Development through
the Private Sector Series
June 2023

TN
No. 36

Access to Credit and the Expansion of Broadband Internet in Peru

Authors:
Antonio Cusato Novelli
José Luis Castillo Mezarina

Access to Credit and the Expansion of Broadband Internet in Peru

Cover page design: David Peña Blanco

June 2023

Access to Credit and the Expansion of Broadband Internet in Peru[*]

Antonio Cusato Novelli[†] José Luis Castillo Mezarina[‡]

June 2023

We exploit the staggered expansion of the internet broadband network to firms and bank branches locations in Peru during the last decade to study non-financial firm performance and bank credit dynamics. Access to broadband unleashes firm growth, increases the chances of entry of firms and reduces the probability of exit in benefited locations. For those firms that had a borrowing relation with a bank before the expansion of broadband, the increase in sales serves as a signal to banks about their profitability, which in turn respond by providing more credit. Entry and exit from the credit market follows a similar pattern as in the case of firms, but the results take longer to materialize after the shock. We can disentangle supply and demand effects, since there is a group of firms and bank branches with different locations and asymmetrical timing for the availability of the technology. Our analysis highlights the importance of the demand channel in the reduction of the observed interest rates, which is consistent with the fact that our credit market results are concentrated among micro and small firms, and firms with thin credit files, which are often perceived as riskier.

Keywords: Broadband internet; Technological Change; Banks; Credit

JEL classification: O33; L86; G21

[*] This study was financed by the Latin America and the Caribbean Research Network of the Inter-American Development Bank Group as part of the project "Financial Inclusion in Latin America and the Caribbean." We would like to thank Alonso Palacios and Claudio Ortega for their excellent research assistance. Also, the project could not have been implemented without Martin Naranjo of the Peruvian Association of Banks, who facilitated the data on credit. We would also like to thank Diego Vera-Cossio, Billy Jack, Daniel Romero and participants at the IDB-IDB Invest Seminar on Financial Inclusion in LAC for their comments. All errors and omissions are the responsibility of the authors.

[†] Universidad del Pacífico, email: a.cusaton@up.edu.pe

[‡] Universitat de Barcelona, email: jlcastillo@ub.edu

1 Introduction

The well-documented correlation between growth and financial development (Levine, 1997) makes financial frictions the single most studied explanation for low levels of firm productivity and misallocation of resources in developing countries (Restuccia and Rogerson, 2017). We aim to make progress on the identification of the causal effect of technology, measure by access to internet broadband technology at the firm and bank level, on credit market frictions and outcomes. We look at the universe of firms with access to credit in the period 2010-2019 in Peru, an emerging market that registered one of the strongest reductions of interest rates during the period, but still reports relatively high levels in relation to other economies.[1] In our paper we document a sequential timing between the arrival of the technology, the improvement of cash flows associated with firm operations, and an increase in borrowing coupled with a reduction in interest rates. Our credit market results are mainly driven by micro-small firms with thin credit files, which suggests that broadband internet can help to relax borrowing constraints (Stiglitz and Weiss, 1981).

The literature that studies shocks to the financial system and the identification of borrowing constraints has typically exploited quasi-exogenous variations in the supply of credit. For example, Khwaja and Mian (2008) study the impact of bank liquidity shocks in Pakistan associated with the collapse of sources of bank's funding in dollars due to an anticipated nuclear test. Banerjee and Duflo (2014) characterizes financially constrained firms analyzing the changes in the eligibility of a targeted lending program in India. Banerjee et al. (2019) use the implementation of a large credit-expansion government program in Thailand to study its impact conditioned on pre-intervention productivity, finding evidence that credit constraints are binding for high productivity households. Paravisini et al. (2014) study the effects of the presence of financially constrained firms in Peru on export performance as a result of a contraction of credit associated with the reduction of banking foreign funding. More recently, Breza and Kinnan (2021) takes advantage of a media scandal about microfinance practices in India, which triggered a government legal response resulting in a massive contraction in the supply of credit, to study the aggregate consequences of the shock. Instead of focusing uniquely on the changes of the supply of credit, we analyze technology shocks to the supply and demand of bank intermediation, exploiting the non-simultaneous arrival of broadband at firms and banks located in different areas.

We start our analysis by geolocating the universe of firms that accessed credit in Peru during 2014 and 2020, and combining this information with the expansion of the broadband network during the same period, where the data on the roll-out is at the level of the smallest administrative division of the country. The staggered roll-out of the national network of fiber optic cables followed a concession in 2014 that connected 180 of the country's 196 provincial capitals. The network allowed consumers and firms to access FTTX (fiber to the X) technology, the fastest technology available. In the following two years, 2015-2017, the average cost per Mbps fell 65%, indicating an increase in competition of operators after the rollout. Importantly, the expansion of the network provides considerable variation in firm's and bank's technology availability across small locations and over time. In addition to this, we show that the expansion of the network is not correlated with baseline characteristics of each location, including credit market outcomes (total credit, number of firms borrowing, number of loans, the size of the firm measure by the number of workers) or population. We do find that certain periods of expansion are explained by measures of distance, where the reference is the capital of the country or the nearest airport. In our baseline specification we account for this issue.

Then we analyze credit market dynamics using a staggered DiD approach, following Sun and Abraham (2021) and focusing on the pre-rollout firm-banks relationships. We find that total credit outstanding per firm starts its expansion four years after the arrival of the network to the area where the firm is located. The increase in credit at the fifth year is a little less than 40%. To implement this estimation, we use the never-treated firms as counterfactual and check the robustness of our results using the last-treated firms. In addition to total credit, we document an expansion in the number of banks that serve a firm, finding the same timing as total credit and an

[1] Comparing data for small and medium firms in advanced and emerging economies, OECD (2020) reports: i) Peru registered the second-largest decrease in rates among 35 countries with data availability between 2018 and 2010, and ii) the country shows the highest interest rate in 2018 among 43 countries (the study analyzes 48 countries, with full data availability for other variables). Naturally, both points are indicative of the potential relaxation and existence of borrowing constraints, respectively.

effect of 20% at year five. The same occurs with the number of loans per firm-bank relationship, with an effect of 5%. In order to look at the entry and exit of firms from the credit market, we aggregate the number of firms with credit at each location, and we calculate the share of firms that enter the market in a particular year, and the share of firms of the previous period that did not register credit in the current period. We find positive effects on entry only after three and four years of the technology shock, while the reduction in exit is reported after the second year.

In terms of the intensive margin indicators, we analyze the size of credit per firm-branch, as well as interest rates. We analyze those firm-branch relations with the same or different locations. When the area of bank branches does not coincide with those of firms, we can look at the early arrival of broadband only at the location of banks, as well as the early arrival of the technology only at the location of firms. While we do not observe an effect for the average size of the loan at the firm-branch level, for those firms and branches that share the same location and for those firms affected early by the arrival of the technology, we find a reduction of interest rates of 4 percentage points. Differently, we find not effects for those relationships where only the bank branch is affected by the arrival of the technology. As noted above, this is a first indication that our results are mainly driven by the demand side channel.

To understand better our findings, we repeat our exercises by firm's size and firm's credit file "thickness." We use an indicator of the Peruvian tax authority to classify firms as micro, small, medium or large, using the information one year before the deployment of the network as the point of reference for the analysis (year 2013). Our measure of credit file "thickness" is the number of loans a firm has in the financial system and we also use the information one year before the beginning of the roll-out of the network. We find that our results about the increase in the average credit for a firm is explained by micro and small firms, as well as firms with thin credit files (just one credit relationship in the system). As pointed out by Abraham and Schmukler (2017), smaller firms are considered more "opaque" than larger firms, simply because they have less public information. Hence, lending depends more on "soft information" collected by bank officials through personalized contacts (Liberti and Petersen, 2018). In the context of our empirical results, broadband facilitates the collection of this information, conditioned on firms having access to the technology.

We complement our credit market analysis with indicators of the firm's performance. In particular, we use the data on the tax authority's registry and an indicator for firm sales ranges (with fifteen categories), to take a look at the intensive margin of firm's performance for the universe of non-financial firms in Peru. For all types of firms, broadband generates a short-term positive shock to our proxy of firm's income. Our estimated impacts are interesting because of their timing; they start one year after the arrival of broadband and peak in year three; these differences begin to diminish in year four. In terms of the extensive margin and the entry and exit of firms at the affected locations, again our results are concentrated in the first years. In the case of exit, we observe a reduction in the probability only one and two periods after the arrival of the technology, while for entry the increase in the probability is concentrated in three and four periods after the shock. As noted above, our credit market results at the firm level only take place at year four, hence, the sequential timing of the mechanism seems clear: after the shock, firms performance improves, and only thereafter are banks willing to provide more funds to firms.

Since we work with a proxy of sales of firms (an indicator for sales ranges), we confirm these results looking at the *Encuesta Nacional de Empresas*, finding the same positive and short-term effects in terms of value added, number of workers, and labor productivity for the case of large firms. The survey's information for other firm size categories is basically cross-sectional, limiting our analysis to the biggest firms. Finally, we discard two potential threats to our identification strategy, the construction of the broadband network, and the expansion of other types of infrastructure. In the first case, we argue that the magnitude of the financial investment per kilometer of the network is negligible and represents only 3% of the investment per kilometer in the construction of highways in Peru. In the second case, we use government public procurement information to show that the expansion of the network does not affect investment projects. To confirm our results, we use the same source and focus on the purchase of goods and services via a government electronic platform, finding positive effects of broadband in this case, as expected.

Related Literature. Our paper is closely related to the literature on information technology and banking competition. Hauswald and Marquez (2003) provides an ambiguous prediction of the effect of technology on competition and interest rates. Focusing just on the effects of information technology on the supply side of credit, an improvement in technology increases the informational advantage of banks that invest in gathering information over those that do not invest, reducing competition and increasing interest rates for borrowers. The author's key assumption is the existence of banks that cannot invest in technology–in other words, higher technology can boost competition and reduce interest rates inly if information is disseminated to other market participants (information externality assumption).

Vives and Ye (2022) also analyze the effects of better information technology on credit market outcomes. In their model, banks face a cost of monitoring/screening that is increasing in the wedge between bank expertise and entrepreneurs project characteristics, denoted by the distance between the bank and the entrepreneur (alternatively, one can interpret this wedge as the physical distance). Investments in information technology can reduce the cost of monitoring/screening without affecting the distance if, for example, the bank buys information management software (that is not specific to the relationship). Also, investments can reduce the distance if, for example, they facilitate the transmission of information for the specific bank-entrepreneur relationship (e.g., investment in communication facilities that allows the exchange of information and opinions within the bank branching network, or between the local borrower and the distant bank headquarters). If investments affects one bank, the situation is as in Hauswald and Marquez (2003), where competition is reduced and banks can charge higher interest rates. If investments affects two banks and if monitoring costs are less affected by distance (as a result of a better information technology), then competition increases and interest rates offered by banks are lower. On the contrary, if investments affect two banks and distance is not affected, then rates do not vary.

In our paper we provide empirical evidence that can be associated with the conditional predictions of Vives and Ye (2022). When broadband arrives only at the branch location, it probably does not affect the distance between banks and firms (since the later are not affected by the technology), and therefore there are no effects on interest rates. Differently, when FTTX technology reaches firms and banks, or at least firms (in our paper small and micro firms with "thin" credit files), the distance between lender and borrower is reduced, and consequently we observe effects on interest rates.

Mazet-Sonilhac (2022) looks at one step before the beginning of the firm-bank relationship, modeling a costly search process that firms perform to locate and match with a bank, in addition to the subsequent bank process of screening projects. His model provides a gravity equation for credit flows between cities, where a reduction in search costs (for example via the expansion of broadband internet) allows firms to meet with more banks and obtain a lower interest rate. Using data on the expansion of broadband internet in France, he shows an average increase of 10% in the share of credit to firms located outside the bank's city affected by the technology. Hence, the author looks at the effects over the supply of credit analyzing the characteristics on credit for those branches benefiting from broadband. Then, taking advantage of the structure of his model and estimated empirical parameters as well as calibrated ones, the author estimates that the expansion of broadband and the consequent reduction in search frictions reduce interest rates for small business by 4.9%. In the context of his model, the reduction of rates is more important in rural areas and medium-sized cities, highlighting the importance of search frictions in these cases. Differently from the author, we do not distinguish between search and informational frictions in our empirical analysis, nor do we study credit flows between cities. In our paper we use more granular data, and we provide direct evidence of the effects of broadband on interest rates, differentiating between the supply and demand channels of credit.

Perhaps the paper closest to ours is D'Andrea et al. (2021), which empirically estimates the effects of broadband on credit in Italy for loans above 30 thousand euros. They also document positive effects on credit, showing, as we do, that there are no effects during the first years of the roll-out. They focus on the supply channel of credit, showing an increase in the productivity of banks, an expansion of their geographical scope, an increase in competition, and a reduction of interest rates. Our results differ from D'Andrea et al. (2021), which assigns an relatively equal contribution to the supply and demand shocks of broadband in Italy, but only using information on the location of branches. We take advantage of the non-simultaneous arrival of broadband at bank-firm relations with different locations, to emphasize the relatively importance of the demand channel. In addition to this, we can discuss effects on micro firms, since we worked with the universe of loans to non-financial firms in Peru. In a previous project, D'Andrea and Limodio (2019) use information on interbank markets and credit at the bank level for African banks, to study the effects of high-speed internet. They use as a natural experiment the staggered arrival in Africa of fiber-optic submarine cables, exploiting the variability in the exact geography and timing of this event. Their results show an expansion of real-time transfers in the interbank market (due to a decrease in 98% in the cost of operating this system), increasing bank liquidity (or reducing liquidity hoarding), and promoting lending to the private sector.

