Credit Demand *versus* Supply Channels: Experimental- and Administrative-Based Evidence

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Abstract

This paper identifies and quantifies –for the first time– the relative importance of borrower (credit demand) *versus* bank (supply) balance-sheet channels. We submit fictitious applications (varying households' characteristics) to the major Italian online-mortgage platform. In this way we ensure that all banks receive exactly the same mortgage applications, and that –for each application– there are other identical ones except for one borrower-level characteristic. We find that: (i) Borrower and bank channels are equally strong in causing (and explaining) loan acceptance (each channel changes acceptance by 50 p.p. for the interquartile range and explains 29% of R-square). (ii) Differently, for pricing, borrower factors are much stronger. (iii) Banks supplying less credit accept riskier borrowers. Finally –exploiting administrative credit register data– we document borrower-lender assortative matching: safer banks have more credit relations with safer firms. Moreover, the measure of credit supply estimated in the experiment (differently from a very similar measure estimated from the *observational* mortgage data) determines bank credit supply to firms and risk-taking in administrative data.

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1 Introduction

Credit is a crucial ingredient of economic growth (Schumpeter, 1912; Miller, 1998; Levine, 2005; Stiglitz, 2010). Moreover, credit is fundamental for financial stability and systemic risk. Strong credit booms are the best predictors of financial crises, which are then generally characterized by large drops in credit (Schularick and Taylor, 2012; Gourinchas and Obstfeld, 2012). Even in the current Covid-19 crisis, credit is important for the crisis dynamics and is at the center of crucial policy measures (e.g. Lagarde, 2020; Powell, 2020; Bruegel, 2020).

For testing theories and for public policy decisions, it is essential to disentangle the non-financial borrower (firm or household) balance sheet (credit demand) channel *versus* the bank lending (credit supply) channel. In this paper we identify and measure the relative importance of each part of the credit channel (borrower demand versus bank supply).

Regarding theory, the borrower balance sheet channel operates on the credit demand-side, e.g. borrower net worth, collateral values, and default risk (see e.g. Bernanke, Gertler and Gilchrist, 1999). The bank lending, or balance sheet, channel operates on the credit supply-side, e.g. bank capital, liquidity, and risk (see e.g. Gertler and Kiyotaki, 2010). Macro-finance and banking models differ in the importance of borrowers' and banks' balance sheet strength and risk and, for instance, models like Holmstrom and Tirole (1997) have both channels at work.

Regarding policy, should policy-makers bailout (if any) borrowers or banks? Policy solutions differ when the factors constraining credit lay on the demand-side, which may require helping households or non-financial firms (see e.g. Mian and Sufi, 2014), versus the supply-side, which may require reforming banks or bank bailouts (see e.g. Bernanke, 2018). For example, in the current Covid-19 crisis, both in U.S. and Europe, public policies target both credit to borrowers (SMEs) and banks' lending capacity (bank liquidity and capital softening).

The literature has not quantified borrower (credit demand) *versus* bank (credit supply) balance sheet channels, despite the importance of these channels for theory and policy. The literature has been plagued with identification problems, using only observational data, characterized by endogenous, assortative matching between borrowers and banks. The credit channel literature has notably advanced with within-firm estimators in credit register data (e.g. Khwaja and Mian, 2008; Amiti and Weinstein, 2018). However, this approach implies that *only* the credit *supply* channel can be identified (trying to control fully for the demand-side with borrower fixed effects). Moreover, even this supply estimator could be biased, as credit demand by some borrowers to some particular banks is differentiated (e.g. Paravisini, Rappoport and Schnabl, 2015). The demand-side may also be difficult to observe, impossible for discouraged borrowers, who think they will not get the loan (especially from some banks), and in many cases only data on credit granted, and not on loan applications, are available.

In sum, despite the importance of credit channels for economic growth and financial stability as well as for testing academic theories and public policy analysis: (i) the relative importance of borrower (credit demand) vs. bank (supply) balance sheet channels has not been quantified; (ii) even the identification of just the credit supply channel has been done with observational data and with strong assumptions on borrower-lender matching that may not hold on the data.

In this paper, we contribute to the literature as we overcome these identification problems by creating and exploiting experimental-based data, thereby identifying (and measuring) the relative importance of the borrower (credit demand) versus the bank (credit supply) balance sheet channels.[1] We submit fictitious mortgage applications (varying households' characteristics) to the major online mortgage platform in Italy. Each application goes to *all* banks, and we submit other identical applications *changing one* borrower-level variable at time. The experiment allows us to solve both the issue of endogenous matching of borrowers into banks, and the issue of a borrower demanding loans with different characteristics to different banks (possibly depending on bank characteristics); moreover, we can compare identical households' applications to all banks differing only in one characteristic. Finally, we exploit the administrative credit register from Italy to show that, in real loan-level data, there is indeed assortative matching between borrowers and banks, and to analyze whether the experimental results have external validity using the administrative (real) data.

Briefly summarized, we find that, the borrower and bank channels are similarly strong in causing —and explaining— loan acceptance in the experimental data. The two channels have an adjusted R-squared of 29.4% and 28.5% respectively, and economically, the associated interquartile range increases loan acceptance by 52.4 percentage points (p.p.) and 50.5 p.p.. Differently, for loan pricing, borrower factors are substantially more important (the borrower channel is at least eight times larger than the bank channel). As the borrower and bank channels explain 58% of loan rejections and because of theory, we analyze interactions of both channels. We find that banks that supply less credit accept on the margin borrowers with higher risk (i.e., those without a permanent job and younger, or those with desired loans with longer maturity).

[1] Bernanke (2007) argues that the bank lending channel can be interpreted as a balance sheet channel (Bernanke, and Gertler, 1989; Bernanke, Gertler and Gilchrist, 1999) for banks. For an early paper on the household balance sheet channel, see Mishkin (1978). See also below more references on our subsection on the contribution to the literature (note also that the literature on credit frictions grew exponentially after the 2008 crisis but for the sake of space we do not cite many relevant theory papers).

Finally, exploiting the credit register data, we show that the estimated bank credit supply from the experiment determines: (i) credit supply to real firms, even more strongly economically and statistically than the key variables used in the literature to proxy for bank balance-sheet strength. (ii) Composition of credit supply with respect to ex-ante borrower risk (bank risk-taking). Differently, a bank credit supply measure based on the (*observational*) real mortgages by banks (a measure otherwise very similar to the one from the experiment on fake mortgage applications) does not affect credit supply to SMEs.

In the remaining part of this Introduction, in more detail, we provide a preview of the different parts of the paper, and discuss the related literature and its contrast with our paper.

Preview of the paper. The experimental data we use is a new and unique dataset of mortgage applications and contract offers. We post fictitious loan applications to the major online mortgage broker in Italy (MutuiOnline) in two months (October 2014 and September 2016); the banks associated to MutuiOnline include e.g. the 10 largest ones in the country, accounting for over 70% of the market for mortgage originations.[2] To submit a loan application, the broker requires the prospective borrower to list both her demographic characteristics (job type, age, income) and the main features of the contract requested (maturity, rate type, amount). We vary those characteristics (for each set of characteristics, we submit other identical ones except for one variable), for a total of 11,520 different combinations (fictitious borrowers) in every period. Since all banks get all the fictitious applications, our final sample comprises almost half a million observations (483,840 borrower-bank-time applications).

For any loan application, the online broker shows a screenshot with the offers from the banks willing to grant the mortgage under the conditions specified in the application. The broker has the credit algorithms of each bank to accept or not an application, and if so, the loan rate offered. Specifically, each offer displayed in the screenshot represents a bank pre-approval decision, which is our measure of acceptance of the mortgage application. With the pre-approval, there is also an offer on the loan interest rate (with and without fees) by each bank that is willing to grant the loan. For the mortgage to be fully approved, the prospective borrower needs to provide further information about herself and the house she intends to buy (e.g. the full name, the current address of residence, the date and place of birth, real estate registry documentation of the house, etc.). Conditional on the borrower not lying on the submission process (e.g. income, house

[2] It is key to highlight that Italy is a bank dominated economy, where nonbank intermediaries are not significant. Moreover, different from the US system (for the so-called conforming loans), there is not a public agency to which banks sell (via securitization) mortgages (risk), but there is just a private securitization market.

characteristics, etc.), the bank pre-approval and pricing are binding.[3] Therefore, the key information for our experiment can be gathered at the pre-approval stage.

Crucially, our experiment ensures that all banks offering their mortgages through the online broker receive the *same* mortgage applications, defined by the *same* borrower *and* loan contract characteristics. Hence, our estimates are not biased by endogenous selection of borrowers into banks (or contracts). Moreover, there is no missing data due to discouraged potential borrowers (riskiest ones) not submitting loan applications.[4] Importantly, for each borrower application, we have other identical ones except for one characteristic.

Therefore, we can measure the relative importance of the borrower (demand) *versus* bank (supply) balance sheet channels. We identify (and measure) borrower and bank factors that affect (and explain) loan acceptances (or loan rates for accepted applications) with borrower and bank fixed effects, respectively, to account for all observed but also all unobservable variation. We can also estimate the relationship between each estimated bank fixed effect in the experimental data with the key observed bank balance sheet characteristics (e.g. capital, liquidity, risk) that proxy for balance sheet strength. As each household has other identical ones except for one variable, we can both measure the impact of each household variable (e.g. permanent job, income, age) on loan acceptance or rates (i.e. by applying a "group-household" fixed effect that includes all fictitious households with identical variables except for the one analyzed), and assess whether banks change their lending differently for ex-ante riskier borrowers (weaker balance sheets or riskier contracts, such as longer-term loans).

We also exploit the administrative, supervisory credit register (owned by the Italian central bank), as well as the administrative bank and firm balance sheet data (see e.g. Ippolito et al., 2016). All these datasets, matched by the fiscal identification number, are subsequently matched to our (new) experimental dataset via each bank identifier. The credit register includes loan-level (observational) data at the bank-firm level. We use this administrative data: (i) to show that banks with different balance sheet strength are more likely to have a credit relationship with borrowers with different risk, i.e. there is borrower-lender sorting in observational data; and (ii) to test whether the bank credit supply measures that we obtain from the experimental data on mortgages determine actual credit supply by banks to real borrowers (firms). We analyze loans to firms as: (i) there are many firms with loans from more than one

[3] Not all pre-approved mortgages ultimately become originated mortgages, as the application can still be rejected at a later moment (e.g. because the home value comes lower than expected after the bank performs its own valuation, or because borrower's characteristics differ from those initially declared), or the borrower can retreat.
[4] Discouraged borrowers are important in real credit markets as shown by e.g. Magri and Pico (2012) and by the data from the Bank of Italy's Survey on Household Income and Wealth.

bank, and hence we can apply firm*time fixed effects (and show whether these effects matter or not with our measures of bank credit supply estimated from the experimental data) and (ii) we have administrative firm variables proxying e.g. for risk (firms are obliged to register their balance sheets, but not households).[5] Moreover, we analyze small and medium enterprises (SMEs) as they are closer to households than large firms.

Our main results based on the experimental data are the following. For the extensive margin of lending, where we test the importance of borrower versus bank factors for the acceptance of applications, we find that the borrower and bank channels are similarly important in causing and explaining loan acceptance. Quantitatively speaking, both channels are strong.

Borrower and bank estimated fixed effects explain a similar share of the adjusted R-squared (29.4% and 28.5% of all variation, respectively). Differently, time effects (the two months of our experiment) play a limited role, as borrower fixed effects alone explain 27.4% of the adjusted R-squared and borrower-time effects just explain 29.4%. Similarly bank and bank-time fixed effects respectively explain 23.2% and 28.5%. In addition, volume requested alone only explains 1% of the adjusted R-squared.

Borrower versus bank factors also have similar economic significance. Moving from the first to the third quartile of the distribution of the estimated borrower(*time) fixed effects increases the acceptance of applications by 52.4 p.p., and by 50.5 p.p. for bank(*time) effects.[6] Without time fixed effects interacted with borrower or bank effects, results are very similar for the borrower and bank channels, 50.0 p.p. and 46.2 p.p. All these estimated effects are large in absolute value, and also relative to the average acceptance of loan applications (43.42%).

For loan pricing, differently, the borrower balance sheet channel is much more important. Borrower*time (bank*time) factors explain 92.2% (56.0%) of the adjusted R-squared of annual loan interest rates (and without interacted time effects, 32.3% vs. just 3.9%).[7] Moreover,

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[5] In countries with taxes on household wealth, one can have household balance sheets, but many countries do not have these wealth taxes, or others have only taxes for only wealthy households (and hence they do not have the universe on household balance sheets). Differently for firms, many countries impose regulations on firms registering their balance sheets, and hence it is easier to have firm balance sheet data, even on private firms.

[6] Bank (or bank*time) fixed effects are obvious dummies for each (real) bank. Regarding the fictitious households, as we said in the main text, a household is a combination of identical household-level variables, including preferred loan characteristics (e.g. maturity), and hence we can have household fixed effects. As we have the exact combination of household characteristics in each time period, hence we can have just household or household*time fixed effects.

