Credit Demand *versus* Supply Channels:

Experimental- and Administrative-Based Evidence

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Abstract

We identify the relative importance for lending of borrower (demand) *versus* bank (supply) factors. We submit thousands of fictitious mortgage applications, *changing one* borrower-level factor at time, to the major Italian online mortgage platform. Each application goes to *all* banks. We find that borrower and bank factors are equally strong in causing and explaining loan acceptance. For pricing, borrower factors are instead stronger. Moreover, banks supplying less credit accept riskier borrowers. Exploiting the administrative credit register, we show borrower-lender assortative matching, and that the bank-level strength measure, estimated on the experimental data, determines credit supply and risk-taking to real firms.

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1 Introduction

Credit is a crucial ingredient of economic growth (e.g. Schumpeter, 1912; Levine, 2005), and it is also key for financial stability (e.g. Schularick and Taylor, 2012; Gourinchas and Obstfeld, 2012). Even in the current Covid-19 crisis, credit has been at the center of crucial policy measures (e.g. the Group of 30, 2020; Lagarde, 2020; Powell, 2020; IMF, 2021).

Credit may change due to borrower factors (the demand side) or bank factors (the supply side), such as net worth, risk, expectations and preferences. In the words of Holmstrom and Tirole (1997, page 3): "*The novelty in our analysis is that we study how these choices are influenced by the financial status of intermediaries as well as of firms. Since our model incorporates both demand factors (changes in collateral) and supply factors (changes in intermediary capital), we can identify a separate "balance sheet channel" and a "lending channel", a distinction that previously has only been discussed in the empirical literature (see Bernanke, 1993).*" In this paper we identify and quantify the importance for credit of borrower (demand) factors vs. bank (supply) factors.

Regarding net worth and risk (balance sheet strength), the credit channel (Bernanke and Gertler 1995) is composed of two key sub-channels: the borrower (firm or household) balance sheet channel –i.e. how borrower (demand-side) factors affect lending decisions– and the bank lending channel (Bernanke 2007), i.e. how lender (supply-side) factors affect lending decisions. Borrower factors are e.g. borrower pledgeable income (collateral) as in Holmstrom and Tirole (1997), or more generally borrower net worth –accounting for total income level and volatility (e.g. Bernanke, Gertler and Gilchrist, 1999)– and borrower preferences on e.g. variable vs. fixed rate mortgage or maturity, which may depend on expectations and willingness to take on interest rate (liquidity) risks (e.g. Campbell and Cocco, 2015). Bank factors are 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' factors and, for instance, models like Holmstrom and Tirole (1997) feature both channels as lending depends on both lender and borrower factors.

For testing theories, it is thus essential to disentangle these borrower (demand) and lender (supply) factors and evaluate their relative size. Moreover, it is also crucial for informing policy makers on whether they should support borrowers or banks. Policy solutions differ when the factors constraining credit are borrower factors, which may require helping households or non-financial firms, or bank factors, which may require reforming banks or bailing them out (see e.g. Bernanke, 2018). For example, during the current Covid-19 crisis public policies included, on the one hand, providing public guarantees to support credit to (or directly lend to) borrowers (notably small and medium enterprises, SMEs) and mortgage (household) moratoria, and, on the other hand, providing capital and liquidity softening to banks to sustain their supply of credit.

Despite the importance of borrower (demand) and bank (supply) factors for macro-finance theories and for public policy analysis, most papers in the (more micro) empirical literature have just pursued the identification of the bank lending (supply) channel (e.g. Khwaja and Mian, 2008; Jiménez et al., 2012), and very few have instead pursued borrower vs. bank channels (Amiti and Weinstein, 2018). However, all these papers are based on observational data with strong assumptions on borrower-lender matching, which may not hold on the data (see e.g. Paravisini, Rappoport and Schnabl, 2017). Further, as we explain in this paper, the identification problems of the relative importance of borrower (demand) vs. bank (supply) factors are larger than isolating the bank channel with observational data. Borrower factors may be difficult to observe, even impossible for discouraged borrowers, who think they will not get the loan, hence do not apply. Crucially, there are not identical borrowers except for just one factor, and hence it is difficult to identify risk-taking and quantify the importance of different borrower factors. Also, in most cases only data on loans granted, not on applications, are available.

We contribute to the literature by overcoming these identification problems: we create and exploit experimental-based data that allow us to identify and measure in the cross-section the relative importance of borrower (demand) vs. bank (supply) factors in lending. We submit fictitious mortgage applications (varying households' characteristics) to the major online mortgage platform in Italy. Each application goes to *all* banks. We submit other identical applications *changing just one* borrower-level variable at time (e.g. borrower income, risk, age, desired loan contract interest rate type and maturity). This setting allows us to solve the problem of endogenous matching of borrowers into banks, and to compare completely identical households' applications to all banks differing only in one characteristic. Finally, we exploit the administrative credit register from Italy to show that there is indeed borrower-lender assortative matching in the real loan-level data, and to analyze whether the experimental results have external validity using the administrative (real) data.

We find that borrower and bank factors are similarly strong in causing —and explaining— loan acceptance in the experimental data. They have an adjusted R-squared of 29.4% and 28.5%, and economically, the associated interquartile range increases acceptance by 52.4 percentage points (p.p.) and 50.5 p.p., respectively. Differently, for loan pricing, borrower factors are much stronger (at least eight times larger than bank factors). As borrower and bank factors just explain 58% of loan rejections and because of theory, we analyze interactions of both types of factors. Banks that supply less credit accept on the margin riskier borrowers. Finally, exploiting the credit register, we show that the estimated bank credit supply from the experiment determines: (i) credit supply to firms (SMEs), even more strongly than the key variables used in the literature; and (ii) the composition of credit supply with respect to borrower risk (risk-taking). Differently, a very similar credit supply measure but estimated on the (*observational*) mortgage credit register data does not affect credit supply to firms.

In the remaining part of this Introduction, we provide a more detailed preview of the different parts of the paper, and discuss the related literature and its differences 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 posted 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 for example the 10 largest ones in the country, accounting for over 70% of mortgage originations.[1] To submit a loan application, the broker requires the prospective borrower to list her demographic (job type, age, income) and the contract requested (loan amount, maturity, rate-type – i.e. fixed or variable) characteristics. We obtain the dataset by varying those characteristics: for each set of characteristics, we submit other identical applications *except for* one variable, for a total of 11,520 different combinations (fictitious applications with certain borrower-contract characteristics) in every period. Also importantly, all banks get *all* the fictitious applications, i.e. every application goes to each bank. Our final sample thus 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 value, etc.), the bank pre-approval and pricing are binding.[2] 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* the *same* (desired) loan contract characteristics. Hence, our estimates are not biased by endogenous selection of borrowers

[1] 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 the (small) private securitization market.

[2] 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 is lower than expected, or because borrower's characteristics differ from those initially declared), or the borrower can retreat.

(including desired loan contracts) into banks. There are also no missing data due to discouraged potential (riskiest) borrowers not submitting applications.[3] Moreover, for each borrower application, we have other completely identical ones except for just one variable, and hence we can compare the relative strength of *different* borrower factors for lending, as well as analyzing risk-taking.

