelman, B. (2012). "Using internet data for economic research". *Journal of Economic Perspectives*, 26, 189–206.

Einav, L. & Levin, J. (2013). "The Data Revolution and Economic Analysis". (19035).

Ericson, K. (2014). "Consumer inertia and firm pricing in the Medicare Part D prescription drug insurance exchange". *American Economic Journal: Economic Policy*, 6(1), 38–64.

Ettredge, M., J. G. & Karuga, G. (2005). "Using web-based search data to predict macroeconomic statistics". *Communications of the ACM*, 48, 87–92.

Foá, G., Gambacorta, L., Guiso, L., & Mistrulli, P. E. (2015). "The Supply Side of Household Finance". (531).

Fondeur, Y. & Karamé, F. (2013). "Can Google data help predict French youth unemployment?". *Economic Modelling*, 30, 117–125.

Fuster, A., Plosser, M., Schnabel, P., & Vickery, J. (2018). "The Role of Technology in Mortgage Lending". (836).

Fuster, A. & Vickery, J. (2013). "Securitization and the fixed-rate mortgage". (594).

Gambacorta, L., Guiso, L., Mistrulli, P. E., Pozzi, A., & Tsoy, A. (2019). "The Cost of Steering in Financial Markets: Evidence from the Mortgage Market".

Gathergood, J. & Weber, J. (2017). Financial literacy, present bias and alternative mortgage products. *Journal of Banking & Finance*, 78, 58–83.

Glaeser, E., Kim, H., & Luca, M. (2017). "Nowcasting the Local Economy: Using Yelp Data to Measure Economic Activity". *NBER Working Paper*, (24010).

Glaeser, E., Kominers, S., Luca, M., & Naik, N. (2018). "Big Data and Big Cities: The Promises and Limitations of Improved Measures of Urban Life". *Economic Inquiry)*, 56(1).

Gomes, F. & Michaelides, A. (2005). Optimal life-cycle asset allocation: Understanding the empirical evidence. *The Journal of Finance*, 60(2), 869–904.

Gorodnichenko, Y., Sheremirov, V., & Talavera, O. (2018). "Price Setting in Online Markets: Does IT Click?". *The Journal of the European Economic Association*, 16(6), 1764–1811.

Granello, D. H. & Wheaton, J. E. (2004). "Online data collection: Strategies for research". *Journal of Counseling and Development*, 82(4), 387–393.

Gurun, U., Matvos, G., & Seru, A. (2016). "Advertising Expensive Mortgages". *Journal of Finance*, 71(5), 2371–2416.

Haan, M. A. & Moraga-González, J. L. (2011). "Advertising for Attention in a Consumer Search Model". *The Economic Journal*, 121(552), 552–579.

Hall, R. E. & Woodward, S. E. (2012). "Diagnosing Consumer Confusion and Suboptimal Shopping Effort: Theory and Mortgage Market Evidence". *The American Economic Review*, 102(7), 3249–3276.

Hertzberg, A., Liberman, A., & Paravisini, D. (2018). "Screening on Loan Terms: Evidence from Maturity Choice in Consumer Credit". *Review of Financial Studies*, 31(9), 3532–3567.

Ho, K., Hogan, J., & Morton, F. S. (2017). "The impact of consumer inattention on insurer pricing in the Medicare Part D program". *The RAND Journal of Economics*, 48(4), 877–905.

Hurst, E., Keys, B. J., Seru, A., & Vavra, J. (2016). "Regional Redistribution through the US Mortgage Market". *The American Economic Review*, 106(10), 2982–3028.

Iscenko, Z. (2018). "Choices of dominated mortgage products by UK consumers". *Financil Conduct Authority, Occasional Paper 33.*

Judd, K. L. (1998). "Numerical Methods in Economics". *MIT Press Books*, 1(0262100711).

Kaldor, N. V. (1950). "The Economic Aspects of Advertising". *Review of Economic Studies*, 18(1), 1–27.

Lancaster, K. J. (1966). "A New Approach to Consumer Theory". *Journal of Political Economy*, 74(2), 132–157.

Lewis, B. R. & Soureli, M. (2006). "The antecedents of consumer loyalty in retail banking". *Journal of Consumer Behaviour: An International Research Review*, 5(1), 15–31.

Liu, J., Longstaff, F., & Pan, J. (2003). "Dynamic asset allocation with event risk". *The Journal of Finance*, 58(1), 231–259.