[7] Volume requested alone (i.e. moving within the "demand curve", or, in other terms, not shifting the "demand curve" by changing e.g. borrower income, employment risk, or age) explains basically 0% of the adjusted R-squared for loan pricing. As explained in the main text, our paper is not about identifying credit demand versus supply, but on the *credit channels*: household balance sheet channel –i.e. changes in household key fundamentals such as income that shifts credit demand (see e.g. Bernanke, Gertler and Gilchrist, 1999) – versus the bank lending channel –i.e. changes in bank key fundamentals such as capital that shifts credit supply (see e.g. Gertler and

moving from the first to the third quartile of the distribution of estimated borrower (bank) fixed effects increase the gross loan rates by 1.2 p.p. (0.15 p.p.), which is high given the average loan rates (2.44%).[8] Therefore, without time fixed effects, for loan pricing, the borrower channel is at least eight times stronger than the bank channel.

Granting applications is moreover positively associated to higher bank capital and size and negatively related to sovereign debt and liquidity holdings (also to loan charge-offs, but in this case, it is not significant at conventional levels). Differently, for pricing, bank observables are not associated to different loan prices, consistent with the previous result that only borrower factors are key in pricing.

Exploiting households with *identical* characteristics except for one variable (household group fixed effects), we show that permanent (vs. fixed-term) jobs, older age, or higher income increase the granting of applications; and if granted, they decrease the rates. There are similar effects for more attractive loan conditions to the lenders, such as shorter-maturity loans, and for fixed rate loans that come with higher loan rates.

We also analyze differential risk-taking as: (i) it is key for the banking literature (Freixas and Rochet, 2008) and for heterogeneous issues such as e.g. household inequality (Rajan, 2011) or misallocation in firms (Hsieh and Klenow 2009), and (ii) the borrower and bank channels (without any interaction) explain a maximum of 58% of loan rejections.

On the one hand, banks with stronger balance sheets could lend more on the margin to riskier borrowers (e.g. due to higher risk-bearing capacity); on the other hand, banks that supply less credit can take more risk to get higher yields to compensate for their lower credit volumes and hence profits (or due to e.g. less skin in the game). We analyze risk-taking by exploiting different observed borrower variables and, as a bank strength measure, the estimated bank fixed effects or even those effects over and above key bank observable variables such as capital, size, risk and liquidity.[9] We find that banks that supply less credit accept on the margin riskier loans (i.e. to borrowers without a permanent job and younger, and with a longer maturity).

Kiyotaki, 2010). For example, we want to answer how much *credit* changes because of differential *household* key balance-sheet factors such as income, employment risk and age versus differential *bank* balance-sheet factors such as bank capital, liquidity and risk.

[8] In pricing, time effects do matter as monetary rates were different in the two periods of our experiment. Only with borrower**time* vs. bank**time* fixed effects, the economic significance is somewhat higher for bank factors.

[9] Bank balance sheet variables may not perfectly measure bank capital (e.g. book value versus market value), risk (NPLs versus risky loans that have not defaulted yet) and liquidity (funding versus market liquidity or actual versus potential liquidity). Moreover, our measure of bank strength over and above bank observables could, for instance, capture management skills, corporate governance, and other unobserved bank variables such as bank reputation which are difficult to capture with observable variables.

Finally, we analyze the external validity of the results using the administrative credit register. Using the bank-level (strength) fixed effects estimated in the experimental data on the granting of *real* loans by banks to SMEs, we find that these bank fixed effects determine actual credit supply to real firms.[10]

We follow the literature and analyze credit growth to firms controlling for firm fixed effects. Estimated effects are *completely identical* if we saturate the (credit register) regressions with firm*time effects or without any control, despite that the R-squared changes by 44 p.p., which suggests exogeneity of our bank-level measure from the experimental data on the supply of credit to actual borrowers in the observational data (following Altonji et al., 2005; Oster, 2019).

Effects are large: moving from the first to the third quartile of bank strength increases credit supply by about 8 p.p. (the average credit growth is just 3.37%). Moreover, the estimated bank-level effects from the experiment are stronger both in statistical and economic terms in explaining the credit supply to real firms than the key bank observables used in the literature to proxy for balance sheet strength (as e.g. different measures of capital, risk, liquidity, and size).

Furthermore, in the actual supervisory credit register based on the administrative data, consistently with the experimental results, weaker bank strength (i.e. banks with less credit supply) implies higher risk-taking in loans, in particular higher supply of credit to riskier firms (based on firm leverage, credit risk scores, loan rate expenses given profitability, and firm liquidity). Moreover, using credit register data, we show that there is positive assortative matching between (stronger) banks and borrowers (i.e., those banks with weaker balance sheets and that provide less credit supply in our experimental data tend to lend more ex-ante to firms with higher risk).

Finally, we construct a measure of bank-level strength (in credit supply) from the credit register of mortgages (real mortgages from real banks), a measure which is a very similar to the one based on the experimental data on mortgages (fake mortgage applications to real banks). We find that only the bank level measure from the experimental data affects the supply of credit to SMEs (the credit register based measure is insignificant), thereby further suggesting crucial borrower and bank endogenous matching problems in observational credit data that limit not only the analysis of the credit supply channel, but also of identifying and measuring the borrower (firm or household) versus bank balance sheet channels.

[10] Results are also significant if we bootstrap standard errors.

Contribution to the literature. Our experimental data allows us to make a crucial contribution to the large literature on the credit channel by identifying (measuring) the borrower (demand) *versus* the bank (supply) *channels*.[11] First, the observational data—that the credit channel literature has used—cannot solve key identification problems due to the endogenous matching between borrowers and banks, and the difficulty in isolating, and even observing, credit demand. While the within-firm (or firm*time) estimator (Khwaja and Mian, 2008), and the large literature that follows it, makes crucial steps in identifying the credit supply channel, estimates may be biased as they rely on the assumption that demand by some firms to banks is identical (Paravisini, Rappoport and Schnabl, 2015). Second, and even more important for the question of our paper, the within-firm (borrower) approach does not allow measuring the relative importance of the borrower (firm or household) *vs.* the bank balance sheet channel.[12]

Identifying (and measuring) the borrower (credit demand) vs. bank (supply) balance sheet channel is not only crucial for the empirical literature (as highlighted above), but also for testing macro-finance (and banking) models and for public policy solutions. Models differ in the relevance of the borrower channel (e.g. Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Bernanke, Gertler and Gilchrist, 1999; Iacoviello, 2005; Jermann and Quadrini, 2012; Liu, Wang and Zha, 2013; Kumhof, Rancière and Winant, 2015; Favilukis, Ludvigson and Van Nieuwerburgh, 2017; Guerrieri and Lorenzoni, 2017) versus the lender channel (e.g. Stein, 1998; Adrian and Shin, 2010; Gertler and Karadi, 2011; Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2012; Angeloni and Faia, 2013; Brunnermeier and Sannikov, 2014; Boissay, Collard and Smets, 2016; Drechsler, Savov and Schnabl, 2017; Miranda-Agrippino and Rey, forthcoming), and e.g. Holmstrom and Tirole (1997) have both channels at work.

Our results inform these theoretical models on which friction is more relevant in the data (Nakamura and Steinsson, 2018), and, specifically they point to very different results for the extensive margin of lending (identical importance of bank and borrower channels) vs. pricing (crucial only the borrower channel). Policy solutions also differ when the factors constraining credit lay on borrowers (demand), and hence policy makers may need to help households (or non-financial firms), as advocated by e.g. Mian and Sufi (2014), vs. banks (credit supply), and hence policy makers may need to bailout or help banks, as advocated by e.g. Bernanke (2018).

[11] See e.g. Khwaja and Mian (2008), Paravisini (2008), Ivashina and Scharfstein (2010), Jiménez et al. (2012, 2014 and 2017), Amiti and Weinstein (2011 and 2018), Schnabl (2012); Iyer et al. (2014). See also papers using more aggregate data such as Kashyap and Stein (2000) and Bernanke and Blinder (1988, 1992).

[12] Moreover, in observational data, certain borrowers, e.g. discouraged ones, may decide not to apply to certain banks, or not apply at all, potentially biasing the estimates of the borrower and bank channels. At the same time, borrower characteristics may also drive the demand for certain loan types; e.g., borrowers with low income may disproportionately apply for, say, longer or variable-rate loans, and this may depend on bank strength.

The remainder of the paper is organized as follows. Section 2 discusses the institutional details of the mortgage market in Italy, the experimental and administrative datasets. Section 3 discusses the empirical strategy and results. Section 4 concludes.

2 Institutional Setting and Experimental and Administrative Datasets

In this section we explain the institutional details of the mortgage market in Italy, as well as the experimental dataset based on the fictitious (online) applications to the major online broker in Italy (which implies applications to all the main banks). We also explain the administrative, supervisory dataset based on Bank of Italy's double (firm and bank) matched credit register.

2.1 Institutional Setting

Mortgages are the main liabilities of Italian households and they account for about 60% of the financial debt of the household sector. On the lender side, the market is dominated by banks, which grant almost the totality of mortgages to households, for a total value of about 80 billion euros in 2016.

The mortgage market is mostly dominated by adjustable rate mortgages (74% of the total outstanding loans in 2015), which are characterized by mortgage installments that vary with the reference rate (typically, the 3 month Euribor).[13] The remaining market share is taken almost entirely by fixed rate mortgages, which are characterized by a predetermined path of mortgage installments to pay off the principal and the interests on the loan. Adjustable rate mortgages with a cap or "mix" rate mortgages, which consist of a part with fixed rate and of a part with adjustable rate, are seldom used. Importantly, mortgages that allow resetting the interest rate (such as the five year-ARMs in the U.S.) do not exist. Indeed, for the whole duration of the mortgage, adjustable rate mortgages have a variable interest rate, while fixed rate mortgages have the same constant rate. The relative share of adjustable and fixed rate mortgages depends strictly on the level of interest rates (Foà et al., 2015): in recent years, the low level of interest rates drove the historical increase in the share of fixed rate mortgages among the new loan originations, which equaled about 45% of the new loans originated in 2015.

Mortgage refinancing became more common since 2008 when a law slashed renegotiation fees. The same law ruled that fees to transfer mortgages across banks had to be significantly reduced, boosting the portability of mortgages. However, until 2013, the prepayments or contract modifications involved just a negligible share of loans (less than 1%). Only after the

[13] Countries differ significantly in the share of adjustable versus fixed-rate mortgage, and in the use of prepayment penalties (Lea, 2010; Badarinza, Campbell and Ramadorai, 2018).

reduction of interest rates at historically low levels, the share of outstanding loans that have been refinanced increased reaching about 7% in 2015.

In 2015 the average loan-to-value (LTV) was about 60% (based on the Regional Banking Lending Survey 2015), about 10 p.p. lower than in 2006. Loans with a LTV above 80% are only 4% of new loans because they are penalized by regulation, as banks need to hold extra capital if they offer those kinds of loans. Average mortgage length was 20 years and less than 20% of new loans had duration above 30 years.

Before deciding whether to grant a mortgage and with the aim of limiting the pre-payment and default risks, the bank considers a few main characteristics of the potential borrower. A striking difference from the US mortgage market is that Italian applicants do not have a FICO score, i.e. a number that represents their creditworthiness. Instead, the bank takes into account the applicant's employment, income level, debt amount required, funds for the down payment, age, type of mortgage, and geographic area. These characteristics impact on the ability to repay the debt and are required by the banks to assess the applicant's risk profile.[14] Finally, the fees that come with a mortgage (application and loan origination fees) are standard administration charges.

2.2 The Experiment, Online Broker, and Datasets

We submit fictitious applications (varying households' characteristics) to the mortgage platform, MutuiOnline (www.mutuionline.it), which is the leading online mortgage broker in Italy, working with the largest commercial banks in the country. Overall, 25 banks are associated with MutuiOnline, and these banks granted around 70% of total new mortgage loans in 2013. Moreover, in 2015 MutuiOnline intermediated about 2.5 billion euros of mortgages, which corresponds to about 6% of the total amount of new loans for home purchase in Italy. MutuiOnline's brokerage activity is free for the potential borrowers; instead, a commission from the affiliated banks may be required when new clients post completed applications. Banks may indirectly charge their clients for the fees of this brokerage activity, still the online brokerage remains one of the cheapest channels for banks to attract and lend to new clients.

To submit a mortgage application though MutuiOnline, the individual has to provide ten pieces of information: (i) whether the house will be the primary residence of the applicant; (ii) the desired type of interest rate (fixed or variable); (iii) the house value; (iv) the desired

[14] Magri and Pico (2011) show that households with low income, high housing costs-to-income ratio, whose head is unemployed or fixed-term employee, and living in the Southern regions of Italy are more likely to be delinquent on their debt.

mortgage amount; (v) the desired mortgage maturity; (vi) the age of the applicant; (vii) the type of the job contract of the applicant (e.g. permanent vs. fixed); (viii) the net monthly income of the applicant; (ix) the municipality of residence of the applicant; (x) the municipality in which the house is located. Since Italian households do not have a FICO score, these are the variables used by banks to perform an evaluation of a household's ability to pay and of the related prepayment and default risks.

Then, for any loan application, MutuiOnline reports the mortgage offers (if any) from the different banks, i.e. it shows a screenshot displaying the offers from those banks that are willing to grant a mortgage for that specific loan/applicant profile. Each offer details a single value for annual percentage rate (APR), net mortgage rate, fees, and monthly installment.[15] Figures A1 and A2 in the Appendix illustrate the on-line form an applicant needs to fill, and the outcome. In this example, only four banks were willing to post an offer.