We identify (and measure) borrower vs. bank factors that determine loan acceptances (or loan rates for accepted applications) with borrower and bank fixed effects, respectively, to account for all borrower and lender variations. As we have two time periods, we can also interact time with borrower and lender fixed effects. Note that our dataset includes bank lending decisions, but these bank decisions may depend on: (i) borrower factors (e.g. risk proxied by income, age and job type, or desired loan rate-type or maturity), and we can even analyze the lending decisions by the same bank at the same time to identical borrowers except for e.g. their income; or (ii) bank factors, and we can even analyze the lending decisions of different banks to the very same borrower, with identical demographic and preferred loan contract characteristics.

Furthermore, we evaluate the relationship between each bank fixed effect estimated using the experimental data, which is our measure of relative bank strength of credit supply, and the key observed bank balance sheet characteristics (e.g. capital, liquidity, risk). Moreover, as each household has other identical ones except for one characteristic, we can measure on loan acceptance or rates the impact of each household factor (e.g. net income, permanent job and age proxying for borrower income level and volatility, and hence risk; maturity and interest rate-type desired by the borrower proxying for preferences/expectations). We apply a "group-household" fixed effect that includes all fictitious households with identical variables except for the one factor analyzed. Given the literature on bank risk-taking (Freixas and Rochet, 2008), we also assess whether different banks change their lending differently for riskier vs. safer borrowers (where weaker balance sheets are due to e.g. lower income, or riskier loan contracts are due to e.g. longer-term loans).

Our aim is not identifying credit demand vs. supply, but the relative strength of borrower (demand) vs. bank (supply) factors (see e.g. Holmstrom and Tirole, 1997). Despite that banks decide on loan outcomes, we can separate whether this decision is due to borrower vs. bank factors via borrower and bank fixed effects in our experimental setting. Our analysis allows to measure by how much credit changes because of changes in key household balance sheet or preferred loan contract characteristics (preferences), as opposed to differential bank factors (bank fixed effects that e.g. capture differential bank balance sheet strength such as capital, or other bank factors). In this way, we measure the relative importance of borrower (demand) vs. bank (supply) factors in lending.

[3] Discouraged borrowers are important in real credit markets as shown by the data from the Bank of Italy's Survey on Household Income and Wealth.

Our main results are the following. For the extensive margin of lending (acceptance of loan applications) we find that borrower and bank factors are similarly important in causing and explaining loan acceptance. Quantitatively speaking, both factors 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 vs. 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.[4] Without time fixed effects interacted with borrower or bank effects, results are very similar for borrower and bank factors (50.0 p.p. and 46.2 p.p., respectively). 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, borrower factors are 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%).[5] Moreover, 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%).[6] Therefore, without time fixed effects, for loan pricing, borrower factors are at least eight times stronger than bank factors.

Granting loan applications is moreover positively associated to ex-ante 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 loan pricing, bank observables are not associated to different loan prices, consistent with the previous result that only borrower factors are key in loan 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

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[4] Bank (or bank*time) fixed effects are 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 (income, age, etc.), including preferred loan characteristics (maturity, rate-type, etc.), and hence we can have household fixed effects. As the combination of household characteristics is the same in each time period, we can have just household or also household*time fixed effects. In the former case, identical borrower (including preferred contract) characteristics would define different applications by the same household, while in the latter one we would also include the time variable (when the application is submitted).

[5] 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.

[6] 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.

granting of applications; and if granted, they decrease the rates. These results are in line with the income-based hypothesis (see e.g. Mian and Sufi, 2009), in which higher income households are also more creditworthy. Moreover, we find that the most relevant income variable considered by banks upon granting a mortgage is not the income level, but the income volatility proxied by the stability of the job (permanent vs. fixed-term contract). There are similar effects for more attractive loan conditions to the lenders, such as shorter maturity loans, and for fixed rate loans that exhibit higher loan rates (which are valued by banks in a period of very low interest rates).

We also analyze differential risk-taking as: (i) it is key for the banking literature (see e.g. Freixas and Rochet, 2008) and for heterogeneous effects, such as household inequality (Rajan, 2011) or misallocation in firms (Hsieh and Klenow 2009); (ii) borrower and bank factors (without any interaction) explain a maximum of 58% of loan rejections. Theoretically effects are ambiguous. 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 obtain higher yields to compensate for their lower credit volumes and hence profits; or, similarly, they can take more risk due to e.g. less capital (skin in the game). We analyze risk-taking by exploiting different observed borrower variables and our bank level strength measure, which is the estimated bank fixed effects or even those effects over and above key bank observable variables such as capital and risk.[7] 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 loans with a longer maturity).

Finally, to analyze the external validity of our results, we exploit administrative datasets: supervisory credit register owned by the Italian central bank matched by the fiscal identification number with the bank and firm balance sheet data (see e.g. Ippolito et al., 2016). All these datasets are subsequently matched to our (new) experimental dataset via each bank identifier. The credit register includes exhaustive loan-level (observational) data. We use this administrative data to show borrower-lender assortative matching in observational data, and 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 bank, and hence we can apply firm*time fixed effects, and (ii) we have administrative firm variables proxying e.g. for risk (firms are obliged to register their balance sheets,

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

but not households).[8] Moreover, we analyze SMEs (rather than large firms) as they are more similar to households.

In our tests, we analyze the bank-level fixed effects (strength in lending) estimated in the experimental data on the granting of loans by banks to SMEs. Importantly, we find that these bank fixed effects determine actual credit supply to real firms. 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 that omitted variables and self-selection problems (following Altonji et al., 2005; Oster, 2019) do not drive the effects from our bank-level measure from the experimental data on the supply of credit to actual borrowers in the observational data. Economic 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%).

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. measures of capital, risk, liquidity, and size). Further, we construct a measure of bank-level strength (in credit supply) from the credit register of mortgages (i.e., based on observational data), a measure that is 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 measure based on the credit register is insignificant). Moreover, in the actual supervisory credit register based on the administrative data, consistently with the experimental results, weaker bank strength (i.e. lower bank credit supply) implies higher risk-taking in loans on the margin; in particular higher supply of credit to riskier firms based on ex-ante firm leverage, credit risk scores, loan rate expenses given profitability, and firm liquidity. Furthermore, using the 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 have more loans to firms with higher risk). In sum, all these last results further suggest the presence of borrower and bank endogenous matching in observational credit data, which may limit not only the analysis of credit supply, but also the identification and quantification of borrower (demand) vs. bank (supply) factors in lending.