Matějka, F. & McKay, A. (2015). "Rational inattention to discrete choices: A new foundation for the multinomial logit model". *American Economic Review*, 105(1), 272–98.

McManus, Doug, L. L. & Yi, M. (2018). "Why Are Consumers Leaving Money On The Ta- ble?". *Freddie Mac Economic Housing Research Insight*.

Mian, A. & Sufi, A. (2011). "House Prices, Home Equity-Based Borrowing, and the U.S. Household Leverage Crisis". *The American Economic Review*, 101(5), 2132–2156.

Michelangeli, V. & Sette, E. (2016). "How does bank capital affect the supply of mortgages?".

Miravete, E. J. & Palacios-Huerta, I. (2014). "Consumer inertia, choice dependence, and learning from experience in a repeated decision problem". *Review of Economics and Statistics*, 96(3), 524–537.

Moscatelli, M., Narizzano, S., Parlapiano, F., & Viggiano, G. (2019). "Corporate default forecasting with machine learning". *Bank of Italy Working Papers (Temi di Discussione)*, (1256).

Nelson, P., . (1970). "Information and Consumer Behavior". *Journal of Political Economy*, 78, 311–329.

Nelson, P., . (1974). "Advertising as Information". *Journal of Political Economy*, 82(4), 729–754.

Nichols, L. M. (1985). "Advertising and Economic Welfare". *The American Economic Review*, 75(1), 213–218.

Nymand-Andersen, P. (2015). "Big data: the hunt for timely insights and decision certainty: Central banking reflections on the use of big data for policy purposes". *IFC Working Paper*, (14).

Ozdemir, S., Zhang, S., Gupta, S., & Bebek, G. (2020). "The effects of trust and peer influence on corporate brand—Consumer relationships and consumer loyalty". *Journal of Business Research*.

Ozga, S. A. (1960). "Imperfect Markets Through Lack of Knowledge". *Quarterly Journal of Economics*, 74(1), 29–52.

Pangallo, M. & Loberto, M. (2018). "Home is where the ad is: interest proxies housing demand". *EPJ Data science*, 7(1), 47.

Robert, J. & Stahl, D. O. (1993). "Informative Price Advertising in a Sequential Search Model". *Econometrica*, 61(3), 657–686.

Robinson, J. (1933). "Economics of Imperfect Competition". *London: MacMillan and Co.*

Robles-Garcia, C. (2019). "Competition and Incentives in Mortgage Markets: The Role of Brokers".

Seenivasan, S., Sudhir, K., & Talukdar, D. (2016). "Do store brands aid store loyalty?". *Management Science*, 62(3), 802–816.

Stigler, G. J. (1961). "The Economics of Information". *Journal of Political Economy*, 69(3), 213–225.

Stigler, G. J. & Becker, G. S. (1977). "De Gustibus Non Est Disputandum". *The American Economic Review*, 67(2), 76–90.

Su, X. (2009). "A model of consumer inertia with applications to dynamic pricing". *Production and Operations Management*, 18(4), 365–380.

Tauchen, G. & Hussey, R. (1991). "Quadrature-Based Methods for Obtaining Approximate Solutions to Nonlinear Asset Pricing Models". *Econometrica*, 59(2), 371–396.

Telser, L. G. (1964). "Advertising and Competition". *Journal of Political Economy*, 72(6), 537–562.

Thaler, R. H. & Sunstein, C. R. (2008). "Nudge: Improving Decisions about Health, Wealth, and Happiness". *Constitutional Political Economy*, 19(4), 356–36.

Tissot, B. (2017). "Big data and central banking". *IFC Bulletin*, (44).

Vicente, M., A.J.López-Menéndez, & R.Pérez (2015). "Forecasting unemployment with internet search data: Does it help to improve predictions when job destruction is skyrocketing?". *Technological Forecasting and Social Change*, 92(c), 132–139.

White, L. & Yanamandram, V. K. (2004). "Why customers stay: reasons and consequences of inertia in financial services". *Managing Service Quality: An International Journal*.