When MutuiOnline shows an offer, it means that the application has been pre-approved (this is our measure of acceptance of the mortgage application).[16] For the mortgage to be fully approved, the prospective borrower needs to provide further information on herself (name, proof of residence, month and place of birth, etc.), the exact address of the house she intends to buy and further details (e.g. the official documents about the house from the real estate registry, a certification from the seller or the real estate agent that the house is free from other mortgages, etc.).

Our experiment exploits the first step of the application process, which ends with the application pre-approval. Thus, our choice to focus on pre-approvals dispenses us from the submission of fake applicant names and house addresses. In a nutshell, our experiment consists of considering a very large number of the possible combinations of the pieces of information about borrower (and her contract) characteristics described above, which are sufficient for the online broker to provide pre-approval decisions and the associated mortgage terms. Pre-approvals are generated by credit scoring models, which are chosen and managed by each bank.

As our experiment does not involve obtaining final offers for a mortgage, but only pre-approvals, it is important to make sure that the pre-approved offers made by the online broker are realistic. First, banks working with MutuiOnline have incentives not to post teaser rates because making false offers through the online broker damages banks' reputation. Moreover,

[15] Menu offers with several combinations of coupons and points do not exist in Italy.
[16] In the paper we use the term "the application has been accepted" when it has been pre-approved and the online broker posted a net mortgage rate, APR, fees, and monthly installment from that bank, as shown in Figure A2 in the Appendix.

the online broker has an implicit commitment that the offers made through the website are true ones and it makes efforts to ensure that banks do not modify the rates offered online. Indeed, the characteristics of the mortgages that are finally disbursed are about the same of those that are pre-approved (Figure A.3 in the Appendix), confirming that pre-approved offers are very similar to the mortgages which are effectively originated. Furthermore, while we acknowledge that online borrowers may be different than those that apply to a physical branch of the bank, the characteristics of the mortgages generated through the two distribution channels are quite similar: for instance, in the first semester of 2016, the share of new variable rate mortgages was equal to about 23% for those granted by MutuiOnline versus 21% for the total (online plus branches, according to supervisory reports data). In the first semester of 2010, the share of new variable rate mortgages was about 40%, both for MutuiOnline and overall.

In sum, conditional on the borrower not lying on the submission process (e.g. income, house characteristics, etc.), the bank pre-approval and pricing are binding, and therefore, the key information for our experiment can be gathered at the pre-approval stage. It is important to highlight that not all pre-approved mortgages ultimately become originated mortgages, as the application can still be rejected at a later moment (for instance, e.g. because the home value comes lower than expected after the bank performs its own valuation, or because borrower's characteristics differ than from those initially declared), or the borrower could retreat.

MutuiOnline cannot partially accept a mortgage application by modifying the contract characteristics. This is not a limitation, since partial acceptance is very uncommon in Italy. Indeed, as confirmed by the Survey on Household Income and Wealth data on the Italian households, in 2012 only about 3% of the mortgage applications for home purchase have been partially accepted. This also occurs in other countries: Agarwal and Ben-David (2018) show that the major US commercial bank they study either fully accepts or rejects residential mortgage applications. Finally, as shown in the descriptive statistics below, the average characteristics of the mortgages offered through MutuiOnline are similar to the official data obtained from supervisor reports and Eurosystem banking statistics on the mortgages that have been actually granted in Italy in our sample period.

To obtain an experimental database of loans, we exploit many different mortgage applications for the purchase of the main residence via the online broker. In particular, we created 11,520 (fictitious) profiles of borrowers. As said above, each application goes to all banks, which is different from the assortative matching between borrowers and lenders in the real market (that we will show also in this paper with the administrative, supervisory credit register). Moreover, for each profile of a borrower, we submit to the online broker other identical profiles except for only one variable (one of the ten pieces of information necessary for the application itself).

We considered different values for borrower age, income, and job type. We set four values for the age which capture 10 years ranges (30 for 25-34, 40 for 35-44, 50 for 45-54, 60 for 55-64 years old), nine values for the net monthly income which capture 500 euros ranges (1,000 for 1,000-1,499; 1,500 for 1,500-1,999; 2,000 for 2,000-2,4999; 2,500 for 2,500-2,999; 3,000 for 3,000-3,499; 3,500 for 3,500-3,999; 4,000 for 4,000-4,500; 4,500 for 4,500-4,999; 5,000 for 5,000-5,499 euros), while the job type falls into five categories pre-selected by the online broker: permanent contract, fixed time contract, self-employed, professional, retired. We consider two types for the mortgage rate (fixed or adjustable), four values for duration (10, 20, 30, 40 years) and eight values for the mortgage amount (60,000; 120,000; 180,000; 240,000; 300,000; 360,000; 420,000; 480,000 euros), which are equal to 60% of the house value.

We choose the LTV in line with data from the Regional Bank Lending Survey, conducted by the Bank of Italy, according to which the median LTV was about 60% in 2014.[17] We also restrict our analysis to mortgage applications for Milan, which is the second largest city in Italy, the major financial and business center, and the major mortgage market.[18] According to data from CRIF Real Estate Services, in April 2015, about 25% of all new daily Italian mortgage originations occur in Lombardy, the region where Milan is located, and, among those, about 50% occur in the city of Milan. Thus, the market of Milan is well suited to study the aggregate dynamics. We submit the applications to the MutuiOnline website in October 2014 and September 2016.

All in all, in each period we submit these 11,520 fictitious applications to the online mortgage application broker. Every application goes to all banks, and, consequently, the application is the same for all banks. The final dataset contains borrower-bank(-time) combinations, detailing which banks are willing to grant a loan, as well as the APR, net mortgage rate, fees, and loan installment that each bank applies to the loans that they are willing to grant.

[17] We fix the LTV in the experiment as our aim is to focus on borrower characteristics (the demand side). The LTV partly reflects a supply-side decision.
[18] As the applications do not directly go to the banks, but banks submit their credit algorithms to accept and reject applications to the online broker (to mechanically accept or not an application), there is no large demand shock from our experiment in Milan.

Out of the 11,520 (fake) borrowers' applications to all (21) banks submitted in the two periods (around half a million borrower-bank observations), about 5.5 per cent were rejected by all banks (these applications are characterized by long maturity combined with old age of the applicant) and about 0.5 per cent were accepted by all banks (none of these applications was submitted by an individual with fixed-term job or retired).[19]

Administrative datasets. We merge the experiment-based database of (willing to grant and rejected) loan applications and rate (APR) offers with three matched administrative datasets from Bank of Italy (the central bank and supervisor of the banks in Italy). The matched administrative datasets are: (i) the comprehensive loan-level credit register, which reports outstanding loan exposures (with minimum size of 30,000 euros) of all banks operating in Italy vis-a-vis Italian non-financial firms, as well as the universe of mortgages from the credit register; (ii) supervisory data on bank balance sheets; and (iii) data on firm financials from the proprietary CADS database, owned by Cerved Group, a member of the European Committee of Central Balance Sheet Data Offices that collects official balance sheet data reported by firms to the Chambers of Commerce, as required by Italian law.

As explained in the Introduction, we analyze loans to firms in the credit register as many firms have loans from more than one bank (and hence we can apply firm*time fixed effects, see Section 3) and we have matched administrative firm balance sheet data (and hence we can analyze risk-taking);[20] and moreover, given our experimental data on mortgages, we analyze small and medium enterprises in real administrative data. Finally, we check whether a bank supply measure from the *observational* mortgage data can determine credit supply to SMEs, and whether results are different based on a bank measure from the *experimental* data (fake mortgage applications to real banks via the online intermediary).

All three datasets are for the months around October 2014 and September 2016. For loans, we analyze the change in credit around those months, and for firm level data, we use the end of previous year (2013 and 2015) balance sheets. For the bank data, we use the closest available from the supervisory reports (June 2014 bank data are matched with the observations obtained from MutuiOnline in October 2014, and June 2016 bank data with those for September 2016) and refer to the bank holding company each bank pertains to. We use consolidated data at the bank holding company level for several reasons. First, this is the relevant level for supervision and for the computation of balance sheet items for regulatory purposes (such as the capital

[19] The final sample includes 21 different banks corresponding to 17 bank holding groups. In the main regressions, we analyze the data at the bank holding group – borrower level.
[20] That is, different lending depending on riskier borrowers (firms).

ratio), which allows us to obtain a proper measure of the strength of each bank balance sheet. Second, lending and funding policies are decided at the banking group level, taking into account the whole funding needs of the banking group (Cremers, Huang and Sautner, 2011). All bank holding companies in our sample are banks themselves. We exclude branches of foreign banks for which we do not have complete balance sheet information and banks that do not have branches in the province of Milan. Overall, our final sample comprises 17 bank holding companies (21 different banks), including the 10 largest banks in the country.[21]

Summary statistics. Table 1 describes the summary statistics of experimental and administrative datasets. In our mortgage sample, about 43% of the loan applications are accepted. Importantly, among the loans accepted, the terms of the loans are in line with the empirical evidence based on official statistics from the Bank of Italy (Bank of Italy, 2016). The mean APR equals 2.44% in our database versus an average of 2.86% between October 2014 and September 2016 in the official statistics. The mean net mortgage rate is 2.26% in our sample versus 2.56% in the official statistics. The mean borrower is 45 years old, with monthly net income of 3,000 euro (net out of taxes and social security, which are very high in Italy compared to US) and a 25-year mortgage loan of 270,000 euro, mechanically reflecting the way we structured the experiment (which also provides large heterogeneity for each measure).

Credit growth to firms by banks from the credit register during the two months of our experiment are on average 3.4% using Davis and Haltiwanger (1992) measure, based on the extensive plus the intensive margin of lending (19.24% if we use change in log credit volume plus one), and 0.75% on average if we only analyze the pure intensive margin (i.e., if we use change in log credit).[22] On average firm ROA (profits to total assets) is 0.4%, firm EBITDA/interest expenses is about 10.5, firm liquidity is 9%, firm leverage is 23.5%, and firm size is 827,000 euros. Importantly, there is very large heterogeneity across each of these firm balance sheet and credit measures.

Regarding bank characteristics, the measure of bank capital, in line with the literature (Iyer et al. 2014, Jiménez et al. 2014), is the capital ratio (a simple leverage ratio defined as Tier 1 capital to total assets) with an average of 6.49%. Besides capital, we also consider other bank-level characteristics that may affect lending: bank short term liquidity, measured by the cash-

[21] Our sample includes: BNL, MPS, Unicredit, Credito Emiliano, Deutsche Bank, UBI, Intesa San Paolo, Banca Sella, Banco Popolare, Banco di Desio e della Brianza, Credito Valtellinese, Banca Popolare dell'Emilia Romagna, Veneto Banca, Banca Popolare di Milano, Carige, Cariparma, Mediobanca (CheBanca). The banking groups associated with Mutuionline are four more, but in our final dataset we drop foreign bank branches and those Italian banks that do not have branches in Milan.

[22] The measure of Davis and Haltiwanger (1992) is the change in credit volume over half of (initial plus final) credit volume.

over-assets, with an average of 0.59% and government bonds-over-assets, with an average of 11.5%; the evolution of credit quality, measured by the net loan charge−offs ratio (loan charge−offs to loans as in Santos, 2011), with an average of 0.86%; bank profitability, measured by the return on assets (profits to total assets, ROA), with an average of 0.04%; bank assets have an average of 133 billion euros. These data indicate that the banks in our sample are, on average, similar to other large European commercial banks (EBA, 2014), even though the net loan charge-offs ratio is higher. Moreover, the bank summary statistics also show large heterogeneity across the banks (e.g. bank capital varies from 4% to 9%).

3 Empirical Strategy and Results

In this section, we discuss our empirical strategy and results, both for the experimental data and for the administrative credit register. All the main Tables, including those on robustness in the Appendix, are at the end of the paper.

3.1 Experimental Data

We analyze the granting of loan applications and the loan pricing. As described in the previous sections, we tackle the identification problems in measuring the borrower (credit demand) versus the bank (credit supply) balance sheet channels by exploiting an experiment (that we described in detailed in the previous section), based on fictitious mortgage applications (with varying borrower risk's intensity) to banks through the major online mortgage broker in Italy. Each application goes to all banks, and e.g. we submit other identical applications changing one borrower-level variable at time. The experiment allows us: (i) to observe loan applications (e.g. there is no discouraged borrowers or only granted credit); (ii) to solve the identification problem of endogenous matching of borrowers into banks (and the related problem of a borrower demanding loans with different characteristics to different banks); (iii) to compare identical households' applications to all banks differing only in one characteristic. Banks with different balance sheet strength obtain identical loan applications, in particular there are in total 483,840 borrower-bank-time pairs.

We analyze the granting of applications and loan rates on a set of fixed effects for each (fictitious) borrower and for each bank, which proxy for the borrower (demand) and the bank (supply) channels, respectively. The borrower channel reflects how important changes in borrower risk and net worth (age, income, job risk, etc.) are for loan acceptance and prices; this is not a movement along the demand curve/schedule, which are changes in volume demanded as price changes for a *given borrower risk,* but thanks to the experiment we exploit changes in the borrower risk –where all banks get the *same* applications and we vary each application changing one variable at time (with identical household characteristics, including her preferred loan characteristics such as loan maturity)–, thereby proxying the borrower channel.