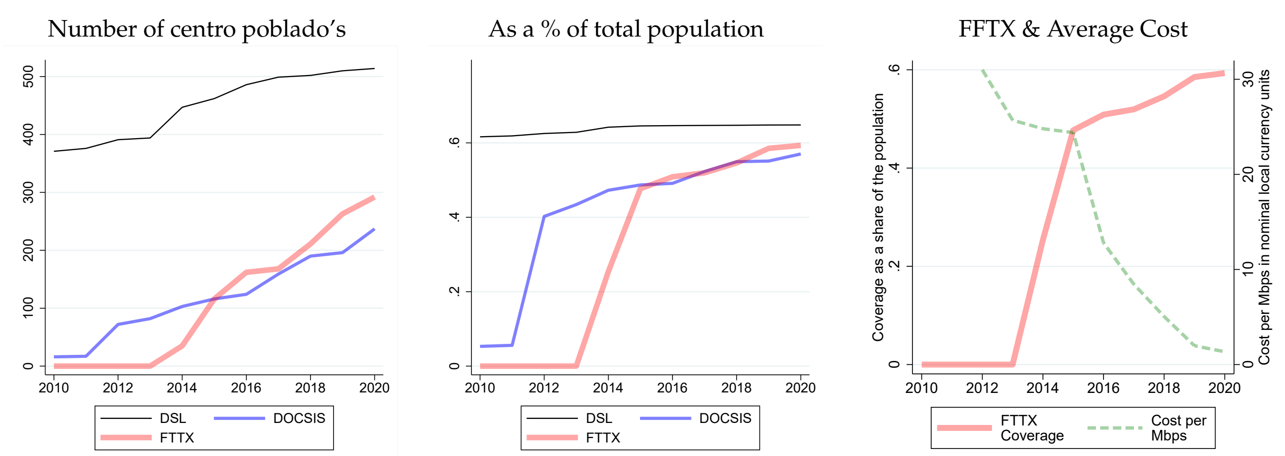
Naturally, our paper is also related to the growing literature that studies the effects of broadband internet. Hjort and Poulsen (2019) also exploits the staggered arrival of submarine cables in Africa to show positive effects on the labor market. Akerman et al. (2015), using Norwegian data, and Bergeaud et al. (2021), using French data, show a skilled-biased increase in the productivity of firms, with gains for skilled workers. Also with data from Norway, Hvide et al. (2022) studies how broadband increases participation in the stock market and closes the gap between individuals' investment decisions and those predicted by portfolio theory. For the same country, Bhuller et al. (2022) study how broadband affects search and hiring in the labor market, showing positive effects on job finding rates and starting wages, while Akerman et al. (2022) documents that broadband expansion lowers information frictions, making the trade patterns of exporters and importers more sensitive to distance and economic size.

2 Data and Context

2.1 Broadband Internet

We have data on broadband coverage at the level of centro poblado (CP), which is the smallest administrative jurisdiction in the country. This administrative division presents 24 regions, where these regions include 196 provinces, and provinces contain 1,874 districts, and those districts include 99 thousand CPs. Access at the CP level is represented by a dummy variable, and the source is the regulator of telecom in Peru (OSIPTEL). The focus of the analysis is on fixed broadband internet. Figure 1 shows the expansion of broadband internet by CP, according to the available technology. DSL technology refers to internet via copper cables, where the speed can be considered relatively low. DOCSIS and FTTX technologies are currently considered broadband technologies. The first uses a fiber-coaxial line to provide internet and provides an intermediate speed level. The second, FTTX, uses optic fiber network to provide the fastest type of internet. Figure 1 also shows the evolution of the average cost per Mbps in Peru.[2] As we can see, the biggest drop in prices occurs after one year of the initial and most important expansion in FTTX coverage (prices drop by 65% between 2015 and 2017).

Figure 1. Expansion of Broadband Internet by Centro Poblado and Cost per Mbps



In our intention to treat estimations we use the FTTX technology as a proxy of broadband expansion. First, according to Figure 1, it boosts competition and lowers prices, proving higher chances of affecting firms and

[2] See Muente Schwarz, R. (2017) for prices up to 2017, and the Peruvian regulator's web page https://punku.osiptel.gob.pe/ for more recent prices.

the credit market. Second, using the fastest technology (FTTX) has a important advantage. As pointed out by Analysys Mason (2020), the problem with copper and cable networks is that they suffer from attenuation. For this reason, while DSL and DOCSIS technologies might face problems at the intensive margin (quality), this is not the case for FTTX technology. Differently from this project, previous papers on the impact of broadband (Akerman et al., 2015; D'Andrea et al., 2021; Bhuller et al., 2022) use DSL technology as their measure of high speed internet, and face this quality problem. Third, since the expansion of the FTTX network started in 2014, we have four years of data before the introduction of this technology (our data on credit represent the period 2010-2020). Information prior to the expansion permits the assessment of the validity of our research design.

The fixed broadband network expansion (DOCSIS and FTTX technologies) in Peru is driven by private and public decisions that interact simultaneously (Argandoña and More, 2020). In the first case, telecommunications companies usually take into account potential demand in future broadband expansion areas, which is linked to population density and income. In the second case, the Peruvian state defines the areas to cover and then opens a tendering procedure in which telecommunication's companies compete to build and operate the infrastructure.

Based on our discussions with tgovernment telecom supervisor officials, we can divide the rollout of broadband (DOCSIS and FTTX) during the period 2010-2020 (in which we have data availability) into two steps. First, the expansion of the DOCSIS technology's infrastructure in the first four years of our sample was mainly driven by the private sector. This initial phase of the rollout of the network was related to those CPs located in the coast of Peru (where economic activity is concentrated and required smaller investments due to favorable geography). Since 2014, the expansion of the network via the FTTX technology included other regions (highlands and jungle areas) and was mainly driven by public sector design. In particular, during 2012 the law for broadband and the construction of the main network of fiber optic was approved (*Ley Nº 29904 – Ley de Promoción de la Banda Ancha y Construcción de la Red Dorsal Nacional de Fibra Óptica*). A key part of the rollout of infrastructure was due to the concession in 2014 of the country's main fiber optic network, which connected the capitals of 180 of the country's 196 provinces. Naturally, the design of this national network was carried out by government officials. The private sector responded to this concession with the expansion of its own optic fiber network, thus increasing market competition. It was in 2016 when the main network started its operations, and with the parallel expansion of the private network, generated the biggest drop in prices observed in our sample.[3]

2.2 Data on Firms and the Credit Registry

Our definition of credit to firms excludes credit to public firms and financial firms.[4] Since we are working with the universe of loans to firms in Peru, we are considering credit for working capital and investment. For example, Ivashina et al. (2022) use Peruvian credit registry data between 2001 and 2018 but account for heterogeneity in the types of loans (asset-based loans, cash-flow loans, trade finance agreements, and leases). Differently from us, they restrict their sample to exclude microfinance institutions and loans below approximately 6 million dollars to study the banking lending channel.

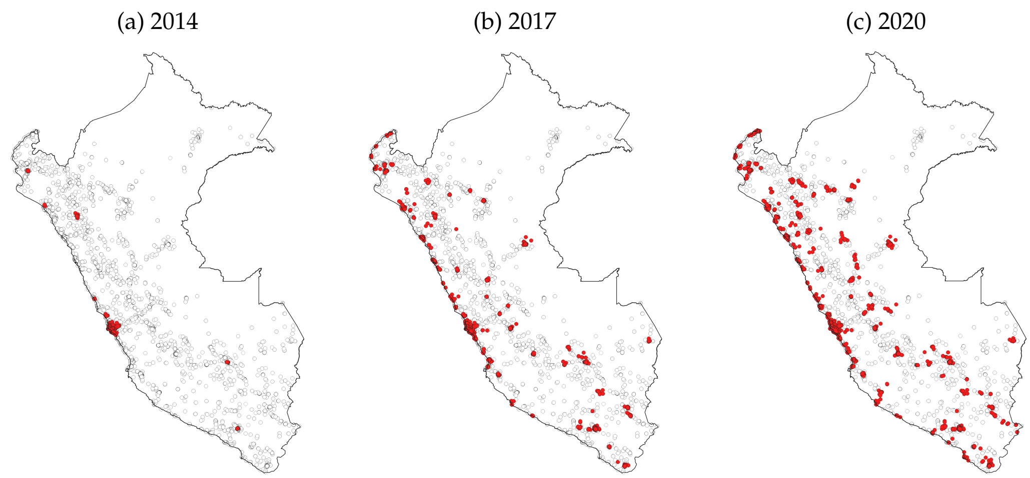
We combine information from the taxpayers registry with the credit bureau data. First, the Peruvian taxpayers registry includes information on the universe of formal firms (defined as those that pay taxes), with the exception of branches of foreign companies located in Peru. This registry contains the fiscal address of each firm, which allows us to geolocate the firms. We also have information on an indicator of a range of sales for each firm. The second database is the Peruvian credit registry, which includes information on the universe of loans and interest payments of firms and persons. Our focus of analysis is only on firms, since we do not have access to a database that provides addresses for persons. This limits the analysis to formal firms that pay taxes.

[3] At the end of 2016, once the national network started its operations, it covered 180 provincial capitals, while the second and third private operators cover 98 and 71 provinces, respectively (Pacheco, L. and More, J. and Argandoña, D., 2017). In 2018, demand for the main fiber optic network was considerably low in comparison to its capacity, since the contract stipulates a fixed cost per Mbps that the concessionaire must charge its clients. That price was relatively high in relation to those charged by other private sector operators, who enjoyed flexibility in setting prices. From the point of view of the concessionaire, the contract makes the government cover the losses or wedge between sales income and operation and investment costs (OSPITEL, 2018).

[4] We are considering corporate credit, and credit to big, medium, small and micro firms.

After combining the information of the two datasets, we have 235 thousand firms with positive outstanding credit for the period 2014-2020, which is the period of the rollout of broadband internet (FTTX technology). We were able to georeference 187 thousand firms, which represent 80% of all firms with positive outstanding credit. In Appendix 1 we report two features of this match (see Table A.1). If we aggregate the data at the *Bank - Firm - Centro Poblado - Year* level, the proportion of firms that we could not georeference is almost the same for micro, small, medium and large firms (between 18% and 19% of the observations). Second, we reject that there are relevant differences in the size of the loans for micro, small, and medium firms between those geolocated and those without location. For these reasons, we do not think that we face a major concern associated with our inability to georeference the universe of firms.

Figure 2. Firms with Access to Credit between 2014 and 2020 (circles), and Those with Access to Broadband Internet (red circles) at Different Points in Time (2014, 2017 and 2020)



Note: The three panels show all the firms with access to credit (in at least one year between 2014 and 2020) as circles (transparent or red). These are the 187.7 thousand firms that were geolocated using the firms' addresses. Among these firms, in red circles are those located in *centros poblados* with access to broadband internet (for three different years). Those with access to credit and broadband totalled 35.9 thousand, 82.2 thousand and 132.5 thousand firms in 2014, 2017 and 2020, respectively.

Figure 2 combines the information about the 187 thousand firms with the expansion of the broadband internet (FTTX technology). The figure shows that in 2014 FTTX technology (red circles) was available in the capital of Peru, Lima, and a few other cities, but the vast majority of firms did not have access to broadband internet. In 2020 there was an important increase of the availability of broadband, but still there were large parts of the country with firms accessing credit but not the FTTX technology (the circles without color). In sum, the figures show a substantial variation of the technology across locations (CPs) and firms with positive credit outstanding over time. Figure A.0 of Appendix 1 shows the map of the city of Cusco in 2014 and 2019, with the centro poblado that has access to broadband and firms with access to credit.

We impose two restrictions on the data. First, we limit the sample period to years between 2010 and 2019 in order to exclude the effects of the COVID crisis during 2020 and the Peruvian government's response. We are left with 155 thousand firms after excluding firms with credit in 2020. Second, to construct the counterfactual we use CPs where low-speed internet is available (DSL technology), or we exclude firms without internet access. This leaves us with 149 thousand firms in our sample.

To carry out the intensive margin analysis, we do not have information about the CP of each bank branch, we only know the district (as we describe before, it is a more aggregate administrative division than the CP). When we look at the data on credit, loans are classified into 92 accounting categories. For each accounting category and firm, we have the branch of the financial institution in charge of this relation, and consequently, we have information of the district for each category-firm pair. When we aggregate the data at the *Bank Branch - Firm - District - Year* level, a firm can have relations with one, two or more branches of the same bank, since it can have more than one type or accounting category of credit. Hence, our data allow us to make comparisons of a firm working with two different banks, as in most of the empirical literature of credit supply shocks, to make comparisons involving a firm working with two different branches of the same bank (with two different locations).