A. Appendix to Chapter 1

French Amortization

We use the French amortization method to estimate the original maturity of the mortgage. This is the most diffused repayment plan among Italian banks, characterized by fixed instalments comprised of interest payments (decreasing) and principal amounts (increasing). For each borrower, we match her total outstanding debt from CR and her loan amount at origination from TAXIA. We compute the principal payment as the difference in the loan outstanding between two consecutive months. The interest payment is the loan outstanding times the interest rate, which is the APR minus loan fees. The APR is directly observable from TAXIA; for loan fees we use the median spread between the APR and the interest rate available from MutuiOnline. To get original mortgage maturity n, we invert the following equation:

$$R = \frac{K \times i}{1 - \frac{1}{1+i^n}} \tag{A.1}$$

where R is the fixed instalment, K is the initial capital, i is the interest rate on the residual capital, and n is the number of payments. Table A.1 shows that the median, mean and maximum maturity in our dataset is similar to the one resulting from official statistics for residential mortgages in Italy (Regional Business Lending Survey, RBLS). Mortgages with maturity greater or equal than 30 years are 19 per cent in our dataset (according to the RBLS they are almost 21 per cent).

Table A.1: Maturity

	Median	Mean	Maximum
CR - our computation	21	22	42
RBLS	22	22	42

Loan-to-Value Inference

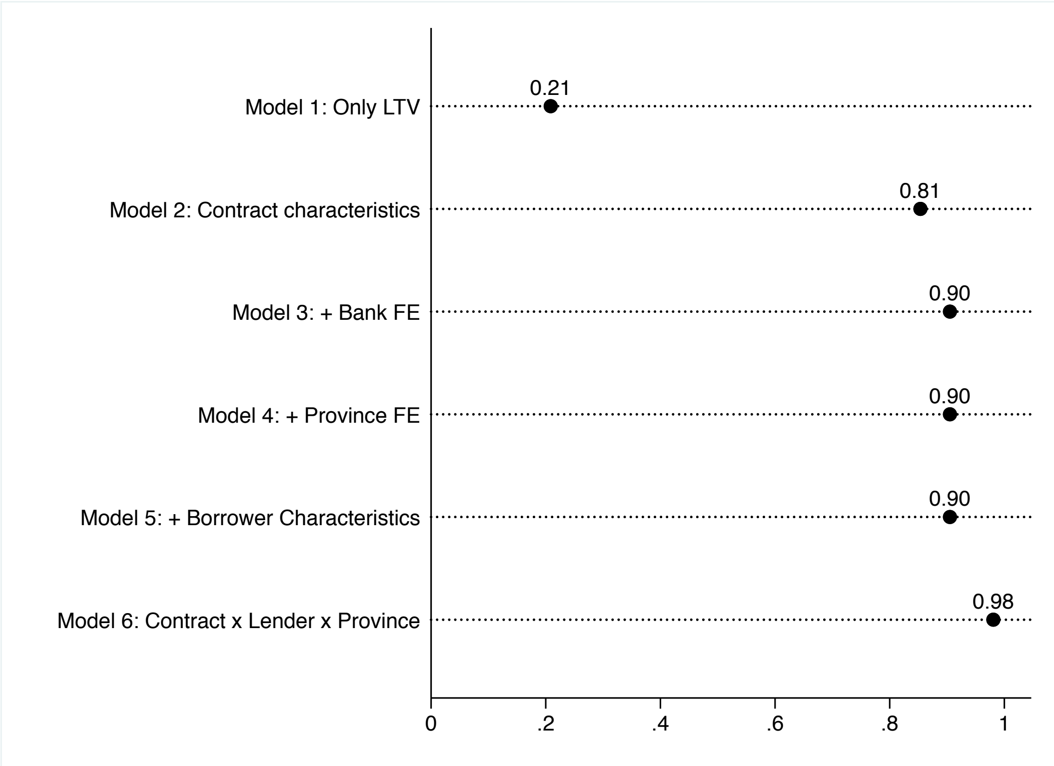
To infer the mortgage loan-to-value, we rely on data from the online platform (MutuiOnline). Importantly, this represents the only source of information on the LTV currently available in Italy.

According to MutuiOnline, dispersion in mortgage pricing is mostly driven by contract characteristics, and in particular by the lender, the rate type (adjustable versus fixed), the mortgage maturity and the LTV, which all together act as summary statistics for all other relevant characteristics, including borrower income, location and job-type.