Similarly, the bank (supply) channel reflects how important are (for loan acceptance and rates) changes in bank net worth and risk (capital, liquidity, risk, business model, even unobserved bank risk and strength). Again, we are not analyzing a movement along the supply curve/schedule (i.e., what is the volume offered conditional on the loan rate for a given bank net worth and risk, see e.g. Bernanke and Lown, 1991).

Given that we have two different months when we submitted the applications, we can also include an interaction with time fixed effects in addition to the borrower and bank fixed effects, i.e. household or bank interacted with time fixed effects. In the first case, a borrower is defined by a set of characteristics, such as age, income, job type, loan contract type such as maturity, etc. (see previous section), and we allow the value of these variables to be repeated in the two periods, and hence we can have borrower or borrower*time fixed effects (i.e., borrower*time fixed effects is like adding the month where we submitted the application as another characteristic). The set of characteristics that we include to define a borrower includes both characteristics of the borrower and of the contract that the borrower is applying for (and thus prefers).

In the second case, bank*time fixed effects allow a bank, e.g. Unicredit, to have different estimated bank level credit supply in the two (time) periods where we submitted the fictitious applications. By estimating fixed effects, we allow for borrower and bank factors to capture all possible heterogeneity, included unobserved one. For example, in the case of a borrower, she has a set of characteristics that are over and above a *linear*, *additive* combination of age, income, contract type, and other characteristics. In the case of a bank, it has some observed characteristics such as its size, capital and liquidity, but also many other ones which are not observed by us (compensation, corporate governance, risk appetite, unobserved risk not captured in supervisory variables, etc.). Note that the estimated bank fixed effects do not refer to a bank credit supply schedule that, for each possible combination of borrower characteristics, it quantifies how much volume supplied offers the bank for each loan rate, but rather a relative bank credit decision (rejection or loan price given acceptance) for the same identical borrower (and exact identical application) compared to other bank (i.e., the definition refers to the bank lending channel versus the borrower balance sheet channel).

The benchmark regression is as follows:

$$Y_{i,b,t} = \alpha\ HouseholdChannel_i + \delta\ BankChannel_b + \varepsilon_{i,b,t} \tag{1}$$

where $Y_{i,b,t} = acceptance_{i,b,t}$ is a dummy equal to 1 if the loan application from borrower *i* to bank *b* in period *t* is accepted (the online broker shows an offer with an APR), 0 otherwise; or $Y_{i,b,t} = APR_{i,b,t}$ offered by bank b to borrower i in period t, conditional on acceptance. $HouseholdChannel_i$ is a set of household (borrower-contract pair) fixed effects (as explained above), or also interacted with time fixed effects (household*time effects). $BankChannel_b$ is a set of bank (or bank*time) fixed effects. These effects capture the strength of the borrower and bank channels as they explain or determine loan rejections and rates respectively.

Table 2 provides the results for our benchmark regressions on the extensive margin of lending. We estimate the household and bank fixed effects and we quantify their economic significance (via the interquartile range) as well as how much they explain of the variation of loan acceptance (via adjusted R-square).

Column 1 shows that the change in the quantity demanded per se explains very little of the adjusted R-squared (1%). Instead, in Column 2 borrower estimated fixed effects account for a large share of the adjusted R-squared (27.4%) and their economic significance is quite high: moving from the first to the third quartile of the distribution of the estimated borrower (household) fixed effects increases the acceptance of loan applications by 50 percentage points.[23] Column 3 repeats the same analysis but adding the time fixed effects (i.e., household*time effects). The adjusted R-squared slightly increases to 29.4% and the economic effects to 52.4 p.p.. It is important to highlight that all these estimated effects are large in absolute value, and also relative to the average acceptance of loan applications, which is 43.42%, or the standard deviation, which is 49.57%.

Column 4 and 5 repeat the same analysis for the bank channel by estimating bank and bank*time fixed effects respectively. Bank estimated fixed effects also explain a large share of the adjusted R-squared (23.2% and 28.5% of all variation respectively). Bank factors also have a large economic significance. In particular, moving from the first to the third quartile of the distribution of the estimated bank fixed effects increases the acceptance of loan applications by 46.2 and 50.5 p.p.. Finally, Column 6 shows similar results for the household and bank channel together (with an adjusted R-squared of 57% and interquartile range of 98.2 p.p.).

In sum, for the extensive margin of lending, we find that the borrower and bank channels are equally strong in causing—and explaining—loan acceptance. Moreover, quantitatively speaking, both channels are very strong.

[23] See Table A1 on the Appendix for the summary statistics of the estimated fixed effects.

Table 3 shows the results for loan pricing. In Panel A, we consider the annual percentage rate gross of fees and commissions (APR), conditional on acceptance. In Panel B, we present estimates for the nominal annual interest rate, net of fees and commissions. According to the two measures of mortgage pricing, similarly to the extensive margin, the quantity by itself explains very little of the adjusted R-squared (Column 1). Columns 2 to 5 indicate that the household channel is substantially more important than the bank lending channel. In particular, borrower factors explain the adjusted R-squared of loan interest rates substantially more than bank factors: for APR, 32.3% against 3.9% without time fixed effects, and 92% against 56% with time effects; for net mortgage rate 33.0% against 3.7% without time fixed effects, and 93.4% and 55.7% with time fixed effects.

Moreover, as Columns 2 and 4 show, borrower factors also have a stronger economic significance than bank factors: moving from the first to the third quartile of the distribution of estimated borrower (bank) fixed effects increase both the APR by 1.2 p.p. (0.15 p.p.) and the net annual interest rate by 1.2 p.p. (0.2 p.p.), respectively. Results for borrower factors are large given that the average gross and net loan rates are 2.44% and 2.26%, respectively (standard deviations are just above 1%).

In pricing, differently from granting of applications, time effects matter significantly, but just because monetary rates were different in the two periods of our experiment. For economic significance, only when considering the borrower*time vs. bank*time fixed effects, the economic significance is somewhat higher for bank (than borrower) factors (see Columns 3 vs. 5, Panel A and B); however, effects are driven by time effects (comparing to column 2 and 4). Finally, Column 6 shows very strong effects in pricing when the borrower and bank channels are estimated together.

Tables 4 and 5 analyze the role of borrower and bank observables in explaining loan acceptance and pricing. Table 4, Panels A and B, focus on borrower factors for loan acceptance and pricing, respectively, while Table 5 considers bank factors.

In Table 4, we analyze the impact of borrower observables, which are applicant's job type (permanent contract, fixed term contract, self-employed, professional, retired), age, income, loan maturity, rate type (fixed or variable).[24] We include borrower (household) group effects (within the same time period), where a group is a set of (fictitious) borrowers in which all the variables (borrower's job type, age, income, house value, mortgage duration, amount, and rate-type), including the month of application, are identical except for one variable (the one at the

[24] In the table, for ease of reading, we present results only for permanent and fixed term job.

top of each column). Moreover, we control for bank*time fixed effects as well. Therefore, we compare *borrowers that are identical except for the category analyzed* in the column and study the granting of the loan application (or the loan rate) from *the same bank in the same month*.

We find that stronger household balance sheets –borrowers with permanent (versus fixed-term) jobs, older, and with higher income– cause higher granting of loan applications (Columns 1, 2, 3, 6; Panel A);[25] and if granted, lower loan rates (Columns 1, 2, 3, 6; Panel B). There are similar effects for more attractive loan conditions to the lenders, i.e. shorter-maturity loans (Column 4, Panels A and B). Banks also prefer fixed (over variable) loan rates, as they charge higher rates (Column 5, Panels A and B).[26]

In Table 5, we analyze bank observables. We use the main bank balance sheet variables that the banking literature use for the strength of bank balance sheets, in particular bank capital, liquidity and size, as well as measures of risk (sovereign debt holdings and non-performing loans proxied by loan charge-offs). Granting applications is positively associated to higher bank capital and size, and negatively related to sovereign debt and liquidity holdings (also to loan charge-offs, but in this case, it is not significant at conventional levels when household*time FE are included). Differently, for loan pricing, these observable bank balance sheet characteristics are not related to the loan pricing (conditional on approval), which is consistent with the previous results from Table 3 that borrower factors are substantially more important in loan pricing than bank factors. Moreover, results in Table 5 are confirmed if we include other bank measures as e.g. bank ROA and deposits among the regressors (see also Table A3 for all the bank observables that include in robustness).

We analyze risk-taking in Table 6. Note that from Table 2 both household and bank factors explain less than 58% of the variation, hence there could be interaction (compositional) effects between both credit channels, and moreover, the banking literature argues about different risk-taking motives for banks with different balance sheet strength (Freixas and Rochet, 2008; Holmstrom and Tirole, 1997). Note that banks with stronger balance sheets could lend more on the margin to riskier borrowers (as they lend more and/or they have higher risk bearing capacity); on the other hand, banks that provide less credit supply can take more risk on the margin to obtain higher yields to compensate for their lower credit volumes (as lower loan

[25] As said above, there are other job categories in addition to permanent versus fixed-term contract (self-employed, professional, retired), but the main action is between permanent contract versus fixed term contract.
[26] In the sample period of low rates, fixed rates are significantly higher than variable ones (see also Table 1 for the summary statistics).

volume decreases bank profitability), or due to e.g. lower skin in the game (based on bank capital in Table 5).

As a measure of the strength of bank balance sheets, we either consider the estimated bank*time fixed effects resulting from equation (1) or the residual from regressing those estimated bank*time effects on the bank observables (bank capital, liquidity, size, sovereign debt holdings, and non-performing loans). We show all results in the paper with both measures, but we include the residual one as benchmark as we want to highlight the limits of observable variables in this paper, e.g. bank balance sheet or in general observational (credit) data.

Column 1 shows the direct effect, without interactions with household characteristics. These (bank strength) residuals not only positively affect the probability of acceptance, but explain about 15% of the R-squared (about the same as all the main bank observable characteristics together, not reported). Results are very similar (all strong economically and statistically) if we do control for the bank observables.

Moreover, columns (2) to (6) show the interaction effects. We find that banks that supply less credit accept borrowers with ex-ante higher risk proxied by: (i) not having a permanent job (i.e. fixed-term job); (ii) younger; and (iii) with a requested longer-term maturity loan. In Table A2 of the Appendix we find similar results with our measure of gross bank strength, i.e. the estimated bank fixed effects (without subtracting bank observables).

3.2 Administrative Credit Register Data

In this sub-section, we use the bank fixed effects estimated in the experimental data (which determine the granting of applications in the experimental data) in conjunction with the matched administrative datasets, including the Italian credit register. The credit register, which includes loan-level data at the bank-firm level, is matched with firm and bank balance sheet data. These administrative data differ from our fictitious (mortgage) applications both in that they are observational *vs.* experimental, but also on mortgages *vs.* SME loans.[27]

We use the administrative data: (i) to show that banks with different balance sheet strength are more likely to have a credit relationship with borrowers with different risk—i.e., there exist a borrower-bank sorting in observational data; and (ii) to test whether the bank credit supply measures obtained from the experimental data (on mortgages) determine actual credit supply by banks to real borrowers (firms), as well as bank risk-taking (i.e., the external validity of our

[27] We focus on loans to SMEs (and not to large firms) as they are more comparable to loans to households. See also Section 2 and Introduction on why we use loans to firms in the credit register.

results). We focus on corporate loans as we can control for borrower fixed effects (as the empirical literature on the credit channel) and as we have measures of borrower risk (for the assortative matching and risk-taking), while we cannot do this in mortgage data. Nevertheless, we also use mortgage data to horse race our bank measure based on experimental mortgage data vis-à-vis a very similar one using the observational one based on the credit register for mortgages.

In Tables 7 and 8, we analyze the change in credit granted by banks to non-financial firms using the credit register data. In Table 7 we analyze overall supply of credit and in Table 8 we analyze compositional effects of credit supply with respect to ex-ante borrower risk (bank risk-taking). We analyze all loans (i.e. intensive and extensive margin) following the standard measure proposed by Davis and Haltiwanger (1992) on change in credit (over an average of credit volume in each period), but we also present results for the intensive margin of lending alone.

Table 7 shows that estimated effects are all statistically significant. That is, using the bank-level (strength) fixed effects estimated in the experimental data on the granting of *real* loans by banks to SMEs, we find that these bank strength measure determines actual credit supply to real firms. Moreover, the estimated credit supply effects are completely identical if we saturate the (credit register) regressions with firm*time effects (Column 4) or without any control (borrower or time, or combination of both, Column 5 or 1) despite that the R-squared increases by 44 p.p., which suggests exogeneity of our bank-level strength measure from the experimental data on actual borrower (credit demand) fundamentals (following Altonji et al., 2005; Oster, 2019).

