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University of Naples Federico II **University of Salerno** **Bocconi University, Milan**

CSEF - Centre for Studies in Economics and Finance
DEPARTMENT OF ECONOMICS AND STATISTICS – UNIVERSITY OF NAPLES FEDERICO II
80126 NAPLES - ITALY
Tel. and fax +39 081 675372 – e-mail: csef@unina.it
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Discrimination of Immigrants in Mortgage Pricing and Approval: Evidence from Italy

Paolo Emilio Mistrulli[*], Md Taslim Uddin[†], and Alberto Zazzaro[‡]

Abstract
In this paper, we explore empirically whether immigrants, other things being equal, pay more for mortgages than natives and whether the probability that banks approve their loan applications is systematically lower. To this aim, we use two extensive and unique dataset of mortgage contracts and banks' requests for initial information about potential mortgagors drawn from the Italian Credit Register for the period 2011-2016, and survey data from the Survey on Household Income and Wealth conducted by the Bank of Italy for the period 2006-2016. We find that immigrants pay 19-24 basis points more than native Italians on single-name mortgages and 28-40 basis points more on jointly-owned ones. This interest rate gap narrows significantly, but does not disappear, when immigrant borrowers' credit history lengthens or if they borrow from a cooperative bank. Finally we find that immigrants have a 2.7% smaller chance of getting a mortgage compared to natives, which decreases for mortgage applications submitted to cooperative banks. Overall, our findings suggest that the disparity of treatment of immigrants in the Italian mortgage market is mostly due to a greater difficulty of banks in assessing the credit-worthiness of culturally distant borrowers. However, we also detect that cultural distance may fuel persistent disparity between migrants and natives.

JEL Classification: G21, J15, J71.

Keywords: Immigrants; discrimination; mortgage lending; interest rates; loan approval.

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[*] Bank of Italy. E-mail: paoloemilio.mistrulli@bancaditalia.it

[†] Independent University Bangladesh. E-mail: mtaslim@iub.edu.bd (*Corresponding author*).

[‡] University of Naples Federico II, CSEF and MoFiR. E-mail: alberto.zazzaro@unina.it

1 Introduction

Discrimination in mortgage lending against immigrants and ethnic minorities has been an important and longstanding issue in academic and policy debate (Ladd, 1998; LaCour-Little, 1999; Turner and Skidmore, 1999). Access to mortgages at affordable and fair interest rates is a major barrier to homeownership (Henderson and Ioannides, 1983; Haurin et al., 1997; Guiso and Jappelli, 2002; Chiuri and Jappelli, 2003; Bayer et al., 2014; Trucchi, 2016; Goodman et al., 2018) and a crucial step towards actual and perceived socio-economic integration of immigrants in the host countries (Borjas, 2002; Constant et al., 2009; Arbaci and Malheiros, 2010; Accetturo et al., 2014; Kara and Molyneux, 2017; Bertocchi et al., 2022).

In this paper we empirically analyze immigrants' access to credit in the Italian mortgage market. We use Bank of Italy's Credit Register (CR) data on mortgages originated by commercial banks operating in Italy in the period 2011-2016 and on banks' requests of initial information about borrowers to the CR in 2015 and 2016. Our main focus is on mortgage pricing: we explore whether immigrants pay more for mortgages than Italian natives and whether the possible different treatment reflects the different credit qualification of mortgagors or can also be due to forms of discrimination by banks. In addition, we complement the interest rate analysis with evidence on the probability of mortgage approval by Italian banks for loan requests from immigrants and natives.

Economic theory provides two well known explanations for discrimination against minorities, based on taste or lack of information between the trading parties (Becker, 1971; Phelps, 1972; Arrow, 1973). In the first case, discrimination in mortgage markets takes place because of personal prejudice or preferences of lenders against a certain minority group. In the second case, unbiased native lenders can use race or ethnicity as a proxy for individual unobserved factors, like family links and social network, that have an impact on credit risk. In this way, due to the lack of complete information about individual borrowers' risk, lenders end up treating differently two otherwise identical native and immigrant mortgagors. At the turn of the two explanations based on preference and information, an additional cause for discrimination can be the cultural distance between native lenders and immigrant mortgagors. Lack of cultural kinship makes it difficult for lenders to understand informational cues about immigrant creditworthiness (Cornell and Welch, 1996) and, at the same time, makes native-born loan officers less likely to empathize with borrowers of an ethnic other than their own and to help them borrow on fair price and non-price terms (Kim and Squires, 1998; Bostic, 2003; Fisman et al., 2017; Albareto et al., 2022; Accetturo et al., 2023).

However, testing for discrimination and disentangling the nature of discrimination in mortgage lending by using real data is especially challenging.[1] First, mortgages are long term and multiple lending from different bank are rare. This implies that a single interest rate figure per borrower is available and it is not possible to control for borrower unobservable characteristics. Second, bank lending policies can provide for formal or informal rules, like minimum mortgage amount cutoffs, requirement for a personal guarantee by a third party or other redlines, which systematically make immigrant borrowers at a disadvantage based on some common characteristics unobservable to econometricians, like family wealth or social kinship. In this case, higher interest rates on mortgages to immigrants or lower probability of loan approval might hide systematic differences between immigrant and native-born borrowers. Third, banks offer borrowers a menu of mortgage terms to choose from, including interest rates, loan down payments, upfront fees and others, which can be not available to researchers. Once again, in a similar context, higher interest rates on mortgages to immigrants might capture their unobservables preferences or characteristics rather than a discrimination in the menu of conditions offered by the banks to immigrants and natives.

In our sample, the unconditional mean interest rate on mortgages made out to immigrants is statistically significantly higher than that on mortgages to Italian natives by 27 basis points (bps); when we distinguish between single-name and joint mortgages this difference is 18 and 32 bps, respectively. To investigate whether this gap reflects discrimination against immigrants and what its possible nature is, we perform various econometric

[1]Some studies have used an experimental setting by using paired testing and email-correspondence methods to compare the response of loan officers to mortgage requests by otherwise identical white and minority applicants, finding evidence of discrimination against the latter group Ross et al. (2008); Hanson et al. (2016).

exercises. First, we condition the effect of immigrant status on mortgage interest rates on observable mortgagors' characteristics and risk factors included in our dataset, and on a set of bank, province and time fixed effects. The disparity in interest rates paid by immigrants and natives remains statistically significant, ranging from 24 to 40 bps for single-name and joint mortgage contracts. Unfortunately, credit register does not contain information about the loan down payments and the income of the mortgagor, two key risk factors that are commonly used by banks to fix the interest rate on mortgages that can systematically differ between immigrants and natives (Elmer and Seelig, 1999; Elul et al., 2010). To address this concern, we use a machine learning approach to generate imputed values for mortgage loan-to-value (LTV) ratios and individual income from survey data reported in the "Survey on Household Income and Wealth" (SHIW) conducted by the Bank of Italy, and we again find that immigrants pay significantly more than native-born Italians (20 bps on single-name mortgages and 29 bps on joint mortgages).

Then, we use the Oaxaca-Blinder decomposition method to separate the average interest rate differential paid by immigrant mortgagors into the part explained by the differences in the explanatory variables between the two groups and the part not explained by the differences in observable characteristics. We find that only 15% of the price gap can be attributed to differences in the individual risk factors and mortgage characteristics, including the imputed income and LTV, while 85% is driven by unobserved factors, consistent with possible unobserved discrimination factors against immigrants.

In addition, we use propensity score matching methods to mitigate possible selection biases and compare mortgages taken up by immigrants to native-born Italians with similar observable characteristics. Even in this case, immigrant mortgagors result to pay higher interest rates than native-born Italians.

Finally, we repeat our regression analysis using survey information on mortgages self-reported by a representative sample of households participating in the Bank of Italy's SHIW, confirming once again the existence of a statistically significant price gap on mortgages taken up by immigrants.

To shed some light on the source of price discrimination against immigrants, first, we consider the country of origin of immigrants. In line with results of Albareto et al. (2022) for loans to sole proprietorship firms, we find that the interest rate gap is the highest for mortgages taken by Asians, Africans and South-Americans, which can be considered the immigrant groups most culturally distant from native-born Italian loan officers, and it is the lowest for mortgages to North American mortgagors. Second, in order to distinguish between statistical- and taste-based discrimination, we look at three sources of heterogeneity. We consider the mortgagors' credit history measured by the number of years since the first appearance in the central credit register. The idea is that if the interest rate gap shrinks for immigrants with a longer credit history, this indicates that the price gap is likely driven by the fact that banks have less information on the unconditional probability of repayments for the group of immigrant mortgagors. Then, we distinguish between dominant bank in the market of mortgages and fringe competitors, and between cooperative and non-cooperative banks. In the first case, the assumption is that large competitors are more likely to take their lending decisions based on automated credit scoring models and statistical information on borrower groups. On the contrary, cooperative banks are expected to have a more in-depth knowledge of the local economy and society and rely on borrower-specific soft information. Our regression results partly support the relevance of statistical-based discrimination, showing that as length of credit history increases the interest rate gap for immigrant mortgagors decreases statistically significantly, as well as for immigrants borrowing from cooperative banks, while we do not find any difference between mortgages granted by dominant and fringe competitors. In any case, although smaller, the effect of immigrant status on the interest rate remains positive and significant regardless of the different availability of specific information that banks have on average on the borrower.

Lastly, we complement the analysis of discrimination in interest rates with evidence on mortgage approvals. Although we do not observe individual loan applications and their final outcome at the approached banks, the Italian CR contains data on the requests for initial information about potential borrowers submitted by each bank to the CR and the loans that they actually approved in the following months. Therefore, using the approach proposed by Jiménez et al. (2012), we analyze the probability that the request for initial information about a borrower made by a bank will be followed by the disbursement of a loan to that borrower by the same bank within a certain span of time. Also regarding loan approvals, regression results confirm that immigrants have more restricted access to credit, showing that they are statistically significantly less likely to receive the mortgage (precisely, immigrants have a 2.7% smaller chance of getting a mortgage compared to natives). Once again, the discrimination effects is significantly lower for loan applications to cooperative banks, while credit history does not seem to have positive effects.

Unequal treatment of mortgage applicants based on race, ethnic and national origin has long been empirically documented for the United States, examining all the lending stages, from mortgage processing (Wei and Zhao, 2022) to mortgage performance (Reid et al., 2017). Studies on mortgage pricing by US banks consistently find that, after controlling for bank, mortgagors, loan and property characteristics, ethnic minorities (African-, Asian- and Hispanic-Americans) are both more likely to borrow at unfavorable terms and pay on average higher interest rates than White Americans. This holds independent of considering average annual rates or overages, prime or subprime mortgages, male or female mortgagors (Black et al., 1978; Courchane and Nickerson, 1997; Black et al., 2003; Boehm et al., 2006; Boehm and Schlottmann, 2007; Bocian et al., 2008; Bayer et al., 2014; Ghent et al., 2014; Cheng et al., 2015; Bayer et al., 2017; Delis and Papadopoulos, 2019; Ambrose et al., 2021; Bartlett et al., 2022).[2]

Unlike the United States, where anti-discrimination laws - such as the Fair Housing Act of 1968, the Equal Credit Opportunity Act of 1974 and the Home Mortgage Disclosure Act of 1975 - have long been enacted to protect ethnic minorities from discrimination in the real estate and in the mortgage market, neither Italy nor the rest of Europe has specific laws to ensure individuals and businesses fair access to the loan markets. The lack of law dealing with this issue is matched by the almost complete lack of empirical studies on the disparity of mortgage pricing against immigrants in European countries. A notable exception is Diaz-

[2]Two exceptions are Crawford and Rosenblatt (1999) and Bhutta and Hizmo (2021). The former explores mortgage prices charged by a major mortgage lender in the US finding that they are broadly race-neutral. Bhutta and Hizmo (2021), document that although Black- and Hispanic-American borrowers pay higher interest rates, they also pay lower up-front costs, consistent with the absence of discrimination against minorities in the multidimensional mortgage pricing and the presence of differences in preferences that lead minorities to choose a different location in the fee-rate schedule than whites.

Serrano and Raya (2014) who analyze a large sample of mortgages to homebuyers mediated by the mortgage brokerage branch of a a real estate company in Spain. They find that immigrants pay 18 basis points higher interest rates for mortgages than do native even after controlling for differences in credit worthiness and other factors.[3] With regard to Italy, Albareto et al. (2022) is the only study of which we are aware that analyzes possible discrimination of immigrants in accessing credit. They look at pricing of lines of credit to sole proprietorship firms. By using central credit register data for the period 2004-2008, they find that interest rates paid by immigrant-owned enterprises are on average 36 basis points higher that those paid by enterprises owned by native-born Italian entrepreneurs, and that this difference is greater for immigrants from Asian and non-Christian countries.[4] We add to their analysis by considering, for the first time in the literature, the pricing of home mortgages to immigrant households.

The rest of the paper is organized as follows. Section 2 presents the context of immigration and mortgage market in Italy. Section 3 presents the data sources, the dependent and independent variables and the empirical strategy. Section 4 discusses our regression results on mortgage contract data drawn from the Credit Register, section 5 presents results using survey data drawn from the SHIW dataset, while section 6 presents results on loan approval. Section 6 concludes.

2 The Italian context

2.1 Immigrants in Italy

Italy is a country of recent immigration. Only from the mid-seventies of the twentieth century, Italy experienced a positive migration balances. In Figure 1 we display the annual inflows of foreign population in Italy starting from 2000 as reported in the OECD International Migration Database.

[3]Kara and Molyneux (2017) study differential access to mortgages in the UK but do not consider interest rate: they find that low-income Black households are significantly less likely to have a mortgage compared to low-income White households.

[4]Few other studies have examined gender discrimination in access to credit in Italy without considering the immigrant status of the borrower (Bellucci et al., 2010; Alesina et al., 2013; Stefani and Vacca, 2013; Calcagnini et al., 2015).

