When Broadband Comes to Banks: Credit Supply, Market Structure, and Information Acquisition*

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Abstract

This paper studies how broadband internet affects bank credit supply to non-financial firms. We rely on loan-level data from the Italian Credit Register and quasi-experimental variation in the diffusion of broadband. Our estimates include firm-time fixed effects to control for the effect of broadband on firm demand. We find that branches in municipalities reached by fast internet increase loan supply and reduce interest rates. The credit expansion results from higher branch productivity, wider geographical reach, and lower local market concentration. Branches connected to fast internet acquire more information on borrowers after loan origination, which is used to improve monitoring.

JEL: G21, O33, D82

Keywords: High-speed Internet, Technological Change, Asymmetric Information, Banks, Credit.

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1 Introduction

The arrival of fast internet is one of the most disruptive innovations in history and has a wide-ranging impact on economic activity. The availability of a massive amount of information and the ability to communicate quickly transforms industries' size and operations.

As an information-intensive business, banking is particularly exposed to the effects of transformations in information technologies (ITs). When information flows are limited, banks face higher information asymmetries, communication costs, and more severe agency problems (Leland and Pyle, 1977). Innovations in information and communication technology, from hardware to software, and the diffusion of internet technologies, mitigate these frictions and play a crucial role in shaping banking activity (Mishkin and Strahan, 1999). As a matter of fact, banks have long relied on cutting-edge technologies to deliver innovative products, streamline loan-making processes and improve their back-office efficiency (Frame et al., 2018).

Despite its relevance and the importance of the banking industry for the smooth functioning of the economy (Levine, 1997), the evidence on the effects of fast internet on bank activities, in particular lending, is scant.[1] A key reason for this is the lack of high-quality administrative data and an identification strategy to deal with the endogeneity of the introduction of the internet, which typically reflects local economic conditions.

This paper studies the effects of access to broadband internet on bank credit supply to non-financial firms and sheds light on the mechanisms behind these effects. We rely on granular microdata from Italy on individual loans and information acquisition on individual borrowers, and we instrument the staggered arrival of broadband through

[1] D'Andrea and Limodio (2023) is an exception. They focus on the effects of high-speed internet in Africa and show that fast internet favored new financial technologies in the interbank market, thus alleviating banks' liquidity risk and promoting lending to the private sector. By contrast, a large literature studies the effects on the banking industry of regulatory reforms (Bertrand et al., 2007), removals of barriers to entry (Cetorelli and Strahan, 2006), shocks of various nature (financial, real, natural disasters), institutional quality, and even the role of culture and ethnicity (Caprio et al., 2007; Grosjean, 2011; Calomiris and Carlson, 2016; Pascali, 2016; Fisman et al., 2017; D'Acunto et al., 2019).

the historical presence of telephone infrastructures (built in Italy mostly right after WW2), controlling for prior characteristics of the local geographical area. To isolate credit supply from demand, we use high dimensional fixed effects regressions.

We document that the arrival of fast internet leads to a credit expansion and is associated with a small reduction in the average price of credit. Broadband access may promote credit supply growth through more efficient information acquisition and processing. It may also boost credit demand by increasing firms' productivity and profitability. We identify the component of the total effect attributable to supply and show that it accounts for one-third of the aggregate effect. Next, we investigate the mechanisms behind our results and document that broadband internet affects the organizational design of banks, with effects on the productivity, market geographical reach, and local banking competition of branches. Additionally, we rely on unique data on banks' information requests to the Italian Credit Register about borrowers' credit histories to provide direct evidence of the role of broadband in reducing asymmetric information.

Our analysis focuses on Italy between 1998 and 2008, the period of expansion of fast internet in the country. Our main dataset includes detailed information on the location of broadband infrastructures, matched with loan-level data from the comprehensive Italian Credit Register and administrative data on bank branch locations, assets, liabilities, and number of employees.

Measuring the impact of access to broadband internet on credit is challenging. Since high-speed internet is not randomly assigned to municipalities, bank credit could be affected by hidden factors other than (but related to) broadband connection. To deal with this source of endogeneity, we exploit quasi-experimental variation and leverage the position of the municipality in the pre-existing telephone infrastructure to proxy (instrument) for broadband availability (Campante et al., 2018). As fast internet services in Italy could only be offered in municipalities connected to high-order telecommunication exchanges via fiber optic, we use the distance between the centroid of the municipality of the branch that manages the loan and these exchange infrastructures (a proxy for the required investment to connect the municipality with the fiber)[2] as a source of variation for the availability of high-speed internet (Ciapanna and Sabbatini, 2008). To further control for the non-randomness in the distribution of the pre-existing telephone network, we interact the above-mentioned distance with a dummy variable for the period after broadband internet became available. Our identification assumption is that whatever correlation existed between the distance to the high-order telecommunication exchange and relevant municipality characteristics, this did not change at the time of the introduction of broadband for reasons other than broadband itself. Finally, since we are interested in how fast internet affects credit supply, we saturate the model with fixed effects that control for time-varying firms' changes induced by broadband. Results from our estimates shed light on the causal effect of fast internet on bank credit supply.

The main findings of the paper can be outlined as follows. We find a positive and statistically significant effect of access to broadband internet on the extensive and intensive margin of lending. A one standard deviation (s.d.) increase in the distance of the municipality of the branch from the broadband infrastructure (after fast internet becomes available), which corresponds to a lower probability of being connected to fast internet, is associated with a relative decrease in the number of loans issued by the branch of 2.4%, and a decrease in the amount of credit granted of 4%. The arrival of broadband also has a statistically significant, albeit economically small, effect on credit price. A one standard deviation increase in the distance from the internet infrastructure is associated with an increase in the average interest rate of 4.8 basis points (b.p.).

These results represent equilibrium outcomes that reflect both demand and supply. The effect of fast internet on credit demand has been indirectly documented in the literature by focusing on firms' productivity (Akerman et al., 2015). By contrast, the ev-

[2] In particular, we exploit a crucial technical characteristic for broadband deployment: the distance between the "Line stage" and the "Urban Group Stage". This distance was irrelevant for voice communication purposes, thus plausibly unrelated to local economic development, but it is critical to provide ADSL as it needs to be covered with optic fiber, which is costlier than standard copper cables.

idence of the effect of broadband on banks' internal activity and organizational design remains scant, notwithstanding the common consensus on the impact of information technologies on the way banks conduct lending (He et al., 2021). The granularity and the structure of our data help us isolate credit supply from other confounding factors. We follow Degryse et al. (2019) and Khwaja and Mian (2008) to separately identify the component of the aggregate effect due to credit supply. In the most demanding specification, we exploit the panel structure of the data and the diffusion of multiple bank relationships in Italy (Gobbi and Sette, 2014) to compare the amounts of credit extended to firms having relationships with branches in municipalities with different distances from the broadband infrastructure. In this way, we can isolate credit supply from demand and, thus, exclude that the variation in total credit is driven by firm-specific needs (which may be affected by the availability of fast internet), in particular by firm productivity. We use high dimensional fixed-effect regressions to control for time-varying industry-location-firm size factors and firms' demand characteristics, and bank-year fixed effects to control for time-varying credit variation that originates from bank-specific policies. In a robustness exercise, we also control for bank specialization to cover the possibility that different banks offer different loan products and more generally have different specializations (Paravisini et al., 2015). When restricting the analysis to credit supply, we find that around 33% of the total effect (63% to 85% for interest rates) is driven by supply-related factors.

To better understand the effect of broadband internet on bank credit supply, we document how productivity, geographical scope, and local competition are affected by the availability of fast internet. We find that the efficiency of branches, measured by branches' labor productivity and credit quality, increases after the arrival of broadband. A one s.d. increase in the distance from the internet infrastructure reduces loans per employee by 3.5%. Standard models suggest that a surge in loan supply may lead to worse lending standards (Berger and Udell, 2004; Foos et al., 2010). If anything, we find that credit quality improves considering that the share of non-performing loans (NPLs) per branch decreases. These findings are in line with Petersen and Rajan

(2002) and Berger (2003), who argue that richer hard information and more efficient back-office activity, fostered by broadband, help both ex-ante screening and ex-post monitoring.

The geographical reach of banks also widens when there is fast internet. Branches operating in municipalities close to the fast internet infrastructure expand their markets beyond standard geographical borders, which typically correspond with provinces (Crawford et al., 2018). We find that connected branches are more likely to originate loans outside their province and that the average distance between the municipality of the branch and the borrower increases. These results are consistent with the view that lower information asymmetries and a drop in communication costs allow banks to reduce the dis-economies of distance and increase ”proximity” (Berger, 2003; Felici and Pagnini, 2008).

Finally, municipalities closer to the internet infrastructure experience a boost in banking competition. This is confirmed by the increase in the number of available bank brands in the municipality and the dynamics of standard proxies of competition: the concentration ratio of the top 5 and top 3 banks, as well as the Herfindahl–Hirschman Index (HHI) of deposits, decrease when the distance from the broadband infrastructure is lower.[3]

A key novelty of our paper is that we provide evidence on how the collection and usage of information by banks for screening and monitoring borrowers changes after the arrival of broadband. We first show that our results are stronger for information-sensitive loans and that information flows within the bank (i.e. between branches and headquarters) explain most of our findings. Then, we find that the average ex-ante credit score of borrowers and pricing at origination are not affected by fast internet. By contrast, a lesser distance from the internet infrastructure is associated with more credit to firms without a credit score and more granular pricing throughout the relationship. Since broadband allows easier access to the information of the credit register,

[3] In the period of our analysis, competition from online lenders is negligible. In 2008, Fineco, part of the Unicredit group, was the sole digital bank in the country. Competition from online lenders increased sensibly only after 2008 (starting with the creation of CheBanca!).

we leverage data on information requests by branches to provide direct evidence of the effect of fast internet on screening and monitoring. We find that access to broadband has a negligible effect on the requests made at loan origination, but leads to a significant increase in the number of inquiries about the borrower during the length of the credit relationship. Overall, we interpret these findings as supporting the idea that broadband induces banks to collect more information at the monitoring stage, thus reducing asymmetric information vis-à-vis borrowers.

As a last step, we document the distributional consequences of branches' access to broadband across borrowers. First, we show that the effects of fast internet are concentrated in small and medium-sized firms (SMEs). There is no effect for micro firms (i.e. those with less than 2 million euros of net revenues). For larger firms, we find a point estimate similar to that for SMEs. Second, we document stronger effects for riskier firms (identified by their z-score). These findings are consistent with our main results which show that broadband internet fosters the acquisition of codifiable information by banks.

Our results are robust to several robustness checks. They are unaffected by the inclusion of control variables at the municipality level, aiming to control for municipality time trends.[4] Similarly, they are robust to the exclusion of large cities. The results hold when running a placebo specification for the period before fast internet was available, and are robust to the bank-specialization test suggested by Paravisini et al. (2015), which we implement following Benetton and Fantino (2021). Finally, they are consistent with the hypothesis that commercial banks and more IT "prone" banks are the primary users of the new technology.

This paper builds and extends on different strands of the literature. It is close to three recent works studying the effects of telecommunication infrastructure on bank intermediation. D'Andrea and Limodio (2023) exploit the staggered arrival of fiber-optic submarine cables in Africa and show that high-speed internet lifts bank lending

[4] Our regressions always account for the persistence of city characteristics. With this test, we also control for hypothetical municipality time trends that are unrelated to broadband but, by chance, starts at the exact time of broadband internet introduction.

through more efficient interbank markets. Lin et al. (2021) study China in the late 19th century and show that the telegraph significantly expanded banks' branch networks. Mazet-Sonilhac (2021) takes the perspective of the firms and shows that broadband internet reduces search frictions, thus affecting the allocation of credit and the dynamics of firm-bank matching. Our paper adds to these works in several dimensions: by focusing on the effects of broadband internet on bank lending; by disentangling credit supply from demand; showing the mechanisms behind these effects; and by providing first direct evidence on information acquisition by banks when performing screening and monitoring activities.

In this way, our paper contributes to the broader literature on the effects of information and communication technology (ICT) on banking. Hauswald and Marquez (2003) provide a theoretical framework showing that the advent of new information technologies generates ambiguous effects on loan prices and competition. Using similar arguments, Vives and Ye (2021) show that IT progress involves an increase in competition intensity when it weakens the influence of bank-borrower distance on monitoring costs. Petersen and Rajan (2002) and Berger (2003) provide intuitions and empirical evidence on the effects of new technologies on the distance between lenders and borrowers. New technologies allow financial intermediaries to substitute soft with hard information, thus increasing the distance between borrowers and lenders. Relatedly, Felici and Pagnini (2008) find that the geographical reach of entry decisions increases for those banks that resort more to ICTs and that the latter has important pro-competitive effects. Degryse and Ongena (2005) and Keil and Ongena (2020) focus on the effects of technologies on bank de-branching, while in a recent paper, Ahnert et al. (2021) find that job creation by young firms in the US is stronger in counties that are more exposed to IT-intensive banks. A set of studies focuses on the effects of internet banking (i.e., access to banking through the internet) on bank performance (DeYoung, 2005; Ciciretti et al., 2009). Other studies focus on the rise of FinTech (De Roure et al., 2016; Buchak et al., 2018; Tang, 2019; Braggion et al., 2020; Di Maggio and Yao, 2020), and document how state-of-the-art information technologies affect bank risk-taking, firms' access to credit, and financial inclusion.