Our estimation methodology relies on the idea that for each combination of lender, rate type, maturity, province, observable for newly originated mortgage contracts from CR and TAXIA, there is only one corresponding LTV with the same combination in the online offer dataset. Figure A.1 shows the Adjusted R-squared of regressions of the offered APR on a set of dummy variables obtained using data from the digital platform only. This set of regressions allows us to get a decomposition of the explanatory power of borrower and contract characteristics. The $Adjusted - R^2$ reaches 90 per cent when we include dummies for contract characteristics and bank FE. Adding dummies for the location of the house and borrower-level controls does not explain the residual variation in the offered APR. Model 6 includes the interaction of the lender, the rate type, the maturity, the LTV and the province; the R-squared is close to one, meaning that any characteristic other than those included in the above regression should bring almost no additional variation in the offered APR.

For new mortgage contracts the LTV is not obervable, but for any observable combination of lender, mortgage rate, maturity, province, and equilibrium APR, Figure A.1 implies that we can uniquely identify the LTV from the corresponding combination in the offer dataset. Table A.2 illustrates this procedure with a very stylized example.

Figure A.1: Explained variation in offered APR: MutuiOnline data



Note: The chart shows the $Adjusted - R^2$ of regressions of the offered APR on a set of dummy variables. Model 1 includes only dummies for the LTV. Model 2 adds dummies for the mortgage rate and maturity. Model 3 adds fixed effects for the lender. Model 4 adds province fixed effects. Model 5 adds dummies for borrower characteristics (age, income level and job type). For tractability of our dataset, we hereby disregard the time dimension and run all regressions at one single date. The chart presents results for the latest available date (December 2018). The $Adjusted - R^2$ for regressions at previous dates are almost identical. *Source:* MutuiOnline.

Table A.2: LTV inference: illustrative example

	Lender	LTV	Rate type	Maturity	Province	Month	APR (%)
CR	A	60*	Fixed-rate	20	Rome	March	1
	B	80*	Fixed-rate	20	Rome	March	2
MutuiOnline	A	60	Fixed-rate	20	Rome	March	1
	A	80	Fixed-rate	20	Rome	March	2
	B	60	Fixed-rate	20	Rome	March	1
	B	80	Fixed-rate	20	Rome	March	2

* Values inferred from MutuiOnline data

Note: The mortgage LTV is not directly observable for originated mortgage contracts. The table illustrates the methodology used to infer it from online platform data. The idea is the following: for each combination of observable characteristics of the mortgage contract (rate type, maturity, province, time) and equilibrium APR available from the Credit Register, there is only one corresponding combination with the same characteristics and the same offered APR in the MutuiOnline dataset, to which is associated a unique value of the LTV. We use this value as a proxy for the LTV at origination.

Robustness

Table A.3: Household's transition towards the rebranding lender

	Switchers			
	(1)	(2)	(3)	(4)
VARIABLES	Rebranding	Rebranding	Rebranding	Rebranding
Previous High	0.186***	0.0368**	0.194***	0.0351**
	(0.0551)	(0.0146)	(0.0553)	(0.0158)
Previous Medium	0.000647	0.00511	-0.00706	0.00552
	(0.0461)	(0.0198)	(0.0445)	(0.0194)
Treated	-0.0613	0.0764	-0.0474	0.0807
	(0.228)	(0.141)	(0.241)	(0.144)
POST	0.183***	0.0418***	0.177***	0.0456***
	(0.0423)	(0.0131)	(0.0420)	(0.0146)
POST × Treated	0.166	-0.0920	0.144	-0.0870
	(0.261)	(0.140)	(0.286)	(0.143)
Previous High × POST	-0.242***	-0.0256	-0.238***	-0.0223
	(0.0539)	(0.0188)	(0.0548)	(0.0189)
Previous High × Treated	-0.610***	-0.161	-0.622**	-0.165
	(0.227)	(0.149)	(0.245)	(0.152)
Previous High × POST × Treated	0.453	0.202	0.462	0.196
	(0.299)	(0.157)	(0.302)	(0.158)
Previous Medium × POST	-0.499***	0.0313	-0.497***	0.0318
	(0.0626)	(0.0235)	(0.0608)	(0.0226)
Previous Medium × Treated	-0.409*	-0.126	-0.422*	-0.123
	(0.228)	(0.166)	(0.242)	(0.160)
Previous Medium × POST × Treated	0.169	0.144	0.176	0.138
	(0.251)	(0.160)	(0.289)	(0.151)
Branches		0.193		0.225
		(0.127)		(0.138)
Bin FE	Y	Y	N	N
Bank chacacteristics	N	Y	N	Y
Borrower chacacteristics	N	Y	N	Y
Observations	1,554	1,554	1,554	1,554
R-squared	0.176	0.927	0.135	0.922

