Does Fintech lending financing costs? Evidence from an emerging market

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Abstract

Using proprietary data of virtually all unsecured working capital loans to small businesses in Brazil, we find that Peer to Peer (P2P) lenders focus on smaller and riskier firms, and provide them cheaper working capital loans than the dominating traditional banks. P2P clients used to find very high interest rate at traditional banks. However, once they borrow from P2Ps they do find a lower rate on subsequent bank loans, indicating an improvement in their bargaining power. Using the staggered implementation of high speed optic fiber internet as an exogenous positive shock to online P2P lending activity, we are able to evaluate which locations benefit most from the entry of P2P lenders. We find that the P2P lenders penetrate relatively more in municipalities that are distant from the main financial centers, and with a pre-fiber monopolistic banking market. After P2P entry, the incumbent banks in these locations drastically decrease their lending rates and expand credit to more businesses.

The views expressed in this Working Paper are those of the authors and do not necessarily reflect those of the Banco Central do Brasil.

I. Introduction

Access to financing is crucial for small businesses. Several studies have shown that credit availability boosts the creation of entrepreneurial firms and spurs their productivity.[1] However, in many countries, especially in emerging markets, small firms face severe credit restrictions. On the other hand, there has been a recent surge of lenders that use new technologies in the financial sector, namely the Fintech lenders. In this study, we wish to understand whether Fintechs can effectively alleviate the credit frictions faced by small businesses in emerging markets. Can Fintech lenders induce a decrease in interest rates charged by the incumbent lenders by fostering competition in the financial sector? Can Fintech lenders provide access to financing for marginalized businesses?

It is well known that Fintechs have lower operating costs than traditional banks, which may allow them to charge a lower interest rate from borrowers and also more easily access distant areas where banks do not operate. If Fintech lenders can act as substitutes to banks as documented by Tang (2019), then the entry of these low-cost lenders could increase the competition against incumbent banks, leading to a reduction in banks' lending rates. This could be particularly evident in markets where banks hold a lot of market power, and also in economies where many firms are geographically distant from the financial centers and spatial price discrimination can occur (see Petersen and Rajan (1994) and Degryse and Ongena (2005)).

In this paper, we test these hypotheses using a rich proprietary dataset that contains virtually all unsecured working capital loans to small and medium companies, from both banks and online Peer-to-Peer (P2P) platforms[2] in Brazil, from 2016 to early 2020 before the Covid 19 pandemic. A set of borrowers' characteristics is also available, including risk rating, size, industry, and employee profile. A novelty of our dataset in the Fintech literature, in addition to the rich borrowers' profile, comes from the record of all borrowers and lenders' working capital history. This feature allows us to identify the previous credit conditions of businesses before and after any particular loan contract. Thus, we can directly measure whether Fintechs improve borrower's conditions in terms of access to finance and lower interest rates. We can also test if any particular firm is able to find subsequent cheaper loans from traditional banks after borrowing from a P2P platform - a sign of increased bargaining power to the

[1] Black and Strahan (2002) and Kerr and Nanda (2009) show that availability of credit affects entrepreneurial firm starts and creative destruction. Krishnan, Nandy and Puri (2015) show that firms' TFP increases following interstate banking deregulations that increased access to bank financing, especially for financially constrained firms. Chodorow-Reich (2014) also shows that bank lending frictions has great significant impact on employment at small and medium firms, whereas no significant effect was found for large firms.

[2] Our definition of a "Fintech" credit company is a Peer-to-Peer (P2P) online platform. P2P lending is also commonly referred to as marketplace lending. Refer to section II for more details about what differentiates a P2P platform from a bank. For a broader definition of "Fintech" and the many areas that they operate see Thakor (2020).

small firms.

Another feature that makes Brazil a good setting to understand the potential benefits of P2P lending is its vast geography and concentrated banking market. The lending-deposit interest rate spread is large and a large number of companies lack access to credit, especially in municipalities that are far from the main financial centers. Under this context, we find that the P2P platforms indeed penetrate more in the areas dominated by a small number of banks, offering a lower interest rate. After the arrival of P2P lenders, the local banks drastically decrease their lending rates and expand credit to more businesses. Thus, our main finding indicates that P2P lenders swiftly reshaped monopolistic banking markets into more competitive ones in Brazil.

Despite our dataset advantages, to connect a reduction in banks' observed rates to an increase in P2P lending is an empirical challenge. Endogeneity comes from the likelihood that the decision of a P2P lender to enter a particular market, at a particular time, is not independent of the incumbent banks' market strategy. Moreover, banks might act strategically to avoid Fintech entry. Thus, the locations where the P2Ps did not enter might not be used as a valid control group to compare with the locations that experienced P2P entry.

To overcome this challenge, our strategy is to use a time and geographical discontinuity in the usage of high speed internet, in the form of optic fiber technology, across Brazilian municipalities. The arrival of optic fiber technology in a municipality depends on its geo-spatial characteristics. Municipalities with similar economic conditions may receive fiber optic internet connection at different times, depending on the geographic landscape and their distance to other areas where the technology is already installed. The Brazilian telecommunications regulatory agency (ANATEL) is responsible for installing the network structure (backbone and backhaul) that supports the provision of high speed data transmission by optic fiber. The technology is implemented gradually according to a national plan[3]. The plan establishes the percentage of unattended locations that must receive the network until a certain time, with no clear economic distinction of which location should receive the technology first. Thus, the arrival of optic fiber technology can be seen as somewhat independent of local banking activity. Moreover, the internet quality upgrade brought by optic fiber can greatly influence the local credit market as online lenders can swiftly access these areas. Therefore, this setting presents an opportunity to contrast the credit market before and after the high speed internet was implemented, performing a difference-in-differences analysis. In this way, the fiber optic arrival would be similar to the arrival of submarine cables in Africa that D'Andrea and Limodio (2019) use as an exogenous technological shock to analyze the impacts in the African banking markets.

To control for potential confounders triggered by optic fiber adoption, we explore a heterogeneity in the treatment effect using (i) different degrees of market concentration, and (ii) a measure of banks' pre-fiber exposure to P2P competition. The

[3]see http://www.planalto.gov.br/ccivil_03/_Ato2019-2022/2021/Decreto/D10610.htm

exposure measure is a propensity score from a logistic regression of a P2P client dummy on loan-specific and firm-specific characteristics. We can then test if the drop in post-fiber bank's lending rate is concentrated on municipalities where local banks had a higher market power and also higher propensity to lend to P2P clients. If competition from P2P lenders is the main driver of banks' responses after optic fiber adoption, then we expect a larger treatment effect in those municipalities.

Our paper has three main findings. First, we characterize in detail the profile of Fintech borrowers in terms of size, riskiness, industry, employee characteristics, and the banking relationship history, if there is any. P2P borrowers are on average smaller and riskier companies than the bank borrowers. They are younger firms, with younger and more educated employees, and have a higher prevalence in economic activities like information and communication technology (ICT) and professional, scientific, and technical services. Moreover, before borrowing from the P2P sector, small and micro firms used to pay a 2.2p.p higher interest rate at traditional banks compared to similar borrowers. This comparison is performed in a sample where we excluded all the P2P loans and every subsequent bank loan for a firm that already borrowed from a P2P platform. Thus, only the ex-ante bank loans of P2P borrowers are compared with usual bank loans from non-P2P borrowers.

Second, we find evidence that P2P platforms indeed serve as a cheaper funding alternative for the firms described above. Conditional on loan characteristics and risk rating, their interest rate is approximately 4.8p.p. lower than the rates offered by traditional banks. We break down these results for different bank size and ownership: large or non-large, private or public, and credit unions. We find a statistically significant lower rate (-7.4p.p.) for P2Ps only when compared to large private banks. This result is not surprising since large private banks have strong market power in Brazil. There are only four of them and they control 50% of the working capital loans market share. We also observe that P2Ps receive relatively more clients that switched (60%) from large private banks, a higher proportion than any other bank type receives. In addition, we identify that after the P2P clients borrow from a P2P platform for the first time, they are able to get a lower interest rate on a subsequent traditional bank loan. We also find that this lower interest rate is significant only for clients that recently borrowed from banks, suggesting that the decrease in price is likely due to an increased bargaining power for the P2P clients instead of other factors like signaling or improvements in their credit conditions.[4]

The third and final set of results unveil how local banks reacted after the supply shock to P2P lending brought about from optic fiber adoption. We find that P2P lending volume and market share significantly increase after the technology is adopted. On average, the P2P platforms steal roughly 2p.p. market share from banks under the

[4]A similar strategy was used by Ongena, Pinoli, Rossi and Scopelliti (2021) to compare loans granted to firms that also issued "minibonds" with the same bank with loans issued to similar non-issuer firms. The lower interest rate obtained by the issuer firms suggests an improvement in their bargaining power.

new high quality internet. A new price equilibrium is reached where banks' lending rate drastically decreases, by 25p.p (one standard deviation), and total funding to firms increases by 15p.p (0.5 standard deviation).

Next, we test for heterogeneity in the treatment effect arising from different degrees of market concentration. If competition from P2P lenders is the main driver of banks' responses, then we expect a larger treatment effect in markets with greater bank concentration. To test this hypothesis, we compute the pre-fiber market share of the four largest Brazilian private banks in every municipality. We first observe a strong indication of credit rationing in the municipalities with high dominance of the large banks. There is a clear negative relationship between the top 4 private banks' market share and the ratio of firms with a working capital loan. Also, interest rates are substantially higher in the municipalities with high market share of the top 4 banks, and the fewer borrowers attended by the banks are on average less risky.

We then analyze if P2P lenders helped to alleviate those credit frictions. First, we find that P2Ps indeed penetrate more in the areas with higher market share of the large private banks. Perhaps this is not surprising, since P2Ps and other online lenders are lower-cost service providers than banks, and they will expectedly enter markets with a higher unattended demand for credit. We do not find evidence of post-fiber entry of additional traditional banks in these locations, suggesting much higher entry barriers for banks than the online lenders. Second, in accordance to a high degree of substitution between banks and P2P lenders as credit providers, we find that municipalities with a higher pre-fiber market concentration of large private banks is associated with: (i) a steeper decrease in post-fiber bank lending rates, (ii) a larger increase in the ratio of firms obtaining bank loans, and (iii) a deterioration in the average risk profile of bank borrowers. These findings indicate that Fintech lending such as online P2P platforms reshapes markets dominated by few traditional banks into more competitive ones, allowing riskier borrowers to gain access to loans from both Fintech lenders and traditional banks and at a cheaper rate.

Overall, our paper highlights the importance of alternative financing sources in markets that suffer from credit rationing due to bank concentration. P2P lending not only has the potential of swiftly providing cheaper funding to marginalized business in the credit market, they can also force a price reduction from the incumbent banks.