[FIGURE 1 AROUND HERE]

In 2007 there was a peak in the entry of new immigrants, with over 510,000 people. After that date, also due to the financial crisis and the strong slowdown of the Italian economy, the annual inflow of immigrants decreased, settling at around 300,000 people per year. In 2018, more than 6 million foreign-born people reside in Italy legally, constituting 10.4% of Italy's total population.

During the years considered in our analysis, Romanians and Albanians are the two most important immigrant communities in Italy, followed by the Moroccan, Chinese and Ukrainian ones (see Table 1). However, there have been substantial changes in the composition of immigrants by nationality with a sharp increase in the number of immigrants from Asian and African countries – Bangladesh (+44%), Nigeria (+44%) and Pakistan (+34%) – and a reduction of immigrants from East Europe – Macedonia (-22%) and Poland (-10%).

[TABLE 1 AROUND HERE]

The housing conditions of foreign-born population in Italy are on overage rather poor, with almost 40% living in overcrowded or substandard dwellings (compared to an average share of almost 20% in other European Union countries), while the share of the foreigners who perceive themselves as discriminated against on the grounds of ethnicity, race, or citizenship is 14%, not different from the European average.[5]

2.2 Italian mortgage market

The mortgage market is a major driver of developed economies. In 2019, the total outstanding residential loans in the eurozone plus the United Kingdom is 54% of the area's GDP, while the amount of new residential loans (consisting of new mortgage loans plus remortgaging with another bank) is 1.19 trillion of euros, equal to 8.2% of GDP (EMF-ECBC, 2021).

Compared to the average for European countries, the mortgage market in Italy is significantly smaller, with a stock of outstanding residential loans and a flow of new mortgages

[5] Data are from OECD *Indicators of immigrant integration*, available at: https://www.oecd.org/els/mig/indicatorsofimmigrantintegration.htm

that are equal to, respectively, 21% and 6% of GDP. Although, Italy is characterized by a high home-ownership rate, households make less use of the mortgage for the purchase of the house. According to the OECD statistics, 71% of Italian dwellings were occupied by owners in 2018, well above the homeownership rate registered in France (60,6%), Germany (43,8%) and the United Kingdom (64,9%). However, made 100 the number of houses occupied by owners, only 14% were occupied by household with a mortgage in place, compared to 61% in the United States, 47% in the United Kingdom, 42% in Germany and a European average of 28%. In 2020, only half of the more than five hundred thousand housing transactions negotiated in Italy are with a mortgage. These figures reflect the lower propensity to borrow of Italian households, whose total debt is 87% of their disposable income in 2018, a value significantly lower than that of France (120%), Germany (93%), Spain (107%), the UK (145%) and the United States (103%) (Guiso et al., 2022).

[FIGURE 2 AROUND HERE]

The average mortgage amount provided by Italian banks in 2020 is 130,000 euros, compared to €277,000 in Germany, €240,000 in the UK and €230,000 in the US (EMF-ECBC, 2021). The cautious stance of Italian banks and households is reflected in the loan-to-value ratio (LTV) of mortgage loans, which is 63% in Italy, and in the share of new loans with an LTV greater than 80% which does not exceed 16%, both values much smaller than the European average of 81% and 56,1%, respectively (Lang et al., 2020).

The two types of mortgage contract offered by Italian banks are the adjustable-rate mortgage (ARM), where the interest rate charged to the borrowers provides for a spread on an underlying reference rate (usually, 1-3 months Euribor), and the fixed-rate mortgage (FRM), where interest rate and installments are fixed for the whole length of the mortgage. In our sample period, just over 28% of the mortgages issued are FRMs. In figure 3 we report the average interest rate charged on FRMs and ARMs. The former has been higher throughout the period 2011-2016, a period of decreasing interest rates (plot (a)). This is true both for mortgages to Italian natives and for those taken up by immigrants, even if the latter pay higher rates independent of the type of contract (plot (b)).

[FIGURE 3 AROUND HERE]

3 Data, variables and statistics

3.1 Datasets

Our main analysis on the pricing of mortgages is at the loan level. We draw data from the Central Credit Register (CR) and the Analytical Survey on Loan Interest Rates (ASLIR) maintained by the Bank of Italy.[6] From the ASLIR we obtain the contractual interest rates on personal loans granted to natural persons and sole proprietorships by a subset of banks in each quarter, including all the main banking groups active in Italy which cover more than 90% of the Italian credit market. Precisely, the reporting banks are required to submit information for each new loan made in a reference quarter to borrowers for whom, at the end of that same quarter, the sum of all the accorded and used loans reported in Central Credit Register is equal to or more than 75,000 euros. The ASLIR also includes data on the identity of the bank originating the loan, the type of contract, the loan size at origination and a number of personal data of the borrower. We complement this information with the date on which the borrower first appears in the Bank of Italy's credit information system obtained from the CR to measure her/his credit history length.

Our dataset includes all the home mortgages in the ASLIR, both for the purchase and renovation of a dwelling, originated between 2011 and 2016. The original dataset has complete records on around 1 million mortgages. To remove outliers, data have been trimmed to the top and bottom one percentile of the interest rate distribution (which represent 19,952 observations). We also exclude the contracts for which the initial duration is less than 5 years (1,992 observations) and the loan size is less than 5,000 euros (1,033 observations).[7] In this way we exclude from the analysis the mortgages that are more likely devoted to small home renovations. Finally, we exclude joint mortgage contracts with more than two co-borrowers to facilitate the identification of the role of the immigrant status of (co-)mortgagors (24,174 observations).[8]

[6] In Italian, the *Rilevazione Analitica dei Tassi di interesse*, also known by the acronym TAXIA (Bank of Italy, 2021).

[7] All the mortgage contracts that we consider in the analysis have a maturity of more than 5 years but data on the exact duration of each contract are not available.

[8] In the whole sample, the maximum number of co-mortgagors in a joint mortgage contract is six.

After these filtering steps, we end up with a sample of 954,341 loans relative to 24 quarters from March 2011 to October 2016, of which 490,189 single-name mortgages and 464,152 joint mortgages.

For robustness, in Section 5 we repeat our regression analysis using survey data at the household level drawn from the Survey on Household Income and Wealth (SHIW) conducted by the Bank of Italy for the period 2006-2016.

Finally, in order to build a measure of loan approval at the bank-applicant level, we use Credit Register data on requests for ”CR first information” submitted by Italian banks about potential borrowers approaching their institute in the period 2015-2016. In sections 5 and 6 we provide a detailed description of, respectively, the SHIW and ”CR first information” datasets and of variables used in the our empirical exercises.

3.2 Credit Register variables for mortgage pricing analysis

Table 2 contains a list of all dependent and independent variables drawn from the CR used in the analysis of mortgage pricing, their definitions, mean values and standard deviations.

[TABLE 2 AROUND HERE]

Our dependent variable is the contractual annual percentage rate charged by banks on mortgage loans (*APR*), including interest payments and any additional fees and costs associated with the transaction. On average, during our sample period the mortgage interest was 3.22%, varying from a minimum of 0.17% to a maximum of 7.73%.

The key explanatory variable of *APR* is *Immigrant*, a dummy that takes the value of 1 for non-Italian born mortgagors and 0 otherwise. In our sample 6% of mortgagors are immigrants. Of these, 70% are from an European country (the majority from Eastern Europe), 11% are Asians, 9% are South Americans, 7% are Africans and just over 1% come from North America and Oceania. Our sample includes both mortgages in the name of a single borrower and mortgages made out to two co-borrowers, indicated by the dummy *Coint* that takes the value 1 for the joint mortgages. The share of single-name mortgages taken out by immigrants – $\sum_i Singleimmi/\sum_i(1-Coint)$ – is 5%, while the share of joint mortgages in two immigrant names or made out to one immigrant co-borrower – given by $\sum_i Cointimmi / \sum_i Coint$ and $\sum_i Cointmix / \sum_i Coint$ – are 6.7% and 6.9%, respectively.

Furthermore, the Central Credit Register includes information on the mortgage loan amount in euros (*Loan amount*), on whether the mortgage is fixed rate or adjustable rate (*Fixed*), on the age and gender of the primary borrower, (*Age* and *Male*), and her/his *Credit history*). In our sample, the average size of a mortgage loan is €139,309 and 28% of them are fixed rate. The average age of mortgagors is 41 years and in 56% of contracts the primary mortgagor is male. The average *Credit history*, which captures the public information about borrowers available to banks, is 2.23 years long.

4 Results on mortgage pricing with CR data

4.1 Univariate analysis

In table 3 we report t-test results for mean differences in loan and borrower characteristics between mortgages made out to native-born Italians and immigrants. We consider mean differences for single-name and joint mortgage contracts (Panel A and Panel B, respectively) and for the full sample, including both types of mortgages (Panel C).

[TABLE 3 AROUND HERE]

Overall, there are statistically significant differences in all the mortgage dimensions between immigrant and native mortgagors. The unconditional mean mortgage rate paid by immigrants is 26 bps higher than that that paid by natives. This gap is greater for joint mortgages (32 bps) than for mortgages made out to single borrowers (18 bps). The average amount of a mortgage jointly owned by immigrants is approximately 16,000 euros less than that granted to two Italian co-borrowers, while for single-name mortgages this difference is approximately 5,900 euros. Finally, immigrants tend to take out ARM loans more frequently than natives.

The individual characteristics of immigrant and Italian native mortgagors are also slightly different. Immigrant mortgagors are younger and female in a larger proportion compared to native ones. Importantly, they have a shorter credit history: the share of immigrant borrowers with no credit history is 81%, compared to 65% for Italian natives, while their average credit history is almost half shorter than for natives (1.14 versus 2.30 years).

4.2 Baseline regression model

We estimate the following multivariate linear regression model of mortgage interest rate:

$$APR_{ijt} = \alpha \cdot Immigrant_j + \sum_{n=1}^{N} \beta_n \cdot X_{ijt}^n + \mu_j + \delta_i + \epsilon_{ijt} \quad (1)$$

where the dependent variable APR_{ijt} is the annual percentage interest rate charged on the mortgage loan granted to borrower *i* by bank *j* in quarter *t*, *Immigrant* is an indicator for the immigrant status of borrower j, X_{ijt} is a set of N mortgage and borrower characteristics, δ_i and μ_j denote, respectively, a series of bank and province fixed effects, where province is the place of residence of the borrower, and ϵ_{ijt} is the error term. The estimated coefficient α represents the interest rate gap between mortgage loans to immigrant and native borrowers.

In our baseline analysis, we use an OLS estimator with robust standard errors and include in X_{ijt} only variables recorded in the ASLIR and CR. Table 4 reports the estimation results. We estimate model (1) separately for the subsample of single-name mortgages in columns [1]-[3], and for joint mortgages in columns [4] and [5]. In the last two columns [6] and [7], we show results for the full sample that includes both type of mortgages. For all the samples, first we consider a specification with only the immigrant status of the mortgagors and the bank, province and time fixed effects, then we present specification with control variables. In the Appendix, we show that our results are qualitatively and quantitatively robust to the inclusion of bank×time and province×time fixed effects, and to the use of robust standard errors clustered at the bank level (see Table A1).

[TABLE 4 AROUND HERE]

Starting from single-name mortgages, the coefficient on *Immigrant* indicates that that non-Italian borrowers pay 24 bps more on mortgages compared to Italian natives. This difference remains broadly stable once we control for observable mortgage and mortgagor characteristics. When we take into account the immigrants' origin and substitute the dummy *Immigrant* with a set of dummies indicating their continent of origin, as in column [3], we find a statistically significant interest rate gap for all the immigrant groups. Interestingly, however, the gap tends to be greater for Asian, Central American and African immigrants (32, 26 and 25 bps, respectively), while Oceanians and North Americans are the least penalized in interst rate conditions, paying, respectively, only 10 and 6 bps more than Italian natives. These results are consistent with findings of (Albareto et al., 2022) for interest rate on credit lines to sole proprietorships owned by immigrant and Italian native entrepreneurs, and, to the extent that African, Asian and South American are the ethnic groups culturally more distant from native-born loan officers, suggest that the interest gap in mortgage pricing may be in part driven by lender-borrower cultural diversity.

The interest gap increases for joint mortgages made out to two immigrant co-borrowers that, on average, pay 40 bps more than mortgages in name of two Italian natives (column [5]). However, for immigrants borrowing together with a native borrower ($Cointmix = 1$), the gap, while remaining statistically significant, is reduced to 12 bps, indicating that the presence of a native-born co-borrower acts as a sort of guarantee for the bank and mitigates the cultural distance with immigrant borrowers. These findings are confirmed in the full sample specification [7]. Compared to single-name mortgages made out to Italian natives, the interest rates on single-name and joint mortgages to immigrants are, respectively, 25 and 49 bps higher, while the interest rate on "mixed" mortgages with immigrant and native co-borrowers is higher by 21 bps.

Moving on to the control variables, the coefficient on loan amount is negative, consistent with previous evidence suggesting that big borrowers have greater bargaining power and are able to achieve better contractual terms Black et al. (2003); Alesina et al. (2013); Albareto et al. (2022). Contractual interest rate on FRMs is about 75 bps higher than that on ARMs. *Age* has a U-shaped marginal effect on the interest rate, reaching its minimum value for 45 years old mortgagors, while we do not find any evidence of economically significant gender gap in interest payments on mortgages, with male borrowers paying, on average, about 2 bps more that the female ones. Finally, the coefficient on *Credit history* is negative and statistically significant, in line with the hypothesis that applicants who are already registered in the CR at the time of taking the mortgage contract are informationally less opaque for the bank and pay lower interest rates.[9]

4.3 Imputing LTV and mortgagors' income: A machine learning approach

The CR and ASLIR do not contain information on the LTV ratio and the income of mortgagors. However, the portion of the lender-assessed value of the house that is covered by the mortgagors' own financial resources and the earning capacity of the latter are two key risk indicators used by banks to decide on the loan application and the related interest rate, which often follows an explicit LTV-interest-rate supply schedule. In addition, both risk factors – LTV ratio and earning capacity – tend to be more severe for immigrant mortgagors than for the Italian native ones.[10] This introduces a possible omitted variable bias in our baseline estimations in table 4, which results in an overestimation of the interest gap towards immigrants.