Our findings also add to the literature on the effects of new telecommunication infrastructures on the real economy (Roller and Waverman, 2001; Forman et al., 2009; Czernich et al., 2011; Kolko, 2012; Akerman et al., 2015; Pascali, 2017; DeStefano et al., 2018; Donaldson, 2018; Steinwender, 2018; Hjort and Poulsen, 2019) and innovates by showing the effect of broadband internet infrastructures on banking.

At last, the paper contributes to the extensive literature on information in financial intermediation (Leland and Pyle, 1977; Campbell and Kracaw, 1980). Stiglitz and Weiss (1992) show that despite the richer strategy space available to lenders, market equilibria can be characterized by credit rationing if information asymmetries are relevant. Liberti et al. (2016) and Liberti and Petersen (2019) argue that new technologies such as credit scoring (Einav et al., 2013), fax machines, and the internet can help reduce information asymmetries and improve credit allocation. In this paper, we show that broadband internet acts on the process of information acquisition by banks and helps reduce asymmetric information through monitoring.

The rest of the paper is organized as follows. Section 2 presents the institutional background in Italy. Section 3 describes our data. Section 4 shows the empirical specifications and the identification strategy. Section 5 reports the main results. Section 6 investigates the mechanisms behind our findings. Section 7 explores some firms' heterogeneity. Section 8 provides robustness checks. Finally, Section 9 concludes.

2 Institutional Background

The study focuses on Italy as it represents an ideal laboratory for our analysis. First, the long history of human settlement in the country allows for the existence of several relatively small municipalities located at a short distance from one another, often separated by geographical barriers (rivers, lakes, mountains). This creates large variation in the distribution of the infrastructure needed to bring broadband to different municipalities, which otherwise have a very similar level of economic activity and development and are just a few miles away. Second, in our sample period, Italy did not experience especially fast growth in credit, nor it experienced a housing bubble, contrary for example to the US, UK, Ireland, or Spain. Third, Italy is a developed economy, mostly bank-dependent, with an economic structure similar to that of other major countries. This strengthens the external validity of our findings. Finally, Italian authorities collect very granular administrative micro-data that are crucial to implementing our empirical analysis both for identification and for analyzing specific outcomes, such as information collection on borrowers, difficult to observe otherwise.

Connection to broadband internet in Italy has been traditionally provided through asymmetric digital subscriber lines (ADSL). ADSL is a data communication technology that enables faster data transmission than a conventional voiceband modem, and it was introduced by the Italian telecommunications incumbent operator, Telecom Italia, in 1999. The development of the ADSL infrastructure was relatively slow in the first years since its introduction. By the end of 2000, only 117 out of the 8,100 Italian municipalities had access to the new technology. Instead, it sped up considerably during the subsequent years. By the end of 2005, about half of all municipalities owned an ADSL line, accounting for approximately 86% of the country's population. Figure 1 reports the time series of broadband adoption in terms of the number of municipalities with access to ADSL, between 1998 and 2008. Given the low access and penetration rates until 2001, we consider this as the last "pre-broadband" year throughout our analysis.[5]

ADSL technology relies on information transmission over conventional copper phone wires. Henceforth, ADSL access depends crucially on the user's position in the pre-existing voice telecommunications (telephone) infrastructure. This was built after World War II, between 1945 and 1960, thus long before our sample period. Technically, the telephone infrastructure consists of three levels: the Line Stage (LS), the Urban Group Stage (UGS), and the Transit Group Stage (TGS). The LS is the last struc-

[5] In figure 2, we plot the time series of xDSL technologies (which include ADSL) coverage, distinguishing between firms and households. The two groups present parallel rates of adoption and firms are primary users of the new internet technologies.

ture where all the providers connect with their equipment, after which the so-called ”last mile”, that reaches the end-users, begins. In Italy, the 10,500 LSs are linked to one of the 628 UGS, which are connected to one of the 65 TGS. To complete the physical architecture of the network, some TGSs are tied to the three international gateways (Milan, Rome, and Palermo), which allow for international communications.

Two parameters are of specific importance for the ADSL deployment and performance. The first is the distance between the end user's premises and the closest telecommunication exchange (the LS), known as the "local loop". If the length of the local loop is above a certain threshold, connection to the ADSL cannot be implemented through traditional copper wires, but it needs fiber optic cables. The second is the distance between the LS and the closest higher-order telecommunication exchange (the UGS). Independently from the length of the local loop, for ADSL to be available, the connection between the LS and the UGS must be through fiber optic cables.

In Italy, the length of the local loop has not constituted a limiting factor for the development of the broadband infrastructure. Since the local loop was a key element in the telephone network, its length was generally short, and the distribution was capillary. Instead, the distance between the LS and the UGS, which was irrelevant for voice communication purposes, has become the primary determinant of the investment needed to provide ADSL to a given area and, consequently, of the timing of ADSL adoption (Ciapanna and Sabbatini, 2008). The latter is behind the choice of our exogenous measure of access to broadband internet, which we illustrate in greater detail in section 4.

As concerns the Italian economy, the financial system has traditionally been bank-dependent. Total assets of the Italian banks during the period of our analysis were around 75% to 108% of the GDP, and the ratio of domestic credit to the private sector by banks over GDP was above 70%.[6] After the liberalization and the large-scale privatization in the early 90s[7], the Italian banking market resembles that of other major

[6] The source is the Global Financial Development Database (GFDD) provided by the World Bank.

[7] These follow the Second Banking Coordination Directive (Bank of Italy, 2003; Angelini and Cetorelli, 2003), which was issued in December 1989.

developed countries, with similar characteristics in terms of access to the banking system, banking depth, efficiency, stability, and concentration. Finally, as regards market-based finance, it is limited to a few larger firms (Pagano et al., 1998). The latter means that for the vast majority of the firms in our sample, which includes the universe of non-financial corporations and therefore is made up mostly of SMEs (the average of net revenues is 6.5 million euros), focusing on bank loans implies studying the main and only source of external finance.

These features of the Italian setting, both the technical deployment of broadband and the characteristics of the credit market, support the external validity of our analysis.

3 Data

Our main dataset combines information from several sources. It includes details on the characteristics of the broadband infrastructure in Italy, paired with matched firm-branch data for the period 1998-2008. We observe information on the amount of credit granted by each bank-municipality pair to every non-financial firm, together with the specific features of the credit relationship (loan type, interest rate, etc.). We have data on the location, opening and closing of bank branches, and data on the number of branch employees and deposits. Our dataset also contains an indicator for the bank's request for information on borrowers sent to the credit register. We observe when the bank makes the query on a prospective or existing borrower, whether the query is extensive or synthetic and how many months back the credit status of the borrower is observed.[8] Finally, we merge bank data with information on the balance sheets of Italian non-financial incorporated firms. Below, we provide some details.

[8] Synthetic query includes information on the overall exposure towards banks, the number of banks, the presence of non-performing loans different from bad loans, and a possible hit of the overdraft limit. The extended request includes information on guarantees provided by third parties to the borrower and the credit register record of the individual shareholders/owners of the firm. Banks can also choose how many months back in time to obtain information about the borrower's relationships with other banks.

Our key dataset includes the precise location of the needed infrastructure for broadband. We collect information on the geographical position and the number of all the LSs and UGSs in Italy. Then, for each municipality in our sample, we compute the geodesic distance between the centroid of the municipality and the closest UGS. We use this variable, interacted with a dummy post-2001, to obtain the source of plausibly exogenous variation in broadband access that we exploit throughout our analysis.[9]

Information on ADSL availability is provided by the Authority for Communications Safeguards (AGCOM). The dataset includes a cross-section of the number of activable broadband lines in each municipality at the end of our sample period and is used to validate the empirical strategy. Since these data lack the time-series component, their use is limited to validation (see section 4).

Data on matched firm-bank relationships are from the Italian Credit Register (CR) held by the Bank of Italy. The CR contains information on the universe of loans and guarantees above 75,000 euros[10] issued by banks and other financial companies. We focus on bank loans (i.e. we exclude guarantees and loans from other financial institutions) and select only loans above the 75.000 threshold[11]. For each credit relationship, we observe data on the bank and the firm involved, the total amount granted, the amount utilized, the composition of the credit (in terms of credit lines, term loans, and loans backed by receivables), its status (performing or not) and the timing of the relationship. Moreover, we observe the municipality of the branch that the borrower selects as the reference for managing the credit relationship. This feature is essential as it allows us to observe the location of the bank with which the borrower interacts. The latter is key to matching data on the loans issued by banks in different municipalities with information on the broadband infrastructure in each municipality.

Data on interest rates are from *Taxia*, which is part of the CR. While a subset of

[9] Data on the location of LSs and UGSs have been kindly provided by Francesco Sobbrio and are used in Campante et al. (2018).

[10] The threshold has been lowered to 30,000 euros after 2008.

[11] Some of the loans in the CR are below 75,000 euros either because of errors or because banks also provide guarantees to the borrower, so that the overall exposure of the bank (loans and guarantees) goes above 75,000 euros. We decide to remove these special observations (1.7% of the sample) and keep credit relationships with loans above 75,000 euros.

the CR, Taxia provides detailed information on interest rates covering more than 80% of total bank lending (Rodano et al., 2013). Such data include the rates charged on outstanding loans (distinguished into credit lines, term loans, and loans backed by receivables) and newly issued loans.

The CR also includes a section containing records on the information requests sent by each bank on prospective and existing borrowers. The queries include a time stamp, the code of the bank submitting it, and the unique borrower identifier which can be matched with its tax identifier. It also includes data on the amount of information requested in the query, particularly whether the query is extensive or synthetic and how many months back the credit status of the borrower is observed. We use these data to study how broadband internet reduces asymmetric information.

Further details on branch deposits and branch employees are from the Supervisory Reports that banks submit to the Bank of Italy (the banking supervisor of the country), whereas data on bank branches are from the Bank of Italy ”Lista succursali”. For each bank branch, we observe its name, bank identifier, group to which it belongs (when relevant), location, and initial and closing date. We match all the data at the branch level using a unique identifier.

Information on firms' balance sheets are from the database collected by CERVED Group. These data provide balance sheets and income statements for the universe of incorporated firms in Italy for the period 1998-2008. Firms not covered are mainly micro firms, sole proprietorships, or small household producers. Throughout our analysis, the sample excludes firms not covered by the CERVED database. We match firms' data with credit register data using the unique firm tax identifier that is common to both data sources.

Finally, we collect information on the local economic activity and the social background of different areas by using publicly available data from the Bank of Italy and the Italian national statistical institute (ISTAT).

Table 1 reports summary statistics associated with our final sample. Panel A refers to data at the municipality level and shows municipalities' geographical distribution

(*North*, *Center*, *South*), as well as statistics on the ADSL underlying infrastructure (the number of LSs and their average distance from the municipality; the number of UGSs and their average distance from the municipality), and the distance from the province capital. Panel B refers to data at the bank-municipality level. It shows the number of loans issued by a bank in a given municipality, the amount of credit granted, and the average interest rate charged. Finally, panel C refers to loan-level data and reports statistics on (granted) loan amounts and average interest rates.

4 Empirical Strategy

The literature provides some guidance on the lending outcomes that can potentially be affected by the availability of broadband. On the one hand, we expect credit outcomes, both the extensive (loans issued) and the intensive (amount of credit) margin, to be positively related to access to fast internet (Petersen and Rajan, 2002; Berger, 2003). On the other hand, the effect of high-speed internet on interest rates is a priori ambiguous. Following Hauswald and Marquez (2003), the effect of new information technologies on credit price is negative (an increase in interest rates) when the informational advantage of the intermediary that gathers information leads to less competition in the credit market. The effect is positive (a decrease in interest rates) when access to information makes data much more widely available to all competitors, thus increasing competition.

We test for the existence of these relationships by focusing on three main outcome variables: the extensive margin of credit (the log number of loans issued); the intensive margin of credit (the log amount of credit granted); and the price of credit (the interest rate).[12] Then, we enrich our analysis with the inclusion of other outcomes with the aim to characterize the underlying mechanisms.

To study the causal impact of broadband on banking outcomes, in the ideal setup

[12] We use a weighted average of the branch's interest rates (credit lines, term loans, and loans backed by receivables), with weights depending on the amount of firms' utilized credit for each loan type.

we would randomly provide branches with different access to fast internet, independently of their dimension, area, and economic environment. Moreover, we would randomly assign firms to branches, regardless of the efficiency of such matches based, for example, on proximity or relationship lending. Then, we would compare loan characteristics of branches with different access to broadband, noticing that the random bank-firm match would isolate the supply component of the effect on loan characteristics. Unfortunately, such an experiment is only ideal, making the task of estimating the causal effect we are after challenging.