2.3 Estimation Sample

To get to our estimation sample, we restrict the analysis to firms with positive credit outstanding for the pre-roll-out period (from 2010 to the first year of the arrival of the technology, 2014). This approach follows the literature that has studied supply shocks to the banking system. Among the papers that impose this restriction are the seminal paper of Khwaja and Mian (2008), which uses granular data on loans in Pakistan to study the impact of liquidity shocks; Paravisini et al. (2014), which combines loan and export information at the firm-bank level in Peru to understand the effects of capital flow reversals on credit and export performance around the Great Recession of 2008; Bottero et al. (2020), which also uses the credit registry in Italy to analyze credit market dynamics in the context of the 2010 Greek bailout and the consequent tightening of the credit supply for banks with high exposure to Italian government bonds; and more recently Ivashina et al. (2022), which repeats the exercise of Paravisini et al. (2014) for the same Peruvian data, but accounts for heterogeneity in the types of loans.

Table 1. Descriptive Statistics, Extensive Margin Analysis for Credit

Data aggregated at the *Firm - Centro Poblado - Year* Level					
	Observations	Mean	sd	p10	p90
Total credit (LCU 000s) per firm from the FS [21,594 firms]	207,647	3,528	31,883	0.5	3,096
Without broadband	102,723	2,620	21,073	17.6	2,501
With broadband	104,924	4,417	39,691	0.0	3,838
Micro-Small [16,943 firms]	162,107	444	1,777	0.0	946
Without broadband	81,907	408	1,316	15.3	857
With broadband	80,200	480	2,148	0.0	1,045
Medium-Large [4,375 firms]	42,954	14,860	63,111	12.2	27,459
Without broadband	19,532	11,803	46,288	79.6	22,770
With broadband	23,422	17,409	74,186	1.5	31,758
Thin-Medium Credit File [16,003 firms]	164,693	573	14,164	0.0	967
Without broadband	83,191	464	4,569	14.8	875
With broadband	81,502	683	19,597	0.0	1,066
Thick Credit File [5,591 firms]	55,028	10,089	56,329	22.5	15,148
Without broadband	25,488	7,896	39,288	134.5	12,011
With broadband	29,540	11,981	67,611	0.0	17,988
Number of bank-firm relations	207,647	2.3	1.3	1.0	4.0
Without broadband	102,723	2.2	1.3	1.0	4.0
With broadband	104,924	2.3	1.3	1.0	4.0
Number of loans per firm-bank r.	207,647	1.7	1.5	0.5	3.0
Without broadband	102,723	1.8	1.4	1.0	3.0
With broadband	104,924	1.6	1.5	0.0	3.0
Exit (%)	207,647	0.08	0.27	0.00	0.00
Without broadband	102,723	0.01	0.12	0.00	0.00
With broadband	104,924	0.14	0.35	0.00	1.00

Note: LCU denotes Local Currency Unit, sd denotes standard deviation, p10 denotes the 10th percentile, and p90 denotes the 90th percentile. LCU are expressed in real terms (in soles of 2019).

For the extensive margin results (aggregating the data at the *Firm - Centro Poblado - Year* level), our estimating sample (207.6 thousand observations and 21.6 thousand firms) accounts for 30% of all observations for the window 2010-2019 and 78.0% of the total amount of performing credit during the same period. The important reduction in the final number of firms of the estimation sample is a direct result of the fact that more than half of the firms registered positive credit only during three years or less.

Table 1 shows the descriptive statistics for the estimation sample for the extensive margin analysis (*Firm - Centro Poblado - Year* aggregation level). Of the total number of firms, a little more than 21 thousand, we classify them by size using an indicator of sales range, and we also classify firms according to their credit file "thickness" using the number of loans the firm presents. In both cases, we use the indicator one year before the start of the roll-out of the infrastructure (the year 2013). In terms of the observations (triplets for *Firm - Centro Poblado - Year*) with and without access to broadband internet, we have a similar number of observations in both cases, even if we look at the subsamples by firm size or credit file "thickness." In terms of average outstanding credit (expressed in constant local currency units), differences in terms of access to broadband are not that big (around 1.3 times in favor of those with access), but differences in terms of firm size or credit file "thickness" are relatively important (33 and 17 times, respectively). Also, in our sample, firms typically have two relations with banks (or have credit with two banks), and on average each firm has almost 2 loans with each bank. In terms of our indicator of exit, those observations with access to internet have much higher chances of exiting the credit market (0.14 versus 0.01 on average).

Table 2. Descriptive Statistics, Intensive Margin Analysis for Credit

Data aggregated at the *Bank Branch - Firm - District - Year* Level	Observations	Mean	sd	p10	p90
Total credit (LCU 000s) per bank-firm [6,950 firms]	42,507	3,212	23,666	1.6	3,881
Without broadband	21,335	2,436	19,264	12.0	3,076
With broadband in banks & firms	17,698	4,138	27,315	0.0	5,516
With broadband only for banks (3 years window)	2,727	3,090	29,824	0.1	1,945
With broadband only for firms (3 years window)	747	3,858	17,620	0.0	8,376
Interest payments / outstanding loan per bank-firm	42,480	0.10	0.10	0.02	0.20
Without broadband	21,332	0.09	0.08	0.01	0.17
With broadband in banks & firms	17,680	0.11	0.11	0.03	0.22
With broadband only for banks (3 years window)	2,721	0.13	0.11	0.03	0.26
With broadband only for firms (3 years window)	747	0.10	0.11	0.03	0.19

Note: LCU denotes Local Currency Unit, sd denotes standard deviation, p10 denotes the 10th percentile, and p90 denotes the 90th percentile. LCU are expressed in real terms (in soles of 2019).

For the intensive margin analysis, the level of aggregation of the data is at *Bank Branch - Firm - District - Year*. Since we have the location of firms and branches at a higher level of aggregation (at the district level), we can construct a measure of broadband availability at the district level z_{dt}, weighting access by population. Then, we define the arrival of FTTX technology at the district level if it is available for at least 90% of the population. Given that we have the location of firms and branches, we can look at the following cases: (a) firms and branches located in the same district, (b) firms and branches with different locations where broadband first arrived at the branch's district, and (c) firms and branches with different locations where broadband arrived first at the firm's district. We focus on these cases for the intensive analysis. Also, for cases (b) and (c), we impose that if broadband is available for the first time in year t at the firm's [branch] district, then the technology should be absent in the branch's [firm] district in periods t, $t+1$ and $t+2$, or we look for cases in which broadband is available for a three-year window on one side (firm or branch). Finally, following Khwaja and Mian (2008), we restrict the sample for the intensive analysis to cases with multiple-bank relations and multiple-branch relations (see the Empirical Approach section below for for a discussion).

Table 2 shows the basic statistics of the sample for the intensive margin analysis. We focus on credit for each firm-branch pair, and on a proxy of the interest rate charge per firm. This proxy is constructed as the annualized interest payments divided by the loan size.[5] First, the number of firms is significantly reduced to 6.9 thousand in this sample, since it is harder to find firm-branch relations with positive credit for the whole period 2010-2014 in which firms display multiple-bank relations and multiple-branch relations. For the total credit number of observations with access to broadband (17,698), 83% of the observations (17,698) correspond to case (a), 12.8% of the number of observations correspond to situations where the technology arrives first at the branch (case (b)), and 3.5% of the observations represent the last scenario, where the technology arrives first at the firm (case (c)). Also, differences in terms of the size of credit or the average interest rate are not large.

[5] This approach has been used by the Peruvian bank regulatory body to report the interest rate: it is calculated as the yearly sum of bank's financial income divided by the 12-month moving average of outstanding credit (Huayta et al., 2017). Since we are working with year-end (as of December) credit data, we multiply the bank's financial income by 12 and divide it by the outstanding level of credit.

3 Empirical Approach

3.1 Baseline Specification

We use the rollout of broadband infrastructure as a natural experiment that provides plausibly exogenous variation in high-speed internet availability (naturally, randomizing the arrival of the technology is not feasible). We propose an event study analysis, which according to Baker et al. (2022), is an empirical approach that is at the core of the evaluation of policy measures in the empirical finance literature. We carry out two exercises, one for the extensive and one for the intensive margin. In the first case we aggregate the data at the *Firm - Centro Poblado - Year* level, using the location of firms. We use the following specification for the extensive margin:

$$y_{ict} = \sum_{k=-\min}^{\max} \delta_k D_{ct}^k + \mathbf{X}\gamma + \eta_d + \tau_t + \varepsilon_{ict} \tag{1}$$

where y_{ict} refers to the outcome of interest for firm i located at centro poblado c during year t. D_{ct}^k is a dummy variable that takes value of one if broadband internet arrives before/after k periods at centro poblado c, and δ_k are our parameters of interest. In our estimations, we analyze a window that goes from minus three years up to a maximum of five years (one year before the Covid crisis). In addition, we include in our specification characteristics at baseline $\mathbf{X}$ and their interactions with a time trend, where these characteristics are correlated with the rollout of the broadband network during certain years (see the following section (3.2)). As in Bhuller et al. (2022), we control for fixed effects at one higher level of aggregation, the district level η_d, to account for differences between very small jurisdictions. We allow for time-varying shocks using τ_t. Standard errors have been clustered at the district level.

For the estimation of equation (1), we use as the counterfactual i) firms that were never treated with the arrival of broadband internet but that have an earlier version of internet technology (DSL), or ii) firms that were treated at the end of the period of analysis, the years 2019-2020. Our estimation sample corresponds to the period 2010-2019.[6] In addition, we implement our estimations following Sun and Abraham (2021), since in the presence of heterogeneous treatment effects across different treatment cohorts, the interpretation of the estimated coefficients is not straightforward.[7]

With the intensive margin analysis we aim to disentangle the effects of broadband between bank supply shocks and firm demand shocks. As we comment on the previous section, we can analyze (a) firms and branches located in the same district, (b) firms and branches with different locations where broadband arrived first at the branch's district, and (c) firms and branches with different locations where broadband arrived first at the firm's district.

Regarding cases (b) and (c), we follow the literature that aims to identify supply and demand shocks in the context of banking. We implement the approach initiated by Khwaja and Mian (2008) to identify a credit supply shock: they use a variable that captures the supply shock (for example, in our context the arrival of the technology only at the branch) and then control for firm-specific demand shocks, under the assumption that these demand shocks are constant across banks. The authors' strategy is to compare loans of the same firm from two different banks (via the inclusion of a firm fixed effect), which are differently exposed to a supply shock (bank liquidity shock in their paper). Their point is that a within-firm comparison fully absorbs changes in demand, and the key assumption is that credit demand is firm-specific (and not bank-specific). In our case, the same logic applies to the analysis of those districts where broadband arrives first at the branch [firm] district. We can control for firm-specific [branch-specific] demand shocks [supply shocks] via the inclusion of time-varying firm [branch] fixed effects.[8]

The specification for the intensive margin analysis for cases (b) and (c), with an aggregation of information at the *Bank Branch - Firm - District - Year* level for firms with multiple-bank relations and multiple-branch relations,

[6] We are not including the year 2020 in our estimations, due to the Covid crisis and the extraordinary measures that the Peruvian Central Bank and the Ministry of Economy implemented to provide liquidity.

[7] There can be cross-lag contamination and the evaluation of pre-trends based on estimated coefficients can be misleading. For a discussion, see Baker et al. (2022) or Roth et al. (2022).

[8] This exercise is different from D'Andrea et al. (2021), the paper closest to ours, since they use the branch location (regardless the firm is located in the same area or not) to identify a supply shock and control for firm demand time-varying fixed effects.

is the following:

$$y_{ibdt} = \sum_{k=-\min}^{\max} \delta_k D_{adt}^k + \mathbf{X}\gamma + \eta_p + \lambda_a + \phi_{-at} + \varepsilon_{ibdt} \qquad a \in \{i, b\} \tag{2}$$

Differently from the extensive margin analysis, we include the bank branch b, and spatial variation is at the district level d. Also, the dummy for the arrival of the technology is not only district specific, but branch (b) or firm (i) specific, and we denote this by $a \in \{i, b\}$ (since the technology arrives early only to the firm's district, or the early arrival happens only for the branch's district). We include fixed effects for province (η_p), where provinces represent a higher level of aggregation of administrative division than a district, and the specification also incorporates fixed effects for firm or branch (λ_a). We control for time-varying effects for $-a$, where $-a = i$ if $a = b$ and $-a = b$ if $a = i$, following the previous discussion about the identification of credit supply shocks. For equation (2), standard errors have been clustered at the province level.

Finally, we also estimate case (a) for the intensive margin specification, where firms and branches share the same location and the same timing of the arrival of FTTX technology. The specification is the same as in equation (2), but we include two time-varying fixed effects ϕ, one for the firm, and another for the bank branch.

3.2 About the Identification Strategy

Our identification strategy, as well as in most of the literature that studies the effects of the expansion of broadband internet, relies on the assumption that the timing of the roll-out is not associated with the determinants of the variables of interest, in our case credit market indicators. Because of this, the natural question that arises is if the pattern of the expansion of broadband is correlated with lagged population, location characteristics, previous infrastructure, or credit market indicators. We carry out an exercise to analyze whether the expansion of broadband is related to baseline CP characteristics (see for example Akerman et al. (2015), Bhuller et al. (2022), or Hvide et al. (2022)), and estimate: $\Delta z_{ct} = \sum_j \gamma_{j,1} 1\,(j = t)\, x_{1,c}^{baseline} + ... + \sum_j \gamma_{j,q} 1\,(j = t)\, x_{q,c}^{baseline} + \lambda_c + \mu_{c,t}$; where Δz_{ct} is a dummy variable that takes the value of one the year of the arrival of FTTX technology at centro poblado c and zero otherwise. $x_{j,c}$ is the baseline characteristic j of CP c. If the timing of the roll-out is completely unrelated to baseline characteristics, then $\gamma_{j,q}$ should not be different from zero, where j is a period after the expansion and q is the studied characteristic. Figure 3 shows the results of this exercise.