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

Contribution to the literature. Our experimental data allow us to make a key contribution to the large literature on the credit channel by identifying the relative importance of borrower (demand) *vs.* bank (supply) factors in lending.[9] Despite that observational loan level data (typically used by the credit channel literature) help in dealing with borrower-lender endogenous matching, they cannot fully solve this key identification problem. While the within-firm estimator (Khwaja and Mian, 2008) and the large literature that follows it make crucial steps in identifying the credit supply channel, these estimates (including Amiti and Weinstein, 2018) may still be biased as they rely on the assumption that within the same period the same borrower is indifferent among its banks, independently of bank specialization (Paravisini, Rappoport and Schnabl, 2017). Furthermore, there is also the difficulty in isolating, even observing, borrower factors, not only from e.g. discouraged borrowers, but also from existing (real) borrowers who are completely identical to each other except for just one factor (e.g. borrower income, risk and also desired loan terms).[10]

Identifying (and measuring) borrower (demand) vs. bank (supply) factors in lending 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) vs. the lender channel (e.g. Stein, 1998; Adrian and Shin, 2010; Gertler and Kiyotaki, 2010; Gertler and Karadi, 2011; 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). Others, e.g. Holmstrom and Tirole (1997), have *both* borrower and bank factors at work. Our results inform these theoretical models on which friction is more relevant in the data: equal importance of bank and borrower factors for the extensive margin of lending, while only borrower factors are crucial for pricing. Policy solutions also differ when the factors constraining credit lay on borrowers, and hence policy makers may need to help households (or firms), as advocated by e.g. Mian and Sufi (2014), or on banks, and hence policy makers may need to bailout or help banks, as advocated by e.g. Bernanke (2018).

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[9] 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). See also papers using more aggregate data such as Kashyap and Stein (2000) at the bank level and Bernanke and Blinder (1988, 1992) at the country level. Our contribution is to identify and quantify the relevance of borrower (demand) and bank (supply) factors in the cross-section; note that we do not analyze changes in credit demand or analyze credit over a cycle. Note also that even in Amiti and Weinstein (2018) the time (common) variation of credit cannot be attributed to borrowers vs. lenders.

[10] 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 importance of borrower vs. bank factors. 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 in turn depend on bank strength.

The remainder of the paper is organized as follows. Section 2 discusses the conceptual framework, the experiment, datasets and the empirical strategy. Section 3 summarizes the results. Section 4 offers some brief concluding remarks.

2 Conceptual framework, experiment, datasets and empirical strategy

In this section we first discuss the conceptual framework for the analysis of lending, its associated channels and the key identification problems. Second, we explain the experiment we conducted in Italy, as well as the institutional setting, the experimental data and the empirical identification strategy. Third, we describe the administrative data and the associated empirical strategy. Finally, we present the summary statistics.

2.1 Conceptual framework

Our paper tackles a key question in the literature on financial intermediation and macro-finance. We analyze lending, namely granting of loan applications and interest rates, and its associated determinants: borrower (demand) factors and lender (bank supply) factors. The seminal paper by Holmstrom and Tirole (1997) sets out a closely theoretical framework, though in their case only balance sheet factors matter and firms can use market finance in addition to bank credit. Nevertheless, their paper clearly highlights that the choices over loan interest rates and financing depend on the net worth of *both* financial intermediaries (banks) and non-financial borrowers (firms in their case) and, consequently, a model that includes both borrower (demand) and lender (supply) factors is critical (see also their page 3).

In this paper we analyze the importance of borrower factors vs. bank factors, which, as Holmstrom and Tirole (1997) argue, are about demand (borrowers) vs. supply (banks). This is crucial to understand the drivers of credit. Given a loan application, a reduction in bank lending can originate from: (1) a change in the supply of credit holding constant the borrower (demand) factors in a given period of time, in the spirit of Bernanke and Lown (1991) that define a bank credit crunch as a "leftward shift in the supply curve for bank loans, keeping constant the interest rate and the quality of potential borrowers", or in Holmstrom and Tirole (1997) for a level of borrower net worth; (2) a change in borrower (demand) factors, including quality (e.g. income level and volatility), in the spirit of Holmstrom and Tirole (1997) or Bernanke and Lown (1991) that state that borrower factors, such as a weakened state of borrowers' balance sheets, could play a role in reducing bank lending. Moreover, borrower preferences and expectations can also play a crucial role (e.g. Campbell and Cocco, 2015).

Our empirical analysis is based on the lending equation of Khwaja and Mian (2008), which they micro-founded in a very stylized model in their paper, and of Amiti and Weinstein (2018):

$$Y_{i,b} = \alpha_i + \beta_b + \varepsilon_{i,b} \quad (1)$$

where $Y_{i,b} = loan\ acceptance_{i,b}$ is a dummy equal to 1 if the loan application from borrower i to bank b is accepted, 0 otherwise; or $Y_{i,b} = Loan\ Rate_{i,b}$ offered by bank b to borrower i, conditional on acceptance.[11] As in Amiti and Weinstein (2018), α_i denotes the "firm-borrowing channel," (in our paper, for borrower factors, we analyze households, i=h, and, in validation tests on observational credit register data, also firms, i=f). β_b denotes the "bank-lending channel" (or more generally bank factors),[12] and the error term satisfies E [$\varepsilon_{i,b}$] = 0. Note that we do not add the time in the equation but these fixed effects also have a *t* subscript.

This empirical approach can be described as follows. First, as in Khwaja and Mian (2008) and in Amiti and Weinstein (2018), it is based on cross-sectional identification; we could add a constant – "secular trend"– as in Khwaja and Mian (2008).[13] Second, we assume that if no bank is willing to lend to a particular borrower (while these banks are lending at the same time to other borrowers), it is because of that particular borrower factors (e.g. too risky or a loan with a negative net present value).[14] Third, the borrower and bank factors that we analyze reflect not only a borrower balance sheet channel (e.g. household labor income level and permanent vs. fixed-term labor contract that affects labor income volatility) and a lending channel (e.g. bank capital, liquidity, risk and size; see Holmstrom and Tirole, 1997; Bernanke and Gertler, 1995; Bernanke, 2007). They also reflect other factors, including proxies for borrower preferences and expectations (see e.g. Campbell and Cocco, 2015), as e.g. the desired maturity and variable vs. fixed rate contract by each household (see Badarinza et al., 2017, among others), since these factors depend on liquidity and interest rate risk that households want to bear (related also to their expectations over future interest rates).[15]

Amiti and Weinstein (2018)'s objective is to separate and quantify lender "shocks" from borrower ones, and hence they analyze lender and borrower (cross-sectional) overall factors, both observable and unobservable. Our objective in this paper is similar. Khwaja and Mian (2008) instead focus on isolating the bank lending channel (in their case observable bank liquidity) from the non-financial

[11] Amiti and Weinstein (2018) and Khwaja and Mian (2008) do not analyze the granting of loan applications or loan rates given data availability, but just granted credit.
[12] A bank, e.g., Unicredit could change its credit supply due to its capital, size and liquidity (key determinants of the bank lending channel), but also due to its potentially different expectations. Therefore, bank factors are more general than the bank lending channel, though in one regression we link the two in this paper. Similarly, household factors are more general than the (borrower) balance sheet channel, as in addition to borrower net worth, borrower expectations and preferences may be important.
[13] For example, Amiti and Weinstein (2018) wrote that their methodology does not let them separate how much of the common shock is due to firm-borrowing vs. bank-lending effects. Thus, they can only identify the sum of the two effects. That is, their analysis (also Khwaja and Mian (2008)) as well as ours is cross-sectional.
[14] Note that the loan volume (and also the associated risk) of each borrower in our sample is extremely small given the size of the loan portfolio of each bank, and hence if none of the banks are accepting a borrower's application it is because of borrower factors (e.g. risk).
[15] For banks, a bank fixed effect captures all unobserved bank heterogeneity, including bank expectations.

borrower channel. A huge empirical literature has followed this approach. To control for the borrower channel, Khwaja and Mian (2008) include firm fixed effects, comparing banks differentially affected by the liquidity shock that change their lending to the same borrower. Borrower fixed effects (as compared to OLS) estimation is necessary because $Cov\ (\alpha_i, \beta_b)$ may be different from zero (as we will argue in this paper, similarly to Khwaja and Mian (2008), this covariance is positive).