A naive approach would compare loan outcomes between branches[13] with different broadband access with the following regression model:

$$Y_{(r)bmt} = \nu + \beta Broadband_{mt} + \gamma X_{(r)bmt} + \text{fixed effects} + \varepsilon_{(r)bmt} \tag{1}$$

where subscripts r, b, m, and t indicate, respectively, relationship, bank, municipality of the bank branch, and year (*r* or *bm* depending on whether the specification refers to credit relationship characteristics or branch characteristics); Y is the outcome variable; *Broadband* represents a measure of access to the ADSL in the municipality of the branch; X includes time-varying controls at the relationship or bank-level; and fixed effects are different sets of dummies depending on the outcome variable.[14] [15]

However, a major concern with the estimates of a model in which we regress branch credit features on branch access to ADSL is that broadband availability is unlikely to be randomly allocated across municipalities, potentially generating a bias in the estimates of model parameters (Comin and Hobijn, 2004). This reason justifies our choice to use a plausibly exogenous proxy for broadband availability in the spirit of an instrumental variable framework.[16]

[13] In our data we can observe the municipality of the branch, therefore, whenever we refer to a *branch*, we mean a couple of bank-municipality, i.e. a *branch* is defined as a bank b, in municipality m.

[14] We define *relationship* to be a triple firm-bank-municipality of the branch.

[15] In all our specifications, we include bank-municipality of the branch and bank-year fixed effects. We saturate the model with more granular fixed effects when the regression is at the relationship level.

[16] In this paper, we use the typical conceptual framework of instrumental variables. Our estimates come from reduced form regressions in which we regress the outcome variable on the instrument. We do not present 2SLS estimates because we lack data on access to fast internet (the endogenous variable)

To deal with endogeneity concerns, we use the geographical distribution of the ADSL physical infrastructure and leverage differences across Italian municipalities in the distance between a municipality and the closest UGS, where the latter represents a key determinant of the cost of supplying fast internet (see section 2). In particular, we exploit the fact that the 628 UGSs dislocated across the country were inherited from the pre-existing telephone network, so their location was determined long before the advent of the internet and was not influenced by the introduction of the ADSL (Impiglia et al., 2004; AGCOM, 2011).[17] The underlying assumption is that the distance to the closest UGS affects the pattern of ADSL roll-out, with municipalities located farther away from UGSs getting later access to broadband internet, ceteris paribus.

Even though the presence and the location of the UGSs precede the development (and even the existence) of broadband in Italy, the spatial distribution of UGSs is itself non-random. To address this further issue, we exploit the panel structure of the data and add bank-municipality fixed effects to our specifications. Finally, to account for potential time-varying confounders, we interact the distance of a municipality to the closest UGS with a dummy for the post-2001 period (i.e., after the introduction of high-speed internet). The latter constitutes our exogenous proxy for ADSL coverage that we use throughout the analysis (see figure A1 for a graphical representation).

The main identifying assumption is that whatever correlation existed between the distance to the closest UGS and relevant municipality characteristics, this did not change at the time of the introduction of the ADSL in the municipality. Indeed, we identify the effect of the change in the impact of the distance on the outcomes of interest, under the assumption that any change in that impact occurs solely because of the availability of broadband internet (Campante et al., 2018).[18]

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at the level of the bank municipality-year, i.e., our data on ADSL availability are only in cross-section and refer to the last year under examination.

[17] Recall that the network of physical infrastructures needed to provide voice telephony services to Italian citizens was built in the post-World War II period, between 1945 and 1960.

[18] In the appendix, table B1, we report a balance table with mean values of geographical and socioeconomic indicators for municipalities below and above the median of distance from the closest UGS, in 2001 (the last year before broadband). The balance table, which reports normalized differences (Imbens and Wooldridge, 2009), shows that the two groups of municipalities are statistically comparable,

The baseline econometric model that we use in this paper is the following:[19]

$$Y_{(r)bmt} = \nu + \beta DistanceUGS \times Post2001_{mt} + \gamma X_{(r)bmt} + \text{fixed effects} + \varepsilon_{(r)bmt} \qquad (2)$$

where *Distance UGS* $\times$ *Post2001* is the (time-invariant, standardized) distance of the branch's municipality centroid to the closest high-order telecommunication exchange (UGS), interacted with the dummy *Post2001*, that takes value 1 for the years after 2001, and zero otherwise; and the other variables are defined as in equation (1). We estimate equation (2) via fixed-effects OLS regressions.[20] The latter include bank-municipality of the branch and bank-year fixed effects. Furthermore, in the regressions at the relationship level, we saturate the model with the inclusion of industry-location-size-year or firm-year fixed effects, in order to isolate the effect of broadband internet on credit supply. Finally, we cluster standard errors at the municipality level.

Importantly, the specification saturated with firm-year fixed effects allows taking care of the possibility that firms borrowing from branches reached by the ADSL are different from those borrowing from branches not reached by broadband. The within-firm-time estimates compare the behavior of different branches lending to the same firm, attenuating these concerns substantially. Moreover, while we focus on the speed of the internet connection of the branch and not of the firm, the two may be correlated. The inclusion of firm-time fixed effects controls for this possibility and exclude that our results are driven by changes in firms' productivity. Last, the arrival of fast internet in a municipality may also increase the ability of clients to access home banking. This is not a relevant issue in our setting because internet banking services for firms were essentially non-existent in the years of our analysis.[21]

although different along some dimensions. This finding alleviates potential concerns related to the persistence of municipality characteristics.

[19] Notice that this is exactly the reduced form regression of a standard 2SLS where $DistanceUGS \times Post2001$ instruments for access to broadband.

[20] This approach is similar to that in Paravisini et al. (2015), Campante et al. (2018), Manacorda and Tesei (2020) and Guriev et al. (2021).

[21] Internet banking was mainly limited to managing deposit accounts for households and for the first examples of online trading. The sophisticated algorithms used today to screen corporate lenders were non-existent. This was partly due to the limited computing power and the high cost of increasing data

The main predictor in our baseline specification is the standardized distance of the municipality of the branch from the closest UGS, interacted with the dummy *Post2001*. The underlying hypothesis is that the farther the municipality is from the critical infrastructure to bring broadband closer to the end users, the lower the probability that a branch accesses fast internet. We validate this hypothesis in table 2, where we report estimates from the following model:

$$Broadband_{m(t)} = \nu + \beta DistanceUGS \times Post2001_{m(t)} + \text{fixed effects} + \varepsilon_{m(t)} \quad (3)$$

here, *Broadband* is the natural logarithm of (one plus) ADSL activable lines in municipality m (at time t), and it is a proxy of the availability of broadband internet in the municipality. Equation (3) represents the first-stage regression in an ideal IV exercise.[22]

Column 1 shows the results in cross-section. Column 2 exploits a two-period structure of the data, where we take t as the pre- or post-broadband period, and we impute the number of lines to be zero in the pre-broadband period for each municipality. Results in table 2 show that all the coefficients are negative and statistically significant, with the F-statistics high and well above the rule-of-thumb thresholds. Our findings are in line with the hypothesis that distance from the closest UGS is negatively correlated with the probability of having access to broadband. The farther the municipality of the branch is from the broadband infrastructure, the higher the probability of not being connected.

The setting just described allows us to answer the main questions of the paper. We study how branches react to the introduction of fast internet both on the extensive and the intensive margin of the credit relationship, as well as on interest rates (section 5).

storage.

[22] Remember the main limitation of our data: we only have a measure of $Broadband$ in cross-section. This motivates our choice to proceed in reduced form, rather than using 2SLS. However, and crucially, we can rely on the work by Campante et al. (2018) which use our exogenous proxy of broadband availability, $DistanceUGS \times Post2001$, at the municipality-year level, as an instrumental variable for access to broadband. The authors hold proprietary data on ADSL coverage for households in Italy, for the period 2000-2005, and show the validity of our proposed instrument. Unfortunately, these proprietary data are currently unavailable to us.

Then, we isolate the effect due to credit supply by means of fixed effects.

Our model also allows us to explore the mechanisms through which broadband internet affects lending (section 6). We keep the same econometric specification at the bank-municipality level and focus on different outcome variables. We use indicators of branch productivity and credit quality to test the effect of fast internet on the lending efficiency of the branch. We study measures of distance and location of the borrowers to test for the geography of the loans once broadband internet is available. Then, we look at outcomes at the municipality level, the number of local competitors and standard measures of market concentration, to test for local competition.

We also explore the deep channels behind our results to further corroborate our findings. We focus on asymmetric information, in particular, how fast internet affects the screening and monitoring of borrowers. To this aim, we use as outcome variables the number of information requests posted to the credit register, the probability the query is synthetic or full, the past months of credit status required in the query, and the dispersion of interest rates at the branch level, a proxy of the ability of banks to price credit risk more finely (see section 6).

Finally, we explore further dimensions of the firm characteristics and investigate whether the effect of broadband is heterogeneous to firm size and proxies of the firm's riskiness (section 7).

5 The Effects of Broadband on Bank Lending

In this section, we report the main results of the paper. We first present preliminary, more aggregate evidence. Next, we implement our preferred empirical strategy and show estimates from the reduced-form specification as in equation (2).

5.1 Motivating Evidence

Our preliminary evidence comes from a standard DiD event study on the (log) number of loans and the (log) amount of credit granted at the bank-municipality level.

We simulate a DiD setting by dividing the sample into two groups. Treated branches are those in municipalities above the median distance from the closest UGS (where access to broadband has a lower probability of occurring). Control branches are those below the median distance from the closest UGS. Then, we consider 2001 as the baseline year (in line with the main analysis) and show the heterogeneous effects of distance at the extensive and intensive margin of branch credit.

The dynamic model specification is as follows:

$$Y_{bmt} = \nu + \sum_{k=-4}^{6} \beta_K I\{K_t = k\} \times far\ distance\ UGS_m + \text{fixed effects} + \varepsilon_{bmt} \tag{4}$$

where $I\{K_t = k\}$ is an indicator function for the relative year from 2001 and $far\ distance\ UGS$ is the dummy variable that distinguishes the treated group from the control group. Figure 3 displays estimated event study coefficients, together with the corresponding 90% confidence interval. We consider a dynamic regression, with the baseline year set at 2001.[23] The top panel focuses on the number of loans. First, we do not find evidence of pre-trends, as the two groups of branches are on a parallel trend before the arrival of high-speed internet. Second, the treatment dynamics show the negative effect of distance - i.e., lower probability of accessing broadband - on the number of loans issued by bank branches. The effect takes one year to materialize, and then monotonically decreases until it reaches a new equilibrium, with a relative decrease in the number of loans issued of roughly 4% after the shock. The bottom panel focuses on the loan amounts and the event study points to similar results.

[23] We also implement the semi-dynamic regression as proposed by Borusyak and Jaravel (2017), dropping the farthest (negative) relative year from the event, in addition to the baseline category. Indeed, Borusyak and Jaravel (2017) show that this is the minimum number of restrictions for point identification. Results resemble those in the main analysis and are available upon request.

Treated and control branches are on a parallel trend before the treatment, and distance is associated with smaller loan amounts (a relative decrease of 6.4% after the shock).

Overall, these preliminary findings indicate a positive relationship between access to broadband internet and bank lending.

5.2 Broadband and Bank Lending

We now implement the baseline specification as reported in equation (2). We aggregate data at the bank-municipality-year level and focus on our three main outcome variables: the extensive margin of credit, i.e., the (natural logarithm of the) number of loans issued by the branch to non-financial firms; the intensive margin of credit, i.e., the (natural logarithm of the) total amount of credit issued by the branch; the average interest rate charged by the branch. Results are reported in Table 3. Column 1 refers to the number of loans and shows a negative and statistically significant coefficient associated with our main predictor. A one standard deviation increase in the distance of the municipality of the branch from the closest UGS results in a 2.4% decrease in the number of loans issued. Column 2 refers to the total loan amount. Similarly to column 1, the coefficient associated with the main predictor is negative and statistically significant. A one standard deviation increase in the distance from the closest UGS results in a 4% decrease in the amount of credit granted. Finally, column 3 refers to the average interest rate charged by the branch. As we can see from the table, a one standard deviation increase in the distance from the closest UGS is associated with a 4.8 b.p. increase in the average interest rate.

Taken together, our findings indicate that the advent of high-speed internet is related to credit expansion. Branches that are reached by the new technology issue more credit, at a lower price, to their corporate clients. This result represents an equilibrium outcome. In what follows, we aim to isolate the component associated with supply and provide insights into the channels driving this effect.

5.2.1 The Supply Channel

Results in the previous section represent equilibrium outcomes. The effect of broadband internet on credit can be the product of two forces acting simultaneously: demand, firms asking for credit, and supply, branches offering credit.