The estimations of Figure 3 refers to the universe of firms and loans; however, the results do not change if we use the estimation sample. The figures indicate that the rollout is not related with most of the variables, except in the case of the distance variables. In the first year of the expansion (2014), there is a very clear negative correlation with the distance to the capital of Peru (Lima), which indicates that the CP's near the capital of Peru were among the first to benefit from the availability of FTTX technology. It is natural that for the private network, which is also included in our coverage indicator by CP, the capital of the country was one of the first areas with service (see Figure 2). In the second year of the expansion (2015), CP's far from the capital (positive correlation) but close to an airport (negative correlation) were benefited. Hence, the technology reached those areas outside the capital that were probably political or economically most relevant (proxy by proximity to an airport). For the rest of the years, results are not statistically relevant.

Figure 3. The Relation Between the Expansion (2014-2020) of Fixed Broadband Internet and the Log of Baseline Centro Poblado Characteristics (2013)

Note: The shadowed areas represent 95% confidence bands. Population and number of houses are in logs. Distances have been calculated as the average distance in Km. (to Lima or the nearest airport) by centro poblado, using the information of geolocated firms. We report the log of the average distance. Previous network refers to the availability of DSL technology and is a dummy variable. The number of firms correspond to those firms geolocated and we use the log of the number. Credit by centro poblado is in real terms (2019 local currency units) and is transformed using logs. The number of loans and the number of workers are in logs. The number of workers is a categorical variable showing different ranges.

Although we did not find significant results for other variables, there seems to be a trend in the yearly evolution of coefficients from positive to negative, in the case of housing, previous network (if the centro poblado had DSL technology) and number of workers per firm, which suggests that the expansion continued to less populated, more remote areas or places that were not previously served by earlier versions of internet technology. Since the earliest papers on the expansion of broadband (Akerman et al., 2015), urbanization has been a variable that has correlated with the expansion of broadband in other countries, hence it is not surprising in relation to the evolution of the point estimates for housing. Importantly, credit market indicators (number of firms, performing outstanding credit, or number of loans) are not only not statistically associated with the rollout, but the coefficients also do not show a consistent trend. In our baseline estimations we control for housing and distance to Lima aggregated at the province level. While we cannot rule out the possibility that time-varying unobservables might have biased our estimations, the inclusion of these controls and the fact that we are using two alternative counterfactuals give us confidence about the validity of our research design.

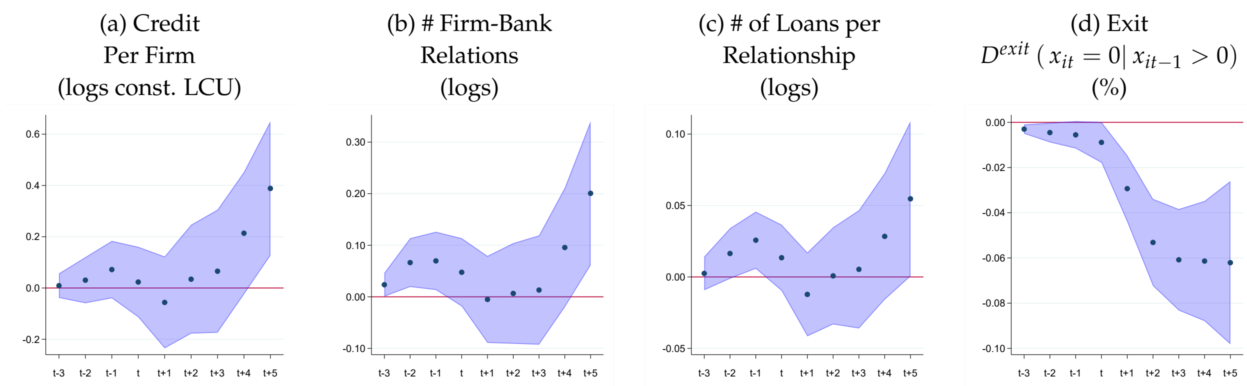
4 Results

4.1 Baseline Results for the Credit Market

Extensive Margin Results. As we mentioned earlier, we have the exact location of each firm with positive credit outstanding and the year of the arrival of the FTTX technology to the area (centro poblado) where the firm is located. Hence, we are able to see the effects of broadband internet over the evolution of the average total credit per firm in a particular location. Our variable of total credit refers only to loans without credit problems (performing loans). If we think about total credit per firm, one or more banks can provide this credit. As we showed in Table 1, on average firms have 2.3 bank relations, and those with the largest number of relations (at the 90th percentile) are served by 4 banks. For this reason we also analyze the impact of broadband over the number of firm-bank relations. In addition to this, for each firm-bank relationship there can be more than one loan. On average, firms in the sample have 1.7 loans per bank. The number of loans per firm-bank relationship is the third variable that we analyze. Our fourth variable of interest is the exit ratio. We define a dummy variable for exit $D^{exit}\left(x_{it}=0|\,x_{it-1}>0\right)$, which takes the value of one if the firm reports no credit this period, conditioned on having positive credit on the previous period, and zero otherwise. With this indicator we can assess the effects of broadband on the share of firms in a particular location that ends all its performing credit relationships with banks.

Figure 4. Total Credit per Firm, Number of Bank-Firm Relations, Number of Loans per Bank-Firm Relationship and Exit

(Data aggregated at the *Firm - Centro Poblado - Year* level)



Note: Period t refers to the year of the arrival of broadband internet to the centro poblado were the firm is located. The shaded area corresponds to the 95% confidence interval, and the vertical line corresponds to the 99% confidence interval. Clustered standard errors at the district level. The estimation includes fixed effects per year and fixed effects by district. The covariates at baseline are housing, distance to Lima, and these variables interacted with time trends.

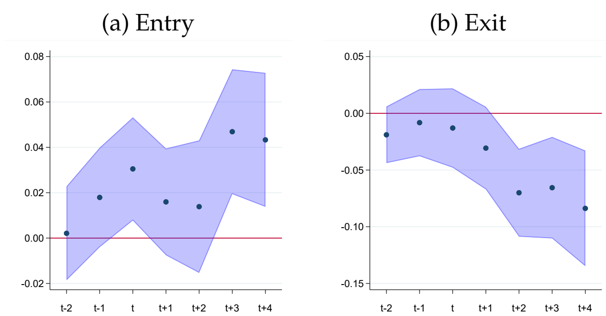
Figure 4 shows our extensive margin results. First, we do not find evidence of pre-trends, except in the case of the number of firm-bank relations. Recall that our counterfactual is those firms with access to internet (proxied by DSL or copper cable technology) but that never access broadband technology. Also, the sample is balanced only for the pre-treatment period in order to analyze results on exit. We start observing results in years $t+4$ and $t+5$ in our main variable of interest, total credit, which indicates that there is a lag between the local availability of broadband and the effects over aggregate borrowing at the firm level. This makes sense, because it takes time from the availability of the technology until the firm's adoption, from the adoption at the firm level and the induced changes in firm behavior, which includes the increase in credit. Since there is no data on firms' adoption, it is not possible to disentangle these effects. This lag in the results for credit has been previously reported by D'Andrea et al. (2021). Regarding our impact results at the end of the sample of analysis, we find that in the fifth year total credit per firm increases 38%, firms are able to borrow from a larger number of banks (with an increase in 20% in the number of credit firm-bank relations), and there is an increase of 5.4% in the number of loans per firm-bank relationship. Our indicator of exit shows a different profile in terms of the timing of the effects. The reduction in the probability of losing credit decreases by 6 percentage points between periods t and $t+3$ and shows no changes for subsequent periods, where the expansion of credit is concentrated.

In terms of previous estimation magnitudes, the work by D'Andrea and coauthors for Italy constitutes our main reference. They find that going from zero to 95% coverage of DSL internet in a municipality (using a survey about household coverage) increases the amount of credit (provided by a bank in a particular municipality) by 47%.[9] This result is relatively similar to our fifth year point estimate (understanding that our dummy indicates full coverage in a CP). [10] In addition, they find an increase of 21% in the number of loans extended by a particular bank for the same expansion of broadband coverage. Differently, our estimate for the fifth year (5%) is much smaller than theirs.

Entry and Exit From the Credit Market. Our previous extensive margin results holds for a balanced panel of firms for the pre-treatment period. By construction, the balanced sample does not allow to analyze the entry of firms. In order to assess the chances of entry and exit using all the information available (without balancing the sample), we aggregate the data at the *Centro Poblado - Year* level. Before aggregating the data, in addition to our exit indicator, we define an entry dummy variable $D^{entry}\,(x_{it} > 0 |\, x_{it-1} = 0)$ that takes the value of one if firm i has positive outstanding credit this period ($x_{it} > 0$), conditioned on having zero outstanding credit the previous year ($x_{it-1} = 0$), and zero otherwise. The probability of entry is simply the sum of the new firms over the total number of firms with credit for each CP (each period's share of new firms), while the exit probability is given by the ratio of the sum of firms that exit the credit market over the number of firms of the previous period (share of firms of the previous period that no longer registers credit). Instead of analyzing the results between $t-3$ and $t+5$ as before, we focus on periods $t-2$ to $t+4$.

Figure 5. Probability of Entry into and Exit from the Credit Market

(Data aggregated at the *Centro Poblado - Year* Level)



Note: Period t refers to the year of the arrival of broadband internet to the Centro Poblado (CP). The shaded area corresponds to the 95% confidence interval. Clustered standard errors at the CP level. The estimation includes year and CP fixed effects. The counterfactual includes those districts without FTTX coverage.

As in the case of the balanced sample (Figure 4), the chances of exit in Figure 5 show the same pattern, a contraction in the probability in periods $t+1$ and $t+2$. In the case of the entry indicator, the arrival of FTTX technology increases the probability of entry by 4 percentage points. Interestingly, our results became significant only for periods $t+3$ and $t+4$, a timing that is consistent with the increase in the average total credit per firm documented in the previous section.

[9] The authors report an increase from zero to a high level of internet (75% coverage) of 28%, where this value for coverage corresponds to category number three in their asymmetric six-point scale of coverage (their regression coefficient is 0.081). To calculate the 47%, we use the value of five in their six-point scale (between 85% and 95% of coverage) and their regression coefficient.

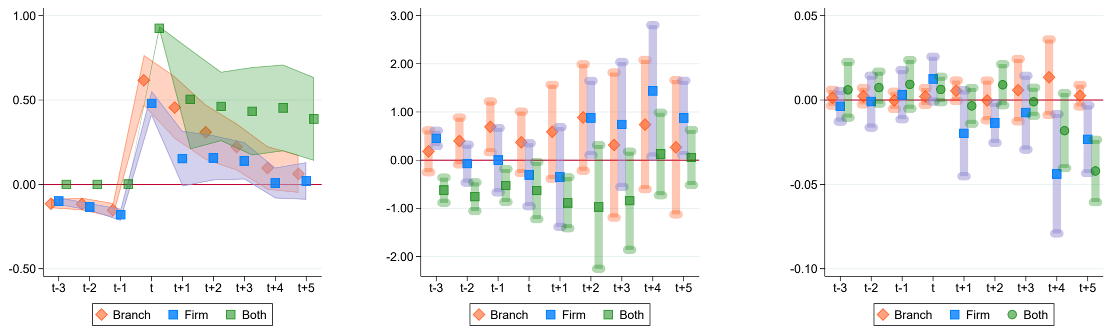
[10] D'Andrea et al. (2021) use data from the Italian credit registry for the period 1998-2008 and data on broadband expansion since 2004. They report that in terms of the population, coverage was 85% in 2005 (their indicator to measure the expansion of broadband). Since they do not have information for the years of the expansion of broadband, when they estimate their event study, they use a semi-dynamic specification, or they do not include in the estimation the coefficients before the arrival of internet (i.e., they cannot test the parallel trends assumption nor study the correlation between the expansion of the network and baseline characteristics). To overcome this issue, in their preferred specification they instrument their coverage indicator with a measure of the distance between the municipality in which the bank operates and the infrastructure that allows the connection. The assumption behind their identification strategy is that the shorter the distance, the earlier the municipality had access to broadband internet.

Intensive Margin and Disentangling Supply and Demand Shocks: In this section we focus on pairs of firms-branches relationships with the same location; and also on pairs with different locations and where the arrival of the broadband internet happened for only firms or, alternatively, only branches, in a three-year window. In this way we can differentiate between shocks to the supply of credit (FTTX technology only affects the bank-branch) and shocks to the demand of credit (the technology arrives at the location of the firm).

Figure 6. Loans and Interest Rates for Firm-Branch Pairs i) Located in the Same District, ii) Located in Districts Where Broadband Arrived Only at the Firm Location in a 3-Year Window, or iii) Only at the Branch District in a 3-Year Window

(Data aggregated at the *Bank Branch - Firm - District - Year* Level)

(a) z_{dt} (b) Credit Per Firm-Branch (in logs of constant LCU) (c) Interest Rate (interest payments/outstanding loan)



Note: Period *t* refers to the year where broadband internet coverage reach at least 90% in the district where the firm or the bank branch is located. The shaded area corresponds to the 95% confidence interval. Clustered standard errors at the province level.