Since there is assortative matching between borrowers and banks in observational data, loan level is necessary for (cross-sectional) identification and the micro-based literature has notably advanced with within-firm estimators in credit register data. However, a limitation of this approach (which also applies to Amiti and Weinstein, 2018) is that the matching between borrowers and banks could not only be endogenous ($Cov\ (\alpha_i, \beta_b) \neq 0$) but also time varying (Paravisini, Rappoport and Schnabl, 2017), and hence even borrower-time and borrower-lender fixed effects cannot control for it. For example, the nuclear shock in Pakistan exploited by Khwaja and Mian (2008) not only affected banks differentially, but potentially also borrowers, based on their propensity to exporting, and these borrowers could then select differentially affected banks in diverse ways. More generally, some banks are more specialized in some borrowers (due to e.g. specialization skills depending on the geographical area or industry) and hence borrowers may prefer some banks in different moments of time (Paravisini, Rappoport and Schnabl, 2017).

Importantly, these studies use observational data, which imply that not only they may suffer from endogenous matching between borrowers and lenders, but also they do not have borrowers, in our case households, that are *identical except for only one* characteristic (e.g. labor income or the desired type of loan). Consequently, existing work cannot identify the importance of individual borrower (demand) factors (e.g. differential income, so differential balance sheet strength), holding constant everything else (e.g. expectations for liquidity and interest rate risks that may imply different preferences on desired maturity and fixed vs. variable loan interest rates).

Related, we can identify risk-taking by analyzing how the same bank (as compared to another bank) changes the credit supply towards borrowers that are identical except for just one borrower factor (e.g. income level, or income volatility depending on borrower job type). Finally, this empirical literature does not analyze loan applications. These are important as different banks may accept applications from the same borrower, but a borrower may prefer some banks to others (due to trade specialization, e.g. Paravisini, Rappoport and Schnabl, 2017) or some banks may prefer some borrowers due to differential bank risk-taking (Jimenez et al., 2014). Furthermore, there may also be unobserved borrower factors in observational data due to discouraged borrowers who do not apply for a loan as they think they will be rejected.

In sum, despite the importance of the borrower (demand) and bank (supply) factors for macro-finance theories and for public policy analysis, most papers have pursued the identification of just the bank lending (supply) channel, and very few have instead pursued the identification of lender vs. borrower channels (Amiti and Weinstein, 2018). Moreover, all these papers have been based on observational data with strong assumptions on borrower-lender matching (also time-varying), which may not hold in the data (see e.g. Paravisini, Rappoport and Schnabl, 2017). In particular, as we have explained in this subsection, the identification problems of the relative importance of borrower (demand) vs. bank (supply) factors are larger than purely isolating the bank channel with observational data.

2.2 Experiment: fictitious applications to the online broker and main dataset

To solve these identification problems, isolate and quantify the importance of borrower (demand) vs. lender (supply) factors, we submit fictitious applications (varying households' factors) 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 factor at time. None of this is possible with observational data.

In particular, we submit fictitious applications (varying households' characteristics) to the leading online mortgage broker in Italy, MutuiOnline (www.mutuionline.it), working with the largest commercial banks in the country.[16] Overall, our sample includes 21 banks that belong to 17 banking groups,[17] and these banks granted around 70% of total new mortgage loans in 2013. Moreover, in 2016 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 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 ways for banks to lend.

To submit a mortgage application through 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);[18] (iii) the house value; (iv) the desired mortgage amount; (v)

[16] 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.

[17] Overall, 25 banks are associated with MutuiOnline but we exclude 4 small banks that are branches of foreign banks for which we do not have complete balance sheet information or banks that do not have branches in the province of Milan, so overall the sample includes 21 banks belonging to 17 banking groups.

[18] The mortgage market is mostly dominated by variable rate mortgages (74% of the total outstanding loans in 2015), which are characterized by mortgage instalments that vary with the reference rate (typically, the 3 month Euribor). Countries differ significantly in the share of variable vs. fixed rate mortgage, and in the use of prepayment penalties (Lea,

the desired mortgage maturity; (vi) the age; (vii) the type of the job contract (e.g. permanent vs. fixed-term); (viii) the net monthly income of the applicant (net of taxes and social security); (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.[19]

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 gross of fees and commissions (APR), net mortgage rate, fees, and monthly instalment.[20] Figures A1 and A2 in the Appendix illustrate the online form an applicant needs to fill, and the outcome. In the example we show, only four banks were willing to post an offer.

When MutuiOnline shows an offer, it means that the application has been pre-approved, which is our measure of acceptance of the mortgage application.[21] 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

2010; Badarinza, Campbell and Ramadorai, 2018). The remaining market share is taken almost entirely by fixed rate mortgages, which are characterized by a predetermined path of mortgage instalments to pay off the principal and the interests on the loan. Variable rate mortgages with a cap or "mixed" rate mortgages, which consist of a part with fixed rate and of a part with variable 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, variable rate mortgages have a variable interest rate, while fixed rate mortgages have the same constant rate. The relative share of variable and fixed rate mortgages depends strictly on the level of interest rates (Foà et al., 2019): 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. 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 reduction of interest rates at historically low levels, the share of outstanding loans that have been refinanced increased reaching about 7% in 2015.

[19] Before deciding whether to grant a mortgage and with the aim of limiting default risk, 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 (similar to other European countries), 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. 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. Finally, the fees that come with a mortgage (application and loan origination fees) are standard administration charges.

[20] Menu offers with several combinations of loan prices and loan volumes do not exist in Italy.

[21] 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 instalment from that bank, as shown in Figure A2 in the Appendix.

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 desired contract) characteristics described above, which are sufficient for the online broker to provide pre-approval decisions and the associated mortgage terms (i.e., loan rates). Pre-approvals and rates are generated by credit scoring models, which are chosen by each bank, and that the online broker (MutuiOnline) has.

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, 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 that 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: e.g., in the first semester of 2016, the share of new variable rate mortgages was equal to about 23% for those granted by MutuiOnline vs. 21% for the total (online plus branches, according to supervisory reports from the central bank). In the first semester of 2014 the share of new variable rate mortgages was about 40%, both for MutuiOnline and overall. Conditional on the borrower not lying on the submission process (e.g. income, house value, 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 (e.g. because the home value comes lower than expected, 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 supervisory 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 observational data (that we will also show in this paper with the administrative, supervisory credit register). Moreover, for each borrower profile, we submit to the online broker other identical profiles (like a "cohort" or group of fictitious households) 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 that 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 that 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 variable), four values for the maturity (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 this loan-to-value (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.[22] 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.[23] According to data from CRIF Real Estate Services, in April 2015, about 25% of all new daily Italian mortgage originations occurred in Lombardy, the region where Milan is located, and, among those, about 50% occurred in the city of Milan. Thus, the market of Milan is well suited for our analysis. We submit the applications to the MutuiOnline website in October 2014 and September 2016.