The relationship between fast internet and credit demand has been indirectly investigated in the literature, mostly by studying firm productivity (Akerman et al., 2015; DeStefano et al., 2018). The idea is that access to broadband increases firm productivity which in turn leads firms to expand their activity and demand more credit. On the other hand, there is scarce evidence on the direct effects of broadband on banks' credit supply and, more generally, on banks' supply strategies. This, although there is consensus on the fact that banks use cutting-edge technologies to deliver innovative products, streamline the loan-making process, and improve back-office efficiency (He et al., 2021).[24]

In the next paragraphs, we provide novel evidence of the effect of broadband internet on credit supply by isolating this component of the aggregate effect. Results are shown in tables 4 and 5, where we exploit the granularity of our dataset and leverage variation at the relationship level (Ali Choudhary and Limodio, 2021). We add to the model high dimensional fixed effects to control for (time-)specific firm characteristics. The latter, are added on top of branch and bank-time fixed effects, which control for branch features and bank-level trends, respectively.[25]

Table 4 refers to the (log) amount of credit granted by the Italian branches to individual borrowers. Column 1 reports our baseline estimates and shows that a one standard deviation increase in the distance from the closest UGS results in a 4.4% decrease in the loan amount. This result is in line with that presented in Table 3, where

[24] Figure A2 in the appendix reports descriptive statistics on the percentage growth of the use of web technologies within bank branches, during the period 2001-2007. These statistics, obtained from the Economic Analysis of the Italian Banking Association (ABI), suggest a sizeable increase in the use of web technologies in the back office activities of banks during the examined period.

[25] These specifications at the firm-bank-municipality-year level also control for the (one-year lagged) share of credit lines on total extended credit to firm f, by bank b, in municipality m, and the (one-year lagged) share of extended credit issued by bank b, in municipality m, to firm f.

the analysis was at the level of the branch. Column 2 adds to the model industry-location-size-time fixed effects, following the recent work by Degryse et al. (2019). The aim is to isolate the component of the total effect due to supply using both single and multi-bank firms controlling for firm-specific characteristics. Our results show that a one standard deviation increase in the distance from the closest UGS, once controlled for demand, is related to a 1.5% decrease in the amount of credit granted. Column 3 saturates the model with the inclusion of firm-by-year fixed effects, following the standard approach of Khwaja and Mian (2008). In this way, we isolate the component due to supply by exploiting variation within firm-time. Differently from the methodology proposed by Degryse et al. (2019), here we restrict the sample to firms with multiple-bank relationships and directly exclude that the effect of broadband comes from increasing firm productivity. Estimates in column 3 mirror those in column 2. A one standard deviation increase in the distance from the closest UGS results in a 1.4% decrease in the loan amount. Taken together, columns 2 and 3 provide robust evidence that almost one-third of the total effect of broadband internet on credit is due to credit supply.

Table 5 replicates our exercise using the interest rate as the dependent variable.[26] Column 1 shows that a one standard deviation increase in the distance from the closest UGS results in a 6.5 b.p. increase in the interest rate. Columns 2 and 3, which isolate supply following Degryse et al. (2019) and Khwaja and Mian (2008) respectively, show that a one standard deviation increase in the distance from the closest UGS results in a 4.1-5.6 b.p. increase in the interest rate. The latter indicates that between 63% and 85% of the total effect of broadband internet on the interest rate is due to credit supply.

These findings represent the core result of the paper. Access to broadband has significant effects on credit supply. Branches connected to fast internet offer more credit at a lower average interest rate.

[26] For consistency with the analysis run at the branch level, we take the average rate across loans in the lending relationship.

6 Mechanisms

Results in the previous section show that the arrival of broadband internet leads connected branches to expand credit more than non-connected ones. This credit expansion materializes on the extensive margin (number of loans), the intensive margin (amount of credit), and the price of credit (interest rates). We document that a substantial part of the effect is due to supply-related factors. In what follows we focus on the mechanisms through which the expansion in credit supply occurs. We focus in particular on the branch's efficiency, its geographical reach, and local competition.

6.1 Lending Efficiency

It is often argued that IT advances play a substantial role in boosting productivity (Draca et al., 2007; Syverson, 2011; Collard-Wexler and De Loecker, 2015), which in turn leads firms to grow (invest more, increase sales, etc.). In the case of banks, higher productivity may lead banks to expand loans, keeping other operating costs constant. In this section, we test whether the efficiency of bank branches in generating loans increases as a consequence of access to broadband internet.

We consider two different indicators for branch efficiency. The first is the loan amount per branch employee, which measures the branch's labor productivity. The second is the share of non-performing loans (NPLs), a proxy of branch credit quality. Petersen and Rajan (2002) and Berger (2003) suggest that new technologies allow banks to reduce asymmetric information. Since high-speed internet enhances screening and monitoring by banks, we expect the effect of broadband on productivity to be positive and significant. On the other hand, the effect of broadband on credit quality is a priori ambiguous. Since marginal borrowers are generally worse than incumbent customers, credit quality could worsen due to credit expansion. However, information on borrowers becomes richer and more timely once new technologies are available. Improved screening and monitoring activities can thus offset the negative effect on credit quality.

Table 6 reports the results from equation (2). Columns 1 and 2 show that a branch's access to broadband internet positively affects its labor productivity, measured as the number of credit lines and extended credit per branch employee. A one standard deviation increase in the distance from the closest UGS is associated with a decrease of 2% in the number of loans per employee and 3.5% in the credit per employee ratio. On the other hand, columns 3 and 4 show that high-speed internet is associated with a slight decrease in the share of NPLs, meaning that credit quality, on average, improves with the expansion of credit.[27]

Altogether, these two findings support the hypothesis that branches' lending efficiency increases after the introduction of broadband. In section 6.4.2, we provide evidence of the deep roots behind this rise in efficiency.

6.2 Geographical Reach

As indirect evidence of the effects of fast internet on information transmission, we look at the geographical reach of banks, a key dimension highlighted in the literature.

Lending is traditionally considered a "local" business, and the distance between lenders and borrowers has been identified as a crucial factor shaping credit relationships, especially those that involve SMEs (Degryse and Ongena, 2005). In this regard, the effect of new technologies can go both ways. On the one hand, Petersen and Rajan (2002) suggest that technology helps break the "tyranny of distance". By reducing the asymmetric information of banks, new technologies allow for increasing capital intensity of lending and thus lending to more distant borrowers. Along the same lines, Berger (2003) shows that technological progress facilitates the geographic expansion of banking organizations by reducing distance-related dis-economies. New services created by technological progress with higher value-added, together with traditional

[27] The latter is in line with Pierri and Timmer (2020), who study the implications of IT in banking for financial stability. They find that a one standard deviation higher pre-crisis IT adoption led to 10% fewer NPLs during the 2007–2008 financial crisis. We find a similar result in Fuster et al. (2019), which finds that faster processing by FinTech lenders does not result in riskier loans. In particular, FinTech default rates are about 25% lower than those for traditional lenders, even when controlling for detailed loan characteristics.

banking services delivered more efficiently, bank monitoring and the control of risk exposures at longer distances and lower costs, contribute to easing the way banks find and finance new clients. Similarly, Liberti and Petersen (2019) show that new technologies (such as the internet) enable banks to expand geographically and can partly explain the increased distance in the borrower-lender relationship. Granja et al. (2022) show that the expansion of lending distance is evidence of either a rapid improvement of technology or increased bank risk-taking. On the other hand, Wilhelm (2001) argues that advances in communication technology and increased capacity for information do not imply a greater exchange of information inside the bank. This is due to the limited incentives for loan officers to transfer information on which they hold monopoly power. Likewise, advances in communication technology may not lead to higher exchanges of information between firms and banks (Bhattacharya and Chiesa, 1995) and between different banks (Padilla and Pagano, 1997). Hence, technological developments may have no effect or negative effects on the distance between lenders and borrowers.[28]

To empirically evaluate the relationship between fast internet and the geographical reach of banks, we look at the effects of broadband internet on the geography of the credit relationship by focusing on new loans originated by Italian branches during the period of our analysis. We define a dummy variable for the loan being originated outside the province of the branch (*Diff. Province*), to measure the effect of broadband internet on the geographical borders (the market) within which the branch operates.[29] Then, we create a direct measure of distance by computing the geodesic distance between the centroid of the municipality of the lender and the exact location of the borrower.

Estimates from equation (2), aggregated at the bank-municipality-year, are reported in table 7. Column 1 refers to the share of new loans originated out of the province.

[28] See also Degryse and Ongena (2005) for empirical evidence on the static nature of the relationship between firms and banks in Belgium, between 1973 and 1997.

[29] In Italy, before the advent of fast internet, provinces defined the borders of bank credit markets (Crawford et al., 2018).

Column 2 refers to the inverse hyperbolic sine of the geodesic distance between the municipality of the branch and the firm. The table shows that access to high-speed internet increases the probability that the branch extends credit outside its province. At the same time, broadband internet is associated with an increasing distance between the borrowing firm and the bank branch.

Our findings align with the literature that documents the shrinking effects of new information technologies on the distance between lenders and borrowers (Petersen and Rajan, 2002; Berger, 2003; Felici and Pagnini, 2008; Liberti and Petersen, 2019). With respect to Granja et al. (2022), our results on the geography of loans, together with those on NPLs, suggest that broadband internet allows for credit market expansion without deterioration of credit quality. These results also suggest that broadband internet can widen local credit markets, with significant consequences for agents involved in the credit relationship and for regulatory and supervisory authorities. In particular, this may be relevant for anti-trust regulation, as the definition of a relevant local market might need to be expanded accordingly.

6.3 Local Competition

The credit expansion following the arrival of broadband internet may be driven by more intense local competition. Hauswald and Marquez (2003) find that when the information gap between banks becomes smaller because of ICT diffusion, there is a softening of the winner's curse that leads to an increase in the intensity of bank competition. Similarly, Vives and Ye (2021) find that banks' competition intensity increases when IT progress involves a weakening in the influence of bank-borrower distance on monitoring costs. In the same vein, Felici and Pagnini (2008) show that new communication and information technologies have significant pro-competitive effects in local banking markets by increasing the geographical reach of bank entry decisions.

We investigate the effects of broadband internet on banking competition by focusing on two measures of competition: the number of (physical) bank competitors in the municipality; and measures of concentration of the local credit market.

On the one hand, Vesala (2000) shows that loan mark-ups were decreasing in Finland, in lock-step with the rapid development of the internet. On the other hand, Gropp et al. (2009) find only a small increase in contestability in the European loan markets despite the impressive technological advances experienced in many countries.

Results on the effects of broadband on local competition are reported in table 8. In column 1, the dependent variable is the (log) number of bank competitors. The table shows that a one standard deviation increase in the distance of the municipality from the closest UGS is associated with a relative decrease in the number of competitors by 2.8%. This decline is coherent with an increase in local competition when the municipality has access to fast internet. In columns 2 to 4, the main dependent variables are standard indicators of concentration of the local credit market: the concentration ratio of the top 5 and 3 banks, and the Herfindahl–Hirschman Index (HHI), computed within the municipality using data on banks deposits.[30] Estimates from the table clearly indicate that an increase in the distance from the closest UGS, i.e. a lower probability of getting access to broadband, leads to a higher concentration of the credit market.

In line with Frame et al. (2018) on the effects of new technologies on banking, our findings document the positive effect of high-speed internet on competition in the local credit markets.

6.4 The Information Channel

In the previous sections, we have provided evidence of the effect of broadband internet on branch productivity, the geography of lending, and banks' local competition. These three channels may explain the expansion of credit documented in section 5 and are all consistent with fast internet allowing a more efficient and cheaper information

[30] As a robustness, we replicate the same exercise by computing standard indicators of competition using data on loans. Results are similar to those in table 8 and are available upon request.

collection by banks. However, this link is only implicit. In this section, we show the effects of broadband on banks' information collection, which is one of the fundamental mechanisms through which our effects originate.

Informational frictions are critical in the borrower-lender relationship. Banks screen and monitor risky projects (Diamond, 1984) and commit to exerting effort by using their financial capital (Holmstrom and Tirole, 1997). Since they engage in repeated interactions with their borrowers, banks collect, process, and re-use customer information (Boot, 2000) to improve their screening and monitoring and reduce information asymmetries. Petersen and Rajan (2002) suggest that new technologies allow banks to collect more information about borrowers, enabling them to change the nature of lending from an emphasis on strict ex-ante screening and costly ex-post monitoring, to fine-tuned screening and frequent ex-post monitoring. Similarly, Berger (2003) documents the increase in profit productivity due to improvements in "back-office" technologies. Vives and Ye (2021) show that IT improvements may reduce monitoring costs, with consequences on bank competition, stability, and welfare. Finally, Liberti et al. (2016) show that access to more information allows banks to expand their lending at a lower price and increase credit per loan officer.

Here, we present direct evidence on the effects of access to broadband on information collection and test whether these effects are related to screening or monitoring.

As a first step, we show that fast internet affects more strongly information-sensitive loans rather than other loans. Our data allow us to distinguish three types of contracts: overdraft loans (credit lines), which are typically uncollateralized; loans backed by receivables; and term loans, which are typically used to fund investment and are generally collateralized (at least by personal guarantees when not by real collateral). We classify overdraft loans and loans backed by receivables as information-sensitive loans[31] and replicate the exercise in table 4, splitting the sample into information-sensitive vis-à-vis term loans. Since the former are more sensitive to information, we

[31] Loans backed by receivables are collateralized by receivables, whose quality depends on the quality of the customers of the borrower. This, in turn, can be evaluated using information about them.

postulate that the effect of broadband must be particularly relevant in this case. Our results are shown in table 9, which adopts the specification with firm-time fixed effects as in Khwaja and Mian (2008). We find that a one standard deviation increase in the distance from the closest UGS is associated with a decrease by 4.3% in the amount of credit granted for information-sensitive loans (column 1). On the other hand, the effect is indistinguishable from zero for term loans (column 2). In columns 3 and 4, we further decompose our effect by distinguishing between credit lines and loans backed by receivables. This exercise has the additional advantage to restrict the analysis to a set of very homogeneous products.[32] As we can see from the table, the effect of fast internet is negative and highly statistically significant both for credit lines and loans backed by receivables. These results corroborate the idea that branches connected to broadband have access to more information and consequently expand credit supply for information-sensitive loans.