Since we have the district of the branches, we aggregate the data at the *Bank Branch - Firm - District - Year* level, and as we explained in Section (2.3), the number of firms in our estimating sample is reduced from 21.6 thousand firms (extensive margin case) to 6.9 thousand firms. Also, recall from Table 2 that we have a little more than 21 thousand observations without treatment, almost 18 thousand observations where FTTX technology arrived at the same time for firms and branches locations (since they have the same location), 2.7 thousand observations where broadband arrived only at the branches districts, and 0.7 thousand observations where the arrival happened only to the firms location. We report the impact of broadband on two results, total credit for the firm-branch relationship and a proxy of the average interest rate. As in the case of the extensive margin, our sample has been balanced for the pre-treatment period, and as discussed previously, we restrict the sample to firms with multiple lenders and with multiple branches.

Figure 6 reports the evolution of the difference in coverage at the district level z_{dt} between treated and non-treated locations associated with firms (or branches) in panel (a). By construction, there is a jump in the indicator at period t, but this wedge is reduced in the following periods, as the non-treated locations are defined as those that did not reach a coverage of 90% (but can report coverage below this threshold). The most important result reported in panels (b) and (c) is that our results are driven by demand shocks associated with the arrival of broadband. For the shocks to the demand for credit (firms locations), positive results for both variables are reported for periods $t + 4$ and $t + 5$, and have the expected direction. However, credit per firm-branch with the same location does not exhibit parallel trends before the arrival of the technology or significant results in the last two periods. Differently, the reduction in interest rates is clear during the last period for pairs with the same location, and for those exposed only to demand shocks. The reduction in rates is 4 percentage points.

Our results holds for a less precise definition of what is a firm or a branch that is only affected by the FTTX shock. In particular, in Appendix 1 we report Figure A.1, where the time window is restricted to only one period. In other words, this definition includes firms [branches] were the technology can arrive to the corresponding branch [firm] district in the following period, and consequently, it is harder to argue that these are purely supply or demand shocks. This can be clearly seem in the evolution of z_{dt}, which jumps at period t but immediately contracts almost to the original level in period $t+1$ (i.e., there is a large number of firm-branches with different locations where the technology arrive to these locations in consecutive years). The results in the Appendix are relatively similar to our baseline case, but estimated with less precision, and in the case of credit, the parallel trends assumptions does not hold. Finally, it is worth remembering that our results for the supply shocks are confined to the effects of the arrival of the technology to a particular branch. Other important supply factors that affect credit, particularly for micro and small firms, have been documented for the Peruvian case by Huayta et al. (2017).

Effects on New Branches: Beyond the intensive margin analysis, another channel that can explain the growth in total credit per firm is the entrance of new bank branches due to the arrival of broadband. D'Andrea et al. (2021) documents that in Italy banks tend to open branches in locations where broadband arrives, conditioned on these locations not being small municipalities. In order to determine if something similar happens in Peru, we aggregate the data at the *District - Year* level, and we calculate the probability of entry as the ratio between the sum of the new branches in each district, over the total number of branches in 2014, the first year of the rollout of broadband in the country. Figure A.2 of Appendix 1 shows the z_{dt} coverage indicator, and the chances of entry. We do not observe any differences between treated locations and the never-treated districts over the years around the arrival of the technology.

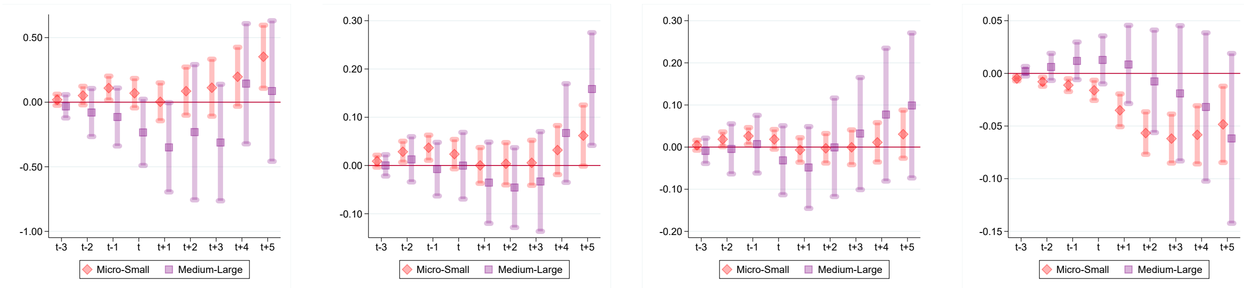
4.2 Effects by Firm Size and Credit File "Thickness"

In this section we provide evidence of heterogeneity by firm size and by credit file "thickness." First, we have the possibility of look at the effects on micro and small firms, since we are working with the universe of firms, differently from the previous literature. In terms of firm size, we estimate two independent regressions: one for micro and small firms, and a second specification for medium and large firms. Firms are classified according to an indicator of sales range one year before the rollout of the infrastructure (2013). The indicator is expressed in terms of a value (UIT) set by the Peruvian tax authority every year. In 2013 a UIT was worth 1,370 thousand dollars. Micro firms are those with annual sales up to 150 UITs (205.5 thousand dollars), and small firms are those with sales higher than 150 UITs up to 1,700 UITs (2.3 million dollars), while the range for medium size firms goes from 1,700 UITs up to 2,300 UITs (3.2 million dollars), and large firms have annual sales higher than 2,300 UITs. Using these categories, we repeat the extensive margin exercise, and the results are reported on Figure 7.

The effects on total credit are relevant only for micro-small firms. Differently, we observe a clear and significant effect for the number of firm-bank relations for both types of firms. We interpret this result as an increase in competition. When broadband internet arrives at a CP, it affects all firms in such a way that they are able to attract more suppliers of funds, regardless of their size. The indicator of the number of loans per firm-bank relationship shows no results. In the case of the exit indicator, again our aggregate results are mainly driven by micro-small firms.

Figure 7. Extensive Margin Results by Firm Size (pre-rollout size)

(a) Total Credit Per Firm | (b) # of Bank-Firm Relations | (c) # of Loans per Bank-Firm R. | (d) Exit

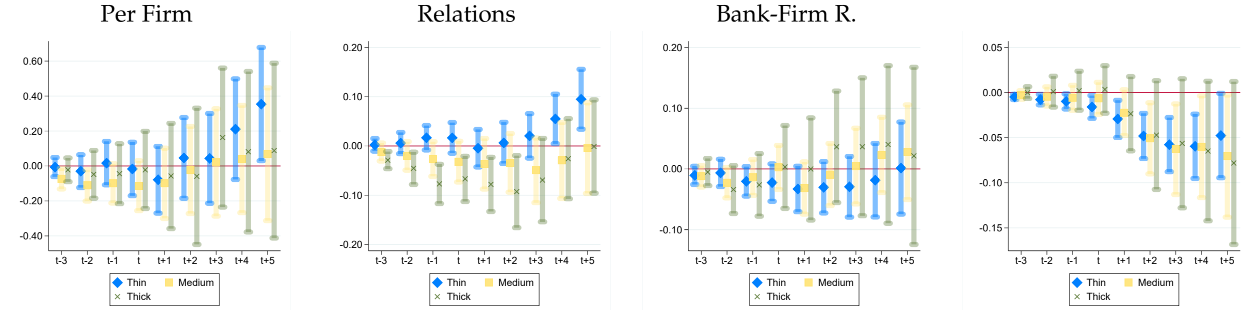


Note: Micro and small firms are those with annual sales in 2013 lower or equal to 2.3 million dollars (following a categorization of sales range formulated by the Peruvian tax authority). Period *t* refers to the year of the arrival of broadband internet to the centro poblado where the firm is located. The line corresponds to the 95% confidence interval. Clustered standard errors at the district level.

We also classify firms according to their credit file "thickness" one year before the rollout of the infrastructure (2013). Blattner and Nelson (2021), using data from a US consumer credit bureau and complementary data sets, show that information disparity (e.g., thin versus thick credit files) leads to inefficient and unequal access to credit markets, since traditional credit scores are not good predictors of default risk for individuals with thin credit files. In the same vein, Di Maggio et al. (2022) show that the use of alternative data by fintech platforms allows the identification of "invisible prime" borrowers, who are consumers with low credit scores and thin credit files but a low propensity to default. In this context, it is relevant to see if the arrival of the FTTX technology has helped to reduce information problems, or if the expansion of credit has been driven mainly by thin credit files. Figure 7 shows this analysis. Following Blattner and Nelson (2021), using 2013 information we define the credit file "thickness" as the number of loans that a firm has in the financial system. We define a thin credit file if the firm has one or two loans (45% of the firms), medium size credit files have between three and four loans (29% of the firms), and thick credit files have between five and 74 loans (26% of the firms). Since our credit bureau data starts in 2010, we cannot measure the file history (the number of years the firm has been interacting with banks).

Figure 8. Extensive Margin Results by Credit File "Thickness" (pre-roll-out file)

(a) Total Credit Per Firm | (b) # of Bank-Firm Relations | (c) # of Loans per Bank-Firm R. | (d) Exit



Note: A thin credit file has one or two loans (45% of the firms), medium size credit files are those between three and four loans (29% of the firms) and thick credit files are those between five and 74 loans (26% of the firms). Period *t* refers to the year of the arrival of broadband internet to the centro poblado where the firm is located. The line corresponds to the 95% confidence interval. Clustered standard errors at the district level.

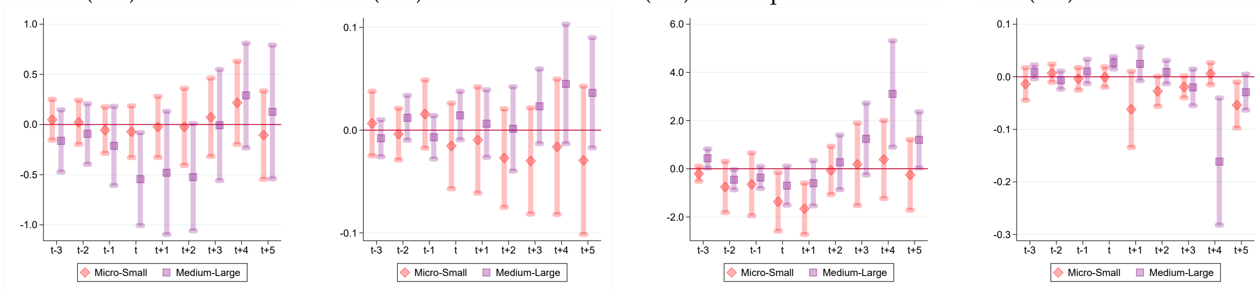
Our results are very clear: all the growth in credit is explained by firms with thin credit files. The same is true when we look at the number of banks serving a firm, a result that we interpret as an increase in competition. In terms of the number of loans per firm-bank relationship, no results are statistically significant. In terms of the exit indicator, there is a short-lived improvement in the indicator for firms with thin lines, as in the case of micro-small firms, although we are able to pick up effects for firms with medium size credit files.

Figure 9. Intensive Margin Results by Firm Size (pre-rollout size)

PANEL [A]: BROADBAND ARRIVES ONLY AT THE BRANCH DISTRICT

PANEL [B] BROADBAND ARRIVES ONLY AT THE FIRM DISTRICT

(A.1) Credit (A.2) Interest Rate (B.1) Credit per Firm-Branch (B.2) Interest Rate



Note: Micro and small firms are those with annual sales in 2013 lower or equal to 2.3 million dollars (following a categorization of sales range formulated by the Peruvian tax authority). Period *t* refers to the year of the arrival of broadband internet at the district of the firm [branch], imposing that the technology does not arrive at the branch [firm] district in a 3 year-window. The shaded lines correspond to the 95% confidence interval. Clustered standard errors at the district level.

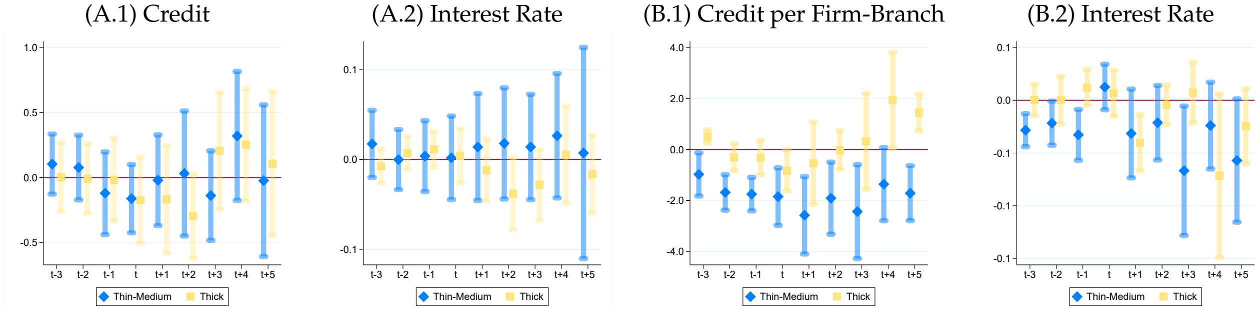
In terms of the intensive margin results, in panel [A] of Figure 9 we do not find any results by firm size when we focus on the supply shocks (the arrival of FTTX technology at the branch and not at the firms district), as in the aggregate case. Panel [B] shows the effects of the demand shocks by firm size. Interestingly, for micro-small firms we observe no effects in terms of the size of credit per firm-branch relationship. Given this result, for smaller firms, which are the ones that explain the credit expansion associated with broadband, the effects seems to be driven entirely by the extensive margin. Differently, the effects of broadband for medium-large firms at the individual level (firm-branch) shows an increase in credit for periods $t + 4$ and $t + 5$. In terms of interest rates, the aggregate drop in rates in period $t + 5$ seems to be driven by micro-small and medium-large firms.