A. Literature

Our findings contributes to the growing literature that analyses the competition between banks and Fintechs. For example, the fact that Fintech lenders focus on smaller riskier borrowers than banks has been documented by Buchak, Matvos, Piskorski and Seru (2018), de Roure, Pelizzon and Thakor (2019) and Tang (2019). Balyuk, Berger and Hackney (2020) also emphasize that the market presence of different bank types plays a key role in the growth of Fintech lending to small businesses. Specifically about the benefits of Fintechs to SMEs, Gopal and Schnabl (2020) finds that Fin-

Tech lenders replace small business lending underserved by banks after the 2008 crisis, and Beaumont, Tang and Vansteenberghe (2021) find that SMEs that take a Fintech loan experience a subsequent 20% increase in bank credit, in comparison to similar firms taking bank loans. Our contribution to this literature is that we expand the potential benefits form Fintech lending to emerging markets, to find that they can substantially improve SMEs credit condition both in terms of access and prices.

Our results also relate to a literature that connects banking competition and access to finance. For example, Jayaratne and Strahan (1996) show that access to finance and economic development increase after restrictions to bank branching are removed. Guzman (2000) argues that banking monopoly is a catalyst of credit rationing. Likewise, Beck, Demirgüç-Kunt and Maksimovic (2005) show that higher banking concentration increases financing obstacles specifically in countries with low levels of economic and institutional development. Butler, Cornaggia and Gurun (2015) attempt to understand how banking competition relates to prices in alternative sources of finance. They show that consumers residing in US counties with larger supply of banks find loans at lower interest rates from Prosper, one of the largest P2P platforms. Our paper complements those studies since we found that P2P lenders have great potential to include small businesses and alleviate credit rationing in financial markets with a high banking concentration.

Finally, our empirical strategy exploiting the introduction of optic fiber directly links our paper to the studies showing that technology improvements can lower Fintech entry costs and challenge banks. Goldstein, Jiang and Karolyi (2019), in a literature review, highlight that "technology is both transforming financial services and creating competitors outside the traditional sectors". Recent studies that found this evidence for different sectors are Fuster, Plosser, Schnabl and Vickery (2019) and Buchak et al. (2018), Bartlett, Morse, Stanton and Wallace (2018), Berg, Burg, Gombović and Puri (2020), Hertzberg, Liberman and Paravisini (2018), Abis (2020) and D'Acunto, Prabhala and Rossi (2019).

II. Context and Data

A. The Brazilian Credit Market

Before we further detail our data and methodology, it is useful to understand the Brazilian financial sector and why it stands as a useful case to measure the impact of less restrictive microcredit policies.

Figure 1 shows the characteristics of the Brazilian credit market and why it stands as a more representative country of global credit markets than the U.S.. In 2020, domestic credit to private sector is 45% of GDP in Brazil, compared to 62.30% in high-income countries and 130% in the US. Non-bank financial institutions assets to GDP is only 4% in Brazil, 18% in high-income countries and 90% in US.. Therefore, Brazilian numbers points to an incipient and scarce credit market that is still very focused on traditional bank lending. These features are much closer to the 137 countries belonging to the group of low, middle and upper-middle income countries, than the 80 countries in the high-income group, according to the World Bank classification. [5]

A likely consequence of Brazil's financial market organization is reflected in the high price and low supply of credit. Also according to the World Bank Catalog 2020, the country bank-lending deposit spread is remarkably high, about 35%, compared to 5% in developed countries. Perhaps not surprisingly, 20% of small and of small and micro business mentioned having credit application denied from banks, and 30% never even had a loan with banks, according to a 2019 survey from SEBRAE [6]. It is under this context that we observe in our data that the vast majority of P2P loans are destined to small and medium companies (SME), to cover their working capital expenses. The US scenario is different. American policies like the Community Reinvestment Act encourage banks to help meet the credit needs of local low-and-moderate income companies. The fact that American SME companies can find relatively high supply of credit from banks probably explains why almost every P2P loan is destined to individuals, 77% of them for the purposes of debt consolidation [7].

B. P2P vs Traditional Bank Lending

Peer-to-peer (P2P) lending is the loaning of money to business or individuals through an online platform that directly matches lenders with borrowers. This whole process, which includes borrowers' risk analysis and debt collection service, is operated solely by a Fintech company, without the need for banks as intermediaries. The P2P borrowers can be individual or small businesses, while lenders, that hold the default risk,

[5] see: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups

[6] SEBRAE is a non profit private entity that supports small businesses in Brazil.

[7] see FEDS notes 2018: https://www.federalreserve.gov/econres/notes/feds-notes/recent-trends-in-small-business-lending-and-the-community-reinvestment-act-20180102.htm

can also be individuals or institutional investors. In summary, the P2P platforms are just a facilitator of loans between investors and borrowers that collects a loan origination fee from their service.[8]

As described by Nemoto, Storey and Huang (2019), P2P platforms face different regulatory regimes depending on the country. The regulatory features vary mainly in terms of the strictness of operational licenses required to operate and whether the originator of the loan can be the P2P platform or a partner bank. Despite these requirements, it is clear that P2P lenders bear much less regulatory costs than traditional banks, which might explain why they have been growing swiftly since the 2008 financial crisis (see Thakor (2020)).

Specifically in Brazil, P2P lending is a very recent activity, with only a few online platforms that started operating in 2016. Originally, P2P Fintechs were necessarily linked to a partner financial institution, which should be authorized, regulated and supervised by the Central Bank of Brazil. P2P loans are originated by the partner financial institution, but the credit risk is transferred to the P2P investor. Therefore, under this structure, there are four agents: the borrower, the investor, the P2P platform, and a partner financial institution. The origination fee received by the P2P Platform is shared with the partner financial institution.

In this setup, there are two types of partnerships. In the first type, the partner financial institutions keep the loans in their books and include it in the Central Bank's credit registry. As long as the loan is not in arrears, the financial institutions would need to allocate regulatory capital, since credit risk is bear by investors. In the second type, the partner financial institutions do not keep the loan in their book, and thus the loan is not in the credit registry.

In an attempt to simplify this setup and foster credit Fintech operations, the Central Bank of Brazil introduced a new regulation in 2018 (BCB resolution 4656) that introduced two new types of financial institutions: *Sociedade de Credito Direto - SCD* (Direct Credit Society) which performs basically balance sheet lending; and *Sociedade de Emprestimo entre Pessoas - SEP* (Peer-to-peer Loan Company), which performs P2P online lending [9]. These new financial institutions have to operate only through online platform lending. Moreover, these institutions can operate independently from the partner financial institutions, thus they can collect the entire origination fee,

[8] There can be problematic incentives from this practice. For example, P2Ps might have the financial incentive to maximize origination of loans at the expense of the default risk beared by the lender. This paper does not analyze these concerns to the P2P investor since we do not observe default for every loan. However, we perform a back of the envelope in Appendix A and find suggestive evidence that Brazilian P2P companies are offering similar loans' performance to investors as a bank would get.

[9] Interestingly, the new operating SCD firms focused on lending to individuals so far, while the SEPs focused on small businesses. Since the scope of this paper is to understand how the increased competition between banks and fintechs favors small businesses, we focus on the last type of company. In our empirical setup, we have both Fintechs operating in partnership with traditional banks and the SEPs.

which is fixed by the regulator at 6%. The requirements in order to open and operate these two fintech types are softer than traditional financial institution. In this way, the new regulation intended to reduce entry barriers in the credit market, and foster competition.

C. Data

The main data for this paper comes from the credit registry operated by the Brazilian Central Bank. As the country main financial regulator, it maintains information about loan contracts signed in regulated financial institution. Thus, we can observe new loans from the same borrower with each lender.

The credit registry has loans from traditional banks, SEPs and P2P Fintechs that operates through partnership and keep the loan in the partner bank's book, as described above. However, the credit registry does not have loans from P2P Fintechs that operates through partnership, but that do not keep the loan in the partner bank books. These cases represent a small share of the whole P2P lending activity. To avoid biases related to this issue, we manually obtained loan data from the largest P2P platform with missing information in the credit registry. But this is a small percentage of the P2P loans in our sample. The vast majority of the P2P loans comes from either SEPs or Fintechs operating with partner banks that register the loans in their book.

For the sake of comparing banks and P2P contracts, we focus on working capital loans for medium, small and micro companies since they comprise almost the entire P2P market. Our data goes from 2016, when P2P activity began in Brazil, to February 2020, before the Covid 19 pandemic affected the market.

We have access to loan characteristics like interest rate, volume, maturity and the ex-ante risk rating of the borrower. The rating is estimated by each financial institution, and they must tie every loan to one of ten risk tiers: AA-A-B-C-D-E-F-G-H. Each risk tier is directly linked to a default probability range and must be based on information and criteria that can be monitored by the regulator. This classification is the reference for capital requirements and loss provisions set by the regulator to every financial institution [10].

However, P2P FinTechs and their partner banks do not have to make provisions for these loans, since they did not bear its credit risk. For this reason the ex-ante risk ratings informed by Fintechs are not informative. In order to overcome this issue, we also use another measure of rating. For each firm, for each month, we check on the credit registry the worst rating registered by traditional financial institutions for the outstanding loans of that firm. This rating should also reflects default probabilities, but it is also subject to central bank's rules regarding eventual arrears of the loans. A drawback of this rating measure is that we do not observe the ratings for firms with no outstanding loans. In our regressions, when fintechs loans are not included,

[10]For more details see $https://www.bcb.gov.br/pre/normativos/res/1999/pdf/res_2682_v2_L.pdf$

we will use the ex-ante risk rating. When fintechs loans are included we will use the measure of rating based on the outstanding loans.

The depth of our data allows us to identify very useful information in terms of market organization. Like how traditional banks and Fintech borrowers differ in terms of risk. How many of the Fintech borrowers are indeed new in the credit market, i.e., did not have relationship with banks whatsoever. For those that had, we can compare the quality of new and old contracts in terms of interest rate, maturity, and amount borrowed. Note that we can also understand how was the relationship of these customers with the traditional banks and how it was affected after borrowing from a Fintech.

Another interesting feature of the data is the classification of banks in different types: large private banks, non-large private banks, public federal banks, public local banks, credit unions, and P2P lenders. This feature allows us to verify which type of banks eventually are affected by fintech competition.

To draw a richer descriptive picture about the borrowers, we complement the dataset with geographic location and quality of the borrowers from the Brazilian Institute of Geography and Statistics (IBGE - Instituto Brasileiro de Geografia e Estatística), and employees' characteristics of each firm from RAIS labor database (Relação Anual de Informações Sociais), made available by the Ministry of Labor. To measure local internet quality, we use municipality-level optic fiber internet availability from ANATEL (National Telecommunications Agency).

III. Banks vs P2Ps. Differences in Borrowers and Prices

A. P2P Borrowers characteristics

This section documents the differences between banks and online P2P borrowers. Tables 1 shows descriptive statistics of both groups in terms of company size, risk, loan volume, interest rate and number of installments. P2P Borrowers are on average smaller and riskier than bank borrowers. They get relatively higher unconditional interest rates. Table 3 presents additional firm-specific characteristics like economic activity and employees' profile from RAIS database. P2P borrowers are younger firms that operate relatively more in economic activities like information technology and professional, scientific, and technical services. They have younger and more educated employees compared to non-Fintech borrowers.