In sum, 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. Moreover, for each application, there are other identical ones except for one borrower-level factor. The final dataset contains borrower-bank(-time) combinations, detailing which banks are

[22] We fix the LTV in the experiment as our aim is to focus on borrower (demand) factors. As it depends on loan volume, it is not a borrower factor that shifts the demand. 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.
[23] As we do not submit many applications and 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.

willing to grant a loan, as well as the APR, net mortgage rate, fees, and loan instalment that each bank applies to the loans that it is willing to grant. Out of the 11,520 (fictitious) 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).

2.3 Experimental data: empirical identification strategy

The experiment with the associated generated data allow us to identify in equation (1) the borrower (demand) vs. lender (supply) factors. As compared to the observational data, and its limitations for empirical identification discussed in subsection 2.1, the experimental setting provides several advantages. First, every borrower applies to each bank, i.e. there is not assortative endogenous borrower-lender matching at the application level, including borrower desired type of loan contracts. Second, we observe decisions on loan application outcomes for all borrower-lender pairs (i.e. no problems of discouraged borrowers or only granted credit), with a total of 483,840 borrower-bank(-time) pairs. Third, we can compare identical households except for one borrower factor in credit conditions from the same bank.

Given this experimental setting, we can estimate the fixed effects for each borrower and lender in equation (1).[24] With the estimated fixed effects, we can compare the explanatory power (via R-squared) of borrower fixed effects (proxying for borrower factors) as compared to bank fixed effects (proxying for lender factors).[25] Note that if e.g. a borrower is rejected by all banks, this is consistent with borrower (bad) quality (as in Bernanke and Lown, 1991). Indeed, the borrowers rejected by all banks are much riskier in our data. Moreover, we can analyze how a change in the interquartile range (or in a standard deviation) of the estimated borrower (or bank) fixed effects change lending conditions (granting of applications and loan rates for accepted applications). The fixed effects capture all observed and unobserved borrower (demand) and bank (supply) factors.

Moreover, we can also analyze observable factors. We analyze how lending conditions change from the same bank to different households who only differentiate each other in one characteristic. For example, a different proxy of borrower balance sheet strength (either different labor income level,

[24] 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. For example, 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.

[25] 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, job 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 policies, corporate governance, risk appetite, unobserved risk not captured in supervisory variables, etc.).

or different employment status, or different age, proxying for income volatility) or to a different proxy of borrower expectations and preferences (a different desired loan contract by the borrower with respect to either maturity or to fixed vs. variable loan rates). In this way, we can analyze which borrower factor matters more in explanatory power and in economic significance. For this analysis, we include borrower (household) group effects, 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. Moreover, we can control for bank*time fixed effects as well to further isolate different borrower factors. Therefore, we compare borrowers that are identical except for one factor and study the granting of the loan application (or rate) from the same bank in the same month. Furthermore, we relate lending by banks or the estimated bank fixed effects to observables that proxy for bank balance sheet strength as e.g. bank capital, size, liquidity, government debt holdings or non-performing loans (NPLs).

Finally, we can analyze bank risk-taking incentives (Keeley, 1991; Holmstrom and Tirole, 1997; Freixas and Rochet 2008; Jimenez et al., 2014). On the one hand, banks with lower net worth (e.g. lower capital or lower lending capacity) may take higher risk on the margin due to lower skin in the game;[26] relatedly, banks with lower credit supply (lower estimated bank fixed effects) may take on the margin higher risk to compensate for their lower profits (due to lower lending) as financial intermediaries have higher profit targets (Rajan, 2005). On the other hand, banks with higher estimated fixed effects (e.g. higher net worth/balance sheet strength) can not only have higher lending capacity but also higher risk-taking capacity (Freixas and Rochet, 2008). For this risk-taking analysis, we introduce in equation (1) interactions of borrower and lender fixed effects and/or observables. As each application from a household has other identical ones except for one variable, not only we can measure the impact of each household variable (e.g. permanent job, income, age, desired maturity and interest rate-type) on loan acceptance or rates by applying a "group-household" fixed effect, but we also assess whether banks change their lending conditions differently for riskier vs. safer borrowers (where riskier borrowers are e.g. due to lower income, or riskier loan contracts are e.g. due to longer-term loans).

There are of course some caveats in our approach. First, as the other micro empirical analyses on credit (e.g. Khwaja and Mian, 2008; Amiti and Weinstein, 2008), our analysis is purely cross-sectional, and thus we cannot provide evidence on the time-series evolution of borrower and bank factors for credit; a key difference with the other papers that use cross-sectional variation is that in

[26] In Holmstrom and Tirole (1997) higher risk-taking by less capitalized banks is via lower bank monitoring (i.e. the borrower is riskier because of lower bank monitoring). More generally, banks can choose borrowers with ex-ante riskier characteristics as in a mean-variance portfolio analysis (Freixas and Rochet, 2008).

our case our data is not observational.[27] Second, we can analyze bank (supply) factors –vs. borrower (demand) factors– via bank and household fixed effects, thereby capturing unobserved and observed factors, and we can even compare identical household borrowers applying to the same bank having only one different household (borrower) factor (via our fictitious household applications). However, we cannot have identical banks except for one observable factor (i.e. identical banks but with differences only e.g. in bank capital). We analyze bank observables but based on the existing (real) banks. Third, our analysis is about lending decisions by banks (loan demand is given) depending on borrower factors (proxying borrower labor income level and volatility, preferences and expectations) and lender factors (capital, liquidity, risk), i.e. we back out the lending decisions by banks based on borrower (demand) vs. bank (supply) factors (see Holmstrom and Tirole, 1997, or Bernanke and Gertler, 1995), but we do not analyze changes in loan demand.

2.4 Administrative datasets and associated empirical strategy

As a validation test of our data and approach, 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 in Italy): (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.

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, following Khwaja and Mian, 2008), while this would not be possible in the case of households. In addition, we can observe firm characteristics by matching administrative firm balance sheet data (and hence we can analyze risk-taking), while this is not possible, in Italy (and in most other countries), for the case of households. Since our experimental data is on mortgages, we analyze SMEs in real administrative data for better comparison. Further, we also analyze whether a bank supply measure from the *observational* mortgage data determines credit

[27] The estimated bank fixed effects do not refer to a bank credit supply schedule that, for each possible combination of borrower characteristics, 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 banks –i.e., the lending decision depends on bank (supply) factors.

supply to SMEs,[28] and whether results are different based on a very similar bank measure obtained from the *experimental* data (fictitious mortgage applications to 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 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, considering 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. Our final sample comprises 17 bank holding companies (21 different banks), including the 10 largest banks in the country.[29]

2.5 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 vs. 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 vs. 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),[30] 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).

[28] Our measure is related to Amiti and Weinstein (2018) but has the key difference that, by being for households (rather than firms), we cannot apply household (or household*time) fixed effects but we can just apply province*time fixed effects to control for borrower (demand-side) fundamentals.

[29] 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 we drop foreign bank branches and those Italian banks that do not have branches in Milan.