Next, we show that the flows of information within the bank are key to explaining our results. Fast internet may affect access to information in two directions. It can facilitate information sharing between lenders and borrowers or it can boost banks' internal information flows. These two alternative explanations come with different testable predictions. If information between lenders and borrowers is what matters, we expect our results to weaken, or even vanish, when firms are not connected to the internet. If instead, internal information flows are the key driver, we expect our results to be stronger when information sharing within the bank was weaker before the arrival of broadband. We test these hypotheses in table 10. Columns 1 to 3 replicate our analysis by gradually removing firms located close to the UGS, i.e., firms with a higher probability of being connected to broadband. The idea is that improvements in communication are larger if both lenders and borrowers have access to fast internet. As we can see from the table, the coefficient associated with our main predictor is almost identical to the baseline when removing the bottom 25th and 50th percentiles of

[32] Credit Lines are the most homogeneous of the credit products. They do not have a fixed maturity and are typically uncollateralized. As regards loans backed by receivables, they are usually short-term as they are repaid when receivables are paid, which typically occurs with a 60-180 days lag.

the distribution, while it is slightly lower when removing the bottom 75th percentile. Our interpretation is that communication between lenders and borrowers, although relevant, is of second order with respect to the improvement in banks' internal information sharing. Columns 4 and 5 corroborate this interpretation. We split the sample into branches located in the same province of the headquarter and branches located in a different province. The idea is that the effect of broadband is larger when previous internal communication was more difficult because of distance (Levine et al., 2020). Results in table 10 show that the effect of fast internet is zero for branches located in the same province of the headquarter, whereas it is in line with the baseline specification for distant branches.[33] Taken together, these findings substantiate the hypothesis that banks' internal exchange of information is first order to explaining the credit expansion documented in section 5.

Finally, in the next two sub-sections, we leverage unique microdata from the Italian credit register containing the queries posted by banks about prospective and current borrowers. As commented in section 3, these data contain a flag if the query is synthetic or extensive and the number of dates back in time for which the bank requires to observe the borrower's credit status. At the same time, we test for loan pricing and the heterogeneous effects across borrowers' credit scores, a classic example of hard information. All these tests allow us to answer the key follow-up questions of the paper: do banks connected to broadband collect more information on the borrowers? Do they acquire information mainly for screening, monitoring, or both?

6.4.1 Screening

Information technology may have important implications for how banks screen their clients (Hauswald and Marquez, 2003; Ahnert et al., 2021). Since new technologies affect information collection, process, and analysis, they can potentially allow for more

[33] In this table, we disentangle supply from demand following the methodology by Degryse et al. (2019). Indeed, a specification with firm-year fixed effects and sample splitting at the bank level proves to be overly demanding. Our results are broadly confirmed when including a triple interaction ($DistanceUGS \times Post2001 \times Diff.Prov$) on the whole sample.

effective screening. In this section, we test whether branches connected to fast internet improve their screening of borrowers through various tests.

First, we study the relationship between access to broadband and the borrower's credit score at origination. If branches with fast internet improve their screening, we expect broadband to be negatively related to the ex-ante credit score of the borrower.[34] We report estimates from this regression in table 11. In column 1, the dependent variable is the natural logarithm of the credit score. In column 2, we define a firm to be risky if its credit score is above 6 (Rodano et al., 2018)[35]. As we can see from the table, the effect of fast internet on the firm's credit score is indistinguishable from zero, both using the specification with the categorical variable and its alternative version with the dummy.

Second, we study the effect of access to broadband on the standard deviation of the interest rates charged on new loans. The idea is to test whether branches connected to broadband price their loans more granularly than non-connected branches. Estimates from this exercise are reported in table 12, column 1. In column 2, we also augment the model by including branch-score fixed effects to control for credit scores' composition. Results from the table show that the effect of fast internet is indistinguishable from zero, also within branch-score brackets.

Third, we study how access to broadband affects the requests for information that banks send to the credit register on prospective borrowers (i.e., firms that are not already clients of the bank). Here, we exploit the granularity of our dataset and test whether branches connected to broadband ask for more/less information at origination. Since this information is only available at the firm-bank level, we restrict our sample to the firms that have a single relationship with the bank, i.e., we exclude firms with multiple branch relationships with the same bank. In the robustness section, we also replicate our exercise on the entire sample and find similar results. Estimates from

[34] Credit scores is a categorical variable which takes values from 1 to 9, where 1 means excellent and 9 is poor.

[35] A loan belongs to the performing class when the firm has a score category between 1 and 6. The loan belongs to the substandard class if the firm has a score between 7 and 9.

this specification are reported in table 13, which shows that connected branches do not behave differently in terms of the information collected on the borrower through the credit register. The probability of sending a query remains unaffected, and so do the characteristics of the information conditionally on asking (both whether the information is synthetic and the extension of the request).

Altogether, our findings indicate that branches reached by broadband internet do not collect more information on borrowers at the screening stage.[36]

6.4.2 Monitoring

Information technology may also enhance the ability of banks to monitor their clients (Petersen and Rajan, 2002; Vives and Ye, 2021). In this section, we describe three pieces of evidence that document the positive effect of access to broadband on borrowers' monitoring.

First, we show that branches connected to fast internet have a higher probability of originating a loan to firms without a credit score or without a credit history. The former probability decreases by 0.2 p.p. for a one standard deviation increase in the distance from the closest UGS, whereas the latter decreases by 1 p.p. These results are reported in table 14 and are coherent with new findings on start-up financing (Ahnert et al., 2021) and FinTech (Di Maggio and Yao, 2020).

Second, we show that banks price risk more finely after the arrival of fast internet for existing loans. This result is reported in table 15, where the dependent variable is the standard deviation of interest rates, and, together with the findings in table 12, indicates that connected branches do not price more granularly at origination, but they adjust interest rates throughout the credit relationship. This result is in line with branches improving their monitoring but not their screening, and it is consistent with the arguments in Petersen and Rajan (2002).

Third, we provide direct evidence on how branches connected to broadband issue

[36] This result is line with Chava et al. (2021), which find that FinTech lenders do not enjoy an informational advantage in screening borrowers.

more inquiries about their clients throughout the relationship. We exploit the fact that fast internet facilitates access to the information of the credit register,[37] and build a measure of monitoring based on the number of queries sent by the bank to the CR on firms that are already customers (Branzoli and Fringuellotti, 2022).[38] As in the analysis on screening, since these data are only available at the firm-bank level, we restrict our sample to the firms that have a single relationship with the bank, i.e., we exclude firms with multiple branch relationships with the same bank. Results are shown in table 16. Columns 1 and 2 report, for each firm-branch-year, the probability of asking a query after the relationship has originated (for coherence with respect to table 13), and the associated number of inquiries. The coefficient of distance is negative and statistically significant in both specifications. In particular, that in column 2 indicates that access to broadband internet is associated with banks asking more queries throughout the relationship. In columns 3 and 4 we keep focusing on the number of inquiries. In column 3, we aggregate the data at the firm-branch-pre(post) broadband level, and measure the number of queries that the branch asks for the same firm before and after fast internet is available. We find that a one standard deviation increase in the distance from the closest UGS is associated with a decrease in the number of inquiries by 0.5%. Finally, in column 4 we look at the total number of inquiries sent by the branch. Again, results are in line with increasing monitoring. A one standard deviation increase in the distance of the branch from the closest UGS is associated with a decrease in the number of queries by 4.9%.

[37] During the period of our analysis, credit register information was transmitted through the National Interbank Network (RNI), the telematic transmission infrastructure of the Italian payment system, which did not rely on the internet. Bank branches, in order to access CR information, had to communicate their requests to their banks' data centers (one for each bank), which in turn were connected to the RNI. Broadband Internet affects the flow of information from the branch to the data center, making more efficient the transfer of requests directed to the interbank network.

[38] Our outcome variable captures a fraction of the potential effect of fast internet on branch office access to information, i.e., the part relating to the collection of information from the credit register. Access to fast internet can affect bank monitoring also through other sources of information, such as the use of email to communicate with borrowers or company business information available online. It is reasonable to think that these measures are to some extent correlated. Here, our proxy is not intended to quantify the overall change in monitoring intensity, but rather to capture observable evidence of the increase in monitoring caused by broadband.

Taken together, these findings indicate that ex-post monitoring is positively affected by the availability of broadband internet. Employees of connected branches take advantage of the new technology to strengthen their monitoring of firms, which in turn increases the branch's efficiency in business lending.

7 Firms' heterogeneity

In this last section, we investigate whether the credit expansion brought about by broadband internet is heterogeneous across different firms' dimensions. This is an interesting issue to identify potential winners and losers from banks' access to new information technologies. We report our results in table 17.

The first three columns refer to the firm's size, which proxies for the easiness of the branch to get information about the firm. Our results show that the effect of fast internet mainly relates to small and medium enterprises, whereas it is virtually nonexistent for micro-enterprises.[39] The reduction in asymmetric information that we document in section 6 characterizes hard information that are easier to codify. Since the lender-borrower relationship for micro-enterprises usually relies on soft information, it is reasonable to expect that the effect of broadband is limited for them.[40]

The last three columns refer to the firm's level of riskiness, which proxies for the ability of the branch to complement standard information coming from the credit score. We distinguish three kinds of firms: safe, whose credit score is below or equal to 4; vulnerable, with a credit score between 5 and 6; and risky, whose credit score is above 6 (Rodano et al., 2018). Our results show that the effect of fast internet is larger for ex-ante riskier firms, both vulnerable and risky. Indeed, these are the firms for which asymmetric information tend to play a major role.

Overall, our findings indicate that firms that can transmit codifiable information to

[39] The definition of micro, small and medium, and large enterprises is based on the official EU categorization, using the revenue criterium.
[40] This result is coherent considering the period under investigation, 1998-2008. In this regard, our work departs from recent developments, where technological innovations are mostly related to increasing access to (and processing of) soft information.

the branch, and are ex-ante riskier, particularly benefit from the introduction of broadband internet. This result is in line with those in section 5, where we show that fast internet facilitates credit expansion, and those in section 6, which suggest the reduction in asymmetric information as one of the main underlying mechanisms.

8 Robustness

We subject our results to several robustness checks.

Our basic identification assumption can be violated if underlying trends affect the outcomes of interest and correlate with our measure of access to the internet. To control for these confounding factors, we augment our specifications in equation (2) with several economic and socio-demographic municipal characteristics from the 2001 Census. We interact each variable with a second-order polynomial-time trend to control flexibly for the possibility of differential time trends. The group of control variables includes the total and elderly population, which account for municipality demography, the number of private firms and employees, which proxy for the economic activity of the municipality, and the distance from the provincial capital, which controls for geographic proximity to the main city. Table B2 reports the estimates related to the intensive margin of bank credit and interest rates, using the specification with firm-year fixed effects, to isolate supply. As we can see from the table, the coefficients keep the same sign as in the baseline specification and remain statistically significant at standard levels. Interestingly, the magnitudes in columns 1 and 2 are only slightly affected by the inclusion of our control variables.

In table B3, we show that our results are robust to the exclusion of branches located in large cities. We drop from the sample the three biggest cities in the country, which are the ones with more than one million residents. All the estimates maintain the same signs and are significant at standard levels. As we can see from the table, the effect of broadband internet on the intensive margin of credit is even larger than in the baseline specification.

In table B4, we address the possibility that our results are picking up some underlying credit trend that is correlated with the diffusion of broadband. We run placebo specifications for the years from 1998 to 2001, assuming that the year pre-ADSL is 1999. Specifically, we restrict our sample to credit relationships from 1998-2001. Then, we create a fake year of introduction of broadband in 2000, such that 1998-1999 represents the pre-broadband period and 2000-2001 is the post-broadband period. Reassuringly, we see no impact of this fictitious access to broadband on credit and prices, supporting the view that pre-existing bank-municipality trends are not driving our results.

In table B5 we reject the hypothesis that our findings reflect bank specialization, in line with the arguments by Paravisini et al. (2015). We follow the methodology suggested by Benetton and Fantino (2021) and include a control variable for bank-industry specialization.[41] The table shows that adding this additional term does not significantly impact our results. Both the coefficients of credit amount and price, reported in columns 1 and 2 respectively, have similar magnitudes and remain statistically significant at standard levels. In our context, this means that the distance of the branch from the closest UGS is uncorrelated with confounding effects related to the banks' industries of expertise. This orthogonality condition helps further disentangle credit supply from credit demand.