Before we directly compare banks and P2P loans' rate, we analyze how was the interest rate that P2P borrowers used to find at traditional banks, before they turn to the P2P sector. We run the regression below to find that they had higher conditional interest rates in their traditional bank loans. The results are presented in Table 4

$$Int.Rate_i = \alpha + \beta(\text{Future P2P Client})_i + X_i + \tau_t + \tau_b + \tau_r + u_i \tag{1}$$

The regressions is estimated from the sample of only traditional bank loans. X_i is a vector of loan variables like log(loan amount), maturity in years, a size dummy, and a dummy indicating whether the firm had any outstanding overdue payment that month. τ_t, τ_b and τ_r are time, bank and ex-ante risk rating fixed effects. The dummy variable "Future P2P Client" indicates whether the firm will have a future P2P loan, but not yet borrowed from them - i.e. the dummy captures the interest rate charged by banks for the P2P borrowers, before they actually migrated to the online sector.

The results indicate that firms that eventually migrate to the P2P sector used to pay roughly 2p.p. higher interest rates at banks. This result is stronger for micro firms, they used to pay 5p.p higher interest while small companies and medium clients paid respectively 1.4p.p. and 0.6p.p. more, already adjusting for factors like size and risk. In the next subsection below, we test whether the P2P sector is a cheaper alternative than traditional banks.

B. P2P Loans characteristics

This section analyzes P2P loan characteristics relative to traditional banks. The amount of information in our data allow us to perform a direct comparison between both types of lenders in terms of loan price. This is done by running the following regression:

$$Int.Rate_i = \alpha + \beta(\text{P2P Loan})_i + X_i + \tau_t + \tau_f + \tau_r + u_i \tag{2}$$

Where *P2P Loan* is dummy indicating a P2P loan, X_i is a vector of the same loan variables as equation () and τ_t, τ_f, τ_r are time, firm and rating fixed effects. It is worth noting that the rating used in this regression are based on outstanding loans for that firm, as described in section II. In this way, we overcome the absence of P2P lenders ratings, but reduce the sample to those firms with outstanding loans. We show results for interest rate as the dependent variable in Table 5. The table shows evidence that firms find better loan conditions in the online lending market. Compared to traditional banks, companies borrow at a risk-adjusted at a rate 3.7p.p lower. However, when we split our sample by company size we only find significance for small sized firms.

Next, we want to understand whether the lower prices happen in comparison to each bank type. This breakdown is done in Table 6. It provides an enlightening result: P2Ps do offer a lower risk-adjusted price only in comparison to large private banks (-7.4p.p.). Interestingly, the coefficient for public local banks shows that they charge an interest rate even lower (5.6bp) than online lenders. All other price differentials were not statistically significant. The results in Table 6 are likely very related to the market power of large private banks in the Brazilian credit market. As shown in Table 1, only four large private banks are responsible for 55% of all the working capital loans in our sample.

This scenario raises the question of whether P2Ps steal more clients from large private banks. This is presented in Table 7. We map all borrowers' loans that switched lenders, that is, the borrower's new loan was booked in a different bank from her previous loan's bank. Of all loans that were "stolen" from another institution, we find that a great number of them (52%) comes from large private banks. This is expected because of the huge market power of large banks in the Brazilian market. However, when we focus on loans stolen by the P2P lenders, we see that a much greater proportion of 65% comes from large banks. This difference of 13% is the greatest between all lenders' types. The numbers suggest that P2P clients find a better alternative of financing in the online marketplace instead of the great spreads charged by traditional large private banks.

We conclude this section highlighting the riskier nature of P2P borrowers along with a lesser coverage and poorer quality of banking services they had access to before turning to the online lending market. Once they switch to this alternative, they find cheaper loans. This scenario suggests that in credit markets dominated by fewer banks, P2P platforms have great potential to increase welfare by improving the credit conditions of smaller players underserved by the traditional banking market.

C. Banks' reaction

We now start our analysis about the competition between banks and P2P lenders. We documented in the sections above that P2P clients are smaller and riskier than the average pool of bank clients. We also observe that a high percentage of P2P clients

(96%) already had a previous loan with a bank, indicating that P2P and banks are roughly competing for the same clients. In this context, a sudden shift in P2P supply should force a price decrease from incumbent banks, specially in monopolistic markets. This is the hypothesis that we formally test in this subsection. The conceptual idea is that if banks and P2P are substitutes, banks will react to an increase in the supply of P2P lending.

We first adopt a more direct approach and estimate whether firms that borrow from P2P platforms find subsequent lower prices in bank loans. To check this, we estimate the following equation, very similar to equation B, but now evaluating the period after the first P2P loan for the firm. The P2P loan can be understood as a treatment effect. We add bank x firm fixed effects τ_{bf}, so we are focusing on the time variation after vs before the treatment for the same bank-firm pair:

$$\text{Int.Rate}_i = \alpha + \beta \text{After P2P}_i + X_i + \tau_t + \tau_{bf} + \tau_r + u_i \tag{3}$$

The "After P2P" dummy indicates a bank loan after that firm borrowed from a P2P platform. Table 9 presents the results dividing the effects by firm and banks size. The dummy coefficients were only significant for micro-sized firms, they indicate that once they borrow from a P2P platform, they get an interest rate reduction of almost 10p.p. on subsequent loans with large banks. We emphasize that this outcome is not driven by changes in borrowers credit repayment quality since such variation is already accounted for in the rating fixed effects.

Yet, with only these results it is not clear to understand what is driving the better loan conditions found by P2P borrowers at traditional banks. There are many potential candidates, for example banks observe when a client borrowed a P2P loan and this can be viewed as a positive signal for repayment quality. To better understand the channel, we differentiate firms based on their relationship with banks and test if firms with a more recent relationship with their preferred bank are the ones getting the post-P2P cheaper loans. If the results are concentrated on firms with a more recent relationship with banks, then they point to an increased bargaining power for the P2P clients against banks, instead of other factors like signaling or improvements in their credit conditions.

Thus, we extend equation 3 by adding an interaction of "After P2P" with another dummy indicating if the client recently issued a loan in the same bank:

$$\text{Int.Rate}_i = \alpha + \beta_1 \text{After P2P}_i + \beta_2 (\text{After P2P}_i \times \text{Recent}_i) + X_i + \tau_t + \tau_{bf} + \tau_r + u_i \tag{4}$$

All variables are the same as equation 3 plus the "Recent" dummy that is equal to 1 if the firm borrowed from the bank in the six months previous to the date of the new post-P2P loan. Table 9 presents the results. We find that the firms with stronger ties to the banks are indeed the ones that get a lower subsequent rate in the banks. We interpret that this price decrease is due to an increased bargaining power for the Fintech clients rather than signaling or changes in credit conditions.

In the next section we take one step further and test whether banks has a greater strategic response to P2Ps and can lower their rates overall to all local customers.

IV. Empirical Strategy Using High Speed Internet Adoption

Our goal is to test if a sudden local shift in P2P lending activity can trigger a price response from the incumbent traditional banks. The exogenous shock to P2P online lending comes from the staggered adoption of optic fiber internet technology from several Brazilian municipalities. As shown in Figures 2, Brazil presents great geographic heterogeneity of internet speed. Figure 3 presents P2P loans volume per quarter around optic fiber implementation. We can see that P2P lending is greatly concentrated in areas where high-speed internet was already adopted several years ago.

The arrival of optic fiber technology in a municipality dependents on its geospatial characteristics. Municipalities with similar economic conditions may receive fiber optic internet connection in different moments in time depending on the location, and geographic landscape. Thus, the arrival of optic fiber technology can be seen as somewhat independent to local banking activity.

Moreover, the internet quality upgrade brought by optic fiber can greatly influence the local credit market as online lenders can swiftly access these areas. Therefore, this setting presents an opportunity to contrast the credit market before and after the high speed internet was implemented, performing a difference-in-differences analysis. In this way, the fiber optic arrival would be similar to the arrival of submarine cables in Africa that D'Andrea and Limodio (2019) use as an exogenous technological shock to analyse the impacts in the African banking markets.

It is expected that P2P lending is greatly influenced by the local quality of internet service provided. Faster browsing speed makes online lending marketplace much more efficient, allowing for the P2P platforms to access distant markets potentially underserved by traditional banks. Moreover, table 3 shows that, compared to non-P2P borrowers, a much larger fraction of the businesses that request a P2P loan comes from information and communication technology (ICT) activities. Therefore, faster internet speed can also boost relative demand for P2P loans in comparison to traditional banks[11]. (Maggio and Yao, 2020) also show that for the U.S. consumer credit "areas with a high-speed internet coverage are also more likely to see more Fintech loans".

Our strategy then is to use this discontinuity and consider the adoption of fiber as a treatment effect. We will test four hypothesis for the after optic fiber period: i) P2P lending increased and indeed gained market share from traditional banks, ii) bank lending rates decrease, iii) firms receive more funding, and iv) banks attend a riskier clientele. To quantify whether firms receive more funding, we calculate a measure of market size. The market size is given by the volume of loans issued plus the outside option size. Following Diamond, Jiang and Ma (2021), we calculate the

[11] for evidence that speed upgrades to internet service providers stimulate ICT, see Augereau and Greenstein (2001)

outside option as the number of firms that did not borrow within a month multiplied by the average loan size, and divide this number by 19.5 which is the average loan maturity. With that, we can finally measure the percentage of funding as the volume of loans issued divided by the market size. This is the dependent variable that we use for hypothesis iii).

Note that the hypothesis being tested are conformable to a monopolistic banking market becoming closer to a competitive one, after P2Ps become relevant. That is, after a competition shock, prices decrease and more clients are attended. We first use all municipalities in our sample. There is a total of 5,535 and only 26 of them did not adopt optic fiber until the end of our sample in 2020. Thus, the control group is formed by the municipalities that never adopted fiber and those not yet treated.

To add robustness to our results, we will also narrow down our sample to the municipalities where P2Ps actually entered the market. In that way, the effects on the local credit market can be linked more directly to the entry of P2P players. Moreover, we also rule out potential confounders triggered by optic fiber adoption by exploring an heterogeneity in the treated municipalities. The heterogeneity comes from a pre-fiber market credit concentration scenario and also a measure of exposure to P2P competition. The idea is that P2P activity should have a stronger effect on markets where banking concentration is high, and also on markets where banks deal with customers more similar to a P2P clientele. We will give more details on these measures in the robustness tests section.

A. New price-quantity equilibrium after Optic Fiber Adoption

We formally test the hypothesis that internet speed indeed boosts P2P lending and reshapes the local credit market by performing the following dynamic difference-in-differences regression with multiple time periods:

$$y_{i,t} = \alpha + \sum_{q \neq t^*} \beta_q (\text{Optic Fiber}_{i,q}) + \tau_i + \tau_t + \epsilon_{i,t}. \tag{5}$$

The Optic Fiber$_{i,q}$ dummy equals one if municipality i has the technology at quarter q from the time of adoption and zero otherwise. The set of controls includes municipality τ_i and month τ_t fixed effects. The β_s coefficients capture the effect of high speed internet on the dependent variable $y_{i,t}$ for every quarter q before and after the adoption of optic fiber. Note that we must omit $q = t^*$ in the interaction, so the coefficients β_q measure the deviation in $y_{i,t}$ from this benchmark. We consider the benchmark as $t^* = -1$, that is, the quarter immediately before optic fiber was adopted.