Standard errors clustered at the province level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The dependent variable is a dummy equal to one for mortgage contracts originated with the group implementing a rebranding strategy. Switchers are indebted borrowers that go to the rebranding lender for the first time since 2000. Previous High, Medium and Low are dummies defined according to the 2018 distribution of newly originated mortgage contracts, and reflect the previous lender's ranking in terms of APR within bin. Bins are combinations of mortgage LTV, maturity and rate type. $POST$ is a time dummy equal to one starting from the third quarter of 2018 and zero before. $Treated$ is a dummy variable equal to one for provinces directly affected by the rebranding and zero for remaining unaffected provinces. $Branches$ is the lender's share of physical branches by province. Bank characteristics include size, capital ratio, liquidity ratio and NPL ratio. Borrower characteristics include age, gender, nationality, and a dummy for past default. First-time borrowers and old clients are excluded. Category excluded is the previous lender with Low price ranking. Data are quarterly.

B. Appendix to Chapter 2

Transition Probability

Table B.1: Transition Matrix: Treated Provinces, Pre-Rebranding

		TO:			
		Low	Medium	Top	Total
	Low	17.5	11.7	3.25	32.4
FROM:	Medium	6.50	36.7	2.0	45.1
	Top	4.63	4.90	12.9	22.4
	Total	28.6	53.2	18.1	100.0

Table B.2: Transition Matrix: Treated Provinces, Post-Rebranding

		TO:			
		Low	Medium	Top	Total
	Low	21.7	9.2	1.5	32.4
FROM:	Medium	11.3	32.1	1.7	45.1
	Top	7.5	6.6	8.3	22.4
	Total	40.5	47.9	11.6	100.0

Note: Tables B.1 and B.2 report the transition matrices of borrowers in treated provinces across lenders with different rankings before and after the rebrading event, respectively. We compare transition probabilities before and after the rebranding within the same set of provinces to exclude the possibility of differences due to geographical characteristics and ensure homogeneity. 32.4% of the households start with a low-price lender, 45% of them with a medium-price, and the remaining 22% with a high-price one. Before the rebranding about 50% of them do not move; while almost 17% switch to a low-price lender. Following the rebranding, the share of households that do not move shrinks to 40%, and the share of those moving to a cheaper lender exceeds 25%. *Source:* CR-MO dataset.

C. Appendix to Chapter 3

MutuiOnline Evidence

Figure C.1: MutuiOnline: example of a mortgage application

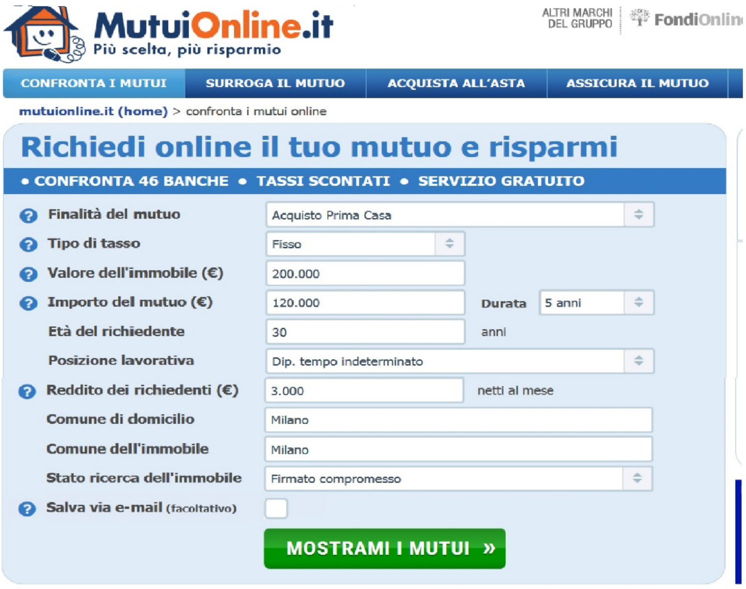
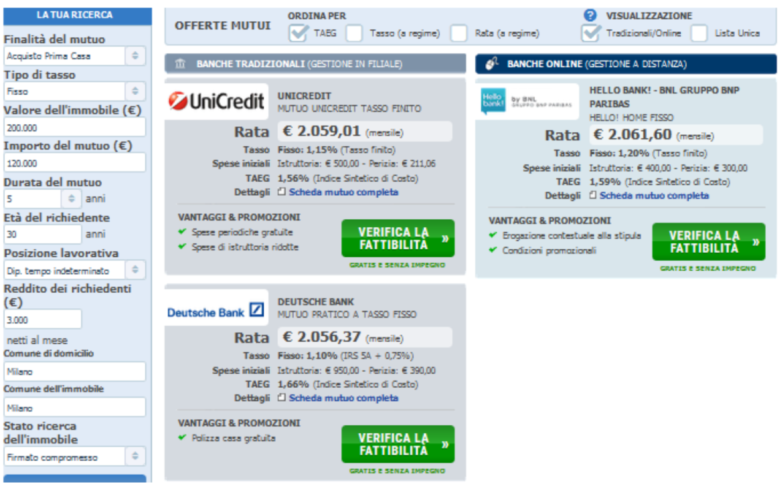