Data on information queries are only available at the firm-bank level, making the matching at the firm-branch level subject to assumptions. In section 6 we have restricted our analysis to firms with a single relationship with the bank, so to avoid possible overlapping in the screening and monitoring requests made by different branches of the same bank. We find this specification first best.[42] While most of the firms borrow from only one bank branch, it is still useful to check that our results hold for the larger sample that we use in the baseline. We test this in tables B6 and B7. As we can see from

[41] Another way to (partially) control for bank specialization would be to add firm-bank fixed effects. However, our setting requires us to exploit credit supply variation across banks with different broadband access. Including firm-bank fixed effects would subsume such variation, thus limiting the comparison between firms borrowing from two branches of the same bank in different municipalities, hardly a common occurrence.

[42] In this way, we avoid measurement errors and the related attenuation bias in the estimate of model parameters.

the tables, our main findings are confirmed. Having access to broadband internet has at most a negative effect on the ex-ante screening of banks (branches ask for less and more synthetic), whereas it has a positive effect on ex-post monitoring.

We conclude by showing that the availability of fast internet affects mainly IT "prone" banks and commercial banks as opposed to cooperative banks. In order to disentangle supply from demand, in this exercise we follow the methodology by Degryse et al. (2019).[43] Table B8, columns 1 and 2, shows that the effect of broadband applies to banks with a non-negligible amount of investments in ICT. We define a dummy variable that is equal to one if the bank is above the 25th percentile of the (scaled) IT-investments distribution, in 2001, and show that high-speed internet benefits banks that invest in new technologies.[44] Then, in columns 3 and 4, we distinguish between commercial banks and cooperative banks, and show that the effect of broadband internet primarily characterizes commercial banks.[45]

9 Conclusion

In this paper, we provide empirical evidence on the effects of broadband internet on bank credit supply to non-financial firms. We combine data on access to the ADSL technology in Italy with firm-bank matched data from the Bank of Italy. We follow 637 banks in 5258 municipalities, from 1998 to 2008, and show that fast internet has a positive effect on the extensive and intensive margin of the credit relationship as well as on credit price.

Our econometric design addresses the endogeneity of broadband diffusion. We exploit the position of the municipalities in the pre-existing voice telecommunications infrastructure and leverage exogenous variation in the probability of the branches ac-

[43] The choice of the latter is due to sampling splitting at the bank level, which makes estimates through firm-year fixed effects overly demanding.

[44] 2001 is the year before the introduction of fast internet. Moreover, since we scale IT investments for the total amount of loans issued, these regressions control for bank size.

[45] Even if confidence intervals for cooperative banks are large enough to partially overlap with those of commercial banks.

cessing broadband. To explore our research question, we implement a reduced-form analysis and present novel results on the effects of fast internet on credit and interest rates, by isolating the component due to credit supply, and elucidating the underlying mechanisms that drive our results.

Our findings highlight that high-speed internet fosters credit supply to non-financial firms, independently from the direct effects on demand. The total amount of credit increases with broadband availability, while the average interest rate goes down. Many channels contribute to this aggregate effect. Access to broadband allows branches to increase their internal efficiency. At the same time, branches reached by fast internet expand their markets and increase the lender-borrower distance. Finally, local competition rises, as reflected by the growth in the number of competitors and by standard competition indicators. Importantly, we document that banks connected to broadband improve their internal information flows by collecting more information to monitor their borrowers. Overall, these results suggest that the deep roots of the increase in bank efficiency, geographical reach, and local competition are to be found in the reduction of asymmetric information brought about by fast internet.

Our findings shed light on the economic impact of the rapid and continuing spread of internet connectivity and show the potential of internet technologies to influence banks' choices.

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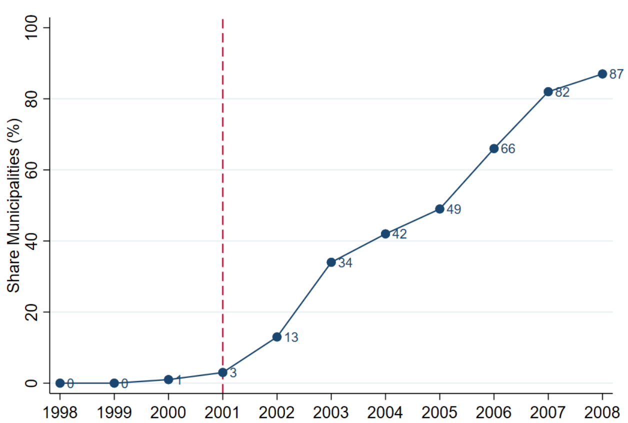
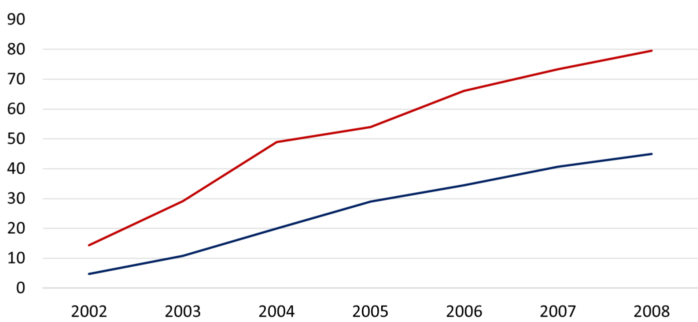
Figures

Figure 1: The evolution of Broadband internet in Italy



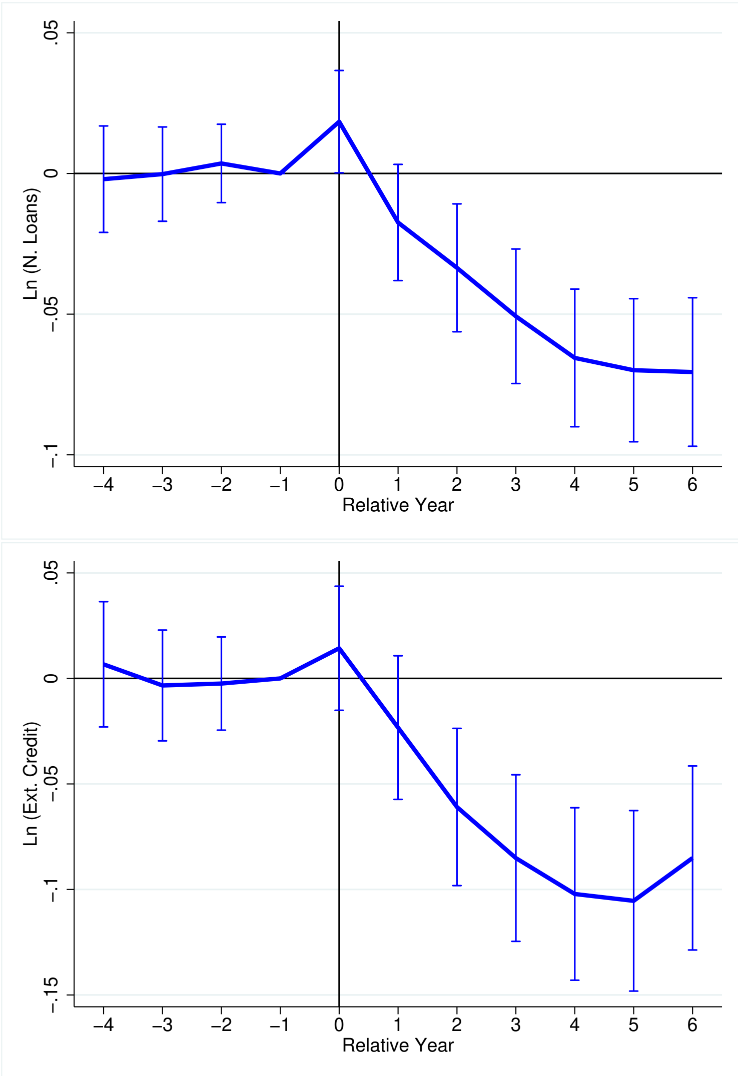
Notes: The diffusion of broadband internet in Italy between 1998 and 2008. On the y-axis, we report the share of municipalities with access to the ADSL technology. On the x-axis, we report the years. The dashed vertical line indicates the end of the pre-broadband period, which we make coincide with 2001. Source: Campante et al. (2018).

Figure 2: Broadband internet, comparison between Firms and Households



Notes: The adoption of broadband internet in Italy between 2002 and 2008, distinguishing between firms and households. On the y-axis, we report the coverage of xDSL technologies, in percentage terms. On the x-axis, we report the years. The red line refers to firms. The blue line refers to households. Source: ICT archive by the ISTAT.

Figure 3: Event study - Number of loans and Extended Credit



Notes: DiD event-study. The treatment group is made up of banks in municipalities above the median distance from the closest UGS (late adopters of ADSL). The control group is made up of banks in municipalities below the median distance from the closest UGS (early adopters of ADSL). Year 0 corresponds to 2002, the first year in which broadband internet is available. The baseline year is 2001. On the x-axis, are the relative years from broadband introduction. In the top panel, on the y-axis is $Ln(N.Loans)$, the natural logarithm of the number of loans issued by the branch. In the bottom panel, on the y-axis is $Ln(Ext.\ Credit)$, the natural logarithm of the total amount of credit granted by the branch.

Tables

Table 1: Summary Statistics

	Mean	sd	p50	N
	Panel A: Municipality			
Municipalities				5,258
Years				11
North	0.58	0.49	1.00	5,258
Center	0.15	0.35	0.00	5,258
South	0.27	0.44	0.00	5,258
Number SLs	1.70	3.82	1.00	5,258
Distance SL	0.44	1.29	0.00	5,258
Number UGSs	0.11	1.03	0.00	5,258
Distance UGS	12.84	8.92	11.39	5,258
Distance prov. capital	22.32	13.03	20.35	5,212
	Panel B: Bank-municipality			
Number of loans	26,71	138.77	8	148,197
Extended credit	28,637.35	289,804.10	3,718.56	148,197
Average interest rate	5.96	2.39	5.87	109,419
	Panel C: Loan			
Extended credit	1,072.01	8,132.08	309.86	3,958,884
Average interest rate	6.57	2.90	6.00	2,047,529

Notes: This table reports summary statistics for our final dataset. Panel A refers to data at the municipality level. We provide information on the municipality's geographical distribution (macro-region and distance from the province capital), as well as on broadband internet underlying infrastructures (number and distance of the closest SL and UGS, respectively). Panel B refers to data at the bank-municipality level. We provide information on the number of loans issued by a bank in a given municipality, the amount of extended credit (in thousands of euros), and the average interest rate charged. Finally, panel C refers to relationship-level data and reports the credit amount and the average interest rate associated with the single firm-bank-municipality relationship.

Table 2: First Stage regressions

	(1) Ln (Activable BB lines)	(2) Ln (Activable BB lines)
DistanceUGS	-0.437***	
	(0.060)	
DistanceUGS $\times$ Post2001		-0.418***
		(0.059)
Prov FE	X	
Mun FE		X
Year FE		X
F-statistic	53.21	50.15
Mean	5643.85	3099.72
R-squared	0.310	0.985
N	4253	7546

Notes: This table reports estimates from OLS regressions as presented in equation (3). The dataset is at the municipality (-year) level. The dependent variable is the natural logarithm of (one plus) the number of activable lines of broadband in municipality m (and year t, when we distinguish between a pre- and a post-broadband period). The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *F-statistic* reports the F-statistic from the regression; *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the municipality (and year) level. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 3: Number of loans, Extended credit, Average rates

	(1) Ln (N. Loans)	(2) Ln (Ext. Credit)	(3) Avg (Rate)
DistanceUGS	-0.024***	-0.040***	0.048**
$\times$ Post2001	(0.008)	(0.011)	(0.023)
Controls	X	X	X
Bank-Mun FE	X	X	X
Bank-Year FE	X	X	X
Mean	28.64	30200612.31	6.02
R-squared	0.928	0.897	0.508
N	126160	126160	88234

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the bank-municipality-year level. The dependent variables are: *Ln(N. Loans)*, the natural logarithm of the number of loans issued by bank b, in municipality m, in year t; *Ln(Ext. Credit)*, the natural logarithm of the amount of loans granted by bank b, in municipality m, in year t; and *Avg(Rate)*, the average interest rate by bank b, in municipality m, in year t. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Controls* refer to the (one-year lagged) share of loans by loan type. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality and bank-year level. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 4: Extended credit

	(1) Ln (Ext. Credit)	(2) Ln (Ext. Credit)	(3) Ln (Ext. Credit)
DistanceUGS	-0.044***	-0.015***	-0.014**
× Post2001	(0.006)	(0.004)	(0.007)
Controls	X	X	X
Bank-Mun FE	X	X	X
Bank-Year FE	X	X	X
ILST		X	
Firm-Year FE			X
Mean	1120004.40	1134604.40	1223090.41
R-squared	0.125	0.532	0.862
N	2964696	2910192	2520498