To address this concern, we adopt a machine learning-based random forest approach (hereafter RF) for missing data imputation. Precisely, we use RF to predict and impute missing income and LTV values for mortgages included in the CR dataset by exploiting survey information on LTV and income contained in the Bank of Italy's SHIW dataset.

RF is a supervised machine learning algorithm proposed by Ho (1995) and Breiman (1996; 2001) for classification and regression problems that recursively identifies split points that subdivide the data into subgroups based on the values of a number of relevant feature variables (or predictors). It has been extended to address data imputation problems by developing various RF missing data algorithms (Tang and Ishwaran, 2017). In RF a large number n of independent decision trees are randomly generated from a training dataset with replacement through bootstrap sampling of k records containing a set of features X_T

[9] Results of table 4 remains qualitatively and quantitatively unchanged when we limit the analysis to mortgage loans above 75,000 euros, the threshold of borrowers' total outstanding loans considered by the ASLIR (results are reported in the online Appendix, table A2.

[10] This find clear confirmation in the Bank of Italy's SHIW dataset, where the unconditional mean values of LTV and income for immigrants are statistically significantly lower than for natives. Precisely, if we pool SHIW waves from 2006 to 2016, conditional on holding a mortgage, immigrants display an average LTV ratio equal to 87% and income equal to 16,018 euros compared to 61% and 28,216 euros of Italian natives (the differences between the means are both statistically significant at the standard 5% significance level).

and an output variables y_T. At each candidate split point in the training process, RF uses a random subset of the features. Finally, each tree generates an output and the final output is obtained by averaging the tree outputs:

$$\hat{y}_T = \frac{f_T(X_T)}{n} \tag{2}$$

where f_T is the regression tree.

Missing values for output variables can be imputed by using the trained RF algorithm on an out-of-training-sample or prediction dataset to compute values based on observed predictors:

$$\hat{y}_P = \frac{f_T(X_P)}{n} \tag{3}$$

RF algorithm has a number of important advantages compared to other data imputation techniques like parametric regression models and non-parameteric k-nearest neighbors machine learning algorithm.[11] It allows for using numerical and categorical features, for including non-linear and interaction terms, as well as for handling possible outliers and collinearity among predictors.

Our training dataset is the Bank of Italy's SHIW dataset, which contains self-reported information on the LTV ratios on the mortgages held by the household of the respondents and their income. LTV ratio and mortgagors' income are our output variables, while as features we use the predictors included in the baseline model (immigrant status, loan amount, interest rate type, mortagors' age, age squared and gender).[12] The prediction dataset is the original CR dataset that does not contain information on LTV and income. We follow the proximity imputation algorithm by using the R package "Random Forest". To achieve a stable error rate, we specified 500 trees.

Regression results are reported in Table 5 for the the samples of single-name and joint mortgages.[13] In columns [1] and [4], we include LTV ratios with the same controls used in the baseline model of Table 4. Consistent with Diaz-Serrano and Raya (2014), we find a

[11]For a comparison among data imputation techniques see Shah et al. (2014) and Tang and Ishwaran (2017).

[12]We exclude credit history from our prediction model as SHIW data does not contain this information.

[13]Table A3 in the Appendix ahow the robustness of results to the inclusion of bank-time and province-time fixed effect and to robust standard errors clustered at the bank level.

positive and statistically significant association between LTV ratios and interest rates paid on mortgages. More importantly, we find that, even after controlling for down payments, the interest rate on single-name (resp., joint) mortgages is for immigrants 20 (resp., 28) bps higher than for native-born Italians.

[TABLE 5 AROUND HERE]

In columns [2] and [5], we add mortgagors' income. As expected, we find that higher earning capacity of mortgagors result in lower mortgage rates. However, even with the same income, immigrants pay more than natives. Finally, in columns [3] and [6] we replicate results classifying mortgagors by the country of origin and, for the sample of joint mortgages and the full sample, distinguishing the loans taken out by two immigrants, two natives and one immigrant and one native co-borrowers. Once again, the findings are consistent with those of the baseline model.

4.4 Oaxaca-Blinder Decomposition

To provide further evidence of unequal treatment between immigrant and native mortgagors, in this section we adopt the Oaxaca-Blinder decomposition approach (Oaxaca, 1973; Blinder, 1973). The aim of the decomposition is to distinguish how much of the average interest rate differential between mortgages made out to immigrants and Italian natives is due to a component that can be explained by differences in explanatory variables assuming that both group of mortgagors receive the same treatment (also referred to as the endowments effect), and an unexplained component arising from differences in the magnitude of the regression coefficients (the coefficient effect). This second component captures the degree of discrimination against immigrant in the mortgage market due to the fact that the same individual characteristic have a different impact on the interest rate of loans granted to immigrant mortgagors and on those granted to native-born Italians.

The Oaxaca-Blinder decomposition of the interest rate gap paid by immigrants starts by running two separate interest rate regressions for two groups of immigrants and native mortgagors:

$$\begin{aligned} r_I &= X_I^{'}\beta_I + \epsilon_I &(4)\\ r_N &= X_N^{'}\beta_N + \epsilon_N &(5)\end{aligned}$$

where $X^{'}$ is a vector including the same set of observable characteristics as in column (3) of Table 4. The differential between the mean interest rates paid by immigrants and natives, $\Delta\bar{r} = \bar{r}_I - \bar{r}_N = \bar{X}_I^{'}\hat{\beta}_I - \bar{X}_N^{'}\hat{\beta}_N$, is then decomposed into two components:

$$\Delta\bar{r} = \underbrace{(\bar{X}_I - \bar{X}_N)^{'}\hat{\beta}_N}_{\text{explained component}} + \underbrace{\bar{X}_I^{'}(\hat{\beta}_I - \hat{\beta}_N)}_{\text{unexplained component}} \tag{6}$$

where $\hat{\beta}_N$ is assumed to be the vector of nondiscriminatory coefficients.

Table 6 depicts the results of the decomposition analysis. The interest paid by immigrants on single-name mortgages is 18.4 bps higher than that paid by natives, while the gap is 19.3 bps on joint mortgages.[14]

[TABLE 6 AROUND HERE]

The individual characteristics of immigrants account only for 14% of the gap in the mortgage rate. This suggests that if immigrant mortgagors were valued by banks in the same way they value the native ones, the different average characteristics that distinguishes the two groups would justify an interest gap of only 2.64 bps. On the other hand, about 86% of the observed interest gap depends on unexplained factors that are behind the different marginal impact that observable characteristics have for the interest rate charged to immigrant and native mortgagors. The unexplained component is even greater in the case of joint mortgages, representing 93% of the interest gap. Therefore, the Oaxaca-Blinder decomposition confirms the existence of possible different treatments of mortgagors based on national origins.

[14]Table A4 in the Appendix reports the underlying regression results of models (4) and (5) for interest rates paid by immigrant and native mortgagors, while in Table A5 we repeat the analysis by using standard errors clustered at the bank level.

4.5 Propensity Score Matching

To identify the effect of the immigrant status of mortgagors on interest rates, we would ideally compare the rates paid by immigrant and native borrowers who were otherwise identical. However, the status of immigrant is not randomly assigned across mortgagors.

To mitigate this concern, we match mortgages held by immigrants to observationally similar mortgages held by Italian natives. We use the propensity score matching (PSM) technique based on a unidimensional balancing score to characterize the probability that the mortgage i is taken up by an immigrant conditional on observables. The objective is to compare mortgages made out to immigrant and native mortgagors that are very similar in terms of the observable characteristics including loan amount, age, credit history, gender and type of loan contract like in our baseline specification. Assuming that there are no significant differences in unobservable characteristics between the two groups of mortgagors, the observed average interest rate gap between mortgages taken up by immigrants and mortgages taken up by the matched group of natives is attributable to the national origin of the mortgagor (Rosenbaum and Rubin, 1983).

We match each immigrant mortgagor to one or more natives on the propensity score by using the nearest neighbor method with replacement, where each native can be paired to more than one immigrant independent of the matching order (Dehejia and Wahba, 2002; Thoemmes and Kim, 2011). In Table 7, we report the average treatment effect on treated (ATT) for matching with one, four and eight mortgages held by Italian natives. Results again indicate that on average immigrants pay significantly more than natives: on single-name mortgages the interest gap is 19 bps, while on the joint mortgages the differential is 33 bps.

[TABLE 7 AROUND HERE]

4.6 Credit history, dominant lenders and cooperative banks

In this section, we try to gauge the role that statistical discrimination and hold-up problems play in mortgage pricing. Precisely, we examine to what extent differences in the availability of information about borrowers between banks contribute to explain why banks charge higher interest rates on mortgages taken up by immigrants.

If we suppose that native-born loan officers are more culturally distant and less empathetic towards immigrants than their fellow citizens (Cornell and Welch, 1996; Frame et al., 2022; Jiang et al., 2023), it is reasonable to expect that banks' lack of borrower-specific information and the presence of relationship-specific mortgage search costs for the latter will be more severe for immigrant borrowers rather than for Italian natives. In this case banks have limited information to infer the creditworthiness of individual borrowers and can use observable group characteristics such as race, ethnicity or nationality as a signal of their ability to repay credit, based on the correlation between these group characteristics and risk indicators (such as the delinquency rate). As a result, an immigrant, although otherwise individually identical to a native borrower, is asked for a higher interest rate because she belongs to a different nationality group which is statistically more risky for the bank (Scalera and Zazzaro, 2001). Bank-mortgagor relationships do not typically repeat over time as bank-firm relationships do, and cannot mitigate asymmetric information and statistical discrimination problems (Bellucci et al., 2010; Albareto et al., 2022). However, the amount of information shared in the banking system through the CR narrow the asymmetry of information with potential borrowers for banks and increase competition in the mortgage market, thus reducing statistical discrimination and and hold-up problems for mortgagors. We proxy information on a mortgagor available to banks with the number of years from which he/she appears in the Central Credit Register and all the banks in the system can track its credit history. Therefore, we augment the baseline model with an interaction term between the immigrant status and his/her credit history, alternatively measured as a continuous variable or as an indicator variable taking the value of 1 for mortgagors having a credit history longer than 3 years and zero otherwise.

Second, we distinguish between the mortgages granted by the five banks that hold the largest share of the mortgage market ($Main\ competitors = 1$) and the other fringe competitors ($Main\ competitors = 0$), and consider the interaction with the immigrant status of the mortgagor. The idea is that the largest competitors rely on automated underwriting systems for their lending decisions more than small competitors. This can be expected to allow large competitors to charge lower interest rate on average, but at the same time lead them to use statistical information to distinguish among group of borrowers.

Finally, in a similar perspective, we examine whether ethnic disparities in the mortgage interest rates are mitigated for immigrants borrowing from cooperative banks ($Cooperative = 1$). The assumption her is that the cooperative banks have a more in-depth knowledge of the various local economic and social realities in which immigrants are embedded. Furthermore, they are less hierarchically organized, reducing asymmetric information between local loan officers and senior managers at the bank headquarters. For both these reasons, we expect that cooperative banks have more soft information about loan applicants and rely more heavily on soft information rather than on recommendations generated by automated underwriting systems.[15]

Results reported in Table 8 suggest that statistical discrimination and hold-up problems play a role in mortgage pricing and explain a part of interest rate differential paid by immigrants. Considering single-name mortgages, specification [1] indicates that immigrants benefit more than natives from the lengthening of their credit history and then the interest gap narrows as their credit history gets longer: for an immigrant with a credit history of 10 years the interest gap reduces by 6.5 bps, while according to column [2] immigrants who entered in Credit Register by more than 3 years pay on average 5.9 bps less than other immigrants (whose interest gap with natives is 25 bps). This suggests that immigrants are ex-ante more opaque than natives and, consequently, gain more from a longer credit history.

Column [3] and [4] show that interest rate disparities against immigrants is on average the same on mortgages granted by dominant and fringe competitors, while immigrants borrowing from cooperative banks pay 10 bps less than immigrants who have the mortgages with other banks.

[TABLE 8 AROUND HERE]

Moving on joint mortgages, results indicate that while mortgagors' credit history (in this

[15] Relatedly, a number of recent papers have documented that minority-owned banks and minority loan officers who are culturally closer to minority mortgagors are more likely to approve their applications than other banks or loan officers (Frame et al., 2022; Hurtado and Sakong, 2022; Jiang et al., 2023).

case, the greatest value of *Credit history* between the two co-mortgagors) contributes to reduce, on average, the interest rate paid by borrowers, it does not help to mitigate the interest gap between immigrant and native mortgagors. By contrast, we find evidence that the immigrant interest gap on joint mortgages is greater for the big lenders than for small banks (54 and 32 bps, respectively), although this difference is not statistically significant. Cooperative banks, on the other hand, confirm their ability to accommodate the demand for mortgages from immigrants at prices that are more in line with those charged to Italian natives compared to other banks (precisely, the immigrant interest gap is 23 bps for mortgages with cooperative banks against 43 bps for those with non-cooperative banks).[16]

On the whole, these results suggest that the disparity of treatment of immigrant mortgagors that we document in tables 4 and 5, cannot be explained only by a greater difficulty in assessing the individual riskiness of these borrowers accurately, but it also captures some persistent factors such as prejudices arising from cultural distances between lenders and borrowers.

5 Evidence from SHIW data

The loan-level data used so far allowed us to have a very accurate estimate of the parameters of the interest rate model for the variables extracted from the Credit Register. However, the lack of information on the LTV ratio and borrowers' income has forced us to resort to a data imputation process that is subject to possible serious measurement errors.