The last two columns also show similar effects with an alternative measure of extensive and intensive margin (using log of credit plus one) and the pure intensive margin using a change in log granted credit. Regarding economic significance, moving from the 25th to the 75th percentile of the distribution of bank strength increases the change in credit supplied by about 8 p.p. (Column 4; the mean growth rate is 3.4%) and the change in credit supplied in the intensive margin by 0.7 p.p. (Column 7; the mean growth rate is 0.8%).[28]

Moreover, accounting also for all the main bank observables (capital ratio, short-term liquidity, government bond holdings, loan charge-offs, ROA, deposits, and total size), our

[28] Note that the R-square is low as change in credit volume in credit register data is about changes in the stock of loans and many loan exposures do not move in the short-term (see e.g. Table 1, all our left-hand side variables' medians have a value of 0).

measure of bank strength based on experimental mortgage data is the most important variable (statistically and economically) in driving credit supply to firms (see Table A3 in the Appendix). Table A4 in the Appendix shows similar results with the gross measure of bank strength, i.e., without cleaning the estimated bank-level effects by bank observables. Note that all the variables are standardized in Table A3 and A4 to facilitate the comparison.

In Table 8, we analyze bank risk-taking. Consistent with the experimental data (Table 6), in the actual credit register, we find that weaker bank strength implies higher credit supply on the margin to ex-ante riskier firms proxied by firm profits (ROA), capacity to pay back debt (EBITDA over interest expenses), liquidity and leverage. That is, banks with lower strength (measured in the experimental data) increases credit to riskier firms on the margin as compared to banks with higher strength, comparing lending to the same firm in the same period.[29]

Table 9 shows with the credit register data that there is an endogenous matching between stronger banks and borrowers, i.e. a positive assortative matching. The results for correlations show high values, e.g. the correlation between bank strength and firm liquidity equals 45%, with firm leverage is -34%, with firm profitability (25%), and with firm capacity to repay 30%. Table A5 in the Appendix provides a confirmation of these results in a regression setting. Finally, Tables A7 and A8 show very similar results with the gross measure of bank strength (i.e., without cleaning the estimated bank-level effects by bank observables). For example, the correlations of the gross measure of bank strength with borrower observables are as follows: with firm profitability equals 43%, with firm liquidity 55%, with firm leverage -56% and with firm capacity to repay 43%.

Finally, we ask whether the bank level credit supply measure that we obtain from the experimental data would provide similar results (on lending to real firms) as a similar measure obtained from the (real) credit register. As our lending (for external validity) is on SMEs and our bank-level credit supply measure (i.e., the experimental data) is on mortgages, we obtain the new bank credit supply measure from the real mortgages, i.e. based on the credit register of mortgages.[30] In particular, we use as a measure of bank strength (bank-level overall credit supply), a set of bank fixed effects obtained applying the approach proposed in Amiti and Weinstein (2018) using the administrative mortgage data from the Italian credit register. As there are no repeated mortgages over a short period of time for the same household, we cannot control for household fixed effects, but we instead add a location fixed effect to control for local

[29] Table A6 in the Appendix confirms the results using our gross bank strength instead.
[30] Note that if we would obtain the bank fixed effects (bank credit supply) from loans to SMEs and we would then apply those bank fixed effects to “determine” loans to SMEs, results would be trivial and non-interesting.

area demand effects. Therefore, we aggregate mortgage loans at the bank-province level, compute the credit growth rates in Q3 2014 and Q3 2016, and regress these credit growth on a set of bank and province fixed effects (see Table A9 for the specification).

The estimated bank fixed effects are a proxy of bank's supply of mortgage loans. However, as highlighted throughout the paper, and especially in the Introduction, this (type of) measure may be biased because of the endogenous selection of borrowers into banks and contracts and because of the phenomenon of discouraged borrowers. To gauge to what extent this measure constructed on realized mortgage data is able to determine credit supply to firms (SMEs), Table A9 shows results of the same regressions as shown in Table 7 (which were based on loans to SMEs but instead using the bank-level strength/credit supply measure constructed from the experimental data). Importantly, the measure of bank strength computed on the real mortgage data is statistically insignificant, differently from the one obtained using experimental data (i.e., based on fake mortgage applications to real banks via the online platform). We interpret this evidence as further highlighting the importance of controlling for the endogenous selection of borrowers into banks and contracts when constructing measures of bank credit supply.

In sum, in the observational data that the credit literature has exclusively used, there is an endogenous matching between borrower and lender fundamentals (a positive assortative matching), which makes it difficult to isolate and measure the borrower (demand) versus the bank (supply) balance sheet channels, and hence it shows the need for experimental data in the identification and quantification of the borrower and bank credit channels.

4 Conclusions

Credit is a key component of economic growth and is fundamental for financial stability and systemic risk. Moreover, for both public policy and testing theories, it is essential to disentangle the (non-financial) borrower (firm or household) balance sheet (credit demand) channel versus the bank lending or balance sheet (credit supply) channel. Macro-finance and banking models differ in the importance of the net worth strength and risk (frictions) of the borrowers' and lenders' balance sheets. Moreover, regarding public policy, given scarce resources, it is important to know whether policy-makers should e.g. help or bailout (if any) borrowers or banks (and hence the relative importance of the borrower and lender channels). For example, in the current (Covid-19 related) crisis, both in the US and in Europe, public authorities are significantly helping both borrowers (households and firms) and banks on credit.

Despite the importance of these channels, the literature has not quantified borrower (credit demand) *versus* bank (supply) channels,[31] as the literature has been plagued with identification problems, using only observational data, characterized by endogenous, assortative matching between borrowers and banks. The Khwaja and Mian (2008) within-firm estimator has notably improved the estimation of the bank supply channel, but it cannot measure the importance of the borrower *versus* lender channel, and it may also have problems to isolate the credit supply channel due to borrower-lender endogenous matching (Paravisini, Rappoport and Schnabl, 2015). Moreover, the demand-side is difficult to observe, impossible for discouraged borrowers, and available datasets are mostly on credit granted, and not on applications.

We overcome these identification problems through exploiting experimental-based data, which allow us to measure the relative importance of borrower (credit demand) vs. bank (supply) channels. We submit fictitious mortgage applications (varying households' characteristics) to the major online mortgage platform in Italy. Each application goes to all banks, and e.g. we submit other identical applications changing one borrower-level variable at time. Moreover, for external validity we also analyze the administrative credit register.

We find that, the borrower and bank channels are equally strong in causing —and explaining— loan acceptance. Each channel has an adjusted R-squared of 29.4% and 28.5%, and economically, the interquartile range increases loan acceptance by 52.4 p.p. and 50.5 p.p., respectively. Differently, for loan pricing, borrower factors are substantially more important (the borrower factors are at least eight times more important than the bank factors). As the borrower and bank channels explain a maximum of 58% of loan rejections and because of theory, we also analyze interactions of both channels. We find that banks that supply less credit accept borrowers with higher risk.

Finally, exploiting administrative credit register data, in addition to showing positive assortative matching between bank and borrower strength, we show that the estimated bank-level effects from the experiment determine overall credit supply by banks to real firms (SMEs), as well as composition of credit supply with respect to risk (bank risk-taking). Differently, a measure based on the real mortgages (otherwise very similar to the one from the experiment on fake mortgage applications) does not affect credit supply to SMEs.

[31] As we explain throughout the paper, our paper is not about identifying credit demand versus supply, but on the *credit channels*: household balance sheet channel (i.e. changes in household key fundamentals such as income that shifts credit demand, see e.g. Bernanke, Gertler and Gilchrist, 1999) *versus* the bank lending channel (i.e. changes in bank key fundamentals such as capital that shifts credit supply, see e.g. Gertler and Kiyotaki, 2010). We want to answer how much *credit* changes because of differential *household* key balance-sheet factors such as income, employment risk and age versus differential *bank* balance-sheet factors such as bank capital, liquidity and risk.

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TABLE 1 – DESCRIPTIVE STATISTICS

Notes: Panel A shows the descriptive statistics for the experimental data. The dummy acceptance is equal to 1 if the mortgage application has been accepted (pre-approved), zero otherwise. Annual percentage rate (APR) is the interest rate gross of all fees proposed by the bank. Net mortgage rate is the interest rate net of all fees proposed by the bank. Installment is the monthly mortgage payment. Gross bank strength and Bank strength are measures of the effect of banks' balance sheets on banks' willingness to accept mortgage applications. Their definition is described in detail in the note to Table 6. Data are from all the mortgage applications submitted to MutuiOnline in two dates (October 2014 and September 2016). Panel B shows the descriptive statistics for the administrative data. Sub-Panel B1 shows the firms' characteristics. Davis-Haltiwanger growth rate (GR) is the change in credit between December and September in 2014 and 2016 divided by the average credit in the two time periods; Δ Log(credit+1) is the change in firms' credit that accounts for new relationships and exit; Δ Log(credit) is the change in firms' credit that does not account for new relationships and exit. Sub-Panel B2 reports bank variables. Short term liquidity is cash over assets; government bonds is government bonds over assets; loan charge-offs is loan charge-offs over total loans. Data are from June 2014 and June 2016 supervisory reports.

	Mean	Sd	P50	Min	Max	Observations
			Panel A. Experimental data			
P(acceptance)(%)	43.42	49.57	0.00	0.00	100	483840
APR (%)	2.44	1.04	2.21	1.04	5.33	210088
Net mortgage rate (%)	2.26	1.02	2.09	0.95	4.91	210088
Tot. fees/mortgage (%)	0.55	0.43	0.45	0.00	2.13	207670
Installment (€)	1,582	1,057	1,381	180	4,848	210088
Borrower's age	45.00	11.18	45.00	30.00	60.00	483840
Net monthly income (€)	3,000	1,291	3,000	1,000	5,000	483840
Mortgage amount (thousand €)	270	137	270	60	480	483840
Maturity (years)	25.00	11.18	25.00	10.00	40.00	483840
Gross Bank Strength	0.00	26.46	0.59	-43.42	36.19	483840
Bank Strength	2.57	18.68	2.58	-35.07	42.04	483840
			Panel B. Administrative data			
			B1. Firms: balance sheet and credit register			
Davis-Haltiwanger GR (%)	3.372	65.88	0	-200	200	468326
Δ Log (credit+1) (%)	19.24	317.7	0	-1713	1709	468326
Δ (credit) (%)	0.748	39.32	0	-1141	1004	427189
ROA	0.00	0.09	0.01	-0.55	0.23	447359
Ebitda/interest exp.	10.53	26.50	4.09	-32.40	265.86	439295
Liquidity	0.09	0.12	0.04	0.00	0.55	431996
Leverage	0.24	0.22	0.20	0.00	0.91	468326
Total assets (thousands €)	827.79	503.89	740.00	1.00	1,944.00	468326
			B2. Banks: supervisory reports			
Capital ratio (%)	6.49	1.27	6.40	3.96	9.21	483840
Short term liquidity (%)	0.589	0.286	0.522	0.041	1.4	483840
Government bonds (%)	11.479	4.804	11.439	0	21.455	483840
Loan charge-offs (%)	0.86	0.42	0.78	0.14	1.61	483840
ROA (%)	0.04	0.30	0.10	-0.90	0.60	483840
Bank assets (billions €)	132.89	213.33	60.85	9.86	919.22	483840

TABLE 2 – PROBABILITY OF ACCEPTANCE: BORROWER AND BANK LENDING CHANNELS

Notes: The table shows OLS regressions for the probability that a mortgage is accepted (pre-approved). Only quantity means that only loan amount requested is included as a control (Column 1). Borrower channel means that only household (HH) fixed effects (FE, Column 2) or household*time FE (Column 3) are included. Household FE are the fixed effects for all possible combinations of applicant's job type, age, income, mortgage maturity, rate type, amount, and house value. In particular, a household fixed effect is a dummy variable that takes the value of one for a set of characteristics both of the borrower (age, income, job type) and of the loan contract requested by the borrower (maturity, fixed versus adjustable rate, loan amount) which characterizes the borrower side of a loan application. HH*time FE add the time dimension (month when the application was submitted) to the previous set of borrower variables. Bank channel means that only bank FE (Column 4) or bank*time FE (Column 5) are included. Bank FE are the fixed effects for the banking group to which the bank belongs. Borrower and bank channels (Column 6) imply that both household*time FE and bank*time FE are included. P75-P25 is the difference between the 75th and the 25th percentiles of the distribution of loan volume multiplied by the estimated coefficient on loan volume (Column 1); for the remaining columns, it is the difference between the 75th and the 25th percentiles of the distribution of the estimated coefficients of the fixed effects for household (Column 2) and it is measured in percentage points, household*time (Column 3), bank (Column 4), bank*time (Columns 5), and both household*time and bank*time (Column 6). "Y", "N" and "-" imply that those controls are included, not included, or spanned by (other) fixed effects. Data are from all the mortgage applications submitted to MutuiOnline in two dates (October 2014 and September 2016).