[30] Taxes and social security are high in Italy as compared to US.

Credit growth to firms by banks from the credit register during the two months of our experiment are on average 3.4% using the Davis and Haltiwanger (1992) measure, based on the extensive plus the intensive margin of lending, and 0.75% on average if we only analyze the pure intensive margin (i.e., if we use the change in log credit).[31] 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 (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, 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, has 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 Results

In this section we first summarize the results based only on the data generated by the experiment. Second, we summarize the results based on the credit register data.

3.1 Results based on the experimental data

In this subsection we first analyze borrower and bank fixed effects (capturing unobserved and observed borrower and bank factors); second, we analyze the role of household and bank observables; and third, we analyze bank risk-taking (interaction effects).

Borrower and bank fixed effects. Table 2 provides the results for our benchmark regressions on the acceptance of loan applications. We estimate the household and bank fixed effects and we quantify their economic significance (looking at the interquartile range) as well as how much they explain of the variation of loan acceptance (analyzing changes in the adjusted R-squared).[32]

In Column 1 we only include the loan amount requested (quantity demanded). Results show 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-

[31] The measure of Davis and Haltiwanger (1992) is the change in credit over half of (initial plus final) credit volume.
[32] Further details on the empirical strategy are described in Section 2.

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.[33] 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.. All these estimated effects are large in absolute value, and also relative to the average acceptance of loan applications, which is 43.4%, or the standard deviation, which is 49.6%.

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 p.p.; and by 50.5 p.p. in the case of bank*time fixed effects. Finally, Column 6 shows similar results for borrower and bank factors together, with an adjusted R-squared of 57% and interquartile range of 98.2 p.p..

Table 3 shows the results for loan pricing. In Panel A, we consider the 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, loan quantity by itself explains very little of the adjusted R-squared and has no economic significance (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 rates, 33.0% against 3.7% without time fixed effects, and 93.4% and 55.7% with time fixed effects, respectively.

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 increases 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 the case of loan pricing, differently from the acceptance of loan applications, time effects matter significantly, but mainly 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,

[33] See Table A1 on the Appendix for the summary statistics of the estimated fixed effects (these are demeaned).

Panel A and B); however, these effects are driven by time effects (comparing Columns 2 and 4 with respect to Columns 3 and 5). Finally, Column 6 shows very strong effects in pricing when the borrower and bank channels are estimated together.

In sum, we find that the borrower and bank channels are equally strong in causing—and explaining—loan acceptance. However, for loan pricing, borrower factors are substantially stronger.

Role of observables. 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; Table 5 considers bank factors.

In Table 4, we analyze the impact of borrower observables: applicant's job type (permanent contract, fixed-term contract, self-employed, professional, retired), age, income, (desired) loan maturity, and (desired) rate type (fixed or variable).[34] Household income is the key net worth factor for most households (Bondt, Gieseck and Tujula, 2020), and hence it is critical for a household balance sheet channel (Mishkin, 1978). In addition, age may also play a critical role (Attanasio et al., 2012; Rios-Rull and Sanchez-Marcos, 2008). Further, while variable rate mortgages are generally attractive as the mortgage instalment is more responsive to lower interest rates (Di Maggio et al., 2017), for risk-averse households with a large mortgage, risky income, high default cost, or low moving probability, fixed rate mortgages are preferable (Campbell and Cocco, 2003). Importantly, the choices of maturity and of variable vs. fixed rate reflect households' expectations about the macroeconomy (interest rate and liquidity risks), including individual future economic conditions, as well as preferences. These are key factors when it comes to assessing the role of borrower (demand) factors for the granting and pricing of mortgage applications (Cocco, 2013; Koijen et al., 2009).

As explained in the empirical strategy, 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 listed at the top of each column in Table 4). Moreover, we control for bank*time fixed effects as well to further isolate different borrower factors. 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 (vs. fixed-term) jobs and with higher income (also older) – cause higher granting of loan applications (Columns 1, 2, 3, 6;

[34] In the table, for ease of reading, we present results only for permanent and fixed-term job. As said above, there are other job categories in addition to permanent vs. fixed-term contract (self-employed, professional, retired), but the main action is between permanent contract vs. fixed-term contract.

Panel A); and if accepted, lower loan rates (Columns 1, 2, 3, 6; Panel B). There are similar effects for more attractive loan risk conditions to the lenders, i.e. shorter-maturity loans (Column 4, Panels A and B). Banks also prefer fixed (over variable) loan rates (during our period of time of very low rate environment), as banks charge higher rates (Column 5, Panels A and B).[35] With respect to economic significance of the coefficients associated to household characteristics, the job type, and specifically a fixed-term contract, has the largest economic effects for loan acceptance, while the rate-type is the most important variable affecting loan rates.

In Table 5, we analyze bank observables. We use the main bank balance sheet variables that the banking literature uses to measure the strength of bank balance sheets, in particular bank capital, liquidity and size, as well as measures of risk (sovereign debt holdings and NPLs proxied by loan charge-offs).[36] 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 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.

Risk-taking. In Table 6 we analyze risk-taking because: (1) 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; (2) as argued in Section 2, the banking literature emphasizes 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 volume decreases bank profitability), or due to e.g. lower skin in the game (based on our finding of bank capital in Table 5 and as discussed in e.g. Holmstrom and Tirole, 1997).

As a measure of the strength of bank balance sheets, we use the estimated bank(*time) fixed effects from equation (1) where we control for borrower*time fixed effects or we use the residual from regressing those estimated bank*time effects on bank observables (bank capital, liquidity, size, sovereign debt holdings, and non-performing loans). We show all results in the paper with both

[35] See also Table 1 for the summary statistics on rates: fixed rates are significantly higher than variable ones.
[36] See e.g. Holmstrom and Tirole (1997), Kashyap and Stein (2000), Freixas and Rochet (2008). Sovereign debt and NPLs are not only key net worth proxies but have been crucial during the Euro Area Sovereign Debt Crisis.

measures, but we include the residual one as the benchmark to highlight the limits of observable variables, e.g. bank balance sheet or in general observational (credit) data. Note that these bank strength variables (either the gross/overall one or the one based on residuals) capture the bank (supply) channel as we control for borrower(*time) fixed effects and there is no endogenous borrower-bank matching in the experimental data. As our measure of bank strength is based on borrower*time fixed effects, we do not control for group-household fixed effects in Table 6 (which are weaker than borrower*time effects), but results are very similar if we include those group effects.

Table 6, Column 1 shows the direct effect, without interactions with household characteristics. These (bank strength) residuals not only positively affect the probability of acceptance, but also explain about 15% of the R-squared (about the same as all the main bank observable characteristics together, not reported).[37] Moreover, 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 more applications from borrowers with ex-ante higher risk proxied by: (i) not having a permanent job (i.e. fixed-term job); (ii) younger; (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 Results using the administrative credit register data

In this subsection, 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 administrative datasets. In particular, we use the supervisory credit register, which includes loan-level data at the bank-firm level, matched with firm and bank balance sheet data. These administrative data differ from our fictitious (mortgage) applications in that they are not only observational *vs.* experimental, but also on SME loans *vs.* mortgages.[38] Moreover, we also use a credit supply measure based on the credit register for mortgages, which has the universe of borrower-bank level mortgages.