As an additional robustness check, we run our econometric analysis using survey data from the Bank of Italy's SHIW (Survey on Household Income and Wealth).[17] The SHIW survey is conducted every other year on a representative rotating panel of about 8,000 households resident in Italy. In the SHIW dataset, basic sample unit is the household and the respondent is the head of the household in charge of the household's financial decisions. As

[16]We repeat the heteterogeneity analysis for the cases of the full sample of single-name and joint mortgages and for the augmented model with imputed LTV ratios and borrowers' income and using joint bank-time and province-time fixed effects and robust standard errors clustered at the bank level. Results, reported in tables from A6 to A9 in the Appendix, are qualitatively and quantitatively almost identical.

[17]This is the same survey that we employed above as training set to derive imputed LTV ratios and mortagors' income.

in the baseline analysis, our key variable of interest is *Immigrant* which takes the value of 1 if the head of the household, defined as the member of the household who is primarily responsible for the financial and economic choices of the household unit, is foreign born. Similarly, self-reported mortgage related information (that is, interest rate, interest rate regime, loan amount, LTV ratio, mortgage destination) are all provided by the head of the household and are asked at the household level. We control for age, education, gender and marital status of the household head and the total income generated by the household. Finally, we include dummies for NUTS2 regions, and dummies for mortgage generating year.

Information on immigrant households are only available since 2006. Therefore, we can use six SHIW waves. For households participating in more than one wave, we include the answers given to the first wave in which information relating to the mortgage taken out by the household appears in the survey and, possibly, the answers relating to a second new mortgage. This leaves us with 2,081 observations. Then, we exclude observations where the reported interest rate is zero or negative or LTV ratio is greater than 1. Our final sample is thus formed by 1,991 mortgages, 91 of which are taken out by immmigrants. Table 9 provides definition and summary statistics of variables from the SHIW used in our analysis. Consistent with Credit Register data, the unconditional mean mortgage rate for mortgages taken up by immigrant households is about 33 bps more than that for their native counterparts (3.72% vs 3.39%), even if this gap is not statistically significant.

[TABLE 9 AROUND HERE]

Table 10 presents the regression results using SHIW data. The interest gap on mortgages taken up by immigrants is still statistically significant and it is slightly greater in magnitude (40 bps) compared to the interest gap resulting from the Credit Register data (34 bps). As expected, LTV and fixed rate mortgages exert a positive impact on mortgage rate, while the effect of household income and loan size are negative. Finally, the coefficient of purchase indicates that borrowers pay less on mortgages taken up for purchasing property rather than for renovation.

[TABLE 10 AROUND HERE]

The Bank of Italy monthly provides intermediaries with information on the total debt towards the credit system of each reported customer.

6 Loan approvals

In this last section, we look at loan approvals by examining whether immigrant loan applicants are less likely to obtain mortgages in comparison to native-born Italian applicants.

The Bank of Italy's Central Credit Register shares information among banks in two ways. First, every month banks automatically receive information about firms and households they are currently lending to. In addition, banks can query the CR for information about legal and natural persons they are not lending to (the so-called requests for ”CR first information”).[18] By law, each bank is allowed to do that only in certain circumstances that are also tracked in the register. One of these occurs when a firm or a natural person asks banks for a loan. In what follows, we focus on these cases only.

Following the approach introduced by Jiménez et al. (2012), we build an indicator for the demand of mortgages at the individual level by using CR data on the banks' requests of first information on natural persons who are not their borrowers. If the bank that has requested information on a particular borrower will grant the loan within a given span of time, say three months, then the loan application is considered successfully approved otherwise it is considered not approved.

In table 11 we report description of variables and descriptive statistics and univariate t-tests for differences between the means of the the groups of Italian native and immigrant loan applicants. Immigrants are 0.8% (resp., 1.66%) less likely to have their loan approved within 3 months (resp., 6 months) from the application than Italian natives.

[TABLE 11 AROUND HERE]

We estimate a linear probability model to test whether immigrants are less able to obtain credit than natives. The equation is the following:

[18]Through ”CR first information”, banks can access information regarding the subject's financial exposure to the banking system, including the number of lending banks, the residual volume of total loans, their technical forms, the use of credit lines and the presence of any defaults or delays in payments.

$$Prob(Approval|_{t-m}d_t = 1)_{ijt} = \alpha \cdot Immigrant_j + \sum_{n=1}^{N} \beta_n \cdot X_{ijt}^n + \mu_j + \delta_i + \epsilon_{ijt} \quad (7)$$

where, conditional on bank i submitting a request for CR first information on person j within the past m months (that is, conditional on bank i receiving a demand for a mortgage by j, ${}_{t-m}d_t = 1$), $Approval$ is a dummy that takes the value 1 if bank i grants a loan to person j at time t, and zero otherwise.

Our sample includes more than 7 million observations related to all information requests on natural persons posted by Italian banks in 2015 and 2016. Regression results are reported in Table 12. We use the 3-months period to assess whether a loan has been approved, conditionally on a loan request, while results for the 6-months period are reported in the Appendix, table A10. Our baseline specifications in odd columns control for the age (and age squared) and the gender of the prospective mortgagor, her credit history in the CR and the presence of co-mortgagors. Then, in even columns we estimate specifications including the imputed mortgagors' income derived using machine learning RF procedure as in the loan pricing model in section 4.3. In this case, however, the training dataset employed to elicit the imputed income includes all the respondent households in the six SHIW waves from 2006 to 2016. Finally, all specifications include bank and province fixed effects and use robust standard errors.[19]

[TABLE 12 AROUND HERE]

Consistent with the hypothesis of disparities in access to credit, immigrants have a lower probability of seeing their loan applications approved by banks. The coefficient estimated for $Immigrant$ is negative and statistically significant in both specifications in columns [1] and [2], indicating that immigrants are on average 2,7% less successful that natives when they ask banks for a mortgage. All control variables have the expected sign, including imputed income, reassuring us of the reliability of our results.

In columns [3]-[8], we augment the model with interactions for borrowers' credit history and distinguish mortgages provided by dominant competitors and cooperative banks.

[19] Again, results are robust to using joint time-bank and time-province fixed effects and to standard errors clustered at the bank level (see the Appendix, tables A11 and A12).

As for the pricing model, disparities in access to credit for immigrants are statistically and economically significantly lower when they apply to cooperative banks: in this case, the approval gap with Italian natives is only 1.5%. This confirm the positive contribution of local, community banks to social integration of immigrants. By contrast, the approval gap widens when immigrants direct their loan applications to dominant competitors, becoming equal to 3.2%. Finally, credit history does not help to mitigate disparity in access to credit, leaving the approval gap economically unaffected.

7 Conclusions

In this paper we have analyzed empirically the interest rate formation in the Italian mortgage market and the probability of mortgage approvals by Italian banks, looking at a possible discrimination against immigrant borrowers. In spite of the importance of affordable access to mortgages for homeownership and social integration of immigrants and ethnic minorities in European countries (Arbaci and Malheiros, 2010; Accetturo et al., 2014; Kara and Molyneux, 2017), this issue is still largely unexplored in the literature.[20]

We have conducted a number of empirical analyses using loan data from the Italian Credit Register for the period 2011-2016 and survey data from the Bank of Italy's Survey on Household Income and Wealth (SHIW) for the period 2006-2011. Our findings consistently document that on average the interest rate on mortgages taken up by immigrants is significantly higher than the interest rate paid by Italian natives. We analyze both single-name and joint mortgage contracts: on the latter, immigrants pay 42 basis points more than Italians, while on single-name mortgages the interest gap is 25 basis points. The interest rate differential is highest for Asian, Central American and African immigrants and it remains statistically significant even after controlling for many loan and individual characteristics. In particular, since Credit Register does not include information on mortgagors' income and mortgages' LTV ratio, first we used random forest machine learning technique to obtain imputed values for these two important interest rate determinants from information contained

[20]o the best of our knowledge, the only exception is Diaz-Serrano and Raya (2014) who analyze the case of Spain.

in the SHIW and Wealth, and second we repeated our analysis on SHIW data. In both cases, we confirmed our baseline results. Oaxaca-Blinder decomposition indicates that the greatest part of the interest rate differential (85% and 93% for single-name and joint mortgages, respectively) can be imputed to the unexplained component capturing possible discrimination effects. Furthermore, we showed that the interest gap is lower for immigrants with a long credit history but it remains statistically significant, thus suggesting that statistical discrimination cannot explain the gap entirely.

As a final step, we have examined the probability of mortgage approvals for the the sub-period 2015-2016. Once again, our findings indicate that for immigrants the probability of having their mortgage application approved is on average statistically lower than for natives.

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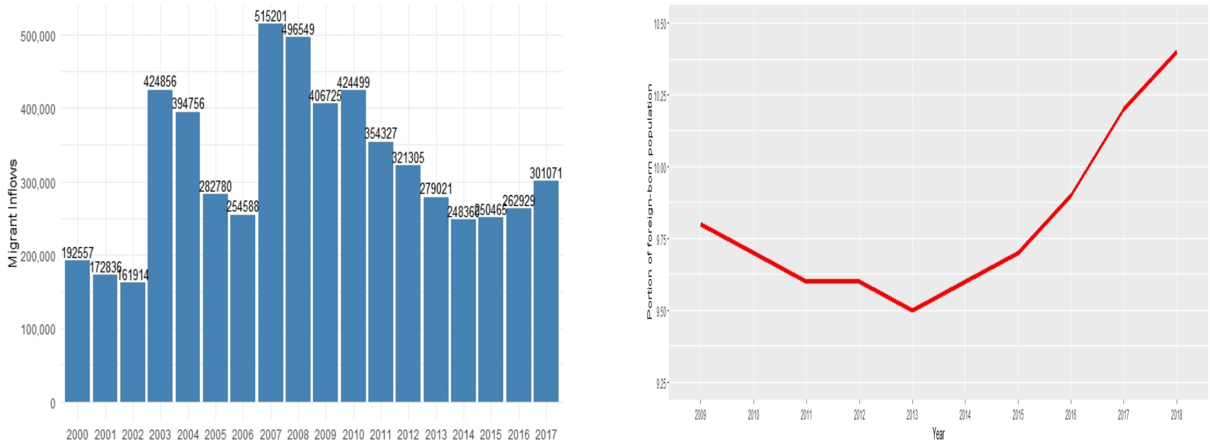
Main figures and tables

Figure 1: Foreign population in Italy.

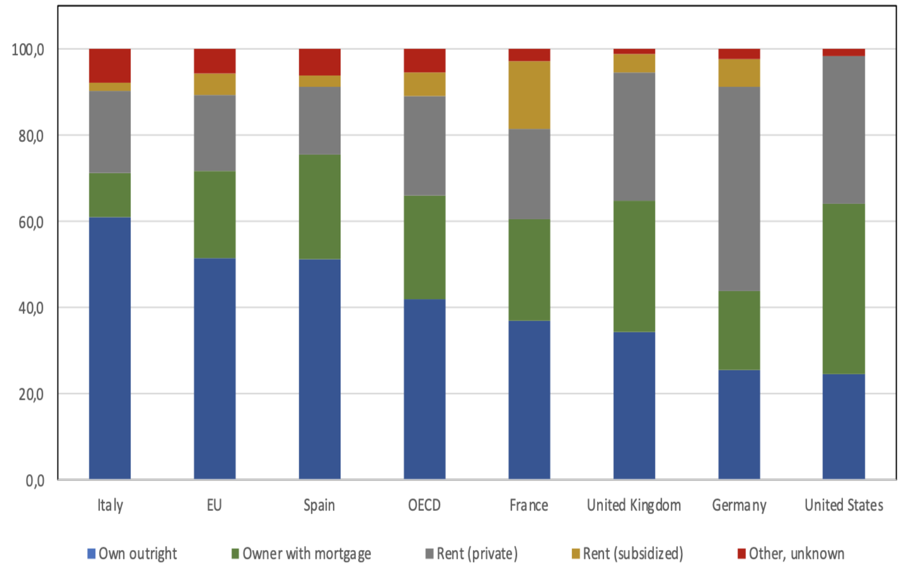


(a) Inflows of foreign population

(b) Share of foreign-born population

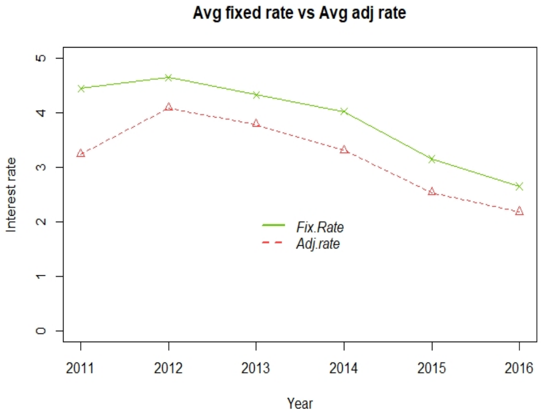
Note. Plot (a) shows the number of foreign-born people legally entered in Italy by year; plot (b) shows the stock of foreign-born population in Italy as percentage of total population. Data source: the ”OECD International Migration Database” available at https://www.oecd.org/migration/keystat.htm.

Figure 2: Housing occupancy rates.

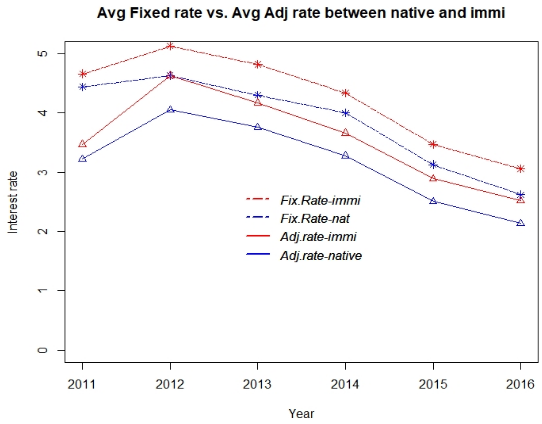


Note. This Figure shows the percentage of households in different tenure types in latest year available (2019 or 2018). Data source: OECD, Housing Market database, available at https://www.oecd.org/housing/data/affordable-housing-database/housing-market.html.