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the firm-bank-municipality-year level. The dependent variable is *Ln(Ext. Credit)*, the natural logarithm of the amount of loans granted by bank b, in municipality m, to firm f, in year t. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. Columns 1 to 3 are saturated in order to isolate the supply from demand. *Controls* refer to the (one-year lagged) share of credit lines on total extended credit to firm f, by bank b, in municipality m; and the (one-year lagged) share of extended credit issued by bank b, in municipality m, to firm f. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality and bank-year level, in column 1. The model is saturated with industry-location-size-time fixed effects in column 2. It adds firm-year fixed effects in column 3. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 5: Interest rates

	(1) Avg (Rate)	(2) Avg (Rate)	(3) Avg (Rate)
DistanceUGS	0.065***	0.041***	0.056***
× Post2001	(0.014)	(0.012)	(0.014)
Controls	X	X	X
Bank-Mun FE	X	X	X
Bank-Year FE	X	X	X
ILST FE		X	
Firm-Year FE			X
Mean	6.53	6.50	6.38
R-squared	0.246	0.393	0.681
N	1489136	1435625	1098313

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the firm-bank-municipality-year level. The dependent variable is *Avg(Rate)*, the average interest rate by bank b, in municipality m, to firm f, in year t. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. Columns 1 to 3 are saturated in order to isolate the supply from demand. *Controls* refer to the (one-year lagged) share of credit lines on total extended credit to firm f, by bank b, in municipality m; and the (one-year lagged) share of extended credit issued by bank b, in municipality m, to firm f. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality and bank-year level, in column 1. The model is saturated with industry-location-size-time fixed effects in column 2. It adds firm-year fixed effects in column 3. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 6: Internal efficiency - Productivity and Credit quality

	(1) Ln (Loan/Empl.)	(2) Ln (Ext./Empl.)	(3) Asinh (NPLs/N. Loans)	(4) Asinh (NPLs(2y)/N. Loans)
DistanceUGS	-0.020**	-0.035***	0.001**	0.001*
× Post2001	(0.008)	(0.012)	(0.000)	(0.001)
Bank-Mun FE	X	X	X	X
Bank-Year FE	X	X	X	X
Mean	1.7	1120163.06	.01	.02
R-squared	0.816	0.803	0.303	0.475
N	124652	124652	124843	145491

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the bank-municipality-year level. The dependent variables are: *Ln(Loan/Empl.)*, the natural logarithm of the ratio between the number of loans and the number of branch employees; *Ln(Ext./Empl.)*, the natural logarithm of the ratio between the amount of credit and the number of branch employees; *Asinh(NPLs/N. Loans)*, the inverse hyperbolic sine of the share of nonperforming loans on total loans; and *Asinh(NPLs(2y)/N. Loans)*, the inverse hyperbolic sine of the share of nonperforming loans (in two years) on total loans. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality and bank-year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 7: Geography of the loans at origination

	(1) Share (Diff. Prov.)	(2) Asinh (Distance)
DistanceUGS	-0.008***	-0.023*
× Post2001	(0.002)	(0.013)
Bank-Mun FE	X	X
Bank-Year FE	X	X
Mean	.16	17.87
R-squared	0.383	0.415
N	98099	94570

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the bank-municipality-year level and focuses on new loans. The dependent variables are: *Share(Diff. Prov.)*, the share of the loans originated outside the province of the branch; and *Asinh(Distance)*, the inverse hyperbolic sine of the average geodesic distance between the centroid of the municipality of the branch and the location of the firm. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality and bank-year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 8: Banks' competition

	(1) Ln (Competitors)	(2) HHI	(3) Share (Top 3)	(4) Share (Top 5)
DistanceUGS	-0.028***	0.005***	0.005***	0.005***
× Post2001	(0.004)	(0.001)	(0.001)	(0.001)
Mun FE	X	X	X	X
Year FE	X	X	X	X
Mean	2.90	.68	.96	.99
R-squared	0.936	0.930	0.670	0.331
N	50990	60888	60888	60888

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the municipality-year level. The dependent variables are: *Ln(Competitors)*, the natural logarithm of the number of competitors in municipality m and year t; *HHI*, the Herfindahl–Hirschman Index of bank deposits in municipality m and year t; *Share(Top 3)*, the share of deposits owned by top 3 banks in the municipality; and *Share(Top 5)*, the share of deposits owned by top 5 banks in the municipality. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the municipality and year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 9: Extended credit - Information-sensitive loans

	(1) Info-sensitive	(2) Term loans	(3) Credit lines	(4) Loans BbR
	Ln (Ext. Credit)	Ln (Ext. Credit)	Ln (Ext. Credit)	Ln (Ext. Credit)
DistanceUGS	-0.043***	0.009	-0.015***	-0.040***
$\times$ Post2001	(0.005)	(0.011)	(0.004)	(0.006)
Controls	X	X	X	X
Bank-Mun FE	X	X	X	X
Bank-Year FE	X	X	X	X
Firm-Year FE	X	X	X	X
Mean	916266.29	1666857.72	888465.77	939235.79
R-squared	0.788	0.713	0.816	0.754
N	2226234	1132318	2060444	1746719

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the firm-bank-municipality-year level. The dependent variable is *Ln(Ext. Credit)*, the natural logarithm of the amount of loans granted by bank b, in municipality m, to firm f, in year t. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. Column 1 refers to the most information-sensitive types of contracts: credit lines and loans backed by receivables. Column 2 refers to term loans. Columns 3 and 4 further decompose the information-sensitive contracts. *Controls* refer to the (one-year lagged) share of credit lines on total extended credit to firm f, by bank b, in municipality m; and the (one-year lagged) share of extended credit issued by bank b, in municipality m, to firm f. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality, bank-year, and firm-year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 10: Extended credit - Branch-borrower vs Branch-HQ

	(1) W/out 25th pc	(2) W/out 50th pc	(3) W/out 75th pc	(4) Diff. HQ Prov.	(5) Same HQ Prov.
	Ln (Ext. Credit)	Ln (Ext. Credit)	Ln (Ext. Credit)	Ln (Ext. Credit)	Ln (Ext. Credit)
DistanceUGS	-0.016*	-0.014	-0.011	-0.016***	-0.001
$\times$ Post2001	(0.009)	(0.010)	(0.011)	(0.004)	(0.007)
Controls	X	X	X	X	X
Bank-Mun FE	X	X	X	X	X
Bank-Year FE	X	X	X	X	X
ILST FE				X	X
Firm-Year FE	X	X	X		
Mean	961766.52	1000414	1030260.81	1121289.72	1252514.81
R-squared	0.861	0.864	0.867	0.538	0.548
N	949155	510478	180559	2275563	570902

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the firm-bank-municipality-year level. The dependent variable is *Ln(Ext. Credit)*, the natural logarithm of the amount of loans granted by bank b, in municipality m, to firm f, in year t. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. Columns 1 to 3 refer to branch-firm connections. Columns 4 and 5 look at branches in different (same) provinces with respect to the headquarter. *Controls* refer to the (one-year lagged) share of credit lines on total extended credit to firm f, by bank b, in municipality m; and the (one-year lagged) share of extended credit issued by bank b, in municipality m, to firm f. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality, bank-year, and firm-year (or industry-location-size-year) levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 11: Screening: Credit score at origination

	(1) Ln (Credit Score)	(2) Dummy (Risky Score)
DistanceUGS	-0.001	0.002
× Post2001	(0.003)	(0.003)
Bank-Mun FE	X	X
Bank-Year FE	X	X
Firm FE	X	X
Mean	4.96	.25
R-squared	0.792	0.635
N	494229	494229

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the firm-bank-municipality-year level and focuses on new loans. The dependent variables are: *Ln(Credit Score)*, the natural logarithm of the firm z-score; and *Dummy(Risky Score)*, a dummy variable indicating whether the firm z-score is above 6 (risky). The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality, firm, and bank-year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 12: Screening: Standard deviation of rates at origination

	(1) Sd (Rates)	(2) Sd (Rates)
DistanceUGS	0.000	0.023
× Post2001	(0.045)	(0.046)
Bank-Mun FE	X	
Bank-Mun-Score FE		X
Bank-Year FE	X	X
Mean	2.07	2.12
R-squared	0.206	0.362
N	52183	39884

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the bank-municipality-year level, for new loans. The dependent variable is *Sd(Rate)*, the standard deviation of the interest rates by bank b, in municipality m, in year t. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality and bank-year levels. In column 2, we also add bank-municipality-z score fixed effects. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 13: Screening: Information queries at origination

	(1) Dummy (Query)	(2) Dummy (Synthetic)	(3) Ln (Delta)
DistanceUGS	0.006	-0.011	-0.004
$\times$ Post2001	(0.006)	(0.009)	(0.009)
Bank-Mun FE	X	X	X
Bank-Year FE	X	X	X
Firm FE	X	X	X
Mean	.54	.23	93.74
R-squared	0.529	0.731	0.506
N	337761	146557	146557

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the firm-bank-municipality-year level and focuses on new loans. The dependent variables are: *Query*, the probability that the branch asks for a query about the firm; *Dummy (Synthetic)*, a dummy for the request being synthetic; and *Ln(Delta)*, the natural logarithm of the number of credit history days asked in the query. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality, bank-year, and firm level. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 14: (No) Score - (No) History at origination

	(1) Dummy (no Credit Score)	(2) Dummy (no in CR)
DistanceUGS	-0.002*	-0.010**
× Post2001	(0.001)	(0.005)
Bank-Mun FE	X	X
Bank-Year FE	X	X
Firm FE	X	X
Mean	.02	.3
R-squared	0.644	0.604
N	506813	687603

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the firm-bank-municipality-year level and focuses on new loans. The dependent variables are: *Dummy(no Credit Score)*, a variable that indicates a firm without a z-score; *Dummy(no in CR)*, a dummy variable that indicates a firm not being already in the credit register. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality, bank-year, and firm levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 15: Monitoring: Standard deviation of rates during the relationship

	(1) Sd (Rates)	(2) Sd (Rates)
DistanceUGS	-0.029**	-0.035***
× Post2001	(0.012)	(0.013)
Bank-Mun FE	X	
Bank-Mun-Score FE		X
Bank-Year FE	X	X
Mean	2.02	2.03
R-squared	0.182	0.348
N	244989	232636

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the bank-municipality-year level. The dependent variable is *Sd(Rate)*, the standard deviation of the interest rates by bank b, in municipality m, in year t. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality and bank-year levels. In column 2, we also add bank-municipality-z score fixed effects. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 16: Monitoring: Number of Inquiries during the credit relationship

	(1) Dummy (Query)	(2) Asinh (N. Inquiries)	(3) Asinh (N. Inquiries)	(4) Asinh (N. Inquiries)
DistanceUGS	-0.003*	-0.003**	-0.005*	-0.049***
$\times$ Post2001	(0.001)	(0.001)	(0.003)	(0.006)
Bank-Mun FE	X	X	X	X
Bank-Year FE	X	X	X	X
Firm FE			X	
Firm-Year FE	X	X		
Mean	.05	.07	.22	.92
R-squared	0.411	0.407	0.386	0.730
N	1541280	1541280	554625	117412

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the bank-municipality-year level. The dependent variables are: *Query*, the probability that the branch asks for a query about the firm; and *Ln(N. Inquires)*, the natural logarithm of the number of inquiries made by bank b, in municipality m, in year t, to firm f, after originating a loan. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality and bank-year levels. In columns 1 and 2, we saturate the model with firm-year fixed effects. In column 3, we add firm fixed effects. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 17: Extended credit - Firms' heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
		Size			Riskiness	
	Micro	Small-Medium	Large	Safe	Vulnerable	Risky
	Ln (Ext. Credit)	Ln (Ext. Credit)	Ln (Ext. Credit)	Ln (Ext. Credit)	Ln (Ext. Credit)	Ln (Ext. Credit)
DistanceUGS	-0.001	-0.014**	-0.014	-0.011	-0.013*	-0.018***
$\times$ Post2001	(0.006)	(0.007)	(0.013)	(0.009)	(0.007)	(0.005)
Controls	X	X	X	X	X	X
Bank-Mun FE	X	X	X	X	X	X
Bank-Year FE	X	X	X	X	X	X
Firm-Year FE	X	X	X	X	X	X
Mean	327724.23	708302.07	7140432.43	1237072.46	1219495.00	1192879.33
R-squared	0.860	0.849	0.744	0.865	0.858	0.856
N	689344	2316732	201215	1980588	848046	531022