Figure C.2: MutuiOnline: example of a mortgage application pre-approval



Source: MutuiOnline website.

Figure C.3: Dataset construction

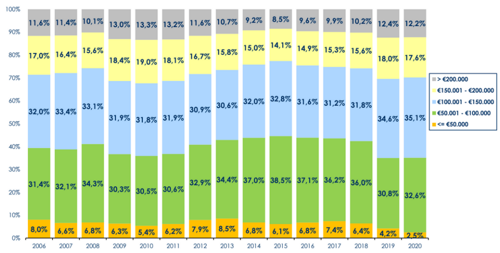
	Profile 1	Profile 2	....	....	....	....	....
Bank 1	offer		offer				
Bank 2		offer	offer		offer		
Bank 3		offer	offer		offer		
Bank 4	offer	offer			offer		
Bank 5				offer			
....				offer			
....				offer		offer	
....		offer				offer	
....	offer		offer			offer	
....	offer		offer				offer
....	offer		offer				offer
....	offer	offer					offer
....	offer			offer		offer	
....	offer			offer		offer	
....	offer						
Bank N							

(a) Month t

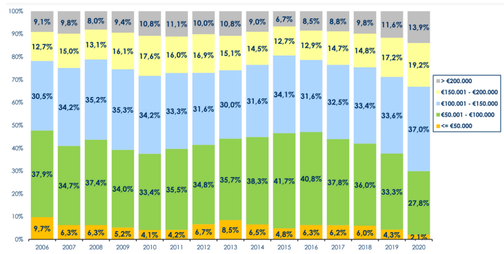
	Profile 1	Profile 2	....	....	....	....	....
Bank 1	offer		offer				
Bank 2		offer	offer		offer		
Bank 3		offer	offer		offer		
Bank 4	offer	offer			no offer	new offer	
Bank 5		new offer		offer			
....				offer			
....				offer		offer	
....		offer				offer	
....	offer		no offer			offer	
....	offer		offer			new offer	no offer
....	offer		offer				offer
....	offer	offer		new offer			offer
....	offer			no offer		offer	
....	offer			no offer		offer	
....	offer						
Bank N							

(b) Month t+1

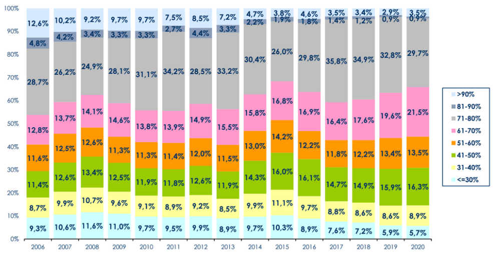
Figure C.4: Mortgage application versus mortgage origination



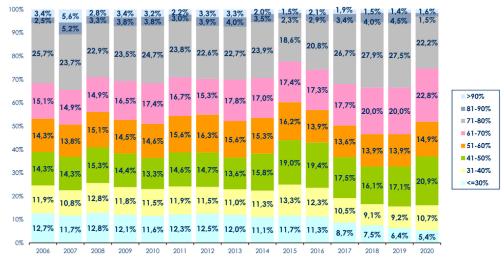
(a) Mortgage application by loan amount



(b) Mortgage origination by loan amount



(c) Mortgage application by LTV ratio



(d) Mortgage origination by loan amount

Note: Data refer to the period 2016-2020. *Source:* MutuiOnline.