Figure 3: Interest rate on mortgage loans.



(a) ARMs versus FRMs



(b) ARMs versus FRMs for immigrants and native

Note. Plot (a) shows the average interest rate in percentage on adjusted-rate and fixed-rate mortgage contracts; plot (b) shows the average interest rates (%) paid by immigrant and native mortgagors on ARM and FRM contracts. Data source: Bank of Italy, Central Credit Register.

Table 1: Top 20 countries of origin of immigrants residing in Italy.

2011		2016	
Romania	9,88,576	Romania	1,151,395
Albania	482,627	Albania	467,687
Morocco	452,424	Morocco	437,485
China	209,934	China	271,330
Ukraine	200,730	Ukraine	230,728
Philippines	134,154	Philippines	165,900
Moldova	130,948	India	150,456
India	121,036	Moldova	142,266
Poland	109,018	Bangladesh	118,790
Tunisia	106,291	Egypt	109,871
Perù	98,603	Perù	103,714
Ecuador	91,625	Sri Lanka	102,316
Egypt	90,365	Pakistan	101,784
Macedonia	89,900	Senegal	98,176
Bangladesh	82,451	Poland	97,986
Sri Lanka	81,094	Tunisia	95,645
Senegal	80,989	Ecuador	87,427
Pakistan	75,720	Nigeria	77,264
Nigeria	53,613	Macedonia	73,512
Serbia	52,954	Bulgaria	58,001

Note. Foreign-born population by country of origin. Data source: the Italian National Statistics Institute (ISTAT), available at http://dati.istat.it.

Table 2: Variables for the mortgage pricing analysis: description and statistics.

Variable	Description	N	Mean (SD)
Dependent variable			
APR	Interest rate on mortgage loans to individual i by bank j (in percentage).	954,341	3.22 (1.15)
Mortgage characteristics			
Loan amount	Amount of outstanding loans (in log).	954,341	11.74 (0.45)
Fixed	Dummy variable, equal to 1 if a loan is fixed rate, and 0 otherwise.	954,341	0 .28 (0.45)
Coint	Dummy variable, equal to 1 if there is a co-borrower in the loan contract, and 0 otherwise.	954,341	0.48 (0.49)
Borrower characteristics			
Immigrant	Dummy variable, equal to 1 if the borrower is non-Italian, and 0 otherwise.	954,341	0.06 (0.23)
Singleimmi	Dummy variable, equal to 1 if the contract has only one immigrant borrower, and 0 otherwise	954,341	0.03 (0.15)
Cointimmi	Dummy variable, equal to 1 if in a contract both primary and Co-borrower are immigrant, and 0 otherwise	954,341	0.03 (0.17)
Cointnat	Dummy variable, equal to 1 if in a contract both primary and Co-borrower are native, and 0 otherwise.	954,341	0.42 (0.49)
Cointmix	Dummy variable, equal to 1 if in a contract immigrant and native participate together as primary and Co-borrower, and 0 otherwise.	954,341	0.03 (0.17)
Europa	Dummy variable, equal to 1 if the borrower is European except Italian, and 0 otherwise.	954,341	0.04 (0.19)
Asia	Dummy variable, equal to 1 if the borrower is Asian, and 0 otherwise.	954,341	0.006 (0.07)
Africa	Dummy variable, equal to 1 if the borrower is African, and 0 otherwise.	954,341	0.004 (0.06)
North America	Dummy variable, equal to 1 if the borrower is North American, and 0 otherwise.	954,341	0.0008 (0.02)

Continued on next page

Table 2: Event study regressions. Baseline – continued from previous page

Variable	Description	N	Mean (SD)
Central America	Dummy variable, equal to 1 if the borrower is Central American, and 0 otherwise.	954,341	0.0005 (0.02)
South America	Dummy variable, equal to 1 if the borrower is South American, and 0 otherwise.	954,341	0.005 (0.07)
Oceania	Dummy variable, equal to 1 if the borrower is Oceanian, and 0 otherwise.	954,341	0.0002 (0.014)
Age	Primary borrower age in years.	954,341	39.79 (9.73)
Male	Dummy variable, equal to 1 if the borrower is male, and 0 otherwise.	954,341	0.56 (0.49)
Main competitors	Dummy variable, equal to 1 for the 5 banks holding the largest share of mortgages in our sample, which amount to 39%, and 0 otherwise.	954,341	0.39 (0.48)
Cooperative	Dummy variable, equal to 1 if the bank is a cooperative bank, which comprises 13.39% of the sample, and 0 otherwise.	954,341	0.1339 (0.34)
Credit history	Number of years since first time appearance in the Central Credit Register.	954,341	2.23 (4.19)

Notes. Data source: Bank of Italy, Central Credit Register and Analytical Survey on Loan Interest Rates, 2011-2016.

Table 3: Univariate analysis.

	Italian natives	Immigrants	Diff.	t-stat
Panel A: Single-name mortgages				
APR	3.16 (1.16)	3.34 (1.09)	-0.18***	-25.66
Loan amount (ln)	11.70 (0.45)	11.65 (0.43)	0.05***	17.81
Fixed	0.27 (0.45)	0.25 (0.43)	0.02***	8.21
Age (years)	39.98 (9.60)	39.78 (8.90)	0.20***	3.44
Male	0.61 (0.49)	0.53 (0.50)	0.08***	24.79
Credit history	2.74 (4.36)	2.06 (3.79)	0.68***	27.47
Observations	465,450	24,739		
Panel B: Joint mortgages				
APR	3.26 (1.15)	3.58 (1.07)	-0.31***	-49.71
Loan amount (ln)	11.79 (0.43)	11.66 (0.32)	0.13***	70.55
Fixed	0.30 (0.46)	0.26 (0.44)	0.04***	16.78
Age (years)	39.74 (10.07)	37.46 (8.10)	2.30***	47.45
Male	0.51(0.50)	0.51(0.50)	-0.00***	-0.65
Credit history	1.78 (4.01)	0.40 (1.88)	1.39***	113.16
Observations	433,063	31,089		
Panel C: Full sample				
APR	3.20(1.15)	3.47(1.09)	-0.26***	-55.53
Loan amount (ln)	11.74 (0.44)	11.66 (0.38)	0.09***	54.59
Fixed	0.29 (0.45)	0.25 (0.43)	0.03***	17.09
Age (years)	39.87 (9.82)	38.49 (8.54)	1.38***	36.82
Male	0.56(0.50)	0.52(0.50)	0.04***	19.61
Credit history	2.30 (4.23)	1.14 (3.00)	1.15***	85.47
Observations	898,513	55,828		

Notes. This tables reports summary statistics for mortgages made out to Italian natives and immigrants, and t-statistics for differences in mean. Single-name mortgages include loans made out to a single borrower. Joint mortgages include loans to two co-borrowers, either both Italian natives or both immigrants, excluding the "mixed" joint contracts made out to a native and an immigrant borrower. Full sample consists of all single-name and joint mortgages. Standard errors in parentheses. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

Table 4: Mortgage pricing regression results: baseline model.

	Single-name mortgages			Joint mortgages		Full sample
	[1]	[2]	[3]	[4]	[5]	[6]
Immigrant	0.247***	0.236***				
	(0.00608)	(0.00563)				
ln(Loan amount)		-0.270***	-0.270***		-0.253***	-0.262***
		(0.00329)	(0.00329)		(0.00363)	(0.00243)
Fixed		0.747***	0.747***		0.761***	0.751***
		(0.00362)	(0.00362)		(0.00348)	(0.00251)
Age		-0.00826***	-0.00818***		-0.0208***	-0.0147***
		(0.000951)	(0.000951)		(0.000895)	(0.000651)
Age-squared		9.19e-05***	9.12e-05***		0.000192***	0.000142***
		(1.11e-05)	(1.11e-05)		(1.03e-05)	(7.54e-06)
Male		0.0226***	0.0222***		0.0110***	0.0126***
		(0.00274)	(0.00274)		(0.00262)	(0.00188)
Credit history		-0.0134***	-0.0134***		-0.00686***	-0.00965***
		(0.000352)	(0.000352)		(0.000376)	(0.000255)
Europa			0.234***			
			(0.00685)			
Asia			0.318***			
			(0.0165)			
Africa			0.248***			
			(0.0191)			
North America			0.0701**			
			(0.0316)			
Central America			0.262***			
			(0.0486)			
South America			0.216***			
			(0.0168)			
Oceania			0.0722			
			(0.0577)			
Cointimmi				0.428***	0.404***	0.489***
				(0.00534)	(0.00499)	(0.00490)
Cointmix					0.117***	0.208***
					(0.00495)	(0.00495)
Singleimmi						0.246***
						(0.00558)
Cointnat						0.0950***
						(0.00202)
Time FE	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
R-squared	0.285	0.367	0.367	0.314	0.400	0.383
Observations	490,189	490,189	490,189	464,152	464,152	954,341

Notes. This table presents the coefficients from OLS regressions for mortgages to natural persons included in the Bank of Italy's Central Credit Register and ASLIR survey in the period 2011-2016. The single-name mortgages sample includes loans in name of a single borrower; the joint mortgages sample includes loans made out to two co-borrowers; the full sample includes both single-name and joint mortgages. The dependent variable is *APR*, the annual interest rate charged to borrowers on granted mortgages in percentage points. Description of explanatory variables is reported in table 2. Robust standard errors are in parentheses. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05.

Table 5: Mortgage pricing regression results: augmented model with imputed LTV ratio and mortgagors' income.

	Single-name mortgages			Joint mortgages		Full sample
	[1]	[2]	[3]	[4]	[5]	[6]
Immigrant	0.218***	0.195***				
	(0.00682)	(0.00681)				
ln (Loan amount)	-0.287***	-0.250***	-0.250***	-0.343***	-0.311***	-0.279***
	(0.00462)	(0.00472)	(0.00472)	(0.00494)	(0.00499)	(0.00337)
Fixed	0.761***	0.751***	0.751***	0.799***	0.773***	0.775***
	(0.00359)	(0.00360)	(0.00360)	(0.00344)	(0.00349)	(0.00251)
Age	-0.00882***	0.00978***	0.00984***	-0.0239***	-0.00427***	-0.000305
	(0.000944)	(0.00106)	(0.00106)	(0.000876)	(0.000957)	(0.000689)
Age-squared	0.000102***	-7.54e-05***	-7.61e-05***	0.000246***	6.04e-05***	1.82e-05**
	(1.11e-05)	(1.20e-05)	(1.20e-05)	(1.02e-05)	(1.09e-05)	(7.87e-06)
Male	0.0236***	0.104***	0.104***	0.0101***	0.0147***	0.0514***
	(0.00273)	(0.00328)	(0.00328)	(0.00253)	(0.00252)	(0.00189)
Credit history	-0.0134***	-0.0132***	-0.0132***	-0.00614***	-0.00576***	-0.00857***
	(0.000349)	(0.000349)	(0.000349)	(0.000368)	(0.000368)	(0.000249)
LTV	0.00155***	0.00113***	0.00109***	0.00801***	0.00737***	0.00376***
	(0.000299)	(0.000299)	(0.000299)	(0.000312)	(0.000312)	(0.000213)
ln (Income)		-0.365***	-0.365***		-0.384***	-0.314***
		(0.00914)	(0.00914)		(0.00691)	(0.00526)
Europa			0.193***			
			(0.00785)			
Asia			0.279***			
			(0.0167)			
Africa			0.205***			
			(0.0192)			
North America			0.0242			
			(0.0314)			
Central America			0.221***			
			(0.0472)			
South America			0.172***			
			(0.0170)			
Oceania			0.0427			
			(0.0567)			
Cointimmi				0.313***	0.284***	0.384***
				(0.00612)	(0.00611)	(0.00553)
Cointmix				0.118***	0.116***	0.167***
				(0.00475)	(0.00473)	(0.00479)
Singleimmi						0.176***
						(0.00601)
Cointnat						0.0543***
						(0.00208)
Time FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES
R-squared	0.377	0.379	0.379	0.441	0.445	0.424
Observations	490,189	490,189	490,189	464,152	464,152	954,341

Notes. This table presents the coefficients from OLS regressions for mortgages to natural persons included in the Bank of Italy's Central Credit Register and ASLIR survey in the period 2011-2016. The single-name mortgages sample includes loans in name of a single borrower; the joint mortgages sample includes loans made out to two co-borrowers; the full sample includes both single-name and joint mortgages. The dependent variable is *APR*, the annual interest rate charged to borrowers on granted mortgages in percentage points. Description of explanatory variables is reported in table 2. LTV is the ratio between the amount of the mortgage and the lender self-assessed value of the house. Income is the mortgagors' income. Both LTV and Income are imputed variables obtained by using the Random Forest algorithm trained on the Banks of Italy's SHIW dataset with the R package "Random Forest". Robust standard errors are in parentheses. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05.

Table 6: Oaxaca-Blinder decomposition of mortgage interest rate gap between immigrants and Italian natives

	Single name mortgages		Joint mortgages		Full sample	
	Mean interest rate	Decomposition	Mean interest rate	Decomposition	Mean interest rate	Decomposition
Immigrants	3.340***		3.579***		3.474***	
	(0.00696)		(0.00606)		(0.00460)	
Natives	3.157***		3.261***		3.205***	
	(0.00170)		(0.00181)		(0.00124)	
Differential	0.184***		0.319***		0.269***	
	(0.00716)		(0.00633)		(0.00476)	
Explained components		0.0269***		0.0479***		0.0443***
		(0.00160)		(0.00141)		(0.000992)
Unexplained components		0.157***		0.271***		0.225***
		(0.00701)		(0.00633)		(0.00470)
Observations	490,189	490,189	432,191	432,191	922,380	922,380

Notes. This table shows results from Oaxaca-Blinder decomposition of the mean interest rate differential between mortgages made out to immigrants and native-born Italians. The explained component (or endowments effect) is the part of the interest rate differential that is attributable to group differences in explanatory variables. The unexplained component (or coefficients effect) is the part of the interest rate differential that is attributable to differences in coefficients of explanatory variables. The decompositions are conducted by excluding all samples where immigrants and natives participate jointly in a contract, in order to find a clear distinction between the differences in mortgage rates between natives and immigrants. For joint mortgages, immigrant refers to the contracts where both participants are immigrants, while in the full sample, immigrant refers to contracts where either one or both participants are immigrants. The underlying regressions on interest rates charged on mortgages to immigrants and natives are reported in Table A4 in the Appendix. A supplementary table in the appendix depicts the results of the Oaxaca-Blinder decomposition using cluster standard errors. See Table **??**. Robust standard errors in parentheses. ***p-value < 0.01, **p-value < 0.05, *p-value < 0.1.