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 exists a borrower-bank assortative matching in observational data; and (ii) to test (validate) 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 results based on the experimental data). We focus on corporate loans as we can control for

[37] Results are also significant if we bootstrap standard errors. Similarly, for the following tables on credit register data.

[38] 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.

borrower fixed effects (as the empirical literature on the credit channel does, see e.g. Khwaja and Mian, 2008) and as we have measures of borrower risk (for the assortative matching and risk-taking); indeed, we cannot do this in observational mortgage data because households do not typically have mortgages from different banks at the same time, nor do we observe household level variables such as net worth. Nevertheless, we also use mortgage data from the Italian credit register to horse race our bank-level credit supply measure based on experimental mortgage data vis-à-vis a very similar measure obtained from the credit register data.

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), 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 this (experiment-based) 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, Columns 5 and 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 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 first to the third quartile 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%).[39] That is, the experimental-based measure of bank strength is statistically and economically significant in the actual lending from banks to borrowers.

Moreover, accounting also for all the main bank observables (capital ratio, short term liquidity, government bond holdings, loan charge-offs, ROA, wholesale deposits, and total size), our measure of bank strength based on experimental mortgage data is the most important variable (statistically and

[39] 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 the medians of our left-hand side variables have a value of 0).

economically) in driving credit supply to firms (see Table A3 in the Appendix). Table A4 shows similar results with the gross measure of bank strength. Note that all the variables are standardized in Tables 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 repay the debt (EBITDA over interest expenses), liquidity and leverage. That is, considering lending to the same firm in the same period, banks with lower strength (measured in the experimental data) provide less credit supply on average, but increase credit to riskier firms on the margin as compared to banks with higher strength. Furthermore, Table A5 in the Appendix confirms the results using our gross bank strength instead.

In the Appendix we show the assortative matching between banks (our measure of bank strength) and firms (based on different measures of risk). Table A6 shows with the credit register data that there is an endogenous matching between stronger banks and safer 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 A7 in the Appendix provides a confirmation of these results in a regression setting. Finally, Tables A8 and A9 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 observational data (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.[40] In particular, we use as a measure of bank strength (bank-level overall credit supply), a set of bank fixed effects obtained through an approach similar to that proposed by Amiti and Weinstein (2018) using the administrative mortgage data from the Italian credit register but with a few important differences. 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 area demand effects. Therefore, we aggregate mortgage loans at the bank-province level,

[40] 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.

compute the credit growth rates in Q3 2014 and Q3 2016, and regress this credit growth on a set of bank and province*time fixed effects (see Table A10 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 Section 2, this (type of) measure may be biased because of the endogenous selection of borrowers into banks and because of the phenomenon of discouraged borrowers. To gauge to what extent this measure constructed on realized (observational) mortgage data is able to determine credit supply to firms (SMEs), Table A10 shows results of the same regressions presented in Table 7 (which were based on loans to SMEs), using the bank-level strength/credit supply measure derived from the real mortgages instead of the one 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 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) vs. the bank (supply) factors. This highlights the need for experimental data in the identification and quantification of the borrower vs. 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 –for lending decisions– (non-financial) borrower (firm or household) factors (the demand side) vs. bank factors (the credit supply side). Macro-finance and banking models e.g. differ in the importance of the net worth strength and risk of the borrowers' and lenders' balance sheets as well as of other channels such as borrower preferences. Moreover, regarding public policy, given scarce resources, it is critical 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 have significantly helped borrowers (firms and households) to access credit as well as banks to supply it.

The literature has advanced mainly using credit register data, but 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 identification of the bank lending channel, but it cannot measure the importance of the borrower *vs.* lender channels and it may, also, not be able to fully isolate the bank lending channel due to time varying borrower-lender endogenous matching (Paravisini, Rappoport and Schnabl, 2017). Moreover, borrower factors (the demand-side) are difficult to observe, impossible for discouraged borrowers. In addition, available datasets mostly include information on credit granted, and not on applications, and it is basically impossible to observe borrowers that are fully identical in all but one key characteristic (e.g. borrower income, risk or desired loan rate type or maturity).

We overcome these identification problems through exploiting experimental data, which allow us to measure the relative importance of borrower vs. bank factors in lending.[41] We submit thousands of fictitious mortgage applications, changing one borrower-level variable at time, to the major online mortgage platform in Italy. Each application goes to all banks. For external validity we also analyze the economic effects on administrative (observational) credit register data of (credit supply) bank strength measures estimated on experimental data.

We find that the borrower and bank lending channels are equally strong in causing —and explaining— loan acceptance. Each channel has an adjusted R-squared of 29.4% and 28.5%, and 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 (they are at least eight times as important as the bank factors). As the borrower and bank channels explain a maximum of 58% of loan application rejections and because of theory, we also analyze interactions of both borrower and bank factors. We find that banks that supply less credit on average are more likely to accept applications from borrowers with higher risk than other banks.

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 constructed on real mortgage data (otherwise very similar to the one from the experiment on fake mortgage applications) does not affect credit supply to SMEs.

[41] As we explain throughout the paper, our paper is not about identifying credit demand vs. supply, but on whether credit decisions depend on borrower (demand side) vs. bank (supply side) factors (see the Introduction and also e.g. Holmstrom and Tirole, 1997). That is, we analyze how bank lending decisions are affected by differential *household* key factors such as income, employment risk, age, desired loan rate type and maturity vs. differential *bank* factors such as capital, liquidity and risk, and even unobservable bank ones.

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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. Instalment 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
Instalment (€)	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 Log (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 FACTORS

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 vs. variable 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 FACTORS

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 vs. variable 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 (fixed-term)	Job type (permanent)	Age	Maturity	Rate-type (fixed)	Income
	(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 (Columns 2 to 6). Job types are permanent contract, fixed-term contract, self-employed, professional, and retired. 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 and maturity 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		Age	Maturity	Rate-type
		(fixed-term)	(permanent)			(fixed)
	(1)	(2)	(3)	(4)	(5)	(6)
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: $\text{GrossBankStrength}_{b,t} = \text{capital}_{b,t} + \text{shliq}_{b,t} + \text{govt}_{b,t} + \text{loans charged} - \text{offs}_{b,t} + \log(\text{assets})_{b,t} + e_{b,t}$, 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 expenses		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

Online 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. 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 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. 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 $\Pr(\text{acceptance})_{HH,b,t} = \text{FE}_{HH} * \text{t} + \text{FE}_b * \text{t}$ 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 – ROBUSTNESS CREDIT REGISTER DATA: CREDIT SUPPLY AND RISK-TAKING

Notes: In Column 1, the independent variable is the gross bank strength; in Columns 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 expenses			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 A6 – 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

TABLE A7 – 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 expenses		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 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 $\text{Pr(acceptance)}_{HH,b,t} = \text{FE}_{HH} * \text{t} + \text{FE}_b * \text{t}$ 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 – 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 $\Pr(\text{acceptance})_{HH,b,t} = \text{FE}_{HH} * \text{t} + \text{FE}_b * \text{t}$ 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 expenses		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