Figure 10. Intensive Margin Results by Credit File "Thickness" (pre-rollout file)

PANEL [A]: BROADBAND ARRIVES ONLY AT THE BRANCH DISTRICT

PANEL [B] BROADBAND ARRIVES ONLY AT THE FIRM DISTRICT

(A.1) Credit (A.2) Interest Rate (B.1) Credit per Firm-Branch (B.2) Interest Rate



Note: A thin credit file has one or two loans (45% of firms), medium size credit files are those between three and four loans (29% of firms) and thick credit files are those between five and 74 loans (26% of firms). Period *t* refers to the year of the arrival of broadband internet at the district of the firm [branch], imposing that the technology does not arrive at the branch [firm] district in a 3-year window. Shaded lines correspond to the 95% confidence interval. Clustered standard errors at the district level.

The intensive margin results according to the 2013 credit file "thickness" are consistent with our results for firm size. For this exercise, we put together those firms with thin files (one loan) and medium size files (two loans) in 2013. This is because, since we are balancing the sample for the pre-rollout period, it is much harder to find firms with thin files that were present during the whole period 2010-2014 (otherwise we do not have enough observations to implement the estimation). Again, if we focus on supply shocks, we find no effects (panel [A]). In terms of credit for thin or medium size firms, the parallel trends assumption does not hold, but we observe a relatively constant difference in relation to the control group, which might suggest that there are no major changes in the size of credit at this level. Finally, in terms of the interest rate, we find reductions in the rates for thin and medium firms in period $t + 3$, although there are significant differences with the control group for the pre-rollout period. We should add that we take our estimates of Figure 10 with caution, given the initial problems with the estimation and the fact that equation (2) involves a highly saturated specification.

4.3 Effects Beyond the Credit Market

To understand better our credit market results, we look at the effects of the arrival of FTTX technology on indicators of firm performance such as the entry/exit of firms and productivity measures.

4.3.1 Universe of Firms: Sales, Entry and Exit

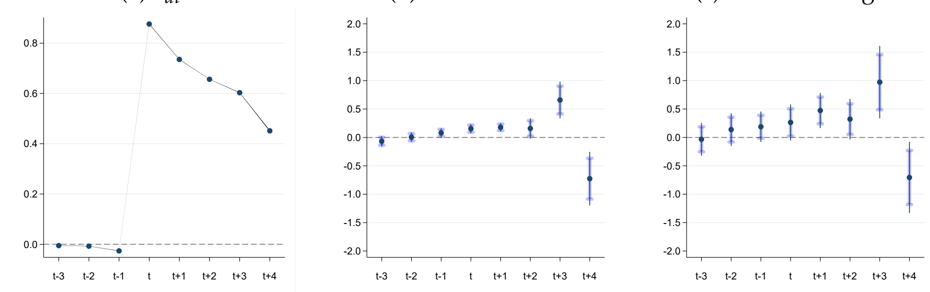
To look at the effects of broadband on sales for the universe of firms in Peru, we exclude financial firms and public enterprises from the information of the taxpayers registry. The administrative records of the tax authority show the district where the firm is located. Our proxy of sales is an asymmetric 15-point indicator that provides ranges for the yearly value of sales per firm. The range is expressed in terms of a reference value (UIT) that is adjusted annually by the Peruvian tax authority. The value in 2013 for the UIT was 1,370 thousand dollars, and in 2019 it was 1,272 thousand dollars. In Appendix 1 we show in Figure A.3 the cumulative distribution of firms in 2013 and 2019 according to the 15-point indicator and the corresponding ranges in dollars. In order to assess broadband effects, we work with the changes in this indicator, whose distribution is shown in Figure A.4 of Appendix 1. Differently from the credit market section, in which we work with a relatively low number of firms, in this section we have a universe for firms between 331 thousand and 524 thousand firms per year. Once we balanced the pre-treatment period (2010-2014), as we did for the credit market, we are left with 222 thousand firms. To account for firm heterogeneity, we include in our estimations, in addition to location and time fixed effects, a group of firms characteristics at baseline (year 2013): sector, number of workers range, firms year creation cohort, and type of tax administration system. We also control for trends associated with these variables, in addition to distance to the capital Lima, population and housing.

Figure 11 shows the results of the analysis by firm size, grouping the micro-small firms and the medium-large firms. The same pattern emerges in both groups, and the same occurs if we split the sample for the four categories. After the arrival of broadband, the indicator of sales range starts improving slowly in $t + 1$ and $t + 2$, shows a very clear increase and the maximum in $t + 3$, and finally the gains in terms of increase in the sales indicator is completely reversed in $t + 4$. The results are interesting for different reasons. First, they are consistent with a narrative where broadband improves firms' performance in the first three years after the arrival of the FTTX technology, and then, since the fourth year after the arrival, it might affect firms' credit conditions. Second, the short-term nature of the impact of broadband differs from previous results in the literature (the counterfactual correspond to those firms never treated with a previous version of the technology). Malgouyres et al. (2021), using French data on importing firms, shows that broadband increases the value of imports and the value of sales. Differently from us, they document a persistent increase in sales up to five years after the rollout.

Figure 11. Change in the Yearly Sales Range [Asymmetric 15-Point Indicator], by Firm Size (pre-rollout size)

(Data aggregated at the *Firm - District - Year* Level)

(a) z_{dt} (b) Micro-Small (c) Medium-Large



Note: Period t refers to the year of the arrival of broadband internet to the district where the firm is located. The lines correspond to the 95% and 99% confidence intervals. Clustered standard errors at the district level. The estimation includes year fixed effects, district fixed effects, and a group of fixed effects associated with firm's characteristics (sector, number of workers range, firms year creation cohort, and type of tax administration system). Trends for distance to the capital, population, housing and firm's characteristics are also included. Firms are those reported by the tax authority registry (we exclude financial firms and public enterprises). Firms were classified according to their size one year before the start of the rollout. The analysis has been carried out for a balanced panel of firms for the pre-treatment period (there are 212 thousand micro-small firms in the pre-treatment period and 9 thousand medium-large firms). The counterfactual includes never-treated firms in districts where the coverage of FTTX technology is less than 90% and the coverage of DSL technology at some point in the sample represents more than 0% of the population.

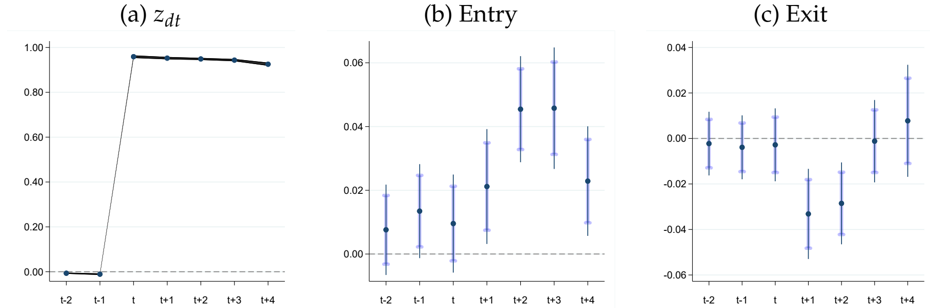
We also explore the dynamics of the probability of entry and exit around the arrival of FTTX technology. We define entry and exit dummies for firms in the same way we did for the credit market analysis. Then we aggregate the data at the *District - Year* level.

Figure 12 shows the results of entry and exit of firms. Panel (a) presents the evolution of our district coverage indicator, and panels (b) and (c) report the evolution of the chances of entry and exit at the district level, around the time of the arrival of FTTX technology. The evolution of the impact on the probabilities is consistent with the timing of our previous results. Chances of entry start picking up one period after the arrival of the technology and show an average increase of 4 percentage points in $t+2$ and $t+3$. Comparing the entry of firms with our previous results on entry to the credit market, we find the same pattern: broadband first affects real activity and then affects the credit market. The reduction in exit probability is of the same size and appears in periods $t+1$ and $t+2$.

Figure 12. Probability of Firm's Entry and Exit

(Data aggregated at the *District - Year* Level)

(a) z_{dt} (b) Entry (c) Exit



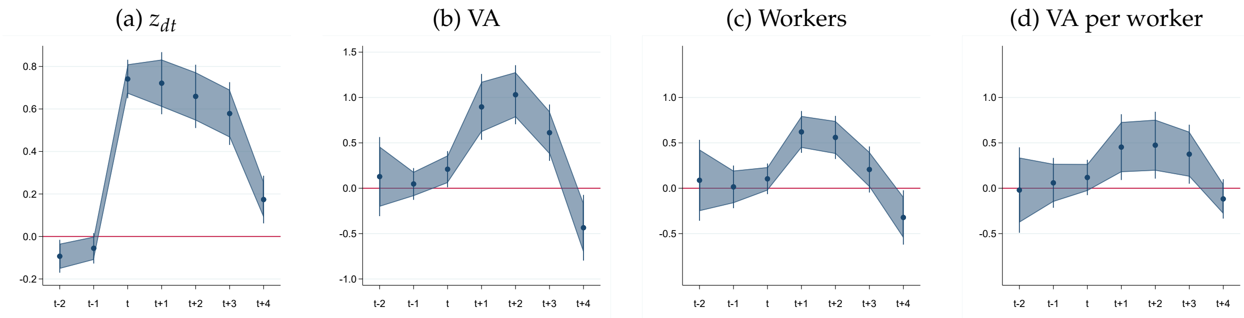
Note: Period t refers to the year of the arrival of broadband internet to the district were the firm is located. The lines correspond to the 95% and 99% confidence intervals. Clustered standard errors at the district level. The estimation includes year and district fixed effects. The counterfactual includes districts where the coverage of FTTX technology is less than 90% and the coverage of the DSL technology at some point in the sample represents more than 0% of the population.

4.3.2 Large Firms: Labor Productivity

Different papers have documented how broadband internet affects firms productivity. Akerman et al. (2015), using Norwegian data, shows that broadband is a skill-biased technological change for firms, increasing (decreasing) the productivity of skilled (unskilled) workers. Bergeaud et al. (2021) finds similar results using French data, the arrival of broadband increases firm productivity and the demand for high-skilled workers. In addition, they show that broadband facilitates firms to outsource some non-core firm jobs, showing gains (loses) in terms of salary of skilled (unskilled) workers who leave the firms. We cannot contribute to this discussion, since we do not have Peruvian information on firms' workers. We do, however, aim to address if the increase in sales documented in the previous section is associated with higher levels of labor productivity of firms.

Figure 13. Large Firms: Value Added (VA), Number of Workers, VA per Worker

(Data at the *Firm - District - Year* Level)



Note: VA is defined as the sum of Commercial Margin (Sales of Merchandise minus Costs of Selling Merchandise), Net Sales of Products, and Services Sales). VA, Workers and VA per worker are expressed in logs. Period t refers to the year of the arrival of broadband internet at the district where the firm is located (if the district has more than 90% of coverage, where the indicator is constructed using information at the Centro Poblado level and population size). The shaded area corresponds to the 95% confidence interval. Clustered standard errors at the district level. The estimation includes year fixed effects. The counterfactual includes never-treated firms in districts where the coverage of DSL technology at some point represents more than 0% of the population.

We only have detailed information about value added and number of workers for large firms. We use the National Survey of Firms for 2014-2017 and 2019 to analyze the effects of broadband. Each year's survey includes a balanced sample for large firms and a yearly cross-sectional survey for medium, small and micro firms. Considering this data restriction, we narrow the analysis to large firms. Figure 12 shows the results of the analysis for our indicator of district broadband coverage z_{dt} (panel (a)), value added (VA) of the firm (panel (b)), number of workers (panel (c)) and our measure of labor productivity (panel (d)), which is the ratio between VA and the number of workers. The results reported in Figure 13 confirm previous results of the literature: broadband seems to boost productivity (last panel).

4.4 Threats to Identification and Robustness

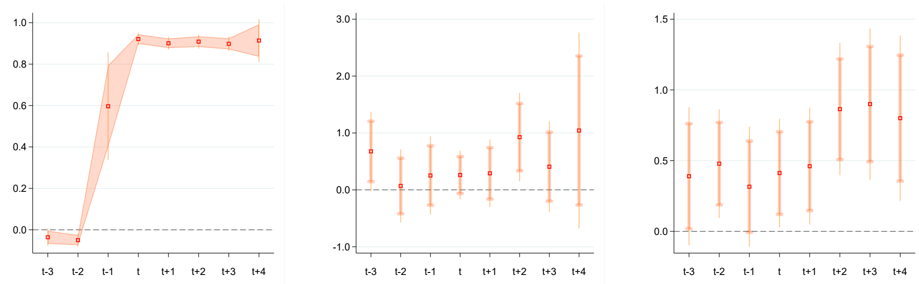
Construction of the Network as a Threat: There are two potential threats to our identification strategy. The first one is that the investment or construction of the broadband network could have generated effects over the firms in each location. The cost of the construction of the 13.5 thousand km of the main fiber optic network totalled 400 million dollars. With these numbers, we have an approximate investment per km equal to 30 thousand dollars. As a reference, the construction of a highway in Peru exceeds one million dollars per km (Ministry of Transportation, 2022). Hence, we are not concerned about the effects of the construction of the network.