The results are presented in Table 10 and Figure 7. They show a sudden increase in P2P lending volume and market share after the arrival of optic fiber. P2P market share significantly increases by 0.1% [12]. After the arrival of the new online lenders, the reaction from the incumbent banks is drastic. Banks' lending rates decrease by up to -25p.p. over the next 10 quarters. Accordingly, the proportion of the market size that is funded increases by 15p.p. Finally, we do not observe any significant change in the risk profile of the clients attended by banks. All coefficients before the adoption of fiber are insignificant, except for the interest rates. There seems to be a pre-trend in the rates as the coefficients start decreasing before the benchmark period. However, once we add an interaction of state and time fixed effect, we still observe a significant price decrease and all coefficients before the adoption of fiber become insignificant, thus we can reject the hypothesis of a pre-trend for interest rates as well.

A.1. Robustness: P2P Entry

To strengthen the link between the decrease in banks' lending rates observed after fiber adoption and the competition channel between banks vs P2Ps, we narrow our sample only to the municipalities where P2Ps actually entered the market. With that, we are left with 545 municipalities. The results are presented in Table 11 and Figure 8. The P2P penetration and the decrease in banks' lending rates are much stronger in those municipalities. P2Ps gain 2.5% market share from banks immediately after optic fiber is adopted. The reduction in banks' lending rates is striking. The rates decrease by almost 50p.p. after the adoption of optic fiber, without any sign of pre-trend. The proportion of the market funded became more volatile, but increases by 25p.p. at the end of 10 quarters. The results regarding borrowers' average rating again were not significant.

At this point, we speculate that banks also react to P2P entry even in those markets where P2P did not actually enter. In fact, the very reason why P2Ps do not enter a particular municipality market might be because banks act preemptively and reduce their lending rates to avoid loosing clients to the new online lending players in general, not only P2P Fintechs. We investigate this further in the next section, where we do not narrow our sample anymore to those markets that experienced P2P entry, yet we identify markets that are much more prone to be affected by P2P competition.

A.2. Heterogeneous Effects: Market Concentration

In this section we evaluate how the intensity of our results varies depending on the characteristics of the municipalities that adopted optic fiber. We focus on two: banking market concentration and exposure to P2P competition. The idea is that municipalities with a more concentrated banking market should attract a higher penetration of P2P loans, and a consequently steeper decline in incumbent banks' prices. The

[12] This result might seem very small, however this is an average that entails several municipalities where P2P did not enter. In the robustness section below, we focus only on the municipalities where P2P actually entered in the local credit market and the results are much stronger

same logic is valid to municipalities where banks are more "exposed" to P2P lending, and we will define this exposure measure formally in the next section below.

We first compute the market share of the four largest Brazilian private banks in each municipality before the arrival of optic fiber. As seen in Table 1, these big four private banks control more than half of SME loans market share in Brazil. We also showed evidence in Tables 6 that large private banks' rates are much higher than P2P rates, suggesting the practice of monopolistic prices. Before we analyze how the post fiber results differ depending on this concentration measure, we present an interesting characteristic: the municipalities with high top 4 banking concentration are poorer. Figure 4 shows a strong negative relationship between the market share of the big four banks and the gdp per capita of the municipality. Moreover, the percentage of firms that is funded is lower in the high concentration municipalities, a sign that credit is rationed these poorer areas. Perhaps not surprisingly, P2P market share is also higher in the areas with high bank concentration, suggesting that poorer clients underserved by banks are the ones demanding more P2P loans.

Therefore, we expect that the hypothesis tested in the previous section are stronger on areas with higher banks market power. We are formally testing whether, after optic fiber is adopted and in areas with a higher pre-fiber market concentration, i) P2P activity increases, ii) bank lending rates decrease, iii) more firms are attended by banks and iv) banks attend a riskier clientele.

Figure 5, present initial evidence confirming the hypothesis. It contrasts municipalities with high and low concentration of large private banks before the adoption of fiber. The division is based on the median, where the "high" group is composed of markets above the median value of pre-fiber large banks market share. As expected, P2P market share is substantially higher in municipalities where the big private banks held a lot of market share. The movement in incumbent banks' prices are clean, Figure 5-B shows a clear parallel downward trend in the average interest rate charged in both areas. The price in the high concentration group is considerably larger, about 25p.p. higher than the low group. Immediately after the fiber technology arrives, the once constant price gap decreases gradually until it practically disappears after 10 quarters.

Finally, Figure 5-C shows also a relatively constant gap in the average risk rating between high and low concentration groups, before fiber is adopted. Interestingly, the clients attended by banks in the high concentration municipalities is less risky [13]. This indicates that in areas where banks have more monopoly power, they focus on better clients and somewhat ignore the riskier ones. With the increased competition against the new P2P lenders, the pool of bank clients becomes riskier, as evidenced the difference between both groups risk rating eventually goes to zero.

The figures already show a strong difference in the intensity of the results depend-

[13] We assigned a number from 1 to 10 to each of the ten risk tiers: AA-A-B-C-D-E-F-G-H-HH, therefore a lower number indicates a less risky client. For more details about the risk tiers see the Data section

ing on the market organization. Yet, we test this competition channel formally by running the following difference-in-difference regression with a triple interaction term:

$$y_{i,t} = \alpha + \beta(\text{Optic Fiber}_i \times \text{Conc}_i \times \text{After}) + \gamma(\text{Optic Fiber}_i \times \text{After}) + \tau_i + \tau_t + \epsilon_{i,t}. \tag{6}$$

Where Conc_i equals the average share of large private banks before optic fiber was adopted. The After_i dummy is equal to 1 for the period after optic fiber was adopted. We include the same set of controls as equations (5). The results are presented in Table 13. After optic fiber is adopted, the relationship between ex-ante market concentration is significant and positive for the log of P2P volume issued and P2P market share. The results are also very strong for the reaction in incumbent banks. Interest rates have a strong negative relationship with the ex-ante market concentration, while the proportion of firms with that borrowed a loan and average banks' risk client are positively related. The results indicate that monopolistic banking markets become more competitive after an increased competition between banks and online lenders.

A.3. Heterogeneous effects: Pre-fiber exposure to P2P lending

We perform an extra robustness analysis to clearly identify the competition against P2P as a driver for the decrease in the prices charged by the incumbent banks. This time we define a measure of exposure to P2P competition by computing a propensity score of a client being a potential P2P borrower. The idea is that traditional banks operating in markets with a higher presence of potential P2P borrowers are more exposed to the P2P competition. As the P2P platforms remotely enter in those markets, we can expect a stronger price response from the incumbent banks.

To measure the propensity score we run a logistic regression of a P2P client dummy on loans and firms' variables:

$$(\text{P2P client})_i = \alpha + \beta_L L_i + \beta_F F_i + u_i \tag{7}$$

The dependent binary variable is equal to 1 if that particular client ever lent from a P2P platform. The control variables L are the loan amount, interest rate, maturity and risk rating. The control variables F are firms characteristics like age, years of bank relationship, number of employees, and employees' average years of education, age, and wage. The predicted value from this regression gives the propensity score measuring how similar the particular client that was issued a loan is to a P2P client.

With this score in hands, we perform the same analysis as we did in the previous section. That is, we explore an heterogeneity in the exposure to P2P in each municipality. We expect that municipalities where banks lend to clients with a higher propensity score will experience more penetration of P2P lenders and a greater reaction in incumbent banks' prices, volume and clients' risk after the upgrade in internet speed. Figure 6, present initial evidence that this indeed happens. Analogous to the previous section, it contrasts municipalities with high and low propensity score before the adoption of fiber. The division is based on the median, where the "high" group is composed of markets above the median score value. The figure shows that, after optic fiber, high score municipalities indeed experience greater P2P penetration, decrease in banks' lending rates, and an increase in the riskiness of banks' borrowers.

We test this result empirically by running a similar regression as (6), but now the interaction term is the exposure to P2Ps in the form of a propensity score:

$$y_{i,t} = \alpha + \beta(\text{Optic Fiber}_i \times \text{Score}_i \times \text{After}) + \gamma(\text{Optic Fiber}_i \times \text{After}) + \tau_i + \tau_t + \epsilon_{i,t}. \tag{8}$$

Table 12 presents the results. The results indicate a stronger reaction from incumbent banks in markets where banks had a higher exposure to P2P competition, measured by the propensity score. In this case however, only the interest rate results are robust to the clustering of standard errors at the municipality level.

V. Conclusion

We provide evidence that P2P platforms provide cheaper credit than traditional large banks in the Brazilian economy, where the banking market is highly concentrated. The pool of clients attended by this type of Fintech lender is different than traditional banks, they are smaller, younger, and riskier firms operating relatively more in technologically intense activities.

P2P clients were also underserved by the banking sector. Most of them were already attendend by banks, however they used to pay higher interest in banks before migrating to the P2P credit market. Once they borrow from those online platforms, they are also able to find a lower interest rate on subsequent bank loans, indicating an improvement in their bargaining power against traditional banks.

Using a time and geographical discontinuity in internet quality as an exogenous shock to P2P lending activity, we identify that a sudden local shift in P2P lending activity triggers a strong reduction in the incumbent traditional banks lending rates as well as an expansion in the share of local fimrs that borrows a working capital loan. When dividing our results depending on the pre-fiber local market characteristics, we find that P2P entry and local banks reaction are stronger in areas with higher banking concentration and exposure to P2P lending.

We hope that this paper highlights that P2P online lending and other types of alternative finance has great potential to alleviate frictions and increase welfare in economies where banks have great market power and many small businesses are credit constrained.

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Table 1. Summary Statistics by lender type

	Private Bank Large	Private Bank Non Large	Public Bank Federal	Public Bank Local	Credit Union	FinTechs
PANEL A. Bank Types Simple Averages						
Medium Firms	0.13	0.47	0.14	0.06	0.06	0.09
Small Firms	0.52	0.41	0.44	0.61	0.40	0.79
Micro Firms	0.34	0.12	0.43	0.33	0.54	0.12
Rating AA/A/B	0.43	0.32	0.47	0.56	0.49	0.31
Rating C/D/E	0.53	0.50	0.49	0.35	0.45	0.65
Rating F-HR	0.04	0.18	0.04	0.08	0.06	0.04
Interest Rate (% EAR)	59.16	43.16	40.10	49.65	34.66	36.73
Maturity (months)	20.55	11.79	25.31	15.91	20.20	20.63
Loan Volume (R$)	83,072	294,615	60,773	24,498	39,298	94,991
Loans per borrower	10.60	35.36	7.31	6.40	22.97	1.34
PANEL B. Bank Types Volume Weighted Averages						
Medium Firms	0.61	0.83	0.48	0.47	0.35	0.22
Small Firms	0.31	0.11	0.34	0.43	0.43	0.73
Micro Firms	0.08	0.06	0.18	0.10	0.22	0.05
Rating AA/A/B	0.41	0.35	0.41	0.41	0.41	0.26
Rating C/D/E	0.54	0.55	0.55	0.49	0.52	0.67
Rating F-HR	0.06	0.10	0.04	0.10	0.08	0.07
Interest Rate	26.54	21.67	29.11	32.21	27.43	29.16
Maturity (months)	26.25	17.39	36.00	23.72	25.39	23.32
N Loans	2,123,354	135,618	605,516	179,025	776,673	3,388
	(55.5%)	(3.5%)	(15.8%)	(4.7%)	(20.3 %)	(0.1%)
N Banks	4	60	4	5	750	6

This table shows working capital loans' variable averages divided by lender type. Data comes from the Central Bank of Brazil (BCB). Lender type size division is based on total assets divided by GDP, following BCB regulations. Each risk tier AA-A-B-C-D-E-F-G-H-HH is directly linked to a default probability range and are calculated by every financial institution based on information and criteria that can be monitored by the BCB.