Table C.1: Distribution of mortgage rate by borrower and contract characteristics

LTV	Mean	Median	Std.Dev	p25	p75
50 per cent	1.27	1.13	0.58	0.80	1.70
60 per cent	1.37	1.25	0.56	0.90	1.75
80 per cent	1.48	1.40	0.58	0.99	1.85
85 per cent	3.01	2.55	0.87	2.13	3.90
Maturity	Mean	Median	Std.Dev	p25	p75
10 years	1.23	1.12	0.59	0.85	1.45
15 years	1.36	1.29	0.63	0.88	1.70
20 years	1.43	1.35	0.65	0.90	1.84
30 years	1.68	1.68	0.71	1.05	2.20
Rate type	Mean	Median	Std.Dev	p25	p75
Fixed	1.87	1.77	0.59	1.50	2.10
Adjustable	1.03	0.94	0.45	0.78	1.13
Income	Mean	Median	Std.Dev	p25	p75
2000 euro	1.44	1.30	0.68	0.93	1.85
4000 euro	1.41	1.28	0.66	0.90	1.80
Employment status	Mean	Median	Std.Dev	p25	p75
Permanent contract	1.42	1.30	0.65	0.90	1.84
Other	1.45	1.27	0.74	0.90	1.84
Age	Mean	Median	Std.Dev	p25	p75
30 years	1.43	1.30	0.67	0.90	1.84
40 years	1.43	1.29	0.67	0.90	1.84
Mortgage type	Mean	Median	Std.Dev	p25	p75
First-time home buyer	1.38	1.20	0.67	0.88	1.80
Subrogation	1.47	1.35	0.67	0.97	1.87
Geographical area	Mean	Median	Std.Dev	p25	p75
North-East	1.42	1.30	0.66	0.91	1.81
North-West	1.43	1.29	0.70	0.88	1.85
Centre	1.43	1.30	0.66	0.90	1.83
South	1.42	1.29	0.66	0.92	1.83
Islands	1.44	1.30	0.69	0.90	1.85

Note: Data are in percentage points and refer to the average values between March 2018 and August 2019. *Source:* MutuiOnline.

Table C.2: Distribution of no-offer rate by borrower and contract characteristics

LTV	Mean	Median	Std.Dev	p25	p75
50 per cent	0.46	0.00	0.50	0.00	1.00
60 per cent	0.46	0.00	0.50	0.00	1.00
80 per cent	0.51	1.00	0.50	0.00	1.00
85 per cent	0.94	1.00	0.24	1.00	1.00
Maturity	Mean	Median	Std.Dev	p25	p75
10 years	0.62	1.00	0.49	0.00	1.00
15 years	0.60	1.00	0.49	0.00	1.00
20 years	0.57	1.00	0.50	0.00	1.00
30 years	0.59	1.00	0.49	0.00	1.00
Interest rate	Mean	Median	Std.Dev	p25	p75
Fixed	0.61	1.00	0.49	0.00	1.00
Adjustable	0.57	1.00	0.49	0.00	1.00
Income	Mean	Median	Std.Dev	p25	p75
2000 euro	0.61	1.00	0.49	0.00	1.00
4000 euro	0.57	1.00	0.49	0.00	1.00
Employement Status	Mean	Median	Std.Dev	p25	p75
Permanent contract	0.35	0.00	0.48	0.00	1.00
Other	0.83	1.00	0.38	1.00	1.00
Age	Mean	Median	Std.Dev	p25	p75
30 years	0.59	1.00	0.49	0.00	1.00
40 years	0.59	1.00	0.49	0.00	1.00
Mortgage type	Mean	Median	Std.Dev	p25	p75
First-time home buyer	0.58	1.00	0.49	0.00	1.00
Subrogation	0.60	1.00	0.49	0.00	1.00
Geographical area	Mean	Median	Std.Dev	p25	p75
North-East	0.59	1.00	0.49	0.00	1.00
North-West	0.59	1.00	0.49	0.00	1.00
Centre	0.59	1.00	0.49	0.00	1.00
South	0.58	1.00	0.49	0.00	1.00
Islands	0.61	1.00	0.49	0.00	1.00

Note: The no-offer rate is defined as 1 minus the share of banks that offer a product for each given profile. Data are in percentage points and refer to the average values between March 2018 and August 2019. *Source:* MutuiOnline.