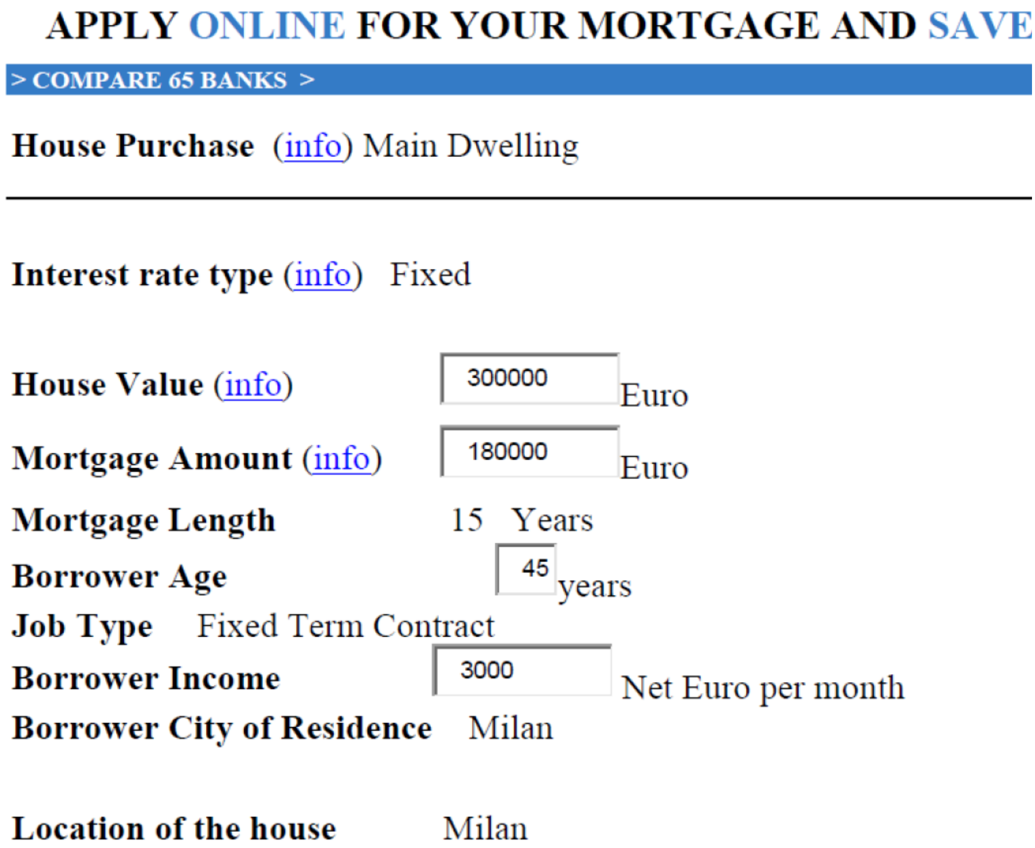
TABLE A10 – CREDIT SUPPLY TO SMES BASED ON BANK STRENGTH COMPUTED ON REAL (CREDIT REGISTER BASED) MORTGAGES TO HOUSEHOLDS

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%**

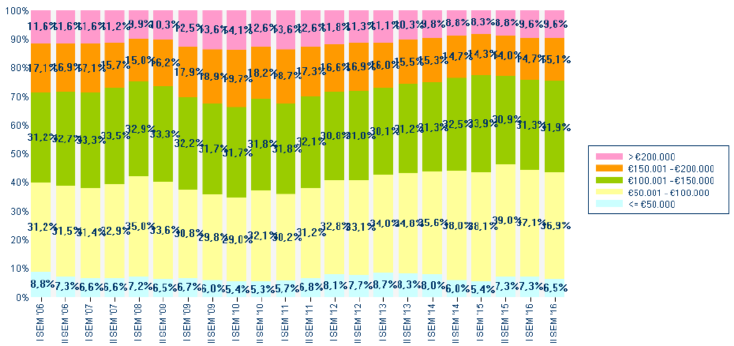
	IW BANK PRIVATE INVESTMENTS MUTUO A TASSO FISSO
Instalment	**€ 945.08** (monthly)
Mortgage Rate	**Fixed: 2.40%**
Loan origination fees	General charges: € 600.00 - Valuation: € 0.00
APR	**2.51%**

	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%**

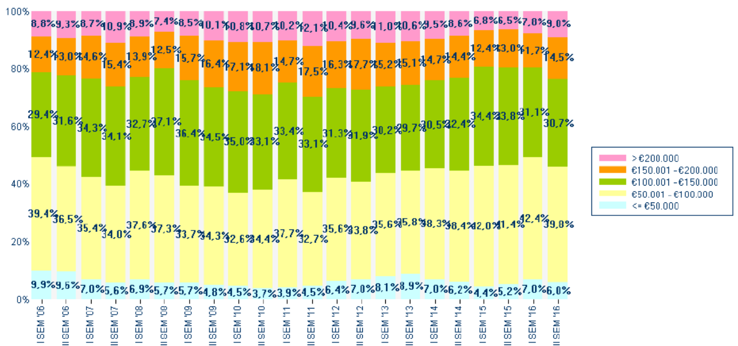
Figure A3: Applications vs. originated mortgages

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

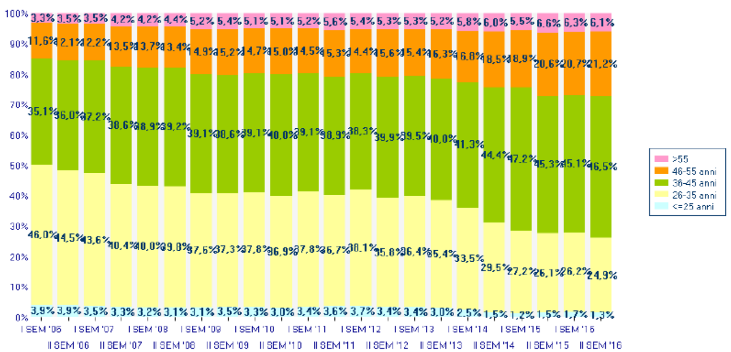
(a) Mortgage applications by amount



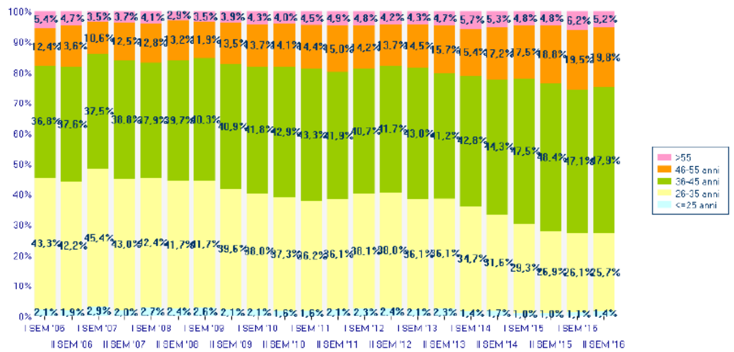
(b) Mortgage contracts by amount



(c) Mortgage applications by age



(d) Mortgage contracts by age



Disclosure statement: Valentina Michelangeli

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The author declares that he has no relevant or material financial interests that relate to the research described in this paper.

Disclosure statement: Enrico Sette

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