Table 2. Banks and P2P Loans summary statistics

	Observations	Mean	Median	Std. Dev.	10th perc.	90th perc.
Banks' interest rate	136,581	49.16	40.06	26.78	26.61	85.19
P2P's interest rate	1,784	37.82	34.33	20.66	21.70	56.45
Banks maturity, in months	136,581	20.84	20.27	9.28	10.46	30.65
P2P Maturity, in months	1,784	20.57	24.08	5.67	12.39	24.84
Bank clients' rating	136,581	3.64	3.60	0.98	2.60	4.50
P2P clients' rating	1,234	4.00	4.00	1.45	2.00	5.00
Banks' Loan Amount	136,581	51,392.55	29,060.39	114,460.51	8,131.18	101,650.00
P2P Loan Amount	1,784	93,037.50	58,000.00	110,068.19	21,000.00	191,000.00
Bank clients' revenue	136,581	45,904,053.70	1,031,467.69	1.22e+10	215,413.20	5,755,687.00
P2P Clients Revenue	1,716	4,581,465.97	1,500,000.00	1.83e+7	96,000.00	7,500,000.00
Total Loans (R$) / Potential Market Size (R$)	275219	0.16	0.00	0.33	0.00	1.00
P2P Market Share (in %)	193,170	0.04	0.00	1.34	0.00	0.00
P2P Market Share (in %), if a P2P loan was issued	1,784	3.38	0.87	7.40	0.22	8.33

This table presents descriptive statistics for banks and P2P loans on a municipality-month level. There are a total of 5,535 municipalities in the sample, over 62 months (Jan/2015 - Feb/2020). Data comes from the Central Bank of Brazil (BCB).

Table 3. Firms Summary Statistics

	Exclusive Bank clients		Clients that borrowed From P2P	
Loan characteristics:				
	Average	Std. Dev.	Average	Std. Dev.
Interest Rate	47.88	30.78	42.06	22.98
Maturity in years	1.81	0.94	1.80	0.62
Loan Amount (R$)	65,100.74	498,290.80	99,292.33	244,832.90
Firms characteristics:				
	Average	Std. Dev.	Average	Std. Dev.
Firm Revenue	51.4×10^6	13.6×10^9	4.03×10^6	16.2×10^6
Firm Age	10.69	9.76	9.43	8.34
Years of Bank Relationship	6.30	8.08	2.99	4.47
Number of Employees	13.86	110.52	18.5	56.1
Employee's Years of Education	11.46	1.88	12.34	1,95
Median Employees' Age	34.31	8.05	34.31	8.05
Total Wage Bill (R$)	25,399.18	295,686.40	38,732.98	116,593.00
Average Wage (R$)	1,463.98	651.53	1,842.19	1,027.96
Economic Activities:				
	Obs	Frequency	Obs	Frequency
Agriculture, Forest and Fishing	5,927	0.46%	11	0.38%
Mining	1,447	0.11%	2	0.07%
Manufacturing	132,310	10.34%	337	11.70%
Construction	55,988	4.37%	103	3.58%
Wholesale and Retail Trade	734,066	57.36%	1096	38.04%
Information and Communication	23,000	1.80%	318	11.04%
Finance, Insurance and Real State	22,161	1.73%	64	2.22%
Professional, Scientific and Technical Services	52,392	4.09%	296	10.27%
Other Services	123,110	14.68%	290	13.15%
Public Administration	64,754	5.07%	275	9.54%

This table shows banks and P2P platform clients characteristics. Data comes from the Central Bank of Brazil (BCB) merged with RAIS labor database (Relação Anual de Informações Sociais). Economic Activities classification comes from CNAE (Clasiificação Nacional de Atividades Econômicas).

Table 4. P2P Clients Interest Rates in Banks

	(1) Int. Rate	(2) Int. Rate	(3) Int. Rate	(4) Int. Rate
Is P2P Client	2.2336***	5.6062***	1.4645***	0.7507**
	(8.79)	(7.53)	(4.43)	(2.33)
Firm Size Sample	All sizes	Micro	Small	Medium
Fixed Effects	Time, Bank, Firm Size and rating			
N Firms	1,248,778	678,592	627,878	118,151
N Firms that ever had a Fintech Loan	1,697	500	1,217	372
N Banks	788	742	707	598
Mean interest rate (% p.y.)	50.14	58.50	47.52	34.42
N Observations	3,659,420	1,427,158	1,769,247	462,937
Adj R2	0.5997	0.6643	0.5429	0.5106

This table shows results from the loan-level regression (1). Sample includes only bank loans, the dummy "Is P2P Client" indicates if the bank loan is for a client that will lend from a P2P platform in the future. Control variables are loan maturity in years and log of loan amount.
Standard errors Clustered at Bank level. t-stats are showed in brackets. Coefficients statistically significant at 1%, 5% and 10% are shown with ***, ** and *, respectively.

Table 5. Risk Adjusted Interest Rates: P2P vs Banks

	(1) Int. Rate	(2) Int. Rate	(3) Int. Rate	(4) Int. Rate
P2P Loan	-3.7602**	-2.4087	-4.3828*	-0.5622
	(-2.13)	(-0.59)	(-1.91)	(-0.45)
Firm Size Sample	All sizes	Micro	Small	Medium
Controls	YES	YES	YES	YES
Fixed Effects		Time, Firm and rating		
N Firms	388,338	134,096	214,925	53,131
N Banks	760	680	685	601
Mean interest rate (% p.y.)	51.54	66.47	49.76	35.24
N Observations	2,027,557	551,798	1,039,940	349,622
N Fintech Loans	1,659	86	1,115	233
Adj R2	0.8399	0.8981	0.8016	0.7735

This table shows results from the loan-level regression (2). Control variables are loan maturity in years and log of the loan amount. Sample includes only loans from firms that had some outstanding loans in the banking system at that moment.
Standard errors Clustered at Bank level. t-stats are showed in brackets. Coefficients statistically significant at 1%, 5% and 10% are shown with ***, ** and *, respectively.

Table 6. Risk adjusted interest rates, by lender type

	(1) Priv. Large	(2) Priv. NonLarge	(3) Public Federal	(4) Public Local	(5) Credit Unions
P2P Loan	-7.4415**	0.3455	-0.5885	4.5751***	-0.4205
	(-2.80)	(0.32)	(-0.51)	(3.85)	(-0.51)
Firm Size Sample	All sizes	All sizes	All sizes	All sizes	All sizes
Controls	YES	YES	YES	YES	YES
N Firms	213,657	10,956	87,894	20,296	83,819
% micro Firms	0.26	0.12	0.34	0.22	0.41
% small Firms	0.56	0.34	0.47	0.69	0.49
N Banks	10	56	10	11	690
Mean interest rate (% p.y.)	62.05	40.06	41.67	54.27	35.63
N Observations	1,040,079	82,136	348,176	102,441	363,620
N Fintech Loans	1,391	789	994	730	936
Adj R2	0.8788	0.8505	0.8007	0.8262	0.6577

This table shows results from the loan-level regression (2). Each column presents a diffenrent sample with only that particular bank type and the Fintechs. The dummy "Fintech Loan" indicates if the loan is from a Fintech instead of a traditional bank. Control variables are loan maturity in years and log of the loan amount. First column includes only loans from firms that had some outstanding loans in the banking system at that moment.
Standard errors Clustered at Bank level. t-stats are showed in brackets. Coefficients statistically significant at 1%, 5% and 10% are shown with ***, ** and *, respectively.

Table 7. Statistics: Loans that Switched Lenders

	% Switched to Banks	% Switched to FinTechs	Number of Switching Loans	Difference: %Fintech - %NonFintech
Private Bank Large	0.519	0.650	290,309	0.132
Private Bank Non Large	0.044	0.045	24,404	0.002
Public Bank Federal	0.221	0.153	123,502	-0.068
Public Bank Local	0.047	0.016	25,999	-0.030
Credit Union	0.170	0.135	94,999	-0.035

This table shows the proportion and number of working capital loans that switched from each lender type to banks and Fintechs. Data comes from the Central Bank of Brazil (BCB).

Table 8. Interest rates, after borrowing from FinTech

	(1) Int. Rate	(2) Int. Rate	(3) Int. Rate	(4) Int. Rate
After 1st Fintech Loan	-1.2046 (-1.53)	-7.8838*** (-2.62)	-0.4316 (-0.55)	
After 1st Fintech Loan x Recent Relation				-2.9010** (-2.10)
After 1st Fintech Loan x Old Relation				-0.4362 (-0.45)
Fixed Effects	Time, Firm x Bank and rating			
Firm Sizes	Micro and Small	Micro	Small	Micro and Small
N Firms	584,594	277,479	312,903	584,594
N Banks	716	686	660	716
N Firm x Banks	643,229	286,683	349,369	643,229
N Observations	2,477,440	993,679	1,369,722	2,477,440
Adj R2	0.8467	0.8777	0.8229	0.8467

This table shows results from the loan-level regressions (3) and (4). Control variables are loan maturity in years and log of the loan amount. The "After First Fintech Loan" indicates a bank loan after that firm borrowed from a P2P platform. The "Recent Relation" dummy is equal to 1 if the firm borrowed from the bank in the six months previous to the date of the new post-P2P loan. Standard errors Clustered at firm level. t-stats are showed in brackets. Coefficients statistically significant at 1%, 5% and 10% are shown with ***, ** and *, respectively.

Table 9. Interest rates, after borrowing from FinTech

	(1) Int. Rate	(2) Int. Rate	(3) Int. Rate	(4) Int. Rate
After 1st Fintech Loan	-1.2046 (-1.53)	-7.8838*** (-2.62)	-0.4316 (-0.55)	
After 1st Fintech Loan x Recent Relation				-2.9010** (-2.10)
After 1st Fintech Loan x Old Relation				-0.4362 (-0.45)
Fixed Effects	Time, Firm x Bank and rating			
Firm Sizes	Micro and Small	Micro	Small	Micro and Small
N Firms	584,594	277,479	312,903	584,594
N Banks	716	686	660	716
N Firm x Banks	643,229	286,683	349,369	643,229
N Observations	2,477,440	993,679	1,369,722	2,477,440
Adj R2	0.8467	0.8777	0.8229	0.8467

This table shows results from the loan-level regressions (3) and (4). Control variables are loan maturity in years and log of the loan amount. The "After First Fintech Loan" indicates a bank loan after that firm borrowed from a P2P platform. The "Recent Relation" dummy is equal to 1 if the firm borrowed from the bank in the six months previous to the date of the new post-P2P loan. Standard errors Clustered at firm level. t-stats are showed in brackets. Coefficients statistically significant at 1%, 5% and 10% are shown with ***, ** and *, respectively.