Parallel Rollout of Other Infrastructures: A second threat considers the possibility that the expansion of FTTX technology coincide with the rollout of other types of infrastructure. In order to assess this second threat, we analyze data on public procurement, which includes public investment projects. In addition to investment projects, we also put emphasis in one type of public procurement contracts that we expect to be affected with the arrival of broadband at the location of the public institution: purchases of goods via electronic catalogs. Differently from other types of procurement contracts, electronic catalogues have been designed for the acquisition of standardized goods via an online platform, run by one public institution (PeruCompras), whose prices have been pre-determined during the compilation of each electronic catalog.

Figure 14. Public Procurement Contracts for Investment Projects and the Purchase of Goods and Services (G&S) Using Electronic Catalogs

(Data aggregated at the *Public Institution - District - Year* level)

(a) z_{dt} (b) Investment Projects (c) G&S Electronic Catalogs



Note: Period t refers to the year of the arrival of broadband internet at the district where the public institution is located (if the district has more than 90% of coverage, where the indicator is constructed using the information at the Centro Poblado level and population size). The lines correspond to the 95% and 99% confidence intervals. Clustered standard errors at the province level. The estimation includes year, province and type of government level (national, regional, municipal) fixed effects. The counterfactual includes never-treated public institutions in districts where the coverage of DSL technology at some point represents more than 0% of the population.

We use information from OSCE, the public institution in charge of supervising public procurement in Peru. The information is at the contract level, and we aggregate data on acquisitions at the *Public Institution - District - Year* level. The sample between 2013-2019 corresponds to all contracts regulated by the Law of Public Procurement, and in addition, we include those contracts via electronic catalogues. As in our previous estimations, we balance the sample of firms for the pre-treatment period. Since we only have data since 2013, we include those firms that had investment projects (or acquisitions via electronic catalogs) during 2013 and 2014. We control for baseline characteristics, such as the distance to the capital Lima, population, housing and the total value of procurement by public institution, to have a proxy of the size of the public institution. As we did before, we also include trends associated with these characteristics. Fixed effects for year, province and public sector level (national, regional, municipal) are also part of the specification.

The results are reported in Figure 14. Panel (b) shows significant results for public investment in period $t+2$, but no effects in the first two years of the arrival of the network, nor in the last two years of our analysis. We are not concerned about this finding since it is hard to argue that this one point result constitutes a parallel and persistent shock that overlaps with the broadband roll-out. Moreover, recall that we document effects on firms in t and $+1$, and our main concern was a potential overlap in effects during these two periods (also note that our point estimates in these two periods are very similar to those in $t-2$ and $t-1$). Panel (c) reports the effects over electronic catalogs. In this case, we do observe a clear and expected impact of broadband since period $t+2$, something that is not picked up using the investment contracts.

Robustness: In a first robustness check, we focus on our extensive margin results (Figure 4). First, we drop the covariates used in our estimation, and their interaction with time trends. Second, we change the counterfactual, and instead of using never-treated firms, we pick the firms treated in the last two years, 2019 and 2020 (including the covariates and their trends). Results are reported in Figure A.5 of Appendix 1. First, when we exclude the covariates, we obtain a similar pattern for the effects, but with higher values. When we focus on the estimations for the last-treated firms, again our results show the same profile but with higher point estimates, with the exception of our exit indicator. The exit indicator shows a contraction, as in the baseline estimation, but it is not statistically significant.

When we carry out the same exercise for the intensive margin analysis, we are left with very few observations for the only treated firms and banks, and our parallel trends assumption does not hold in this case. However, we are able to estimate the effects over interest rates, using as counterfactual those firms and banks that share the same district and that were treated in 2019 and 2020. Figure A.6 of Appendix 1 shows the results. In our baseline estimates, interest rates fell by 1.81% in $t + 4$, and using the last treated, rates fell by 2.32% for the same period (we cannot estimate $t + 5$).

The Expansion of DOCSIS Technology: Instead of assigning placebo shocks to different locations and periods, we can exploit the deployment of DOCSIS technology, as shown in Figure 1. The expansion of the network started in 2011, and as shown in the same figure, during the first four years of their rollout the cost per Mbps falls only 20%. Hence, differently from the FTTX network, which involved the construction of the main network of fiber optic in the country and an almost an immediate decline in prices of 65%, we do not expect to see effects of the same order of magnitude in a window of five periods after treatment. The results for the extensive margin analysis are shown in Figure A.7 of Appendix 1, and as expected, we do not observe effects of the expansion of network associated with this technology. Then we repeat the exercise using our indicator of ranges for firm's sales, and we report no effects on the universe of firm's sales in Peru in Figure A.8 of Appendix 1.

5 Conclusions

In this paper we study the effects of broadband internet on the credit market. After the rollout of the network, we show an improvement in the economic activity of those benefited areas: firms grow in terms of sales, and there are higher (lower) chances of entry (exit) of firms. After observing these effects, we report an increase in credit for firms-banks with an ongoing relationship. Also, the probability of entry (exit) to the credit market increases (decreases). Our first contribution is to document this sequential timing in effects on economic activity and loan market outcomes.

The second contribution of our paper is to empirically disentangle the effects of broadband between the supply of credit (bank branches) and the demand of credit (firms), since the presence of pairs of branches-firms located in different areas allows us to isolate the effects. We find the demand channel seems to be the most important one, observing a reduction in market interest rates for those pairs with the same location, and for those pair with different locations and where broadband arrives only at the firm's location. We do not find effects when the technology only affects bank branches. This demand channel is consistent with the characterization of firms that benefit from broadband: these are relatively small firms with "thin" credit files.

References

Abraham, F. and Schmukler, S. L. (2017). Addressing the SME finance problem (English). Technical report.

Akerman, A., Gaarder, I., and Mogstad, M. (2015). "the skill complementarity of broadband internet". *The Quarterly Journal of Economics*, 130(4):1781–1824.

Akerman, A., Leuven, E., and Mogstad, M. (2022). Information frictions, internet, and the relationship between distance and trade. *American Economic Journal: Applied Economics*, 14(1):133–63.

Analysys Mason (2020). Full-fibre access as strategic infrastructure: strengthening public policy for Europe. Technical report.

Argandoña, D. and More, J. (2020). Las redes de transporte de fibra óptica, microondas y satelital y su rol para promover la expansión de la cobertura de los servicios públicos de telecomunicaciones: reporte y mapas de cobertura. Technical Report OSIPTEL.

Baker, A. C., Larcker, D. F., and Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, 144(2):370–395.

Banerjee, A., Breza, E., Townsend, R., and Vera-Cossio, D. (2019). Access to Credit and Productivity: Evidence from Thai Villages. Technical report.

Banerjee, A. V. and Duflo, E. (2014). Do firms want to borrow more? testing credit constraints using a directed lending program. *The Review of Economic Studies*, 81(2 (287)):572–607.

Bergeaud, A., Malgouyres, C., Mazet-Sonilhac, C., and Signorelli, S. (2021). Technological Change and Domestic Outsourcing. Working Papers halshs-03265792, HAL.

Bhuller, M., Kostol, A., and Vigtel, T. (2022). The Internet, Search Frictions and Aggregate Unemployment. Review of economic studies, revise & resubmit.

Blattner, L. and Nelson, S. (2021). How Costly is Noise? Data and Disparities in Consumer Credit. Papers 2105.07554, arXiv.org.

Bottero, M., Lenzu, S., and Mezzanotti, F. (2020). Sovereign debt exposure and the bank lending channel: Impact on credit supply and the real economy. *Journal of International Economics*, 126:103328.

Breza, E. and Kinnan, C. (2021). Measuring the Equilibrium Impacts of Credit: Evidence from the Indian Microfinance Crisis*. *The Quarterly Journal of Economics*, 136(3):1447–1497.

D'Andrea, A. and Limodio, N. (2019). High-Speed Internet, Financial Technology and Banking in Africa. Technical report, Accepted at *Management Science*.

D'Andrea, A., Pelosi, M., and Sette, E. (2021). Broadband and Bank Intermediation. Technical report.

Di Maggio, M., Ratnadiwakara, D., and Carmichael, D. (2022). Invisible primes: Fintech lending with alternative data. Working Paper 29840, National Bureau of Economic Research.

Hauswald, R. and Marquez, R. (2003). Information technology and financial services competition. *The Review of Financial Studies*, 16(3):921–948.

Hjort, J. and Poulsen, J. (2019). The Arrival of Fast Internet and Employment in Africa. *American Economic Review*, 109(3):1032–79.

Huayta, A., Garcia, A., and Sotomayor, N. (2017). Análisis de la competencia que enfrentan las instituciones microfinancieras peruanas y el impacto sobre su estabilidad financiera. Technical report, Superintendencia de Banca, Seguros y AFP.

Hvide, H. K., Meling, T. G., Mogstad, M., and Vestad, O. L. (2022). Broadband internet and the stock market investments of individual investors. Working Paper 30383, National Bureau of Economic Research.

Ivashina, V., Laeven, L., and Moral-Benito, E. (2022). Loan types and the bank lending channel. *Journal of Monetary Economics*, 126:171–187.

Khwaja, A. I. and Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4):1413–42.

Levine, R. (1997). Financial development and economic growth: Views and agenda. *Journal of Economic Literature*, 35(2):688–726.

Liberti, J. M. and Petersen, M. A. (2018). Information: Hard and Soft. *The Review of Corporate Finance Studies*, 8(1):1–41.

Malgouyres, C., Mayer, T., and Mazet-Sonilhac, C. (2021). Technology-induced trade shocks? evidence from broadband expansion in france. *Journal of International Economics*, 133:103520.

Mazet-Sonilhac, C. (2022). Information Frictions in Credit Markets. Technical report.

Ministry of Transportation (2022). Lineas de cortes para la formulacion y evaluacion de proyectos de inversion en carreteras interurbanas. Technical report.

Muente Schwarz, R. (2017). Evolución de la industria de telecomunicaciones e intensidad competitiva. Technical report, Osiptel.

OECD (2020). *Financing SMEs and Entrepreneurs 2020*.

OSPITEL (2018). Situacion del sector telecomunicaciones: Informe presentado al congreso. Technical report.

Pacheco, L. and More, J. and Argandoña, D. (2017). Infraestructura de fibra optica en el peru. Technical report.

Paravisini, D., Rappoport, V., Schnabl, P., and Wolfenzon, D. (2014). Dissecting the Effect of Credit Supply on Trade: Evidence from Matched Credit-Export Data. *The Review of Economic Studies*, 82(1):333–359.

Restuccia, D. and Rogerson, R. (2017). The causes and costs of misallocation. *Journal of Economic Perspectives*, 31(3):151–74.

Roth, J., Sant'Anna, P. H. C., Bilinski, A., and Poe, J. (2022). What's trending in difference-in-differences? a synthesis of the recent econometrics literature.

Stiglitz, J. E. and Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American Economic Review*, 71(3):393–410.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199. Themed Issue: Treatment Effect 1.

Vives, X. and Ye, Z. (2022). Information Technology and Bank Competition. Technical report.

Appendix 1

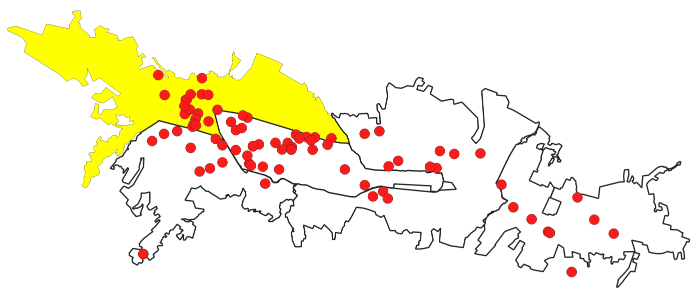
Table A.1. Geolocation of Firms, Descriptive Statistics

	Observations				Average Loan (constant LCU, 000s)			
	No	*Yes*	Total	% *No*	*No*	*Yes*	*Difference*	p-value
Micro firms	160,320	671,009	831,329	0.19	94.7	101.8	-7.1	0.20
Small firms	120,242	522,511	642,753	0.19	253.8	253.3	0.5	0.92
Medium firms	7,448	33,695	41,143	0.18	725.2	783.7	-58.5	0.21
Large firms	33,334	156,627	189,961	0.18	4,212.1	5,428.3	-1,216.2	0.00

Note: *Yes* denotes those observations with firms that have been geolocated, while *No* denotes the opposite case. LCU denotes Local Currency Units, and are expressed in real terms (soles of 2019). The p-value correspond to the t-test regarding if the *Difference* is different from zero. Data for the period 2010-2020 has been aggregated at the *Bank - Firm - Centro Poblado - Year* level.