	Only quantity	Borrower channel		Bank channel		Borrower and bank channels
	(1)	(2)	(3)	(4)	(5)	(6)
Adj. R^2	0.011	0.274	0.294	0.232	0.285	0.570
P75-P25 (p.p.)	-9.096	50.0	52.381	46.155	50.464	98.249
Only quantity	Y	-	-	N	N	-
HH FE	N	Y	-	N	N	-
Bank FE	N	N	N	Y	-	-
HH*time FE	N	N	Y	N	N	Y
Bank*time FE	N	N	N	N	Y	Y
Observations	483840	483840	483840	483840	483840	483840

TABLE 3 – LOAN PRICING: BORROWER AND BANK LENDING CHANNELS

Notes: The table shows OLS regressions for loan pricing, measured by the annual percentage rate gross of all fees and commissions (Panel A), or by the nominal annual interest rate, net of fees and commissions (Panel B). Only quantity means that only loan amount supplied is included as a control (Column 1). Borrower channel means that only household (HH) fixed effects (FE, Column 2) or household*time FE (Column 3) are included. Household FE are the fixed effects for all possible combinations of applicant's job type, age, income, mortgage maturity, rate type, amount, and house value. In particular, a household fixed effect is a dummy variable that takes the value of one for a set of characteristics both of the borrower (age, income, job type) and of the loan contract requested by the borrower (maturity, fixed versus adjustable rate, loan amount) which characterizes the borrower side of a loan application. HH*time FE add the time dimension (month when the application was submitted) to the previous set of borrower variables. Bank channel means that only bank FE (Column 4) or bank*time FE (Column 5) are included. Bank FE are the fixed effects for the banking group to which the bank belongs. Borrower and bank channels (Column 6) imply that both household*time FE and bank*time FE are included. P75-P25 is the difference between the 75th and the 25th percentiles of the distribution of loan volume multiplied by the estimated coefficient on loan volume (Column 1); for the remaining columns, it is the difference between the 75th and the 25th percentiles of the distribution of the estimated coefficients of the fixed effects for household (HH, Column 2), household*time (Column 3), bank (Column 4), bank*time (Columns 5), and both household*time and bank*time (Column 6). "Y", "N" and "-" imply that those controls are included, not included, or spanned by (other) fixed effects. Data are from all the mortgage applications submitted to MutuiOnline in two dates (October 2014 and September 2016).

	Only quantity	Borrower channel		Bank channel		Borrower and bank channels
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Annual percentage rate			
Adj. R^2	0.003	0.323	0.922	0.039	0.560	0.976
P75-P25 (p.p.)	-0.096	1.2	0.927	0.154	1.627	1.256
Observations	210088	210088	210088	210088	210088	210088
			Panel B. Net mortgage rate			
Adj. R^2	0.0	0.33	0.934	0.037	0.557	0.978
P75-P25 (p.p.)	-0.015	1.228	0.862	0.201	1.573	1.155
Observations	210088	210088	210088	210088	210088	210088
Only quantity	Y	-	-	N	N	-
HH FE	N	Y	-	N	N	-
Bank FE	N	N	N	Y	-	-
HH*time FE	N	N	Y	N	N	Y
Bank*time FE	N	N	N	N	Y	Y

TABLE 4 – ROLE OF BORROWER OBSERVABLES

Notes: Panel A shows results for the probability of acceptance; Panel B for the annual percentage rate, gross of all fees and commissions. The main household observables are reported in the top row. Profiles are defined as a combination of all identical households observables (borrower's job type, age, income, mortgage maturity, amount, rate-type, and house value). HH Group includes all (fictitious) households with all the same observables except the one at the top. Job types are permanent contract, fixed term contract, self-employed, professional, and retired. Data are from all the mortgage applications submitted to MutuiOnline in two dates (October 2014 and September 2016). Standard errors in parentheses are standardized at the HH Group-time. *** $p<0.01$, ** $p<0.05$,*$p<0.1$.

	Job type		Age	Maturity	Rate type	Income
	(fixed term)	(permanent)			(fixed)	
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Probability of acceptance			
HH observable	-43.26***	12.14***	0.08***	-0.50***	0.89***	3.86***
	(0.33)	(0.10)	(0.02)	(0.01)	(0.13)	(0.12)
HH Group*time FE	Y	Y	Y	Y	Y	Y
Bank*time FE	Y	Y	Y	Y	Y	Y
Observations	483840	483840	483840	483840	483840	483840
R^2	0.55	0.44	0.45	0.45	0.57	0.58
			Panel B. Annual percentage rate			
HH observable	0.01***	0.00	-0.00***	0.01***	1.13***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
N. offers per profile	Y	Y	Y	Y	Y	Y
HH Group*time FE	Y	Y	Y	Y	Y	Y
Bank*time FE	Y	Y	Y	Y	Y	Y
Observations	210088	210088	210088	210088	210088	210088
R^2	0.98	0.98	0.97	0.97	0.91	0.98

TABLE 5 – ROLE OF BANK OBSERVABLES

Notes: Bank observables are capital ratio, short term liquidity, government bonds over assets, loan charged-offs over total loans and log assets. As a measure of loan pricing, we consider the APR, which is the annual percentage rate on the mortgage, gross of all fees and commissions (Columns 3 and 4). Mortgage data are from all the loan applications submitted to MutuiOnline in two dates (October 2014 and September 2016). Bank data are from the supervisory reports. Standard errors clustered at bank-time level. *** p<0.01, ** p<0.05,*p<0.1.

	Pr(accept)		Loan pricing	
	(1)	(2)	(3)	(4)
Capital ratio	11.44***	10.32***	-0.12	-0.03
	(2.09)	(3.14)	(0.13)	(0.04)
Short term liquidity	-21.05*	-23.29*	-0.25	0.18
	(10.66)	(11.99)	(0.55)	(0.19)
Government bonds	-1.49**	-1.49*	0.00	0.01
	(0.70)	(0.74)	(0.03)	(0.01)
Loan charge-offs	-14.05*	-8.96	0.80*	-0.00
	(7.88)	(10.67)	(0.41)	(0.12)
Log assets	14.16***	14.08***	0.02	-0.05
	(3.28)	(3.22)	(0.16)	(0.06)
HH*time FE	N	Y	N	Y
Observations	483840	483840	210088	210088
R^2	0.15	0.46	0.13	0.93

TABLE 6 – RISK-TAKING

Notes: We analyze the impact on acceptance of bank strength (column 1) as well as its interaction with observable HH characteristics (column 2 to 6). Job types are permanent contract, fixed term contract, self-employed, professional, and retired. Debt service-to-income ratio is the ratio of monthly instalment to monthly income; missing values have been replaced with the maximum value observed for this variable. Bank strength is measured as the residual from the regression of gross bank strength on bank main characteristics: $\text{GrossBankStrength}_{b,t} = \text{capital}_{b,t} + \text{shliq}_{b,t} + \text{govt}_{b,t} + \text{loancharged} - \text{offs}_{b,t} + \log(\text{assets})_{b,t} + \text{e}_{b,t}$, where $\text{capital}_{b,t}$ is bank capital over assets; $\text{shliq}_{b,t}$ is short term liquidity measured as cash over assets; $\text{govt}_{b,t}$ is government bonds over assets; $\text{loancharged} - \text{offs}_{b,t}$ is loan charged-offs over total loans. $\text{GrossBankStrength}_{b,t}$ is the bank*time FE resulting from the regression $\Pr(\text{acceptance})_{HH,b,t} = \text{FE}_{HH} * \text{t} + \text{FE}_b * \text{t}$ based on the experimental data on mortgages. Age, maturity, debt service-to-income ratio have been demeaned. Data are from all the mortgage applications submitted to MutuiOnline in two dates (October 2014 and September 2016). Standard errors clustered at bank-time level in parentheses. *** p<0.01, ** p<0.05,*p<0.1.

	Probability of acceptance					
		Job type (fixed term)	Job type (permanent)	Age	Maturity	Rate type (fixed)
Bank strength	1.03***	1.17***	0.99***	1.03***	1.03***	0.97***
	(0.09)	(0.12)	(0.09)	(0.09)	(0.09)	(0.10)
HH observable		-41.40***	11.65***	0.06	-0.46***	0.59
		(4.40)	(1.32)	(0.06)	(0.07)	(1.05)
Bank strength*HH observable		-0.72***	0.19**	0.01**	-0.02***	0.12
		(0.24)	(0.07)	(0.00)	(0.00)	(0.07)
Observations	483840	483840	483840	483840	483840	483840
R^2	0.15	0.28	0.16	0.15	0.17	0.15

TABLE 7 – CREDIT REGISTER DATA: CREDIT SUPPLY TO REAL FIRMS BASED ON EXPERIMENTAL-BASED BANK STRENGTH

Notes: Bank strength is measured as the residual from the regression of gross bank strength on bank main characteristics: $\text{GrossBankStrength}_{b,t} = \text{capital}_{b,t} + \text{shliq}_{b,t} + \text{govt}_{b,t} + \text{loans charged} - \text{offs}_{b,t} + \log(\text{assets})_{b,t} + \text{e}_{b,t}$, where $\text{capital}_{b,t}$ is bank capital over assets; $\text{shliq}_{b,t}$ is short term liquidity measured as cash over assets; $\text{govt}_{b,t}$ is government bonds over assets; $\text{loan charge} - \text{offs}_{b,t}$ is loans charged-offs over total loans. $\text{GrossBankStrength}_{b,t}$ is the bank*time FE resulting from the regression $\Pr(\text{acceptance})_{HH,b,t} = \text{FE}_{HH} * \text{t} + \text{FE}_b * \text{t}$ based on the experimental data on mortgages. In Columns 1 to 5, the dependent variable is the Davis-Haltiwanger growth rate, i.e. the change in credit between December and September in 2014 (or in 2016 for the second period) divided by the average credit in the two time periods. Column 5 has the same sample as column 4 but with no fixed effects. In Column 6, the dependent variable is the difference between the log (credit amount + 1) in December and September in 2014 (or in 2016 for the second period). In Column 7, the dependent variable is the difference between the log (credit amount) in December and September in 2014 (or in 2016 for the second period), this measure takes into account relationships that remained active between September and December). Firm-bank data are from the Italian Credit Register in 2014 and 2016. P75-P25 is the difference between the estimated value of the growth in firms' credit when the bank strength moves from the 75th to the 25th percentile of its distribution. "Y", "N" and "-" imply that those controls are included, not included, or spanned by (other) fixed effects. Standard errors in parentheses are double clustered at bank-time and firm level. *** p<0.01, ** p<0.05,*p<0.1.

	Extensive + Intensive margin						Only intensive margin
	Davis-Haltiwanger credit growth measure					Log(credit +1) change	Log(credit) change
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bank strength	0.319**	0.332**	0.299**	0.314***	0.329**	1.587***	0.0294**
	(0.126)	(0.124)	(0.116)	(0.0944)	(0.144)	(0.500)	(0.0134)
Time FE	N	Y	Y	-	N	-	-
Firm FE	N	N	Y	-	N	-	-
Firm*time FE	N	N	N	Y	N	Y	Y
Observations	543831	543831	468326	303371	303371	303371	260403
R^2	0.01	0.01	0.36	0.45	0.01	0.45	0.42
P75-P25 (p.p.)	8.053	8.392	7.559	7.924	8.293	40.05	0.742

TABLE 8 – CREDIT REGISTER DATA: RISK-TAKING BASED ON EXPERIMENTAL-BASED BANK STRENGTH

Notes: The independent variables are the bank strength and its interaction with the firm's main characteristics. Bank strength is measured as the residual from the regression of gross bank strength on bank main characteristics: $\text{GrossBankStrength}_{b,t} = \text{capital}_{b,t} + \text{shliq}_{b,t} + \text{govt}_{b,t} + \text{loancharged} - \text{offs}_{b,t} + \log(\text{assets})_{b,t} + \text{e}_{b,t}$, where $\text{capital}_{b,t}$ is bank capital over assets; $\text{shliq}_{b,t}$ is short term liquidity measured as cash over assets; $\text{govt}_{b,t}$ is government bonds over assets; $\text{loan charge} - \text{offs}_{b,t}$ is loans charged-offs over total loans. $\text{GrossBankStrength}_{b,t}$ is the bank*time FE resulting from the regression $\Pr(\text{acceptance})_{HH,b,t} = \text{FE}_{HH} * \text{t} + \text{FE}_b * \text{t}$ based on the experimental data on mortgages. The dependent variable is the Davis-Haltiwanger credit growth rate. P75-P25 is the difference between the estimated value of the growth in firms' credit when the bank strength moves from the 75th to the 25th percentile of its distribution. Firm-bank data are from the Italian credit register in 2014 and 2016. Standard errors are double clustered at the bank-time and firm level in parentheses. *** p<0.01, ** p<0.05,*p<0.1.

	Credit growth			
	(1)	(2)	(3)	(4)
Bank strength	0.314***	0.299***	0.297***	0.357***
	(0.0943)	(0.0938)	(0.0905)	(0.0942)
Bank strength*ROA	0.462**			
	(0.173)			
Bank strength*EBITDA/interest exp.		0.00129***		
		(0.000410)		
Bank strength*Firm liquidity			0.217*	
			(0.122)	
Bank strength*Firm leverage				-0.167***
				(0.0516)
Firm*time FE	Y	Y	Y	Y
Observations	291316	293596	281111	303371
R^2	0.445	0.441	0.443	0.445
P75-P25 (p.p.)	7.823	7.892	7.874	7.792

TABLE 9 – MATCHING BANK-FIRM ON CREDIT REGISTER DATA: CORRELATION MATRIX

Notes: Bank strength is measured as the residual from the regression of gross bank strength on bank main characteristics: $\text{GrossBankStrength}_{b,t} = \text{capital}_{b,t} + \text{shliq}_{b,t} + \text{govt}_{b,t} + \text{loan charge} - \text{offs}_{b,t} + \log(\text{assets})_{b,t} + \text{e}_{b,t}$, where $\text{capital}_{b,t}$ is bank capital over assets; $\text{shliq}_{b,t}$ is short term liquidity measured as cash over assets; $\text{govt}_{b,t}$ is government bonds over assets; $\text{loan charge} - \text{offs}_{b,t}$ is loans charged-offs over total loans. $\text{GrossBankStrength}_{b,t}$ is the bank*time FE resulting from the regression $\Pr(\text{acceptance})_{HH,b,t} = \text{FE}_{HH} * \text{t} + \text{FE}_b * \text{t}$ based on the experimental data on mortgages. Firm-level characteristics are averaged at bank*time level across the firms included in the credit register sample. Firm-bank data are from the credit register in 2014 and 2016.