Table 10. Dynamic Difference-in-Differences results

	Log P2P Amount		P2P Share		Banks' rate		% Market with a loan	
Timing	β	s.e.	β	s.e.	β	s.e.	β	s.e.
−10	0.002	(0.010)	−0.018	(0.016)	13.332	(9.652)	0.039	(0.064)
−9	−0.006	(0.013)	−0.050	(0.037)	13.944	(8.652)	−0.031	(0.064)
−8	−0.008	(0.012)	−0.046	(0.032)	15.211**	(7.573)	−0.009	(0.059)
−7	−0.005	(0.009)	−0.024	(0.022)	12.526*	(6.634)	−0.055	(0.051)
−6	−0.007	(0.008)	−0.020	(0.017)	12.432**	(5.578)	0.009	(0.043)
−5	−0.013*	(0.008)	−0.030	(0.019)	10.700**	(4.510)	−0.042	(0.038)
−4	0.016	(0.018)	−0.005	(0.016)	9.254***	(3.547)	0.004	(0.033)
−3	0.016	(0.017)	0.008	(0.018)	4.578*	(2.603)	−0.015	(0.029)
−2	0.006*	(0.004)	−0.002	(0.007)	0.452	(1.541)	0.044*	(0.023)
−1		()		()		()		()
1	0.041*	(0.021)	0.107*	(0.062)	−7.828***	(2.510)	0.052*	(0.027)
2	0.003	(0.006)	0.003	(0.014)	−9.036***	(3.458)	0.089***	(0.029)
3	0.018***	(0.006)	0.020**	(0.008)	−11.172**	(4.416)	0.078**	(0.033)
4	0.035**	(0.014)	0.043**	(0.021)	−16.097***	(5.438)	0.082**	(0.039)
5	0.036***	(0.012)	0.033**	(0.014)	−17.943***	(6.438)	0.112***	(0.043)
6	0.030***	(0.012)	0.049*	(0.030)	−19.403***	(7.467)	0.110**	(0.048)
7	0.035***	(0.013)	0.048**	(0.019)	−23.243***	(8.498)	0.081	(0.053)
8	0.028**	(0.013)	0.061**	(0.031)	−25.455***	(9.528)	0.111*	(0.059)
9	0.025*	(0.013)	0.054**	(0.025)	−26.784**	(10.562)	0.146**	(0.064)
10	0.044***	(0.017)	0.084**	(0.034)	−28.335**	(11.599)	0.159**	(0.070)
Obs	136,605		136,605		85,457		85,456	
R^2	0.268		0.059		0.797		0.681	

This table presents the time dummy coefficients and municipality-clustered standard deviations from regression (5). Control variables include municipality averages loan risk rating, maturity, and interest rates. All regressions have municipality and time fixed effects. For the market reaction regressions (columns 3-5), we consider only periods where at least 5 loans were issued. Data comes from the Central Bank of Brazil (BCB). Internet data comes from ANATEL (National Technology Agency).. Coefficients statistically significant at 1%, 5% and 10% are shown with ***, ** and *, respectively.

Table 11. Dynamic Difference-in-Differences results. Municipalities with P2P entry.

	Log P2P Amount		P2P Share		Banks' rate		% Market with a loan	
Timing	β	s.e.	β	s.e.	β	s.e.	β	s.e.
−10	−0.254	(0.179)	−0.887**	(0.425)	5.850	(14.051)	−0.346	(0.299)
−9	−0.652**	(0.291)	−2.360**	(1.128)	6.893	(9.824)	−0.071	(0.271)
−8	−0.551*	(0.303)	−1.825*	(1.080)	12.179	(9.070)	−0.080	(0.208)
−7	−0.610**	(0.244)	−1.469	(1.032)	8.059	(12.936)	−0.434***	(0.123)
−6	−0.496*	(0.264)	−1.181	(0.762)	21.072**	(8.658)	−0.197	(0.147)
−5	−0.432*	(0.259)	−1.224*	(0.735)	9.595*	(5.666)	−0.051	(0.152)
−4	0.237	(0.562)	−0.496	(0.663)	−1.135	(18.740)	0.124	(0.089)
−3	0.359	(0.417)	0.197	(0.493)	0.220	(10.173)	−0.164	(0.110)
−2	−0.100	(0.085)	−0.248	(0.219)	0.222	(4.301)	−0.086	(0.099)
−1		()		()		()		()
1	0.770*	(0.454)	2.407*	(1.336)	−12.299	(7.813)	0.124	(0.094)
2	−0.127	(0.120)	−0.056	(0.316)	−12.966*	(6.860)	−0.022	(0.111)
3	0.036	(0.097)	0.431**	(0.181)	−20.175***	(7.393)	0.040	(0.119)
4	0.413	(0.254)	0.857**	(0.388)	−26.482***	(9.132)	0.192*	(0.113)
5	0.293	(0.207)	0.564***	(0.217)	−31.559***	(9.294)	0.241**	(0.100)
6	0.292	(0.183)	1.011*	(0.539)	−34.502***	(10.213)	0.148	(0.123)
7	0.430*	(0.226)	0.971**	(0.383)	−41.262***	(10.853)	0.073	(0.128)
8	0.365**	(0.179)	1.216**	(0.492)	−42.833***	(11.589)	0.106	(0.132)
9	0.367**	(0.181)	1.104***	(0.356)	−46.291***	(12.578)	0.230*	(0.134)
10	0.601***	(0.200)	1.526***	(0.485)	−47.393***	(13.395)	0.242*	(0.144)
Obs	24,120		24,120		22,090		22,090	
R^2	0.246		0.067		0.841		0.552	

This table presents the time dummy coefficients and municipality-clustered standard deviations from regression (5), with the sample limited to municipalities that had P2P loans. Control variables include municipality averages loan risk rating, maturity, and interest rates. All regressions have municipality and time fixed effects. For the market reaction regressions (columns 3-5), we consider only periods where at least 5 loans were issued. Data comes from the Central Bank of Brazil (BCB). Internet data comes from ANATEL (National Technology Agency).. Coefficients statistically significant at 1%, 5% and 10% are shown with ***, ** and *, respectively.

Table 12. Heterogeneous results: interaction with propensity score

			Panel A: Non-clustered Standard Errors		
	(1) Log P2P Amount	(2) P2P Share	(3) Banks' interest rate	(4) % Firms with loan	(5) Bank clients' rating
After × Exposure	1.005***	0.339**	-61.476***	0.183**	0.668*
	(0.290)	(0.134)	(6.065)	(0.075)	(0.359)
After	-0.412***	-0.146**	25.218***	-0.093***	-0.288*
	(0.133)	(0.062)	(2.786)	(0.035)	(0.165)
Observations	22,271	22,271	22,271	22,271	22,271
R-squared	0.050	0.037	0.705	0.776	0.200
			Panel B: Standard Errors Clustered at Municipality Level		
	(1) Log P2P Amount	(2) P2P Share	(3) Banks' interest rate	(4) % Firms with loan	(5) Bank clients' rating
After × Exposure	1.005	0.339	-61.476***	0.183	0.668
	(0.744)	(0.233)	(19.818)	(0.165)	(0.507)
After	-0.412	-0.146	25.218***	-0.093	-0.288
	(0.326)	(0.102)	(8.868)	(0.074)	(0.230)
Observations	22,271	22,271	22,271	22,271	22,271
R-squared	0.050	0.037	0.705	0.776	0.200

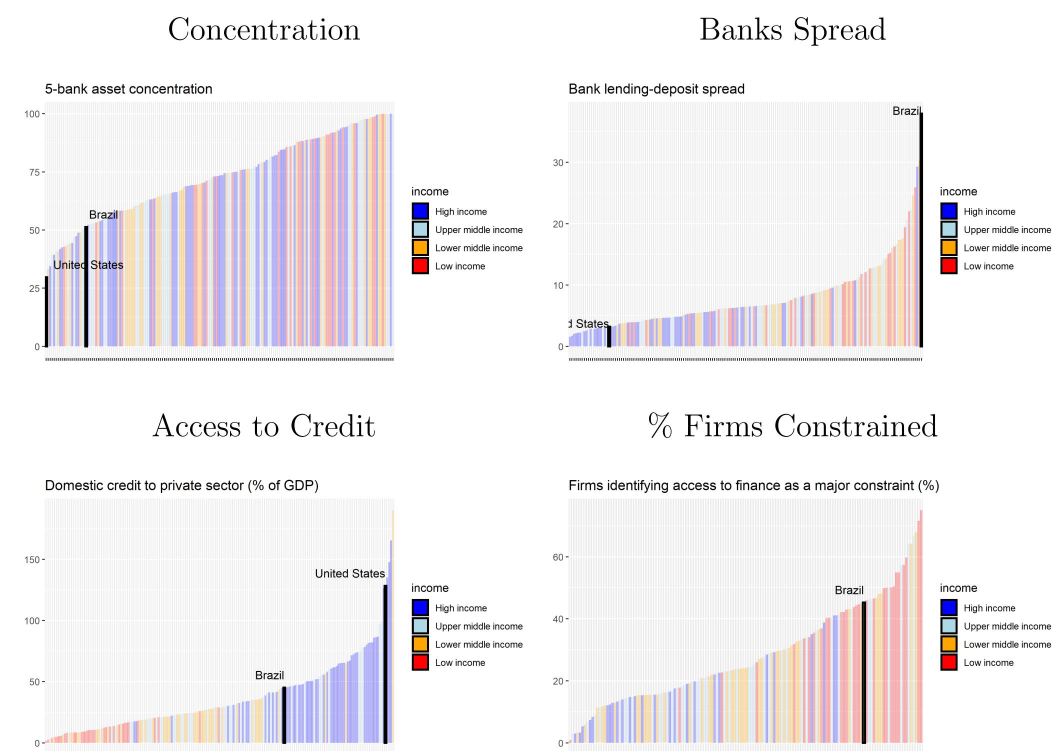
This table presents the coefficients and municipality-clustered standard deviations from regression (6). All regressions have municipality and time fixed effects. Data comes from the Central Bank of Brazil (BCB). Internet data comes from ANATEL (National Technology Agency).. Coefficients statistically significant at 1%, 5% and 10% are shown with ***, ** and *, respectively.