Table C.3: Fixed-rate mortgages

	Mean	p10	p25	p50	p75	p90	Min	Max	Std.Dev
				5 largest banking groups					
Interest rates	1.98	1.25	1.5	1.8	2.2	3.65	0.5	4.05	0.77
APR	2.17	1.44	1.69	1.98	2.36	3.83	0.69	4.43	0.79
				Other significant institutions					
Interest rates	1.87	1.25	1.55	1.85	2.2	2.58	0.4	3.73	0.5
APR	2.05	1.45	1.74	2.05	2.34	2.69	0.78	3.29	0.47
				Less significant institutions					
Interest rates	1.89	1.3	1.51	1.8	2.2	2.56	0.85	4.4	0.54
APR	2.1	1.5	1.71	2.02	2.37	2.88	1.03	4.72	0.55
				Subsidiaries					
Interest rates	1.81	1.2	1.5	1.71	2.15	2.44	0.61	3.08	0.48
APR	1.94	1.35	1.61	1.85	2.29	2.57	0.82	3.13	0.45
				Online banks					
Interest rates	1.75	1.3	1.5	1.7	1.99	2.2	0.6	3.84	0.4
APR	1.82	1.37	1.57	1.76	2.03	2.28	0.6	3.95	0.39

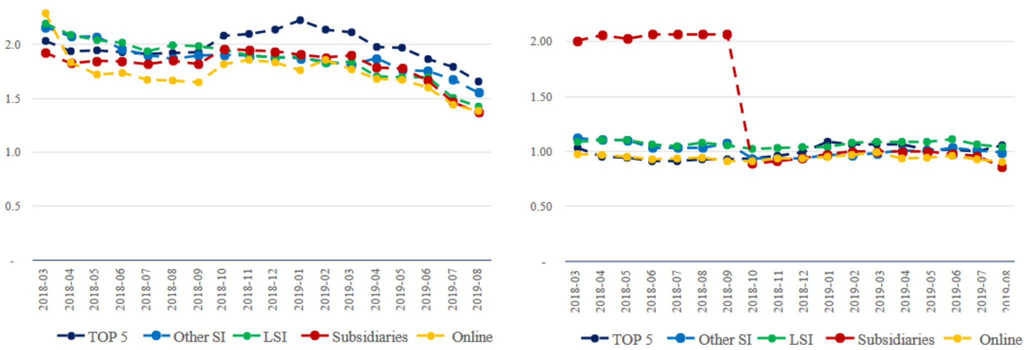
Note: Data are in percentage points and refer to the average values between March 2018 and August 2019. *Source:* MutuiOnline.

Table C.4: Adjustable-rate mortgages

	Mean	p10	p25	p50	p75	p90	Min	Max	Std.Dev
				5 largest banking groups					
Interest rates	0.99	0.58	0.73	0.88	1.08	2.03	0.33	2.28	0.45
APR	1.15	0.74	0.9	1.02	1.23	2.12	0.43	2.52	0.47
				Other significant institutions					
Interest rates	1.02	0.58	0.8	1.0	1.2	1.4	0.24	1.95	0.31
APR	1.18	0.78	1.0	1.2	1.34	1.55	0.51	2.03	0.28
				Less significant institutions					
Interest rates	1.07	0.65	0.7	0.9	1.15	1.83	0.42	3.43	0.52
APR	1.25	0.77	0.88	1.1	1.36	2.05	0.52	3.8	0.55
				Subsidiaries					
Interest rates	1.38	0.66	0.86	1.07	1.46	2.9	0.4	2.9	0.77
APR	1.51	0.8	0.97	1.23	1.47	2.98	0.55	3.27	0.79
				Online banks					
Interest rates	0.94	0.68	0.79	0.95	1.04	1.25	0.53	1.59	0.22
APR	0.99	0.77	0.88	0.99	1.07	1.24	0.57	1.61	0.2

Note: Data are in percentage points and refer to the average values between March 2018 and August 2019. *Source:* MutuiOnline.

Figure C.5: Offer rate by bank category



(a) Fixed rate (b) Adjustable rate

Note: Data are in percentage points. *Source:* MutuiOnline.