	Bank strength	Firm ROA	EBITDA/interest expenses	Firm liquidity	Leverage
Bank strength	1				
Firm ROA	0.256	1			
EBITDA/interest expenses	0.300	0.909	1		
Firm liquidity	0.455	0.884	0.907	1	
Leverage	-0.344	-0.907	-0.867	-0.909	1

Appendix

TABLE A1 – SUMMARY STATISTICS ON FIXED EFFECTS

Notes: The table shows the summary statistics for the fixed effects estimated in Tables 2 and 3.

	Mean	Sd	P50	Min	Max	Observations
	Regressions on acceptance (Table 2)					
Col.2 HH FE	-0.00	26.77	11.34	-43.42	42.29	483840
Col.3 HH*time FE	-0.00	28.35	4.20	-43.42	56.58	483840
Col.4 Bank FE	-0.00	23.89	-1.25	-37.59	30.07	483840
Col.5 Bank*time FE	0.00	26.46	0.59	-43.42	36.19	483840
Col.6 HH*time FE	0.00	28.35	4.20	-43.42	56.58	483840
Col.6 Bank*time FE	0.00	25.42	2.10	-39.11	35.68	483840
	Regressions on annual percentage rate (Table 3, Panel A)					
Col.2 HH FE	0.00	0.62	-0.30	-1.01	1.02	209315
Col.3 HH*time FE	-0.00	1.00	-0.13	-1.28	2.17	207371
Col.4 Bank FE	0.00	0.21	-0.01	-0.67	0.62	210088
Col.5 Bank*time FE	0.00	0.78	-0.33	-0.82	1.44	210088
Col.6 HH*time FE	-0.00	1.01	-0.09	-1.10	2.18	207371
Col.6 Bank*time FE	0.00	0.24	-0.10	-0.32	0.70	207371
	Regressions on net mortgage rate (Table 3, Panel B)					
Col.2 HH FE	-0.00	0.61	-0.23	-1.00	1.01	209315
Col.3 HH*time FE	-0.00	0.99	-0.11	-1.19	2.13	207371
Col.4 Bank FE	-0.00	0.20	0.06	-0.78	0.46	210088
Col.5 Bank*time FE	0.00	0.76	-0.45	-0.81	1.30	210088
Col.6 HH*time FE	-0.00	0.99	-0.13	-1.13	2.11	207371
Col.6 Bank*time FE	0.00	0.21	-0.09	-0.25	0.62	207371

TABLE A2 – ROBUSTNESS RISK-TAKING: PROBABILITY OF ACCEPTANCE

Notes: In each column, the independent variables are the gross bank strength, the household observable reported at the top of the column, and the interaction between the gross bank strength and the household observable. Debt service-to-income ratio is the ratio of monthly instalment to monthly income. Gross bank strength is the bank*time FE resulting from the regression $\Pr(\text{acceptance})_{HH,b,t} = \text{FE}_{HH} * \text{t} + \text{FE}_b * \text{t}$. Data are from mortgage applications submitted to MutuiOnline in two dates (October 2014 and September 2016). Standard errors clustered at bank-time level in parentheses. *** p<0.01, ** p<0.05,*p<0.1.

	Probability of acceptance				
	Job type		Age	Maturity	Rate type
	(fixed term)	(permanent)			(fixed)
	(1)	(2)	(3)	(4)	(5)
Gross bank strength	1.15***	0.96***	0.78***	1.34***	0.96***
	(0.07)	(0.05)	(0.13)	(0.08)	(0.05)
HH observable	-43.26***	12.14***	0.08	-0.50***	0.89
	(4.04)	(1.28)	(0.06)	(0.06)	(1.03)
Gross bank strength*HH observable	-0.77***	0.19***	0.00*	-0.01***	0.09**
	(0.17)	(0.05)	(0.00)	(0.00)	(0.03)
Observations	483840	483840	483840	483840	483840
R^2	0.41	0.27	0.26	0.28	0.26

TABLE A3 – CREDIT REGISTER DATA: BANK STRENGTH VERSUS BANK OBSERVABLES

Notes: The dependent variable is the Davis-Haltiwanger growth rate, i.e. the change in credit between December and September in 2014 and 2016 divided by the average credit in the two time periods. Bank strength is measured as the residual from the regression of gross bank strength on bank main characteristics: $\text{GrossBankStrength}_{b,t} = \text{capital}_{b,t} + \text{shliq}_{b,t} + \text{govt}_{b,t} + \text{loan charge} - \text{offs}_{b,t} + \log(\text{assets})_{b,t} + \text{e}_{b,t}$, where $\text{capital}_{b,t}$ is bank capital over assets; $\text{shliq}_{b,t}$ is short term liquidity measured as cash over assets; $\text{govt}_{b,t}$ is government bonds over assets; $\text{loan charge} - \text{offs}_{b,t}$ is loans charged-offs over total loans. $\text{GrossBankStrength}_{b,t}$ is the bank*time FE resulting from the regression $\Pr(\text{acceptance})_{HH,b,t} = \text{FE}_{HH} * \text{t} + \text{FE}_b * \text{t}$ based on the experimental data on mortgages. Wholesale deposits is interbank deposits and repos to total assets. Column 6 includes the same sample as in Column 5. "Y", "N" and "-" imply that those controls are included, not included, or spanned by (other) fixed effects. Mortgage data are from loan applications submitted to MutuiOnline in two dates (October 2014 and September 2016). Firm-bank data are from the credit register in 2014 and 2016. Bank data are from supervisory reports in 2014 and 2016. Variables are standardized. Standard errors in parentheses are double clustered at bank*time and firm level. *** p<0.01, ** p<0.05,*p<0.1.

	Credit growth					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank strength	0.0706**	0.0694*	0.0527*	0.0515*	0.0659***	0.0697*
	(0.0342)	(0.0343)	(0.0274)	(0.0274)	(0.0233)	(0.0358)
Capital ratio	0.0330	0.0321	0.0356	0.0474	0.0443**	0.0368
	(0.0309)	(0.0319)	(0.0322)	(0.0284)	(0.0209)	(0.0327)
Short term liquidity	0.0526	0.0532	0.0226	0.0125	0.00861	0.0436
	(0.105)	(0.107)	(0.0990)	(0.0886)	(0.0689)	(0.114)
Government bonds	-0.0136	-0.0124	-0.00541	-0.00917	-0.00765	-0.00713
	(0.0351)	(0.0329)	(0.0345)	(0.0290)	(0.0219)	(0.0362)
Loan charge-offs	0.0360	0.0408	0.0772	0.0386	0.00333	0.0238
	(0.0566)	(0.0773)	(0.0593)	(0.0518)	(0.0403)	(0.0523)
ROA	-0.0598	-0.0573	-0.0504	-0.0817	-0.103**	-0.0825
	(0.0714)	(0.0753)	(0.0586)	(0.0582)	(0.0503)	(0.0765)
Wholesale deposits	0.00118	0.00487	0.0179	0.00414	-0.0140	-0.00468
	(0.0370)	(0.0399)	(0.0380)	(0.0354)	(0.0289)	(0.0410)
Total size	-0.0379	-0.0391	-0.0315	-0.0205	-0.0148	-0.0354
	(0.0482)	(0.0510)	(0.0499)	(0.0443)	(0.0338)	(0.0502)
Time FE	N	Y	Y	-	-	N
Firm FE	N	N	Y	Y	-	N
Industry*province*time FE	N	N	N	Y	-	N
Firm*time FE	N	N	N	N	Y	N
Observations	543831	543831	468326	445706	303371	303371
R^2	0.018	0.018	0.374	0.432	0.454	0.022

TABLE A4 – ROBUSTNESS CREDIT REGISTER DATA: GROSS BANK STRENGTH VS BANK OBSERVABLES

Notes: The dependent variable is the Davis-Haltiwanger growth rate, i.e. the change in credit between December and September in 2014 and 2016 divided by the average credit in the two time periods. GrossBankStrength$_{b,t}$ is the bank*time FE resulting from the regression $\mathrm{Pr(acceptance)}_{HH,b,t} = \mathrm{FE}_{HH} * \mathrm{t} + \mathrm{FE}_b * \mathrm{t}$ based on the experimental data on mortgages. Short term liquidity is cash over assets; Government bonds is government bonds over assets; Loan charge-offs is loans charged-offs over total loans; Wholesale deposits is interbank deposits and repos to total assets. Column 6 includes the same sample as in Column 5. Mortgage data are from loan applications submitted to MutuiOnline in two dates (October 2014 and September 2016). Firm-bank data are from the credit register in 2014 and 2016. Bank data are from supervisory reports in 2014 and 2016. Variables are standardized. Standard errors in parentheses are double clustered at bank*time and firm level. “Y”, “N” and “-” imply that those controls are included, not included, or spanned by (other) fixed effects. *** p<0.01, ** p<0.05,*p<0.1.

	Credit growth					
	(1)	(2)	(3)	(4)	(5)	(6)
Gross bank strength	0.0935**	0.0920*	0.0698*	0.0683*	0.0873***	0.0697*
	(0.0452)	(0.0454)	(0.0364)	(0.0363)	(0.0309)	(0.0358)
Capital ratio	-0.00740	-0.00760	0.00543	0.0179	0.00660	0.0368
	(0.0470)	(0.0470)	(0.0434)	(0.0400)	(0.0305)	(0.0327)
Short term liquidity	0.107	0.107	0.0635	0.0525	0.0598	0.0436
	(0.101)	(0.0997)	(0.0910)	(0.0788)	(0.0615)	(0.114)
Government bonds	0.00602	0.00693	0.00924	0.00516	0.0107	-0.00713
	(0.0298)	(0.0278)	(0.0306)	(0.0251)	(0.0188)	(0.0362)
Loan charge-offs	0.0633	0.0677	0.0976	0.0586	0.0289	0.0238
	(0.0659)	(0.0826)	(0.0614)	(0.0536)	(0.0432)	(0.0523)
ROA	-0.0598	-0.0573	-0.0504	-0.0817	-0.103**	-0.0825
	(0.0714)	(0.0753)	(0.0586)	(0.0582)	(0.0503)	(0.0765)
Wholesale deposits	0.00118	0.00487	0.0179	0.00414	-0.0140	-0.00468
	(0.0370)	(0.0399)	(0.0380)	(0.0354)	(0.0289)	(0.0410)
Total size	-0.100*	-0.101*	-0.0781*	-0.0661*	-0.0731**	-0.0354
	(0.0493)	(0.0497)	(0.0443)	(0.0372)	(0.0285)	(0.0502)
Time FE	N	Y	Y	-	-	N
Firm FE	N	N	Y	Y	-	N
Industry*province*time FE	N	N	N	Y	-	N
Firm*time FE	N	N	N	N	Y	N
Observations	543831	543831	468326	445706	303371	303371
R^2	0.018	0.018	0.374	0.432	0.454	0.022

TABLE A5 – MATCHING BANK-FIRM ON CREDIT REGISTER DATA

Notes: The dependent variable is the bank strength, measured as the residual from the regression of gross bank strength on bank main characteristics $\text{GrossBankStrength}_{b,t} = \text{capital}_{b,t} + \text{shliq}_{b,t} + \text{govt}_{b,t} + \text{loan charge} - \text{offs}_{b,t} + \log(\text{assets})_{b,t} + \text{e}_{b,t}$, where $\text{capital}_{b,t}$ is bank capital over assets; $\text{shliq}_{b,t}$ is short term liquidity measured as cash over assets; $\text{govt}_{b,t}$ is government bonds over assets; $\text{loan charge} - \text{offs}_{b,t}$ is loans charged-offs over total loans. $\text{GrossBankStrength}_{b,t}$ is the bank*time FE resulting from the regression $\Pr(\text{acceptance})_{HH,b,t} = \text{FE}_{HH} * \text{t} + \text{FE}_b * \text{t}$ based on the experimental data on mortgages. Regressors are firm-level characteristics. Firm-bank data are from the credit register in 2014 and 2016. Standard errors clustered at bank*time level in parentheses. *** p<0.01, ** p<0.05,*p<0.1.

	Bank strength			
	(1)	(2)	(3)	(4)
ROA	4.637*			
	(2.377)			
EBITDA/interest exp.		0.0199**		
		(0.00737)		
Firm Liquidity			6.201**	
			(2.332)	
Firm leverage				-3.130**
				(1.351)
Observations	447359	439295	431996	468326
R^2	0.000	0.001	0.001	0.001

TABLE A6 – ROBUSTNESS CREDIT REGISTER DATA: CREDIT SUPPLY AND RISK-TAKING

Notes: In Column 1, the independent variable is the gross bank strength; in Column 2 to 5, the independent variables are the gross bank strength and its interaction with the firm's main characteristics. Gross bank strength is measured as the bank*time FE from the regression $\Pr(\text{acceptance})_{HH,b,t} = \text{FE}_{HH} * \text{t} + \text{FE}_b * \text{t}$ based on the experimental data on mortgages. The dependent variable is the Davis-Haltiwanger growth rate. P75-P25 is the difference between the estimated value of the growth in firms' credit when the gross bank strength moves from the 75th to the 25th percentile of its distribution. Firm-bank data are from the credit register in 2014 and 2016. Standard errors double clustered at bank*time and firm level in parentheses. *** p<0.01, ** p<0.05,*p<0.1.