Table 7: The matching procedure: Average treatment effect on treated

	Single-name mortgages	Joint mortgages	Full sample
No. of controls matched	Average treatment effect (ATT)	Average treatment effect (ATT)	Average treatment effect (ATT)
n=1	0.192***	0.331***	0.256***
	(0.00862)	(0.0099)	(0.006)
n=4	0.189***	0.3305***	0.259***
	(0.00717)	(0.0085)	(0.0052)
n=8	0.1904***	0.3312***	0.2579***
	(0.0069)	(0.0082)	(0.005)

Notes. This table reports the difference in mean between mortgage interest rates paid by immigrants (treated units) and natives nearest to immigrants (non-treated units). Non-treated mortgages are assigned to the control group base on propensity score estimates for the probability of a loan is taken up by immigrants. We ran the "teffects" command in Stata to estimate the average treatment effect (ATT) using a nearest-neighbor matching method with a caliper of 0.01 without replacement on the sample of mortgages to natural persons included in the Bank of Italy' Central Credit Register in the period 2011-2016.
***p-value < 0.01, **p-value < 0.05, *p-value < 0.1.

Table 8: Mortgage pricing regression results: borrowers' credit history, dominant lenders and cooperative banks

	Single-name mortgages				Joint mortgages			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Immigrant	0.2498***	0.2514***	0.2348***	0.2512***				
	(0.0063)	(0.0063)	(0.0067)	(0.0062)				
Cointimmi					0.4043***	0.4042***	0.3243***	0.4319***
					(0.0051)	(0.0051)	(0.0060)	(0.0055)
Credit history	-0.0132***				-0.0068***			
	(0.0004)				(0.0004)			
Immigrant $\times$ Credit history	-0.0065***							
	(0.0016)							
Cointimmi $\times$ Credit history					-0.0018			
					(0.0024)			
$\mathbb{1}$(Credit history>3 yrs)		-0.1245***				-0.0672***		
		(0.0032)				(0.0038)		
Immigrant $\times$ $\mathbb{1}$(Credit history>3 yrs)		-0.0588***						
		(0.0138)						
Cointimmi $\times$ $\mathbb{1}$(Credit history>3 yrs)						-0.0158		
						(0.0224)		
Immigrant $\times$ Main competitors			0.0045					
			(0.0123)					
Cointimmi $\times$ Main competitors							0.2125***	
							(0.0103)	
Immigrant $\times$ Cooperative				-0.1024***				
				(0.0148)				
Cointimmi $\times$ Cooperative								-0.1997***
								(0.0122)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Prov FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.3672	0.3673	0.3672	0.3672	0.4003	0.4002	0.4008	0.4005
Observations	490,189	490,189	490,189	490,189	464,152	464,152	464,152	464,152

Notes. This table presents the coefficients from OLS regressions for mortgages to natural persons included in the Bank of Italy's Central Credit Register and ASLIR survey in the period 2011-2016. The single-name mortgages sample includes loans in name of a single borrower; the joint mortgages sample includes loans made out to two co-borrowers. The dependent variable is *APR*, the annual interest rate charged to borrowers on granted mortgages in percentage points. Description of moderators is reported in table 2. All columns include the same control variables of specifications [2] and [5] in Table 4. Table **??**, a supplementary table in the appendix reports the coefficients from OLS regressions using the same specifications with Bank$\times$Time and Province$\times$Time joint fixed effects, and clustered standard errors. Robust standard errors are in parentheses. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05.

Table 9: Variables from SHIW surveys. Description and statistics

Variable	Description	N	Native Mean (S.D)	Immigrant Mean (S.D)	Diff.	t-stat
Dependent variable						
Mortgage Rate	Interest rate charged on mortgage loans to household i (in percentage)	1,955	3.35 (2.35)	3.59 (2.22)	-0.24	-1.01
Mortgage Characteristics						
Loan amount	The initial amount of mortgage loan (in log).	1,531	11.22 (0.80)	11.55 (0.45)	-0.33***	-5.76
Fixed	Dummy variable, equal to 1 if the loan is fixed rate, and 0 otherwise.	1,955	0.41 (0.49)	0.34 (0.47)	0.07	1.35
LTV	Loan amount over the house value.	1955	60.98 (29.01)	86.73 (19.57)	-25.75***	-11.87
Purchase	Dummy variable, equal to 1 if a mortgage loan is for the purchase of household residence, and 0 otherwise.	1,955	0.67 (0.47)	0.77 (0.42)	-0.10**	-2.18
Duration	Number of years to repay the mortgage.	1,955	18.10 (7.62)	22.54 (6.39)	-4.45***	-6.39
Borrower characteristics						
Immigrant	Dummy variable, equal to 1 if the head of the household is foreign-born, and 0 otherwise.	1,955	1,865	90		
Income	The disposable income of the head of the household (in log).	1,948	10.02 (0.72)	9.5 (0.89)	0.53***	5.93
Age	Age of the head of the household in years.	1,955	42.05 (11.61)	36.12 (8.17)	5.93***	6.22
Male	Dummy variable, equal to 1 if the head of the household is male, and 0 otherwise.	1,263	0.65 (0.48)	0.66 (0.48)	-0.01	-0.19
Education	Categorical variable (1-8) that indicates the educational level of the head of the household; it takes value 1 for the head of the household having no education and value 8 for postgraduate qualification	1,955	4.60 (1.57)	4.36 (1.46)	0.24	1.52
Married	Dummy variable, equal to 1 if the head of household is married and 0 otherwise.	1955	0.75 (0.43)	0.86 (0.33)	0.10**	-2.66

Notes. Data source: Bank of Italy, The Survey on Household Income and Wealth (SHIW), 2006-2016. This table presents the description of variables used in the regression analysis of Table 10, summary statistics for immigrant and Italian natives household heads, and t-statistics for differences in mean.

Table 10: Regression results for SHIW data

	[1]	[2]	[3]
Immigrant	0.4795***	0.4771***	0.3988**
	(0.1575)	(0.1589)	(0.1666)
Purchase	-0.8023***	-0.7873***	-0.7798***
	(0.0913)	(0.0945)	(0.0948)
LTV	0.0054***	0.0054***	0.0040**
	(0.0018)	(0.0018)	(0.0019)
Fixed	0.6376***	0.6358***	0.6315***
	(0.0821)	(0.0822)	(0.0821)
ln(Loan size)	-0.4785***	-0.4454***	-0.3618***
	(0.0775)	(0.0842)	(0.0902)
Duration		-0.0053	-0.0085
		(0.0068)	(0.0071)
Age		-0.0276	-0.0236
		(0.0211)	(0.0213)
Age-squared		0.0003	0.0002
		(0.0002)	(0.0002)
Male		0.0363	0.1081
		(0.0848)	(0.0936)
Education			-0.0457
			(0.0305)
Married			0.0024
			(0.0998)
ln(Income)			-0.1437**
			(0.0656)
Time FE	YES	YES	YES
Region FE	YES	YES	YES
R-squared	0.2709	0.2720	0.2766
Observations	1,524	1,524	1,518

Notes. This table presents the coefficients from OLS regressions. The dataset includes self-reported information on mortgages taken out by households participating in the Survey on Household Income and Wealth (SHIW) carried out by the Bank of Italy every two years in the period 2006-2016. The dependent variable is the annual interest rate charged to borrowers on granted mortgages in percentage points. Description of explanatory variables is in table 9. Robust standard errors in parentheses. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05.

Table 11: Variables from CR first information. Description and statistics

Variable	Description	N	Native Mean (S.D)	Immigrant Mean (S.D)	Diff.	t-stat
Dependent variable						
Approval $\mid {}_{t-3}d_t = 1$	Dummy variable, equal to 1 if bank i submitting a request for CR first information on natural person j grants a mortgage loan to j within the next three months, and 0 otherwise.	7,300,097	0.133 (0.34)	0.132 (0.34)	0.001	2.339**
Approval $\mid {}_{t-6}d_t = 1$	Dummy variable, equal to 1 if bank i submitting a request for CR first information on natural person j grants a mortgage loan to j within the next six months, and 0 otherwise.	7,300,097	0.1447 (0.35)	0.1423 (0.34)	0.0024	4.77***
Mortgage Characteristics						
Coint	Dummy variable, equal to 1 if there is co-borrower in loan contract, and 0 otherwise.	7,300,097	0.106 (0.31)	0.154 (0.36)	-0.047	-93.09***
Borrower characteristics						
Immigrant	Dummy variable, equal to 1 if the prospective mortgagor j about which bank i submit a request of CR first information is foreign-born, and 0 otherwise.	7,300,097	6,782,477	517,620		
Income*	The disposable income of the head of the household (in log).	7,300,097	22924.89 (6391)	15335 (4604)	7589.21	1.1e+03***
Age	Age of the prospective mortgagor j in years.	7,300,097	50.32 (12.48)	45.51 (10.07)	4.82	325.61***
Male	Dummy variable, equal to 1 if the prospective mortgagor j about which bank i submit a request of CR first information is male, and 0 otherwise.	7,300,097	0.645 (0.47)	0.644 (0.48)	0.001	2.21**
Credit history	Number of years since first time appearance of the prospective mortgagor in the Central Credit Register.	7,300,097	3.77 (5.7)	2.69 (4.6)	1.08	157.59***

Notes. Notes. Data source: Bank of Italy, Central Credit Register, 2015-2016. This table presents the description of variables, summary statistics, separately for immigrants and natives, and well as t-statistics for differences in mean.

Table 12: Loan approval regression results.

	[1])	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Immigrant	-0.025***	-0.027***	-0.024***	-0.026***	-0.025***	-0.027***	-0.026***	-0.028***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Age	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age-squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.016***	0.018***	0.016***	0.018***	0.016***	0.018***	0.016***	0.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Credit history	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Coint	0.325***	0.324***	0.325***	0.324***	0.325***	0.324***	0.325***	0.324***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln (Income)		-0.005***		-0.005***		-0.005***		-0.005***
		(0.001)		(0.001)		(0.001)		(0.001)
Immigrant × Credit history			-0.001***	-0.001***				
			(0.000)	(0.000)				
Immigrant × Main competitors					-0.005***	-0.005***		
					(0.002)	(0.002)		
Immigrant × Cooperative banks							0.014***	0.013***
							(0.002)	(0.002)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.216	0.216	0.216	0.216	0.216	0.216	0.216	0.216
Observations	7,300,072	7,300,072	7,300,072	7,300,072	7,300,072	7,300,072	7,300,072	7,300,072

Notes. This table presents the coefficients from LPM regression for the request of CR first information made by bank in the period 2015-2016. The dependent variable is a dummy that takes the value 1 if a mortgage loans is granted conditional on banks' submitting a first information CR request within a 3-months period before the loan disbursement, and 0 otherwise. Description of explanatory variables is in table 11. ln(Income) is the logarithm of mortgagors' income. Income is an imputed variable obtained by using the Random Forest algorithm trained on the Banks of Italy's SHIW dataset with the R package "Random Forest". Robust standard errors in parentheses. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05.

Appendix: additional tables

Table A1: Mortgage pricing regression results: baseline model with Bank×Time and Province×Time joint fixed effects, and clustered standard errors.

	Single-name mortgages			Joint mortgages		Full sample
	[1]	[2]	[3]	[4]	[5]	[6]
Immigrant	0.234***	0.222***				
	(0.0342)	(0.0323)				
ln (Loan amount)		-0.265***	-0.265***		-0.246***	-0.257***
		(0.0170)	(0.0170)		(0.0200)	(0.0170)
Fixed		0.809***	0.810***		0.828***	0.816***
		(0.0712)	(0.0712)		(0.0786)	(0.0747)
Age		-0.00800*	-0.00794*		-0.0202***	-0.0141***
		(0.00442)	(0.00440)		(0.00625)	(0.00529)
Age-squared		9.02e-05*	8.96e-05*		0.000187***	0.000137**
		(4.65e-05)	(4.64e-05)		(6.34e-05)	(5.39e-05)
Male		0.0230***	0.0227***		0.0102***	0.0128***
		(0.00720)	(0.00724)		(0.00321)	(0.00317)
Credit history		-0.0122***	-0.0122***		-0.00659***	-0.00896***
		(0.00261)	(0.00261)		(0.00204)	(0.00206)
Europa			0.221***			
			(0.0338)			
Asia			0.296***			
			(0.0509)			
Africa			0.229***			
			(0.0319)			
North America			0.0663**			
			(0.0301)			
Central America			0.253***			
			(0.0627)			
South America			0.203***			
			(0.0325)			
Oceania			0.0712			
			(0.0572)			
Cointimmi				0.406***	0.379***	0.457***
				(0.0767)	(0.0778)	(0.0831)
Cointmix					0.113***	0.197***
					(0.0203)	(0.0273)
Singleimmi						0.232***
						(0.0348)
Cointnat						0.0890***
						(0.0108)
Bank×Time FE	YES	YES	YES	YES	YES	YES
Province×Time FE	YES	YES	YES	YES	YES	YES
R-squared	0.318	0.403	0.403	0.348	0.438	0.418
Observations	490,189	490,189	490,189	464,152	464,152	954,341

Notes. This table presents the coefficients from OLS regressions for mortgages to natural persons included in the Bank of Italy's Credit Register in the period 2011-2016. The single-name mortgage sample includes loans in name of a single borrower; the joint mortgage sample includes loans made out to two co-borrowers; the full sample includes both single-name and joint mortgages. The dependent variable is *APR*, the annual interest rate charged to borrowers on granted mortgages in percentage points. Description of explanatory variables is reported in table 2. Robust standard errors clustered standard errors at the bank level are in parentheses. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05.