Table 13. Heterogeneous results: interaction with propensity score

	(1)	(2)	(3)	(4)	(5)
	Log P2P Amount	P2P Share	Banks' interest rate	% Firms with loan	Bank clients' rating
Panel A: Non-clustered Standard Errors					
After × Exposure	0.163***	0.050**	-29.349***	0.052***	0.309***
	(0.052)	(0.024)	(1.054)	(0.014)	(0.064)
After	-0.042	-0.019	12.789***	-0.037***	-0.146***
	(0.034)	(0.016)	(0.698)	(0.009)	(0.042)
Observations	22,255	22,255	22,255	22,255	22,255
R-squared	0.050	0.037	0.714	0.776	0.201
Panel B: Standard Errors Clustered at Municipality Level					
	(1)	(2)	(3)	(4)	(5)
	Log P2P Amount	P2P Share	Banks' interest rate	% Firms with loan	Bank clients' rating
After × Exposure	0.163**	0.050**	-29.349***	0.052**	0.309***
	(0.072)	(0.024)	(2.066)	(0.026)	(0.096)
After	-0.042**	-0.019**	12.789***	-0.037**	-0.146***
	(0.019)	(0.008)	(1.132)	(0.015)	(0.065)
Observations	22,255	22,255	22,255	22,255	22,255
R-squared	0.050	0.037	0.714	0.776	0.201

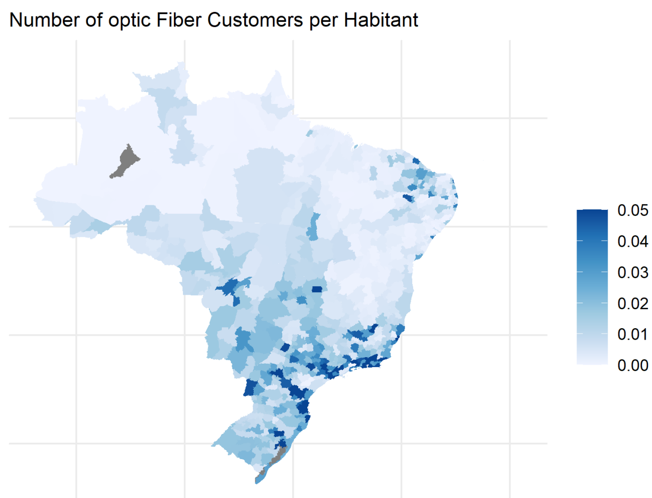
This table presents the coefficients and municipality-clustered standard deviations from regression (8). All regressions have municipality and time fixed effects. Data comes from the Central Bank of Brazil (BCB). Internet data comes from ANATEL (National Technology Agency).. Coefficients statistically significant at 1%, 5% and 10% are shown with ***, ** and *, respectively.

Figure 1. Banking and credit market organization by country income level



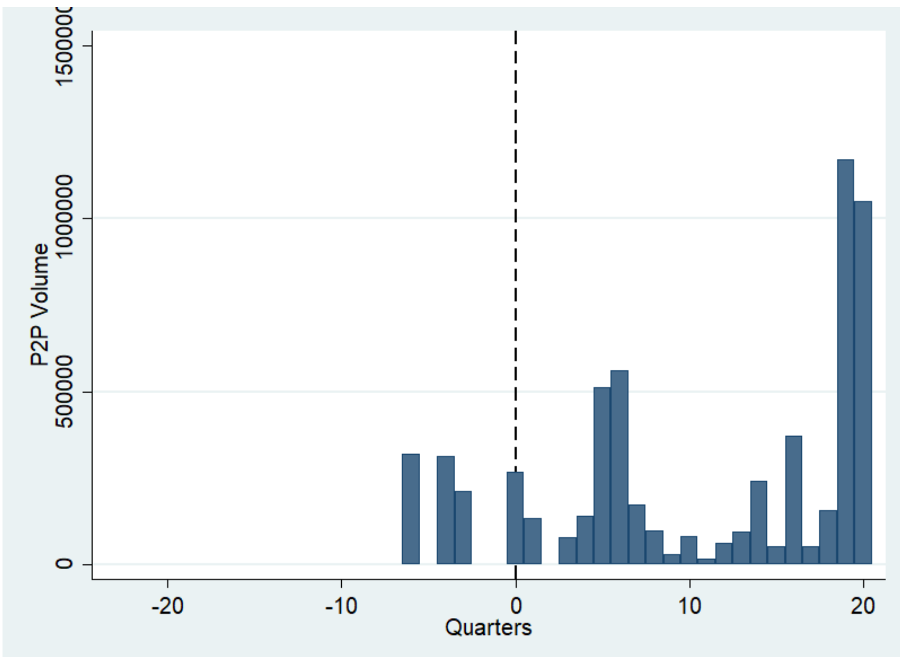
Data comes from the World Bank - Global Financial Development Database (https://www.worldbank.org/en/publication/gfdr/data/global-financial-development-database). e plots were elaborated based on the 4 income level classification for countries from the World Bank

Figure 2. Number of optic Fiber Customers per Habitant, by Brazilian Micro-Region



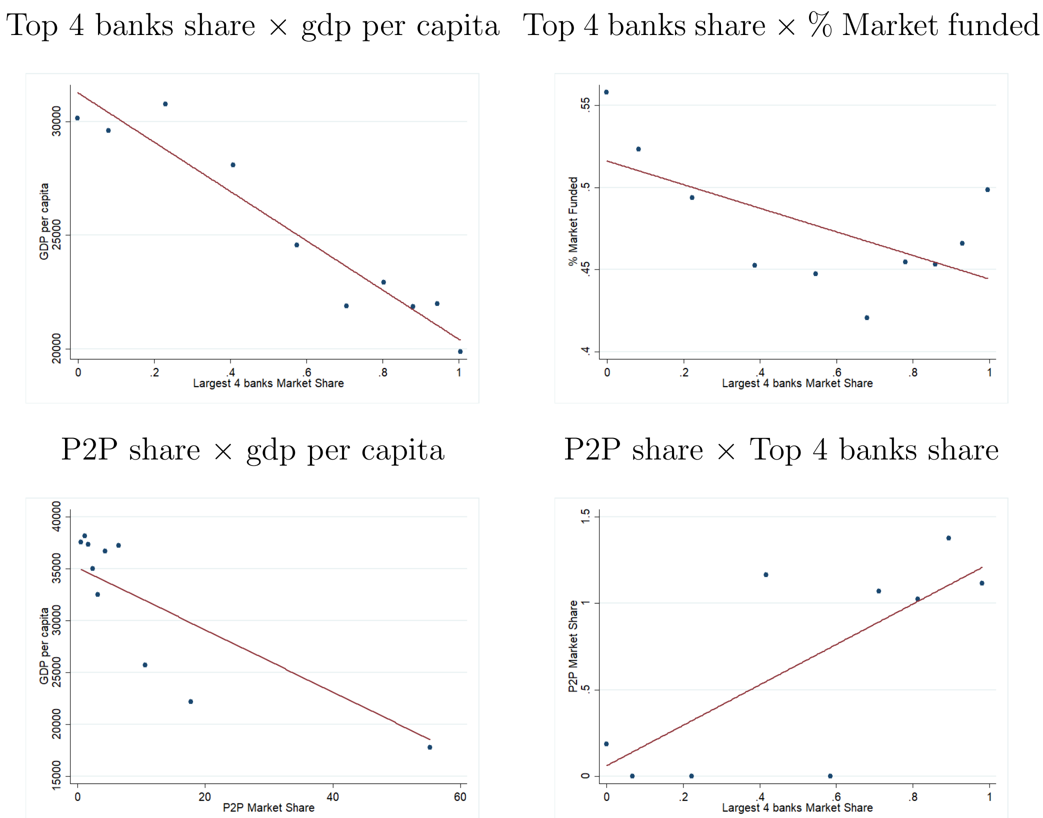
This figure plots the micro region average number of optic fiber customers per habitant. Internet data comes from ANATEL (National Technology Agency) and micro region classification comes form IBGE (Instituto Brasileiro de Geografia e Estatística)

Figure 3. P2P Volume around Optic Fiber Adoption



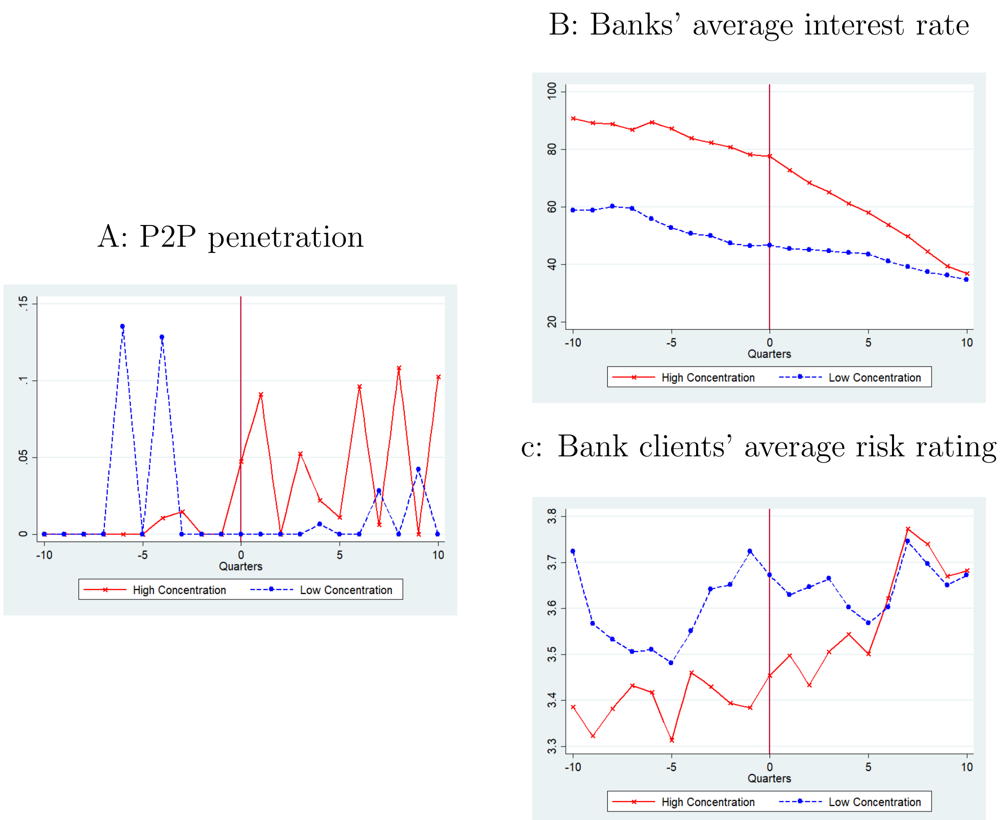
This figure plots the total loan amount borrowed from Fintechs, by the years around adoption of optic fiber technology. Data comes from the Central Bank of Brazil (BCB). Internet data comes from ANATEL (National Technology Agency).

Figure 4. Binscatters: top 4 banks market share and P2P penetration, by municipality.