	Credit growth				
	(1)	(2)	(3)	(4)	(5)
Gross bank strength	0.121*	0.119*	0.114*	0.112*	0.143**
	(0.0598)	(0.0603)	(0.0597)	(0.0591)	(0.0621)
Gross bank strength*ROA		0.226*			
		(0.121)			
Gross bank strength*EBITDA/interest exp.			0.000727**		
			(0.000279)		
Gross bank strength*Firm liquidty				0.138*	
				(0.0733)	
Gross bank strength*Firm leverage					-0.0826**
					(0.0373)
Firm*time FE	Y	Y	Y	Y	Y
Observations	303371	291316	293596	281111	303371
R^2	0.441	0.441	0.438	0.440	0.441
P75-P25 (p.p.)	6.044	5.945	6.106	6.129	6.05

TABLE A7 – ROBUSTNESS: MATCHING BANK-FIRM ON CREDIT REGISTER DATA

Notes: The dependent variable is the gross bank strength; it is measured as the bank*time FE from the regression $\text{Pr(acceptance)}_{HH,b,t} = \text{FE}_{HH} * \text{t} + \text{FE}_b * \text{t}$ based on the experimental mortgage data. Regressors are firm-level characteristics. Firm-bank data are from the credit register in 2014 and 2016. Standard errors clustered at bank*time level in parentheses. *** p<0.01, ** p<0.05,*p<0.1.

	Gross bank strength			
	(1)	(2)	(3)	(4)
Firm ROA	7.391**			
	(3.227)			
EBITDA/interest exp.		0.0287***		
		(0.00879)		
Firm liquidity			9.252***	
			(2.965)	
Firm leverage				-6.017***
				(2.176)
Observations	447359	439295	431996	468326
R^2	0.001	0.001	0.002	0.003

TABLE A8 – ROBUSTNESS: MATCHING BANK-FIRM ON CREDIT REGISTER DATA, CORRELATION MATRIX AT THE BANK LEVEL

Notes: Gross bank strength is measured as the bank*time FE from the regression $\Pr(\text{acceptance})_{HH,b,t} = \text{FE}_{HH} * \text{t} + \text{FE}_b * \text{t}$ based on the experimental data on mortgages. Firm-level characteristics are averaged at bank*time level across the firms included in the credit register sample. Firm-bank data are from the credit register in 2014 and 2016.

	Gross bank strength	Firm ROA	EBITDA/interest expenses	Firm liquidity	Firm leverage
Gross bank strength	1				
Firm ROA	0.432	1			
EBITDA/interest expenses	0.434	0.909	1		
Firm liquidity	0.551	0.884	0.907	1	
Firm leverage	-0.565	-0.907	-0.867	-0.909	1

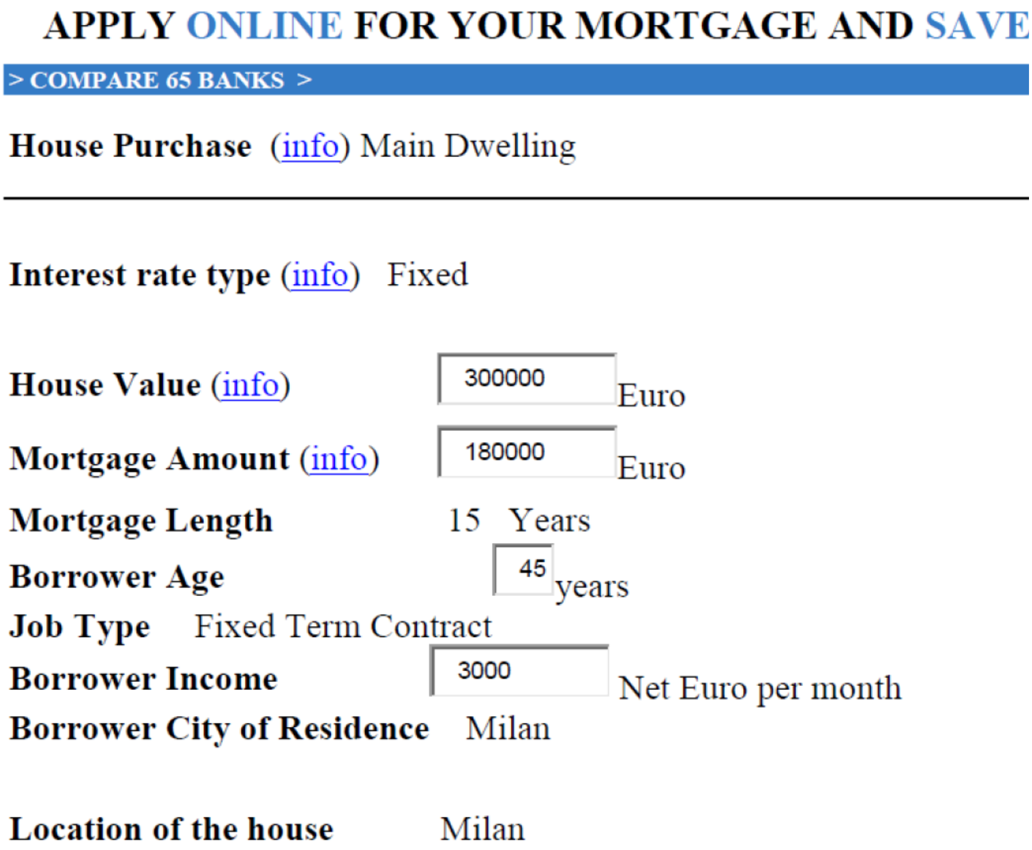
TABLE A9 – CREDIT SUPPLY TO SMES BASED ON BANK STRENGTH COMPUTED ON REAL (CREDIT REGISTER BASED) MORTGAGES TO HOUSEHOLDS

Notes: In Columns 1 to 5, the dependent variable is the Davis-Haltiwanger growth rate, i.e. the change in credit between December and September in 2014 (or in 2016 for the second period) divided by the average credit in the two time periods. Column 5 has the same sample as column 4 but with no fixed effects. In Column 6, the dependent variable is the difference between the log (credit amount + 1) in December and September in 2014 (or in 2016 for the second period). In Column 7, the dependent variable is the difference between the log (credit amount) in December and September in 2014 (or in 2016 for the second period), this measure takes into account relationships that remained active between September and December). Firm-bank data are from the Italian credit register in 2014 and 2016. The measure of bank strength is a bank fixed effect computed on the sample of real mortgages granted to households from the credit register aggregated at the province level and applying the methodology in Amiti and Weinstein (2018). This is obtained as follows: $\text{GrowthRateOfMortgages}_{p,b,t} = \text{FE}_p * \text{t} + \text{FE}_b * \text{t}$ where p denotes provinces. The regression is estimated through weighted least squares, where weights are the initial volume of mortgages in a province by the bank. The bank strength measure is the estimated FE_b. This regression is run using two time periods, July-September 2014 and July-September 2016. Standard errors clustered at bank*time level in parentheses. *** p<0.01, ** p<0.05,*p<0.1.

	Credit growth						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bank strength	-0.109	-0.159	-0.196	-0.168	-0.140	-0.764	-0.0296
	(0.253)	(0.341)	(0.238)	(0.209)	(0.231)	(1.085)	(0.0877)
Time FE	N	Y	Y	-	N	-	-
Firm FE	N	N	Y	-	N	-	-
Firm*time FE	N	N	N	Y	N	Y	Y
Observations	543831	543831	468326	303371	303371	303371	260403
R^2	0.000	0.000	0.358	0.440	0.000	0.446	0.420

Figure A1: MutuiOnline mortgage application

Notes: The figure shows the mortgage application form available from the website of MutuiOnline (we translated the webpage from Italian). Upon filling this form, a mortgage applicant see which banks are willing to make an offer. The application form has been filled on June 20, 2016. The website and its content is copyright of MutuiOnline.


APPLY ONLINE FOR YOUR MORTGAGE AND SAVE

> COMPARE 65 BANKS >

House Purchase (info) Main Dwelling

Interest rate type (info) Fixed

House Value (info) 300000 Euro

Mortgage Amount (info) 180000 Euro

Mortgage Length 15 Years

Borrower Age 45 years

Job Type Fixed Term Contract

Borrower Income 3000 Net Euro per month

Borrower City of Residence Milan

Location of the house Milan

Figure A2: MutuiOnline: the pre-approval

Notes: The figure shows the banks willing to make an offer to the applicant posting the request shown in Figure A1. In this case 4 banks pre-approved the applicant. Each pre-approving bank posts the amount of the monthly instalment, the net mortgage rate, the loan origination fees, and the APR. The form these pre-approval offers refer to has been submitted on June 20, 2016. The website and its content is copyright of MutuiOnline.

	INTESA SANPAOLO MUTUO DOMUS FISSO
Instalment	**€ 914.86** (monthly)
Mortgage Rate	**Fixed: 2.05%**
Loan origination fees	General charges € 600.00 - Valuation: € 320.00
APR	**2.23%**

	BANCADINAMICA MUTUO BANCADINAMICA
Instalment	**€ 945.08** (monthly)
Mortgage Rate	**Fixed: 2.40%** (IRS 20A + 1.30%)
Loan origination fees	General charges: € 900.00 - Valuation: € 275.00
APR	**2.53%**

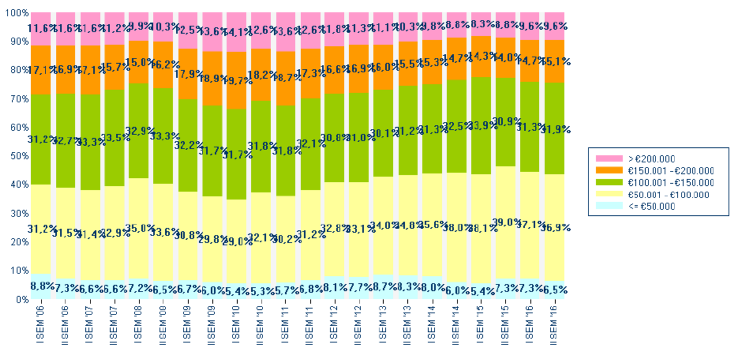
	IW BANK PRIVATE INVESTMENTS MUTUO A TASSO FISSO
Instalment	**€ 945.08** (monthly)
Mortgage Rate	**Fixed: 2.40%**
Loan origination fees	General charges: € 600.00 - Valuation: € 0.00
APR	**2.51%**

	ING DIRECT MUTUO ARANCIO FISSO
Instalment	**€ 975.01** (monthly)
Mortgage Rate	**Fixed: 2.74%** (IRS 20A + 1.65%)
Loan origination fees	General charges: € 0.00 - Valuation: € 0.00
APR	**2.80%**

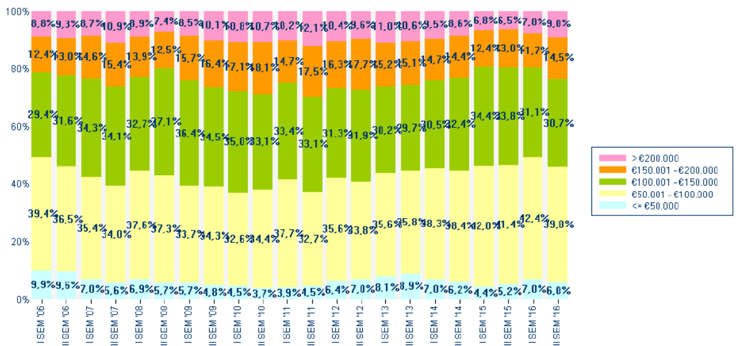
Figure A3: Applications versus originated mortgages

Notes: The figure shows the distribution of applications and concluded contracts by mortgage amount and applicant's age (Source: Mutuionline).

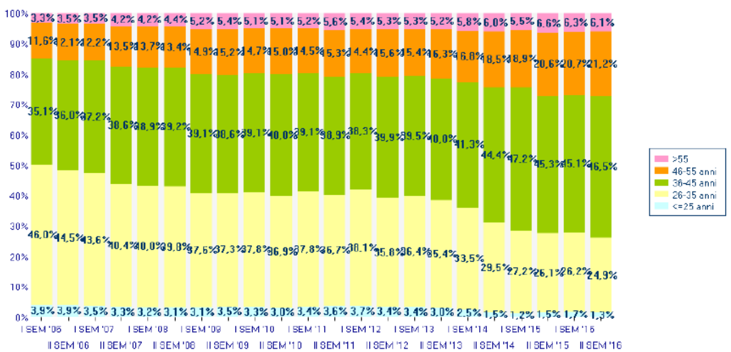
(a) Mortgage applications by amount



(b) Mortgage contracts by amount



(c) Mortgage applications by age



(d) Mortgage contracts by age