Table A2: Mortgage pricing regression results: baseline model for Loan amount ≥ €75,000.

	Single-name mortgages			Joint mortgages		Full sample
	[1]	[2]	[3]	[4]	[5]	[6]
Immigrant	0.247***	0.236***				
	(0.00608)	(0.00563)				
Immigrant	0.242***	0.227***				
	(0.00620)	(0.00572)				
ln (Loan amount)		-0.340***	-0.340***		-0.311***	-0.327***
		(0.00358)	(0.00358)		(0.00395)	(0.00265)
Fixed		0.749***	0.749***		0.765***	0.754***
		(0.00368)	(0.00368)		(0.00352)	(0.00255)
Age		-0.00708***	-0.00701***		-0.0191***	-0.0131***
		(0.000963)	(0.000963)		(0.000906)	(0.000659)
Age-squared		8.04e-05***	7.98e-05***		0.000172***	0.000125***
		(1.13e-05)	(1.13e-05)		(1.04e-05)	(7.65e-06)
Male		0.0236***	0.0233***		0.0105***	0.0128***
		(0.00277)	(0.00277)		(0.00264)	(0.00190)
Credit history		-0.0111***	-0.0111***		-0.00594***	-0.00791***
		(0.000358)	(0.000358)		(0.000381)	(0.000258)
Europa			0.227***			
			(0.00696)			
Asia			0.300***			
			(0.0168)			
Africa			0.230***			
			(0.0195)			
North America			0.0762**			
			(0.0317)			
Central America			0.259***			
			(0.0483)			
South America			0.205***			
			(0.0169)			
Oceania			0.0512			
			(0.0588)			
Cointimmi				0.427***	0.390***	0.482***
				(0.00538)	(0.00502)	(0.00492)
Cointmix					0.115***	0.213***
					(0.00499)	(0.00499)
Singleimmi						0.237***
						(0.00567)
Cointnat						0.102***
						(0.00205)
Time FE	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
R-squared	0.288	0.374	0.375	0.315	0.405	0.389
Observations	466,785	466,785	466,785	449,503	449,503	916,288

Notes. This table presents the coefficients from OLS regressions for mortgages to natural persons included in the Bank of Italy's Credit Register in the period 2011-2016. The single-name mortgage sample includes loans in name of a single borrower; the joint mortgage sample includes loans made out to two co-borrowers; the full sample includes both single-name and joint mortgages. The dependent variable is *APR*, the annual interest rate charged to borrowers on granted mortgages in percentage points. Description of explanatory variables is reported in table 2. Robust standard errors are in parentheses. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05.

Table A3: Mortgage pricing regression results: augmented model with imputed LTV ratio and mortgagors' income, and with Bank×Time joint fixed effects, Province×Time joint fixed effects and clustered standard errors.

	Single-name mortgages			Joint mortgages		Full sample
	[1]	[2]	[3]	[4]	[5]	[6]
Immigrant	0.193***	0.172***				
	(0.0294)	(0.0281)				
ln (Loan amount)	-0.291***	-0.258***	-0.257***	-0.343***	-0.308***	-0.277***
	(0.0311)	(0.0323)	(0.0322)	(0.0286)	(0.0293)	(0.0291)
Fixed	0.829***	0.820***	0.820***	0.844***	0.818***	0.818***
	(0.0697)	(0.0699)	(0.0699)	(0.0773)	(0.0774)	(0.0734)
Age	-0.00849*	0.00843**	0.00849**	-0.0236***	-0.00242	0.00142
	(0.00444)	(0.00413)	(0.00411)	(0.00673)	(0.00737)	(0.00563)
Age-squared	0.000101**	-6.00e-05	-6.06e-05	0.000244***	4.40e-05	2.54e-06
	(4.69e-05)	(4.46e-05)	(4.45e-05)	(7.02e-05)	(7.66e-05)	(5.90e-05)
Male	0.0247***	0.0983***	0.0979***	0.00990***	0.0148***	0.0542***
	(0.00806)	(0.00943)	(0.00944)	(0.00314)	(0.00299)	(0.00424)
Credit history	-0.0121***	-0.0119***	-0.0119***	-0.00574***	-0.00534***	-0.00804***
	(0.00252)	(0.00250)	(0.00250)	(0.00193)	(0.00193)	(0.00195)
LTV	0.00232	0.00192	0.00189	0.00854***	0.00784***	0.00413*
	(0.00197)	(0.00195)	(0.00194)	(0.00275)	(0.00274)	(0.00221)
ln(Income)		-0.333***	-0.332***		-0.414***	-0.341***
		(0.0317)	(0.0317)		(0.0300)	(0.0243)
Europa			0.171***			
			(0.0294)			
Asia			0.248***			
			(0.0466)			
Africa			0.178***			
			(0.0289)			
North America			0.0145			
			(0.0344)			
Central America			0.202***			
			(0.0584)			
South America			0.150***			
			(0.0265)			
Oceania			0.0349			
			(0.0620)			
Cointimmi				0.274***	0.243***	0.331***
				(0.0591)	(0.0579)	(0.0630)
Cointmix				0.113***	0.110***	0.151***
				(0.0197)	(0.0195)	(0.0256)
Singleimmi						0.149***
						(0.0324)
Cointnat						0.0435***
						(0.0101)
Time × bank FE	YES	YES	YES	YES	YES	YES
Time × Province FE	YES	YES	YES	YES	YES	YES
R-squared	0.414	0.416	0.416	0.450	0.454	0.432
Observations	490,189	490,189	490,189	464,152	464,152	954,341

Notes. This table presents the coefficients from OLS regressions for mortgages to natural persons included in the Bank of Italy' Credit Register in the period 2011-2016. The dependent variable is *APR*, the annual interest rate charged to borrowers on granted mortgages in percentage points. Description of explanatory variables is in table 2. LTV is the ratio between the amount of the mortgage and the lender-assessed value of the house. Income is the mortgagors' income. Both LTV and Income are imputed variables obtained by using the Random Forest algorithm trained on the Banks of Italy's SHIW dataset with the R package "Random Forest". Robust standard errors clustered standard errors at the bank level are in parentheses. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

Table A4: Interest rate regression underlying the Oaxaca-Blinder decomposition of Table **??**

	Single name mortgages		Joint mortgages		Full sample	
	[1]	[2]	[3]	[4]	[5]	[6]
ln (Loan amount)	0.0118***	-0.122	0.0284***	0.947***	0.0184***	0.252
	(0.000688)	(0.205)	(0.000701)	(0.241)	(0.000423)	(0.156)
Fixed	-0.00720***	0.00888**	-0.0129***	-0.00806**	-0.00984***	-0.000842
	(0.000881)	(0.00426)	(0.000774)	(0.00370)	(0.000582)	(0.00279)
Age	0.00385***	0.658***	0.107***	1.354***	0.0470***	0.971***
	(0.00114)	(0.230)	(0.00350)	(0.201)	(0.00172)	(0.152)
Age-squared	-0.00632***	-0.322***	-0.0999***	-0.577***	-0.0468***	-0.454***
	(0.00114)	(0.117)	(0.00338)	(0.0987)	(0.00167)	(0.0758)
Male	-0.00173***	-0.00109	2.62e-05	-0.00433	-0.000220**	0.00218
	(0.000277)	(0.00761)	(5.74e-05)	(0.00644)	(0.000108)	(0.00489)
Credit history	0.0265***	0.00223	0.0258***	-0.000547	0.0358***	-0.0110***
	(0.00100)	(0.00422)	(0.000687)	(0.00136)	(0.000544)	(0.00193)
Observations	490,189	490,189	432,191	432,191	922,380	922,380

Notes. This table shows the OLS regression results generated during the Oaxaca blinder decomposition analysis using the Bank of Italy's Central Credit Register and ASLIR survey in the period 2011-2016, which decomposes the difference in the mean of mortgage rates between immigrants and natives into two components: the explained component due to differences in the coefficients, and the unexplained component due to differences in the characteristics of the two groups. The single-name mortgages sample includes loans in name of a single borrower; the joint mortgages sample includes loans made out to two co-borrowers; the full sample includes both single-name and joint mortgages. The dependent variable is *APR*, the annual interest rate charged to borrowers on granted mortgages in percentage points. Description of explanatory variables is reported in table 2. Robust standard errors are in parentheses. ***p-value < 0.001, **p-value < 0.01, *p-value $<$ 0.05.

Table A5: Oaxaca-Blinder decomposition of mortgage interest rate gap between immigrants and Italian natives with clustered standard errors at bank level

	Single name mortgages		Joint mortgage		Full sample	
	Mean interest rate	Decomposition	Mean interest rate	Decomposition	Mean interest rate	Decomposition
Immigrants	3.340***		3.579***		3.474***	
	(0.0358)		(0.0817)		(0.0582)	
Natives	3.157***		3.261***		3.205***	
	(0.0411)		(0.0414)		(0.0408)	
Differential	0.184***		0.319***		0.269***	
	(0.0295)		(0.0866)		(0.0623)	
Explained components		0.0269***		0.0479***		0.0443***
		(0.00592)		(0.0108)		(0.00849)
Unexplained components		0.157***		0.271***		0.225***
		(0.0282)		(0.0830)		(0.0594)
Observations	490,189	490,189	432,191	432,191	922,380	922,380

Notes. This table shows results from Oaxaca-Blinder decomposition of the mean interest rate differential between mortgages made out to immigrants and native-born Italians. The explained component (or endowments effect) is the part of the interest rate differential that is attributable to group differences in explanatory variables. The unexplained component (or coefficients effect) is the part of the interest rate differential that is attributable to differences in coefficients of explanatory variables. Robust standard errors clustered standard errors at the bank level are in parentheses. ***p-value < 0.01, **p-value < 0.05, *p-value $<$ 0.1.

Table A6: Mortgage pricing regression results: borrowers' credit history, dominant lenders and cooperative banks (full sample)

	Full Sample			
	[1]	[2]	[3]	[4]
Singleimmi	0.2628***	0.2642***	0.2485***	0.2592***
	(0.0062)	(0.0062)	(0.0066)	(0.0061)
Cointimmi	0.4895***	0.4878***	0.4040***	0.5192***
	(0.0050)	(0.0050)	(0.0058)	(0.0054)
Cointmix	0.2077***	0.2060***	0.2077***	0.2075***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)
Cointnat	0.0951***	0.0936***	0.0953***	0.0949***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Credit history	-0.0095***			
	(0.0003)			
Singleimmi $\times$ Credit history	-0.0082***			
	(0.0016)			
Cointimmi $\times$ Credit history	-0.0002			
	(0.0025)			
$\mathbb{1}$(Credit history>3 yrs)		-0.0920***		
		(0.0024)		
Singleimmi $\times$ $\mathbb{1}$(Credit history>3 yrs)		-0.0745***		
		(0.0136)		
Cointimmi $\times$ $\mathbb{1}$(Credit history>3 yrs)		0.0010		
		(0.0224)		
Singleimmi $\times$ Main competitors			-0.0099	
			(0.0120)	
Cointimmi $\times$ Main competitors			0.2306***	
			(0.0100)	
Singleimmi $\times$ Cooperative				-0.0909***
				(0.0145)
Cointimmi $\times$ Cooperative				-0.2165***
				(0.0119)
Time FE	YES	YES	YES	YES
Prov FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
R-squared	0.3827	0.3827	0.3829	0.3828
Observations	954,341	954,341	954,341	954,341

Notes. This table presents the coefficients from OLS regressions for mortgages to natural persons included in the Bank of Italy's Central Credit Register and ASLIR survey in the period 2011-2016. The dependent variable is *APR*, the annual interest rate charged to borrowers on granted mortgages in percentage points. Description of moderators is reported in table 2. All columns include the same control variables of specifications [6] in Table 4. Robust standard errors are in parentheses. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05.

Table A7: Mortgage pricing regression results: borrowers' credit history, dominant lenders and cooperative banks with Bank×Time and Province×Time joint fixed effects, and clustered standard errors.]

	Single-name mortgages				Joint mortgages				Full sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Immigrant	0.2322***	0.2338***	0.2152***	0.2351***								
	(0.0370)	(0.0375)	(0.0245)	(0.0361)								
Singleimmi									0.2450***	0.2465***	0.2287***	0.2434***
									(0.0404)	(0.0410)	(0.0240)	(0.0381)
Cointmix									0.1969***	0.1955***	0.1970***	0.1967***
									(0.0273)	(0.0273)	(0.0274)	(0.0273)
Cointnat									0.0891***	0.0878***	0.0894***	0.0889***
									(0.0109)	(0.0109)	(0.0110)	(0.0108)
Cointimmi					0.3792***	0.3794***	0.2905***	0.4039***	0.4569***	0.4558***	0.3617***	0.4834***
					(0.0790)	(0.0791)	(0.0240)	(0.0838)	(0.0842)	(0.0841)	(0.0288)	(0.0893)
Credit history	-0.0120***				-0.0066***				-0.0088***			
	(0.0026)				(0.0020)				(0.0021)			
Immigrant x Credit history	-0.0047											
	(0.0035)											
Cointimmi x Credit history					-0.0006				0.0004			
					(0.0040)				(0.0038)			
Singleimmi x Credit history									-0.0061			
									(0.0038)			
Credit history¿3years		-0.1123***				-0.0635***				-0.0847***		
		(0.0225)				(0.0178)				(0.0175)		
Immigrant x Credit history¿3years		-0.0431										
		(0.0331)										
Cointimmi x Credit history¿3yrs						-0.0093				0.0019		
						(0.0350)				(0.0319)		
Singleimmi x Credit history¿3yrs										-0.0569		
										(0.0373)		
Immigrant x Main competitors			0.0223									
			(0.0904)									
Cointimmi x Main competitors							0.2352*				0.2570*	
							(0.1392)				(0.1518)	
Singleimmi x Main competitors											0.0085	
											(0.0805)	
Immigrant x Cooperative				-0.0866*								
				(0.0461)								
Cointimmi x Cooperative								-0.1755**				-0.1909**
								(0.0850)				(0.0906)
Singleimmi x Cooperative												-0.0756*
												(0.0421)
Time X bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time X Province FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.4032	0.4032	0.4032	0.4032	0.4377	0.4376	0.4383	0.4379	0.4179	0.4178	0.4182	0.4180
Observations	490,189	490,189	490,189	490,189	464,152	464,152	464,152	464,152	954,341	954,341	954,341	954,341

Notes. This table presents the coefficients from OLS regressions for mortgages to natural persons included in the Bank of Italy's Central Credit Register and ASLIR survey in the period 2011-2016. The single-name mortgages sample includes loans in name of a single borrower; the joint mortgages sample includes loans made out to two co-borrowers. The dependent variable is *APR*, the annual interest rate charged to borrowers on granted mortgages in percentage points. Description of moderators is reported in table 2. All columns include the same control variables of specifications [2], [5], and [6] in Table4. Robust standard errors clustered standard errors at the bank level are in parentheses. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05.

Table A8: Mortgage pricing regression results- Augmented model: borrowers' credit history, dominant lenders and cooperative banks

	Single-name mortgages				Joint mortgages				Full sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Immigrant	0.2149***	0.2144***	0.1980***	0.2145***								
	(0.0072)	(0.0072)	(0.0075)	(0.0070)								
Singleimmi									0.1926***	0.1935***	0.1780***	0.1894***
									(0.0065)	(0.0065)	(0.0069)	(0.0064)
Cointimmi					0.2839***	0.2836***	0.2060***	0.3126***	0.3846***	0.3824***	0.3003***	0.4146***
					(0.0062)	(0.0062)	(0.0069)	(0.0065)	(0.0056)	(0.0056)	(0.0063)	(0.0059)
Cointmix									0.1674***	0.1662***	0.1674***	0.1671***
									(0.0048)	(0.0048)	(0.0048)	(0.0048)
Cointnat									0.0545***	0.0535***	0.0547***	0.0543***
									(0.0021)	(0.0021)	(0.0021)	(0.0021)
Credit history	-0.0125***				-0.0058***				-0.0084***			
	(0.0004)				(0.0004)				(0.0003)			
Immigrant × Credit history	-0.0069***											
	(0.0015)											
𝟙(Credit history>3 yrs)		-0.1147***				-0.0547***				-0.0794***		
		(0.0031)				(0.0037)				(0.0024)		
Immigrant × 𝟙(Credit history>3 yrs)		-0.0647***										
		(0.0132)										
Immigrant × Main competitors			0.0055									
			(0.0117)									
Immigrant × Cooperative				-0.1021***								
				(0.0142)								
Cointimmi× Credit history					-0.0006				0.0001			
					(0.0023)				(0.0023)			
Cointimmi× 𝟙(Credit history>3 yrs)						-0.0086				-0.0002		
						(0.0214)				(0.0214)		
Cointimmi× Main competitors							0.2073***				0.2265***	
							(0.0096)				(0.0094)	
Cointimmi× Cooperative								-0.2026***				-0.2208***
								(0.0117)				(0.0114)
Singleimmi× Credit history									-0.0078***			
									(0.0015)			
Singleimmi× 𝟙(Credit history>3 yrs)										-0.0746***		
										(0.0131)		
Singleimmi× Main competitors											-0.0082	
											(0.0114)	
Singleimmi× Cooperative												-0.0914***
												(0.0138)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Prov. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.4071	0.4070	0.4070	0.4071	0.4451	0.4450	0.4455	0.4453	0.4243	0.4242	0.4245	0.4244
Observations	490,189	490,189	490,189	490,189	464,152	464,152	464,152	464,152	954,341	954,341	954,341	954,341

Notes. This table presents the coefficients from OLS regressions for mortgages to natural persons included in the Bank of Italy's Central Credit Register and ASLIR survey in the period 2011-2016. The single-name mortgages sample includes loans in name of a single borrower; the joint mortgages sample includes loans made out to two co-borrowers; the full sample includes both single-name and joint mortgages. The dependent variable is *APR*, the annual interest rate charged to borrowers on granted mortgages in percentage points. Description of explanatory variables is reported in table 2. LTV is the ratio between the amount of the mortgage and the lender self-assessed value of the house. Income is the mortgagors' income. Both LTV and Income are imputed variables obtained by using the Random Forest algorithm trained on the Banks of Italy's SHIW dataset with the R package "Random Forest". All columns include the same control variables of specifications [2], [5] and [6] in Table 5. Robust standard errors are in parentheses. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05.

Table A9: Mortgage pricing regression results- Augmented model: borrowers' credit history, dominant lenders and cooperative banks with Bank×Time and Province×Time joint fixed effects, and clustered standard errors.

	Single-name mortgages				Joint mortgages				Full sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Immigrant	0.1803***	0.1801***	0.1644***	0.1849***								
	(0.0325)	(0.0332)	(0.0337)	(0.0319)								
Cointimmi					0.2424***	0.2424***	0.1552***	0.2678***	0.3314***	0.3294***	0.2372***	0.3583***
					(0.0592)	(0.0591)	(0.0418)	(0.0642)	(0.0644)	(0.0640)	(0.0401)	(0.0701)
Singleimmi									0.1587***	0.1599***	0.1444***	0.1601***
									(0.0375)	(0.0383)	(0.0339)	(0.0360)
Cointmix									0.1507***	0.1494***	0.1508***	0.1505***
									(0.0256)	(0.0256)	(0.0258)	(0.0256)
Cointnat									0.0437***	0.0425***	0.0440***	0.0435***
									(0.0101)	(0.0102)	(0.0103)	(0.0101)
Credit history	-0.0118***				-0.0053***				-0.0080***			
	(0.0025)				(0.0019)				(0.0020)			
Immigrant × Credit history	-0.0037											
	(0.0034)											
Cointimmi × Credit history					0.0004				0.0008			
					(0.0040)				(0.0038)			
Singleimmi × Credit history									-0.0047			
									(0.0038)			
𝟙(Credit history>3 yrs)		-0.1103***				-0.0505***				-0.0765***		
		(0.0216)				(0.0168)				(0.0164)		
Immigrant × 𝟙(Credit history>3 yrs)		-0.0367										
		(0.0329)										
Cointimmi × 𝟙(Credit history>3 yrs)						-0.0047				0.0032		
						(0.0342)				(0.0317)		
Singleimmi × 𝟙(Credit history>3 yrs)										-0.0481		
										(0.0374)		
Immigrant × Main competitors			0.0241									
			(0.0906)									
Cointimmi × Main competitors							0.2317*				0.2544*	
							(0.1374)				(0.1517)	
Singleimmi × Main competitors											0.0109	
											(0.0803)	
Immigrant × Cooperative				-0.0877*								
				(0.0473)								
Singleimmi × Cooperative												-0.0768*
												(0.0431)
Cointimmi × Cooperative								-0.1760**				-0.1931**
								(0.0830)				(0.0896)
Time X bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time X Province FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.4159	0.4160	0.4159	0.4160	0.4539	0.4539	0.4545	0.4541	0.4316	0.4316	0.4320	0.4318
Observations	490,189	490,189	490,189	490,189	464,152	464,152	464,152	464,152	954,341	954,341	954,341	954,341

Notes. This table presents the coefficients from OLS regressions for mortgages to natural persons included in the Bank of Italy's Central Credit Register and ASLIR survey in the period 2011-2016. The single-name mortgages sample includes loans in name of a single borrower; the joint mortgages sample includes loans made out to two co-borrowers; the full sample includes both single-name and joint mortgages. The dependent variable is *APR*, the annual interest rate charged to borrowers on granted mortgages in percentage points. Description of explanatory variables is reported in table 2. LTV is the ratio between the amount of the mortgage and the lender self-assessed value of the house. Income is the mortgagors' income. Both LTV and Income are imputed variables obtained by using the Random Forest algorithm trained on the Banks of Italy's SHIW dataset with the R package "Random Forest".All columns include the same control variables of specifications [2], [5] and [6] in Table 5. Robust standard errors clustered standard errors at the bank level are in parentheses. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05.

Table A10: Loan approval regression results. (Dep. var.: Approval | $_{t-6}d_t = 1$).

	[1])	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Immigrant	-0.027***	-0.029***	-0.025***	-0.027***	-0.026***	-0.028***	-0.028***	-0.030***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Age	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age-squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.017***	0.019***	0.017***	0.019***	0.017***	0.019***	0.017***	0.019***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Credit history	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Coint	0.342***	0.342***	0.342***	0.342***	0.342***	0.342***	0.342***	0.342***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(Income)		-0.005***		-0.005***		-0.005***		-0.005***
		(0.001)		(0.001)		(0.001)		(0.001)
Immigrant×Credit history			-0.000***	-0.000***				
			(0.000)	(0.000)				
Immigrant×Main competitors					-0.003	-0.003		
					(0.002)	(0.002)		
Immigrant×Cooperative banks							0.013***	0.013***
							(0.002)	(0.002)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.226	0.226	0.226	0.226	0.226	0.226	0.226	0.226
Observations	7,300,072	7,300,072	7,300,072	7,300,072	7,300,072	7,300,072	7,300,072	7,300,072

Notes. This table presents the coefficients from LPM regression for the request of CR first information made by bank in the period 2015-2016. The dependent variable is a dummy that takes the value 1 if a mortgage loans is granted conditional on banks' submitting a first information CR request within a 6-months period before the loan disbursement, and 0 otherwise. Description of explanatory variables is in table 11. ln(Income) is the logarithm of mortgagors' income. Income is an imputed variable obtained by using the Random Forest algorithm trained on the Banks of Italy's SHIW dataset with the R package "Random Forest". Robust standard errors in parentheses. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05.

Table A11: Loan approval regression results. (Dep. var.: Approval | $_{t-3}d_t = 1$).

	[1])	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Immigrant	-0.025***	-0.027***	-0.023***	-0.026***	-0.024***	-0.027***	-0.026***	-0.028***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Age	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age-squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.016***	0.018***	0.016***	0.018***	0.016***	0.018***	0.016***	0.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Credit history	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Coint	0.324***	0.323***	0.324***	0.323***	0.324***	0.323***	0.324***	0.323***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(Income)		-0.005***		-0.005***		-0.005***		-0.005***
		(0.001)		(0.001)		(0.001)		(0.001)
Immigrant× Credit history			-0.001***	-0.001***				
			(0.000)	(0.000)				
Immigrant×Main competitors					-0.005***	-0.005***		
					(0.002)	(0.002)		
Immigrant× Cooperative banks							0.013***	0.013***
							(0.002)	(0.002)
Bank×Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Province×Time FE	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.220	0.220	0.220	0.220	0.220	0.220	0.220	0.220
Observations	7,299,490	7,299,490	7,299,490	7,299,490	7,299,490	7,299,490	7,299,490	7,299,490

Notes. This table presents the coefficients from LPM regression for the request of CR first information made by bank in the period 2015-2016. The dependent variable is a dummy that takes the value 1 if a mortgage loans is granted conditional on banks' submitting a first information CR request within a 3-months period before the loan disbursement, and 0 otherwise. Description of explanatory variables is in table 11. ln(Income) is the logarithm of mortgagors' income. Income is an imputed variable obtained by using the Random Forest algorithm trained on the Banks of Italy's SHIW dataset with the R package "Random Forest". Regressions include bank×time and province×time fixed effects. Robust standard errors in parentheses. ***p-value $<$ 0.001, **p-value $<$ 0.01, *p-value $<$ 0.05.

Table A12: Loan approval regression results. (Dep. var.: Approval | ${}_{t-6}d_t = 1$).

	[1])	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Immigrant	-0.026***	-0.029***	-0.025***	-0.027***	-0.026***	-0.028***	-0.027***	-0.029***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Age	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age-squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.017***	0.019***	0.017***	0.019***	0.017***	0.019***	0.017***	0.019***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Credit history	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Coint	0.342***	0.341***	0.342***	0.341***	0.342***	0.341***	0.342***	0.341***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(Income)		-0.005***		-0.005***		-0.005***		-0.005***
		(0.001)		(0.001)		(0.001)		(0.001)
Immigrant×Credit history			-0.000***	-0.000***				
			(0.000)	(0.000)				
Immigrant×Main competitors					-0.003	-0.003		
					(0.002)	(0.002)		
Immigrant×Cooperative banks							0.013***	0.013***
							(0.002)	(0.002)
Bank×Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Province×Time FE	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.229	0.229	0.229	0.229	0.229	0.229	0.229	0.229
Observations	7,299,490	7,299,490	7,299,490	7,299,490	7,299,490	7,299,490	7,299,490	7,299,490

Notes. This table presents the coefficients from LPM regression for the request of CR first information made by bank in the period 2015-2016. The dependent variable is a dummy that takes the value 1 if a mortgage loans is granted conditional on banks' submitting a first information CR request within a 6-months period before the loan disbursement, and 0 otherwise. Description of explanatory variables is in table 11. ln(Income) is the logarithm of mortgagors' income. Income is an imputed variable obtained by using the Random Forest algorithm trained on the Banks of Italy's SHIW dataset with the R package "Random Forest". Regressions include bank×time and province×time fixed effects. Robust standard errors in parentheses. ***p-value $<$ 0.001, **p-value $<$ 0.01, *p-value $<$ 0.05.