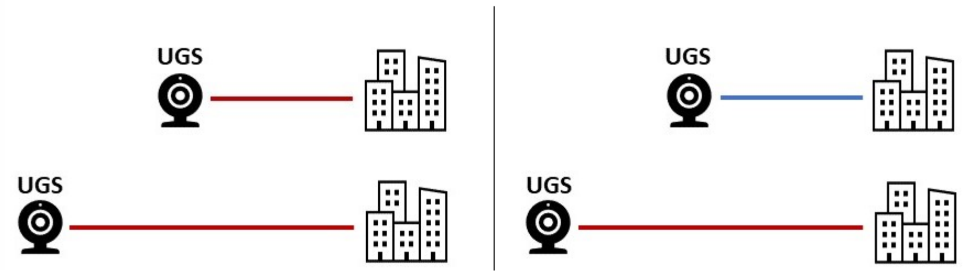
Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the firm-bank-municipality-year level. The dependent variable is *Ln(Ext. Credit)*, the natural logarithm of the amount of loans granted by bank b, in municipality m, to firm f, in year t. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. Firm size is measured using data from *INPS*, the Italian National Institute for Social Security, and it is defined following EU directives. Micro firms have sales turnover lower than 2ml of euros. Small and medium firms have sales turnover higher than 2ml but lower than 43ml of euros. Large firms have sales turnover higher than 43ml of euros. A firm is *Safe* if its z-score is below 5. A firm is *Vulnerable* if its z-score is between 5 and 6. A firm is *Risky* if its z-score is above 6. *Controls* refer to the (one-year lagged) share of credit lines on total extended credit to firm f, by bank b, in municipality m; and the (one-year lagged) share of extended credit issued by bank b, in municipality m, to firm f. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality, bank-year, and firm-year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Internet Appendix to

When broadband comes to banks: credit supply, market structure, and information acquisition

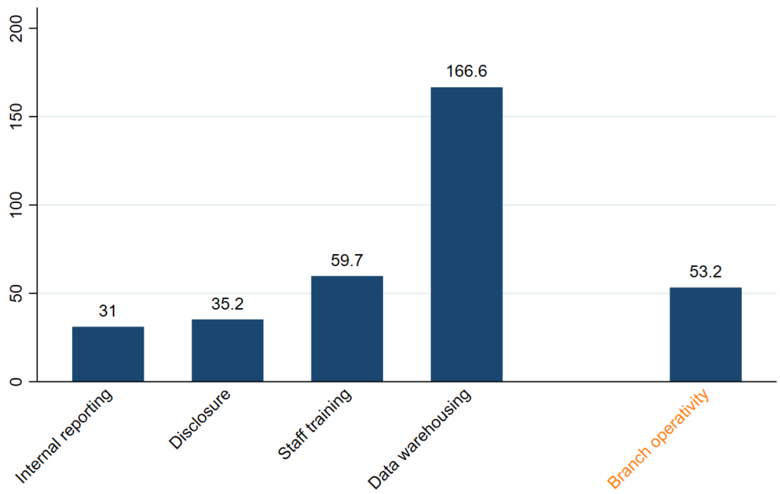
Appendix A Additional Figures

Figure A1: A simple graph on Identification



Notes: Identification strategy. On the left, we report the pre-broadband period, namely the period before 2002. Here, the distance of the municipality of the branch from the closest UGS is an irrelevant feature. On the right, we report the post-broadband period. Once the ADSL is available, the distance of the municipality of the branch from the closest UGS becomes crucial. The closer the municipality is to the UGS, the lower the cost of accessing the new technology, and the higher the probability of being an early adopter. We integrate this methodology with firm-time fixed effects to isolate credit supply.

Figure A2: Banks' usage of web technologies



Notes: Bank usage of web technologies. This graph reports the percentage growth in the use of web technologies by Italian banks, per type of activity, during the period 2001-2007. Source: Economic Analysis - Italian Banking Association (ABI).

Appendix B Additional Tables

Table B1: Balance Table on Pre-determined municipality characteristics

	(1) Close	(2) Far	(3) Norm. diff.	(4) Obs.
Area (Sq. Km)	33.82	55.16	**(-.27)**	5071
Altitude (meters)	212.24	362.75	**(-.41)**	5071
Coast	.10	.10	(0)	5071
South	.22	.32	(-.17)	5258
Distance prov. capital	17.37	27.26	**(-.58)**	5212
Pop. young	2859.01	976.28	(.16)	5258
Pop. adults	7540.14	2434.46	(.15)	5258
Pop. old	2790.74	1004.22	(.13)	5258
Pop. university	1248.14	243.21	(.11)	5258
Families	5894.16	1944.1	(.14)	5258
Foreigners	380.81	110.72	(.10)	5258
Houses	6844.39	2781.27	(.13)	5258
Buildings	2547.41	1717.6	(.16)	5258
N. firms	1239.12	373.92	(.14)	5258
N. employees	4626.47	1191.72	(.14)	5258
SL per capita	.26	.47	**(-.37)**	5258
UGS per capita	.01	0	(.25)	5258

Notes: This table reports a balance table on average municipalities' characteristics in 2001. Column 1 refers to municipalities that are below the median distance from the closest UGS. Column 2 refers to municipalities that are above the median distance from the closest UGS. Column 3 reports the normalized difference as proposed in Imbens and Wooldridge (2009). This is the difference in averages by treatment status, scaled by the square root of the sum of the variances, and represents a scale-free measure of the difference in distributions. Values exceeding 0.25 are considered sensitive for linear regressions. Finally, column 4 reports the number of observations. The list of covariates under evaluation is the following: *Area*, is the total area, in square kilometers, of the municipality; *Altitude*, is an indicator of the altimetric zone; *Coast*, is a dummy variable for the municipality being on the coast; *South*, is a dummy variable for the municipality being in the South of the country; *Distance prov. capital*, is the distance, in kilometers, from the province capital; *Pop. young*, is the number of young people; *Pop. adults*, is the number of adult people; *Pop. old*, is the number of elderly people; *Pop. university*, is the number of people with a university degree; *Families*, is the number of families; *Foreigners*, is the number of foreign people; *Houses*, is the number of houses; *Buildings*, is the number of buildings; *N. firms*, is the number of active private firms; *N. employees*, is the number of employees working in private firms; *SL per capita*, is the number of SL divided by total population; *UGS per capita*, is the number of UGS divided by total population. Most of these data come from the ISTAT census of 2001.

Table B2: Extended credit and Interest rates - with controls

	(1) Ln (Ext. Credit)	(2) Avg (Rate)
DistanceUGS	-0.011**	0.036**
$\times$ Post2001	(0.006)	(0.017)
Controls	X	X
Controls 2	X	X
Bank-Mun FE	X	X
Bank-Year FE	X	X
Firm-Year FE	X	X
Mean	1224550.35	6.38
R-squared	0.862	0.681
N	2511703	1094002

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the firm-bank-municipality-year level. The dependent variables are: *Ln(Ext. Credit)*, the natural logarithm of the amount of loans granted by bank b, in municipality m, to firm f, in year t; *Avg(Rate)*, the average interest rate charged by bank b, in municipality m, to firm f, in year t. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Controls* refer to the (one-year lagged) share of credit lines on total extended credit to firm f, by bank b, in municipality m; and the (one-year lagged) share of extended credit issued by bank b, in municipality m, to firm f. *Controls 2* refers to some municipality characteristics (total and elderly population, the number of private firms operating in the municipality, the number of employees, and the distance from the provincial capital) interacted with a second-order polynomial-time trend. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality, bank-year, and firm-year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table B3: Extended credit and Interest rates - without large cities

	(1) Ln (Ext. Credit)	(2) Avg (Rate)
DistanceUGS	-0.024***	0.051***
× Post2001	(0.005)	(0.015)
Controls	X	X
Bank-Mun FE	X	X
Bank-Year FE	X	X
Firm-Year FE	X	X
Mean	1017539.33	6.33
R-squared	0.874	0.682
N	2153678	954705

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the firm-bank-municipality-year level. The dependent variables are: *Ln(Ext. Credit)*, the natural logarithm of the amount of loans granted by bank b, in municipality m, to firm f, in year t; *Avg(Rate)*, the average interest rate charged by bank b, in municipality m, to firm f, in year t. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Controls* refer to the (one-year lagged) share of credit lines on total extended credit to firm f, by bank b, in municipality m; and the (one-year lagged) share of extended credit issued by bank b, in municipality m, to firm f. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality, bank-year, and firm-year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table B4: Extended credit and Interest rates - placebo

	(1) Ln (Ext. Credit)	(2) Avg (Rate)
DistanceUGS	0.001	0.028
× Post2001	(0.004)	(0.022)
Controls	X	X
Bank-Mun FE	X	X
Bank-Year FE	X	X
Firm-Year FE	X	X
Mean	1056604.90	6.72
R-squared	0.861	0.710
N	594672	218318

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the firm-bank-municipality-year level, for years from 1998 to 2001. The dependent variables are: *Ln(Ext. Credit)*, the natural logarithm of the amount of loans granted by bank b, in municipality m, to firm f, in year t; *Avg(Rate)*, the average interest rate by bank b, in municipality m, to firm f, in year t. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Controls* refer to the (one-year lagged) share of credit lines on total extended credit to firm f, by bank b, in municipality m; and the (one-year lagged) share of extended credit issued by bank b, in municipality m, to firm f. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality, bank-year, and firm-year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table B5: Extended credit and Interest rates - bank specialization

	(1) Ln (Ext. Credit)	(2) Avg (Rate)
DistanceUGS	-0.016**	0.039***
× Post2001	(0.007)	(0.014)
Controls	X	X
Bank-Mun FE	X	X
Bank-Year FE	X	X
Firm-Year FE	X	X
Mean	1223090.41	6.38
R-squared	0.862	0.681
N	2520498	1098313

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the firm-bank-municipality-year level. The dependent variables are: *Ln(Ext. Credit)*, the natural logarithm of the amount of loans granted by bank b, in municipality m, to firm f, in year t; *Avg(Rate)*, the average interest rate by bank b, in municipality m, to firm f, in year t. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Controls* refer to the (one-year lagged) share of credit lines on total extended credit to firm f, by bank b, in municipality m; and the (one-year lagged) share of extended credit issued by bank b, in municipality m, to firm f. In this regression, we add a control for bank-industry specialization following Benetton and Fantino (2021). *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality, bank-year, and firm-year levels. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table B6: Information queries at origination - full sample

	(1) Dummy (Query)	(2) Dummy (Synthetic)	(3) Ln (Delta)
DistanceUGS $\times$ Post2001	0.014*** (0.005)	-0.012* (0.006)	-0.002 (0.006)
Bank-Mun FE	X	X	X
Bank-Year FE	X	X	X
Firm FE	X	X	X
Mean	.45	.24	99.97
R-squared	0.398	0.602	0.415
N	686387	268573	268573

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the firm-bank-municipality-year level and refers to the full sample. The dependent variables are: *Query*, the probability that the branch asks for a query about the firm; *Dummy (Synthetic)*, a dummy variable for the request being synthetic; and *Ln(Delta)*, the natural logarithm of the number of credit history days asked in the query. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality, bank-year, and firm level. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table B7: Number of inquiries - full sample

	(1) Dummy (Query)	(2) Asinh (N. Inquires)	(3) Asinh (N. Inquires)	(4) Asinh (N. Inquires)
DistanceUGS	-0.001	-0.001	-0.010***	-0.029***
$\times$ Post2001	(0.001)	(0.001)	(0.003)	(0.006)
Bank-Mun FE	X	X	X	X
Bank-Year FE	X	X	X	X
Firm FE			X	
Firm-Year FE	X	X		
Mean	.09	.09	.21	2.29
R-squared	0.372	0.367	0.329	0.798
N	3008063	3008063	1015807	128934

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the bank-municipality-year level and refers to the full sample. The dependent variables are: *Query*, the probability that the branch asks for a query about the firm; and *Ln(N. Inquires)*, the natural logarithm of the number of inquiries made by bank b, in municipality m, in year t, to firm f, after originating a loan. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. *Mean* refers to the mean of the dependent variable; *R-squared* is the R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality and bank-year levels. In columns 1 and 2, we saturate the model with firm-year fixed effects. In column 3, we add firm fixed effects. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table B8: Extended credit - Banks' heterogeneity

	(1) Medium-High ICT Ln (Ext. Credit)	(2) Low ICT Ln (Ext. Credit)	(3) Banks Ln (Ext. Credit)	(4) CCs Ln (Ext. Credit)
DistanceUGS	-0.022***	0.004	-0.016***	0.010
× Post2001	(0.005)	(0.006)	(0.004)	(0.011)
Controls	X	X	X	X
Bank-Mun FE	X	X	X	X
Bank-Year FE	X	X	X	X
ILST FE	X	X	X	X
Mean	1168482.62	1076146.7	1188030.17	616788.02
R-squared	0.530	0.564	0.531	0.616
N	2151219	621675	2656174	211354

Notes: This table reports estimates from OLS regressions as presented in equation (2). The dataset is at the firm-bank-municipality-year level. The dependent variable is *Ln(Ext. Credit)*, the natural logarithm of the amount of loans granted by bank b, in municipality m, to firm f, in year t. The main predictor is the interaction between *Distance from UGS* (standardized) and a dummy variable *post2001*. Columns 1 and 2 refer to banks that are above the 25th percentile of the (scaled) ICT-investments distribution. Columns 3 and 4 refer to commercial banks and cooperative banks, respectively. *Controls* refer to the (one-year lagged) share of credit lines on total extended credit to firm f, by bank b, in municipality m; and the (one-year lagged) share of extended credit issued by bank b, in municipality m, to firm f. *Mean* refers to the mean of the dependent variable; *R-squared* is the adjusted R^2; and *N.* refers to the number of observations. Fixed effects are at the bank-municipality, bank-year, and industry-location-size-year level. Standard errors, in parentheses, are clustered at the municipality level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.