Figure A.0. Expansion of Centros Poblados with Fixed Broadband FTTX (yellow areas) and Firms with Credit (red dots) in the City of Cuzco

(a) 2014



(b) 2019

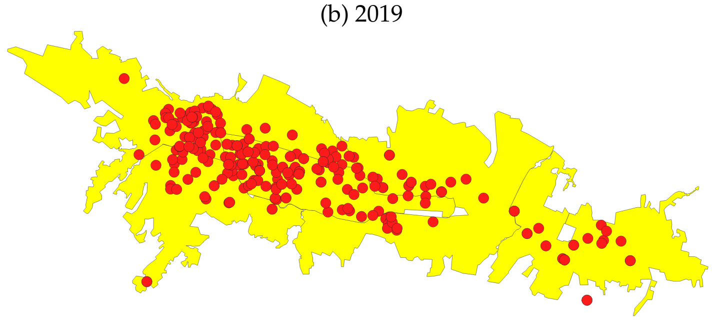
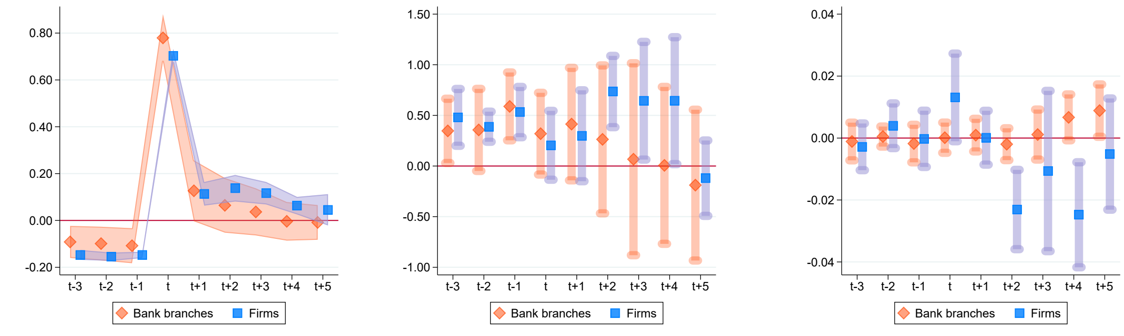


Figure A.1. Loans and Interest Rates for Firm-Branch Pairs Located in Different Districts, Where Broadband Arrived Only at the Firm District in a 1-Year Window, or Only at the Branch District in a 1-Year Window

(Data aggregated at the *Bank Branch - Firm - District - Year* Level)

(a) z_{dt} | (b) Credit Per Firm-Branch (in logs of constant LCU) | (c) Interest Rate (interest payments/outstanding loan)

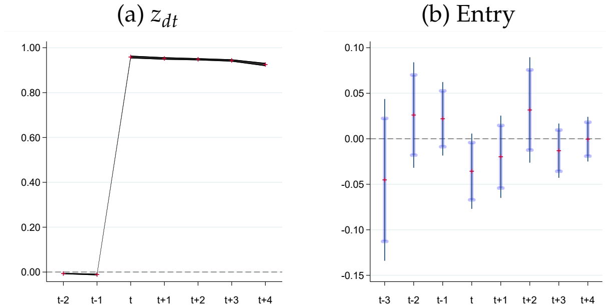


Note: Period t refers to the year where broadband internet coverage reaches at least 90% in the district where the firm or the bank branch is located. Horizontal lines correspond to the 95% confidence interval. Clustered standard errors at the province level.

Figure A.2. Probability of a Bank Branch's Entry

(Data aggregated at the *District - Year* Level)

(a) z_{dt} | (b) Entry



Note: The probability is calculated as the number of new branches per district over the number of branches at the first year of the arrival of the technology to any location (the year 2014). Period t refers to the year of the arrival of broadband internet at the district were the firm is located. The lines correspond to 95% and 99% confidence intervals. Clustered standard errors at the district level. The estimation includes year and district fixed effects. The counterfactual includes those districts where the coverage of FTTX technology is less than 90% and the coverage of DSL technology at some point in the sample represents more than 0% of the population.

Figure A.3. Cumulative Distribution of Firms according to a Yearly
Sales Range Variable [Asymmetric Fifteen Point Indicator], 2013 and 2019

(The ranges of annual sales are expressed in 000s of dollars)

(a) All (b) Balanced Panel (2010-2014)

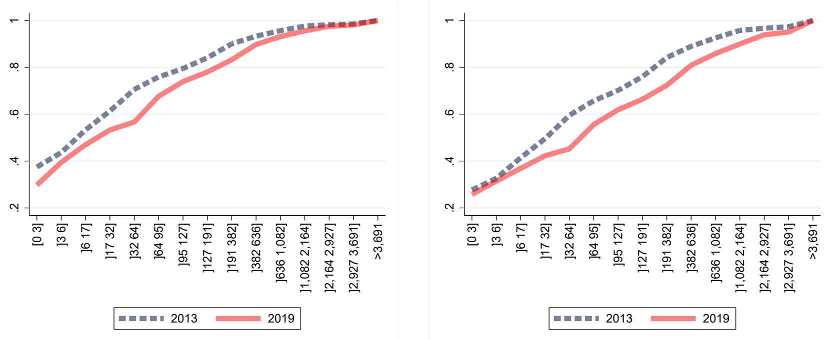


Figure A.4. Distribution of Yearly Changes in the
Sales Range Variable [Asymmetric Fifteen Point Indicator], 2010-2019

(an increase/decrease in 1 point indicates a jump (reverse) into the following (previous) category)

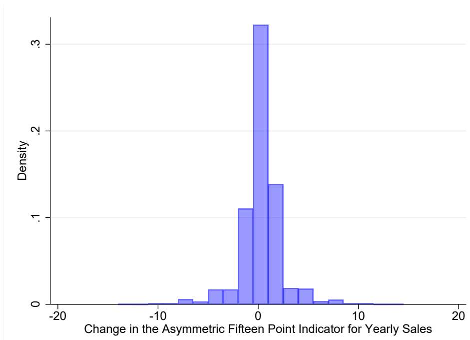
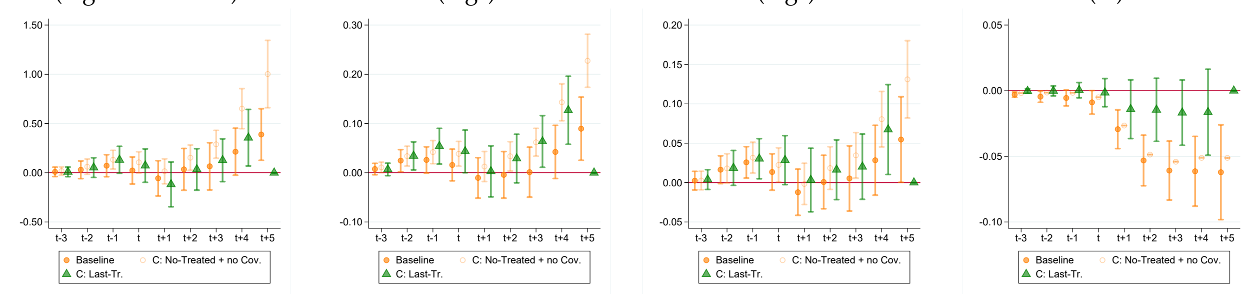


Figure A.5. Robustness for Total Credit Per Firm, Number of Bank-Firm Relations, Number of Loans per Bank-Firm Relationship and Exit, without Covariates and Using the Last-Treated Firms (2019-2020)

(Data aggregated at the *Firm* - *Centro Poblado* - *Year* level)

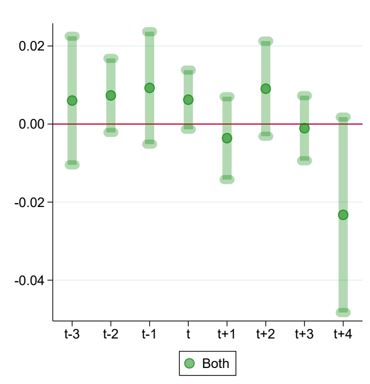
(a) Credit Per Firm (logs const. LCU)	(b) # Firm-Bank Relations (logs)	(c) # of Loans per Relationship (logs)	(d) Exit $D^{exit}\,(x_{it} = 0 \mid x_{it-1} > 0)$ (%)



Note: Period t refers to the year of the arrival of broadband internet at the centro poblado were the firm is located. The bars correspond to the 95% confidence interval. Clustered standard errors at the district level. The estimation includes fixed effects per year and by district. *Baseline* uses to the never treated as counterfactual. *No treated + no cov.* denotes the baseline estimates with no covariates. *C: Last-Tr.* denotes Last-Treated as counterfactual, which are the firms cohorts where FTTX technology arrived in 2019 and 2020 (both years are excluded from the estimations).

Figure A.6. Robustness for Interest Rates Using the Last-Treated Firms (2019-2020) for Firms and Banks that Share the Same Location

(Data aggregated at the *Bank Branch* - *Firm* - *District* - *Year* Level)

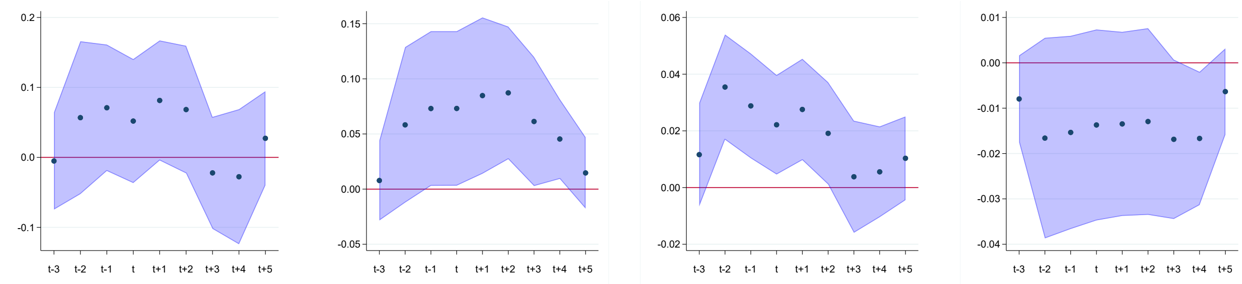


Note: Period t refers to the year where broadband internet coverage reaches at least 90% in the district where the firm and the bank branch is located. The shaded area corresponds to the 95% confidence interval. Clustered standard errors at the province level.

Figure A.7. The Effects of the Rollout of the DOCSIS Technology on Total Credit Per Firm, Number of Bank-Firm Relations, Number of Loans per Bank-Firm Relationship and Exit

(Data aggregated at the *Firm* - *Centro Poblado* - *Year* level)

(a) Credit Per Firm (logs const. LCU) | (b) # Firm-Bank Relations (logs) | (c) # of Loans per Relationship (logs) | (d) Exit $D^{exit}\left(x_{it}=0 \mid x_{it-1}>0\right)$ (%)

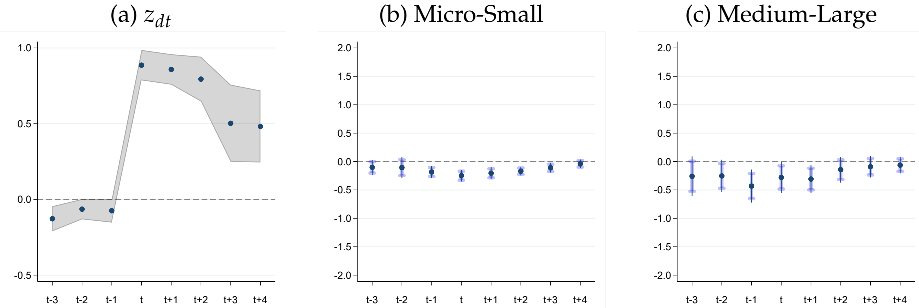


Note: Period *t* refers to the year of the arrival of DOCSIS technology to the centro poblado where the firm is located. The shaded area corresponds to the 95% confidence interval, and the vertical line corresponds to the 99% confidence interval. Clustered standard errors at the district level. The estimation includes fixed effects per year and fixed effects by district. The covariates at baseline are housing, distance to Lima, and these variables interacted with time trends.

Figure A.8. The Effects of the Rollout of the DOCSIS Technology on the Change in the Yearly Sales Range [Asymmetric Fifteen Point Indicator], by Firm Size (pre-rollout size)

(Data aggregated at the *Firm* - *District* - *Year* Level)

(a) z_{dt} | (b) Micro-Small | (c) Medium-Large



Note: Period *t* refers to the year of the arrival of broadband internet at the district where the firm is located. The lines correspond to the 95% and 99% confidence intervals. Clustered standard errors at the district level. The estimation includes year fixed effects, district fixed effects, and a group of fixed effects associated with firm's characteristics (sector, number of workers range, firm's year creation cohort, and type of tax administration system). Trends for distance to the capital, population, housing and firm's characteristics are also included. Firms are those reported by the tax authority registry (we exclude financial firms and public enterprises). Firms were classified according to their size one year before the start of the rollout. The analysis has been carried out for a balanced panel of firms for the pre-treatment period. The counterfactual includes never-treated firms that belong to districts were the coverage of DOCSIS technology is less than 90%, the coverage of the DSL technology at some point in the sample represents more than 0% of the population, and coverage of the FTTX technology is zero.