Each variable consists of municipality averages. The bin-scatter plots show the cross-sectional relationship between the deciles of each variable. We purged the effect of time by regressing them on a constant and month fixed effects. The plots show the residual of this regression. Data comes from the Central Bank of Brazil (BCB)

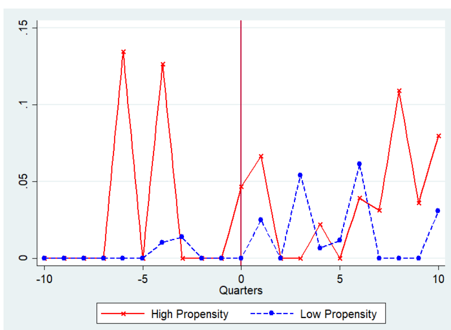
Figure 5. Effect of Optic Fiber Adoption on Local Credit Markets. Division by Concentration



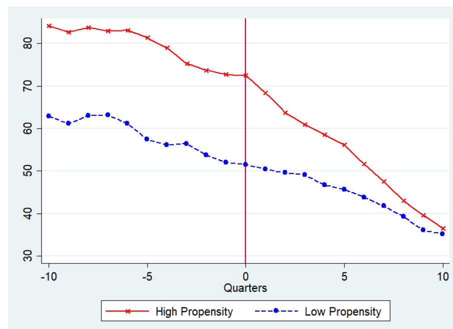
The plots present averages for 1,110 Brazilian municipalities that adopted fiber after 2015, when our sample begins. For each municipality, we calculate the market share of the largest four private banks in Brazil <u>before</u> optic fiber internet was adopted. We then calculate the quarter-averages around optic fiber adoption for all municipalities above or equal to the median market share, which we call "High Concentration", and below the median, which we call "Low Concentration". Data comes from the Central Bank of Brazil (BCB)

Figure 6. Effect of Optic Fiber Adoption on Local Credit Markets. Division by P2P Propensity Score

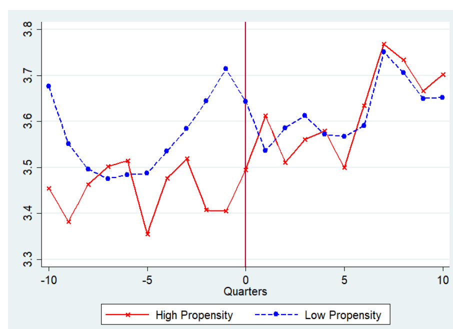
A: P2P penetration



B: Banks' average interest rate



c: Bank clients' average risk rating

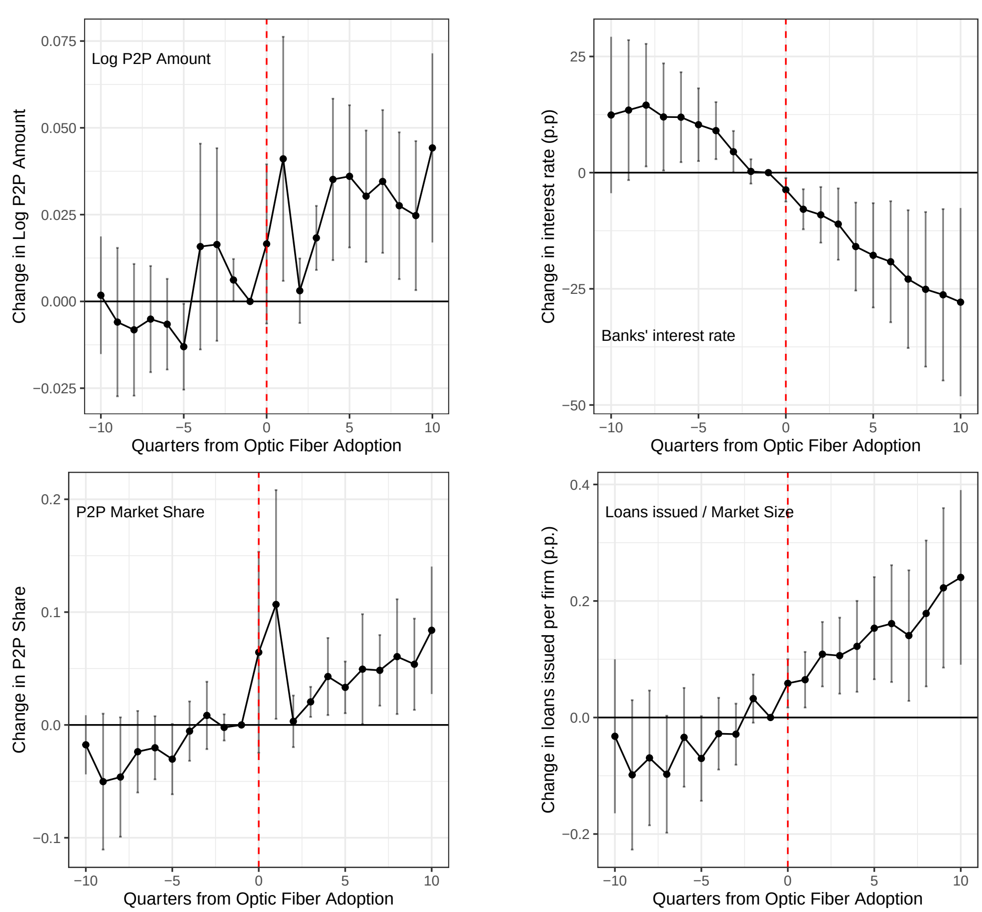


The plots present averages for 1,110 Brazilian municipalities that adopted fiber after 2015, when our sample begins. For each municipality, we calculate borrowers propensity score as in (7) <u>before</u> optic fiber internet was adopted. We then calculate the quarter-averages of this score around optic fiber adoption for all municipalities above or equal to the median, which we call "High Propensity", and below the median, which we call "Low Propensity". Data comes from the Central Bank of Brazil (BCB)

Figure 7. Regression Coefficients: dynamic difference-in-differences

A: P2P penetration

B: Market reaction

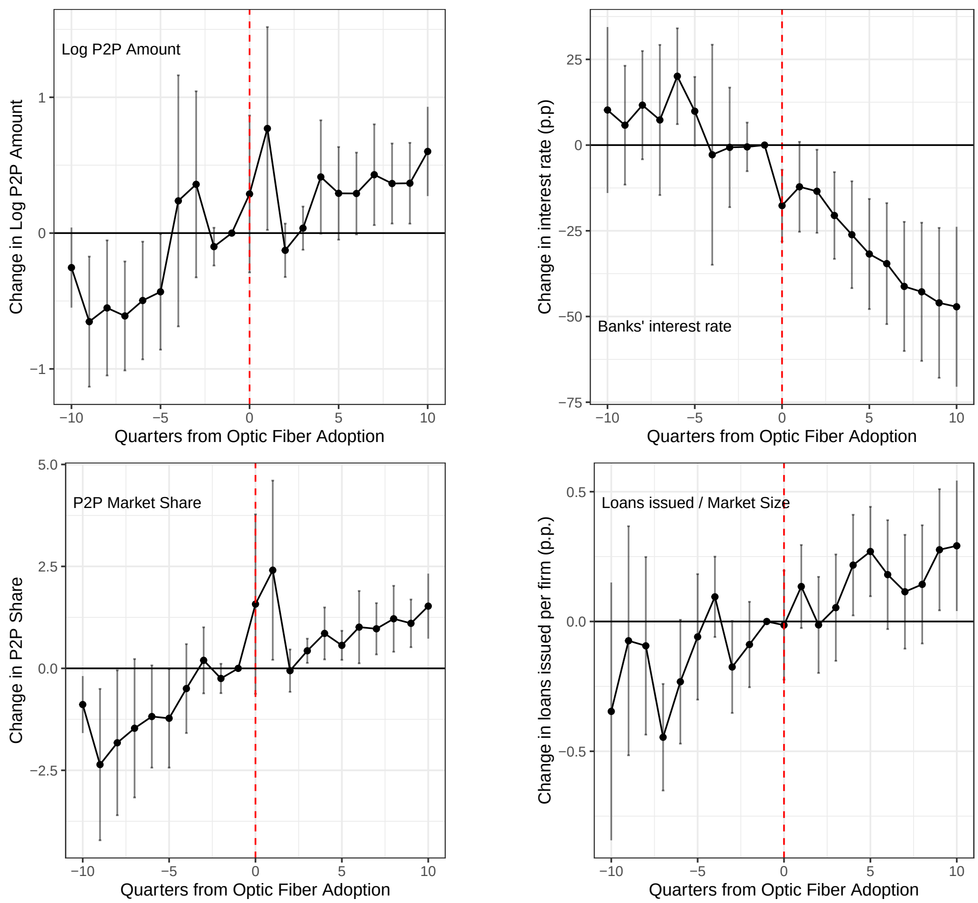


This figure plots the time dummy coefficients and 90% level municipality-clustered standard deviations from regression (5). Control variables include municipality averages loan risk rating, maturity, and interest rates. All regressions have municipality and time fixed effects. For the regressions in Panel B, we consider only periods where at least 5 loans were issued. Data comes from the Central Bank of Brazil (BCB). Internet data comes from ANATEL (National Technology Agency).

Figure 8. Robustness. Regression Coefficients: dynamic difference-in-differences

A: P2P penetration

B: Market reaction



This figure plots the time dummy coefficients and 90% level municipality-clustered standard deviations from regression (5), with the sample limited to municipalities that had P2P loans. Control variables include municipality averages loan risk rating, maturity, and interest rates. All regressions have municipality and time fixed effects. For the regressions in Panel B, we consider only periods where at least 5 loans were issued. Data comes from the Central Bank of Brazil (BCB). Internet data comes from ANATEL (National Technology Agency).

A. Appendix - Loans Performance

This section explains a back of the envelope calculation for the ex-post returns of P2P and bank loans. We assume that outstanding debt is not recovered for 90 days or more for the delinquent borrowers. We also omit from the calculation all operational and regulatory costs. The assumptions are applied for both the banks and P2P sector. We calculate the returns as:

$$\text{Estimated Returns} = (1 - d) * (1 + r) - 1$$

Where d is the 90 day average default rate and r is the loan interest rate.

We use data from the Banco Central do Brazil (BCB) Annual Banking Economy Report 2019 (https://www.bcb.gov.br/publicacoes/relatorioeconomiabancaria) and from a report to investors from the largest Brazilian P2P company (Nexoos).

The table below presents the estimates. We estimate that, before costs and recoveries after 90-day default, banks get an average return of 9.5% on their loans and 15% for loans to small and medium companies. Individuals that lend to similar companies through online platforms get 13.5%.

Table A.1. Estimates of Loan Performance: Banks vs Fintechs

	Banks - All loans	Banks - SME loans	P2Ps - SME loans
Interest rate (per year)	11.09 %	19.90 %	26.10 %
Deliquency rate	1.45 %	4.07 %	9.90 %
Estimated Returns	9.48 %	15.02 %	13.53 %

This table presents average interest rates (r) and average 90 days delinquency rate (d) for banks and P2P lenders working capital loans. Aggregate information for all bank loans is available from Banco Central do Brazil (BCB) Annual Banking Economy Report 2019 (https://www.bcb.gov.br/publicacoes/relatorioeconomiabancaria). Averages for only small and medium entreprises comes from BCB internal data. P2P average comes from the largest Brazilian P2P company (Nexoos) report to individual investors. Returns are estimated assuming that outstanding debt is not recovered for 90 days or more delinquent borrowers, by the following equation: