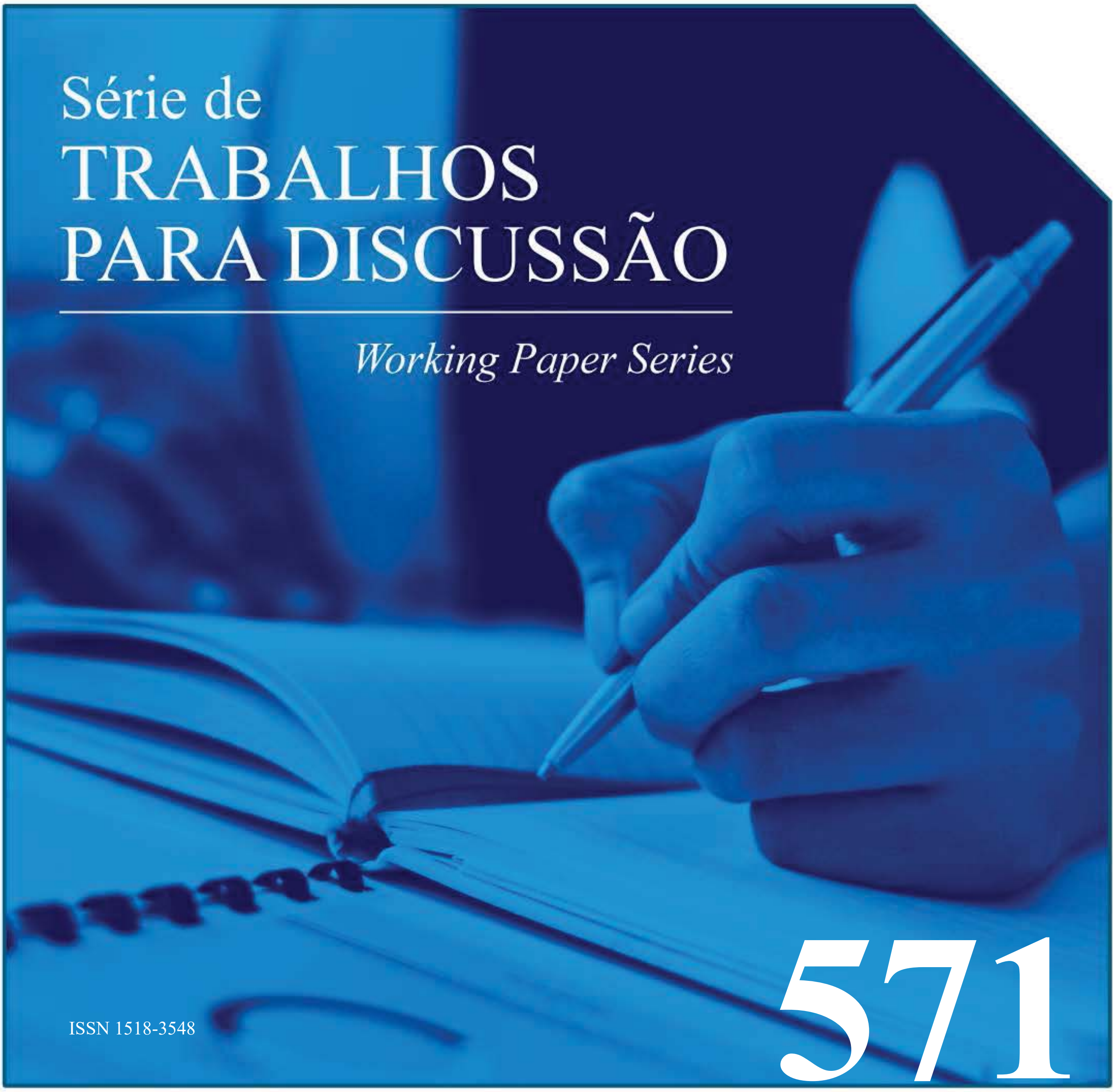

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Does Fintech Lending Lower Financing Costs? Evidence From An Emerging Market

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Non-technical Summary

Access to adequate financing is crucial for small businesses. However, in many countries, especially in emerging economies, small firms face severe credit restrictions due to imperfect lending markets.

In this paper, we examine whether Fintech lending can alleviate the credit frictions faced by small businesses. To accomplish this task, we use a dataset that contains virtually all unsecured working capital loans to micro, small and medium companies, from both banks and online Peer-to-Peer (P2P) platforms in Brazil.

The paper is divided into three parts: 1) a loan-level analysis; 2) a market-level analysis; and 3) a model to illustrate the welfare gains and uncover the mechanism in the credit market when P2P platforms compete with banks.

In the first part, we compare banks' and P2P contracts at the loan level. We initially characterize the P2P clients profiles: they are smaller, younger and riskier firms, with younger and more educated employees, and with economic activities related to professional services and technology. Moreover, P2P platforms penetrate relatively more in municipalities that are distant from the main financial centers, where banking markets are oligopolistic. Moreover, firms that borrow from P2Ps used to pay 1.3 percentage points (pp) higher rates with traditional lenders, before their first P2P loan. However, these firms are able to find a 1.4 pp lower rate on subsequent traditional bank loans after their first P2P loan. This indicates that banks respond to the new competition and try to regain their runaway clients. Finally, we document that P2P lenders offer 4 pp lower risk adjusted rates than traditional lenders.

In the second part, we find that banks react to P2Ps at the municipality level. After P2P entry in a market, incumbent banks decrease their lending rates and expand credit to more businesses, increasing social welfare. Prior to the entry of P2P lenders, the average annual interest rate charged by the banks was quite high and variable: 67% with a 23 pp standard deviation. After P2P entry, it decreases by 3 pp, while the volume of loans issued by banks increases by 66%. These effects are only statistically significant in municipalities with high banking concentration.

In the third part, we estimate a structural model of demand for credit to provide intuition for the empirical results and measure welfare effects. The model is able to uncover the mechanism of how a unique competitor like a P2P platform can force a wide strategic response from banks. In a counterfactual experiment using the model, we remove the P2P platforms from the markets and estimate social welfare from P2P entry. Without competition from the online platforms, the interest rates charged by banks increase substantially, especially for riskier borrowers.

The main novelty of this work is to show that Fintechs have the potential to challenge oligopolistic banks and induce a reaction from them. This matter has been greatly overlooked by the academic literature since P2P activity is new in emerging countries. Most of the studies focus on developed markets where the banking sector is competitive. Our results suggest countries that face a highly concentrated banking market can greatly benefit from policies promoting new technologies in the financial sector.

Sumário não Técnico

O acesso a financiamento adequado é crucial para as pequenas empresas. No entanto, em muitos países, especialmente nas economias emergentes, as pequenas empresas enfrentam severas restrições de crédito devido a mercados de empréstimos imperfeitos.

Neste artigo, examina-se se os empréstimos de fintech podem aliviar os problemas de acesso ao crédito enfrentados por pequenas empresas. Para realizar essa tarefa, usa-se uma base de dados que contém praticamente todos os empréstimos de capital de giro não garantidos para micro, pequenas e médias empresas, tanto de bancos quanto de plataformas de Peer-to-Peer (P2P) no Brasil.

O artigo está dividido em três partes: 1) uma análise em nível de empréstimo; 2) uma análise em nível de mercado; e 3) um modelo para ilustrar os ganhos de bem-estar e descobrir o mecanismo no mercado de crédito quando as plataformas P2P competem com os bancos.

Na primeira parte, comparam-se os contratos dos bancos e P2P no nível do empréstimo. Caracterizam-se inicialmente os perfis dos clientes P2P: são empresas menores, mais jovens e mais arriscadas, com funcionários mais jovens e com maior escolaridade e com atividades econômicas relacionadas a serviços profissionais e tecnologia. Além disso, as plataformas P2P penetram relativamente mais em municípios distantes dos principais centros financeiros, onde os mercados bancários são oligopolistas. As empresas que tomam empréstimos de P2Ps costumavam pagar taxas 1,3 pontos percentuais (pp) mais altas com os credores tradicionais, antes de seu primeiro empréstimo P2P. No entanto, essas empresas conseguem encontrar uma taxa 1,4 pp menor nos empréstimos bancários tradicionais subsequentes ao primeiro empréstimo P2P. Isso indica que os bancos respondem à nova concorrência e tentam reconquistar seus clientes perdidos. Por fim, documentamos que os credores P2P oferecem taxas ajustadas de risco 4 pp mais baixas do que os credores tradicionais.

Na segunda parte, documenta-se que os bancos reagem aos P2Ps no nível do município. Após a entrada P2P em um mercado, os bancos incumbentes diminuem suas taxas de empréstimo e expandem o crédito para mais empresas, aumentando o bem-estar social. Antes da entrada dos credores P2P, a taxa de juros média anual cobrada pelos bancos era bastante alta e variável: 67% com desvio padrão de 23 pp. Após a entrada do P2P, diminui 3 pp, enquanto o volume de empréstimos feitos pelos bancos aumenta 66%. Esses efeitos somente são estatisticamente significativos em municípios com alta concentração bancária.

Na terceira parte, estima-se um modelo estrutural de demanda por crédito para fornecer intuição para os resultados empíricos e medir efeitos de bem-estar. O modelo descreve o mecanismo de como um concorrente peculiar como uma plataforma P2P pode forçar uma ampla resposta estratégica dos bancos. Em um experimento contrafactual usando o modelo, removemos as plataformas P2P dos mercados e estimamos o bem-estar social a partir da entrada P2P. Sem a concorrência das plataformas *online*, as taxas de juros cobradas pelos bancos aumentam substancialmente, principalmente para tomadores de maior risco.

A principal contribuição deste trabalho é mostrar que as Fintechs têm potencial para desafiar bancos oligopolistas e induzir uma reação deles. Este assunto tem sido bastante negligenciado pela literatura acadêmica, uma vez que a atividade P2P é nova em países emergentes. A maioria dos estudos foca em mercados desenvolvidos onde o setor bancário é competitivo. Nossos resultados sugerem que países que enfrentam um mercado bancário altamente concentrado podem se beneficiar de políticas que promovam novas tecnologias no setor financeiro.

Does Fintech Lending Lower 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 online Peer-to-Peer (P2P) lenders focus on smaller and riskier firms already served by banks. P2P clients get lower interest rates compared to traditional banks. Once they borrow from P2Ps, they find a lower rate on subsequent bank loans, indicating that banks try to recapture runaway borrowers. In response to P2P entry, incumbent banks in oligopolistic markets decrease their lending rates by 2.5 percentage points and expand credit to older firms with difficulty accessing credit. We rationalize these findings in a structural IO model of the banking sector, where banks and P2Ps have different profit functions and compete for clients with risk heterogeneity. We use the estimated model to calculate welfare gains. P2Ps significantly increase social welfare in oligopolistic markets by offering lower interest rates to riskier borrowers and forcing the banks to do the same. Welfare gains range from 10% of the local output in municipalities with only one incumbent bank to 1% in those with five banks.

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

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1 Introduction

We quantify the competitive implications and welfare effects following the entry of online Peer-to-Peer platforms (P2P) into local banking markets in Brazil. P2P lending is among the fastest growing segments in modern financial markets, and its interaction with banks has gained attention in the finance literature (see Thakor (2020)) and among financial regulators (Nemoto et al. (2019)). Naturally, when a new competitor arrives, existing lenders may react. However, little is known about the competitive response by banks or about the spillover and welfare effects of a new competitor in the banking sector. This response can be particularly evident in markets where banks hold a lot of market power, like in most emerging economies.

To do so, we use data on virtually all working capital loans from banks and P2P platforms to small businesses in Brazil from 2016 to 2020. Our empirical strategy is twofold. First, we take advantage of the vast banking market heterogeneity to match the municipalities where P2Ps issued a loan with similar ones without P2P loans, allowing us to estimate the local effects from P2P entry accurately. Second, we exploit the local introduction of optical fiber internet as a quasi-natural experiment enabling P2P entry to confirm the previous estimates. Our main contributions are: (i) to identify the reaction from incumbent banks caused by the P2P platforms' arrival and (ii) to estimate a structural model of the banking sector to quantify the elasticity of loan demand and calculate welfare effects. We find that the competition between banks and P2P lenders is a first-order effect depending on the number of local lenders.

The main results are as follows. First, we document that P2P lenders predominantly focus on firms with a preexisting relationship with banks, offering them four percentage points (pp) lower risk-adjusted rates. More importantly, after a firm borrows from a P2P platform, they are able to find a 1.4 pp lower rate on subsequent bank loans. This result indicates that banks view P2P platforms as a valid competitor - in accordance with previous findings in the literature (see Tang (2019) - and try to regain runaway borrowers. Second, we turn to the municipality-level analysis to find that P2P entry triggers significant local spillover effects. Incumbent banks respond to the P2P competition by reducing interest rates by three pp[1] and increasing the volume of loans in *reais* (R$) issued per firm by 7%. These effects are only statistically significant in municipalities with high banking concentration. Moreover, we find evidence that existing firms with difficulty accessing credit are the ones that benefit from this scenario instead of new firms. Third, social welfare increases monotonically with the number of existing lenders. The effect ranges from 10% of the local output in the municipalities with only one incumbent bank to 1% in those with five banks. In less concentrated municipalities, the welfare gains are close to zero. Our findings indicate that P2Ps play a pivotal role in reducing credit frictions in oligopolistic markets.

We first evaluate the profile of P2P borrowers and compare banks' and P2P contracts at the loan level. We find that P2Ps focus on smaller and riskier firms and penetrate relatively more in

[1] Prior to the entry of P2P lenders, the average annual interest rate charged by the banks was quite high and variable: 59% with a 23pp standard deviation.

poorer municipalities that are distant from the main financial centers, where the banking markets are highly concentrated. Table 1 indicate that P2P lenders' market shares at the municipality level strongly correlate with the distance to the state capital, local HHI index, and local GDP per capita. No other type of lender presented high correlation magnitudes for all three variables. Not even non-profit institutions that usually target areas with credit restrictions, like public banks and credit unions.

These findings are consonant with the lower costs of P2P platforms. Since they do not operate with brick-and-mortar branches, they can easily access distant locations where traditional banks have much higher entry costs. In addition, P2P platforms do not bear regulatory and loss provision costs, which gives them a comparative advantage over banks to focus on riskier borrowers in poorer cities. Despite these special features of the P2P platforms, we document that they do not lend to firms not served by banks. Only five 5% of the P2P borrowers are firms without a previous relationship with a traditional bank.

In terms of interest rates, P2P lenders offer 5.2 pp lower risk-adjusted rates compared to the average 48% average charged by traditional lenders. Relative to the largest private banks that hold a lot of market power in Brazil, P2Ps charge a 7.4 pp lower interest rate. Moreover, firms that borrow from P2Ps used to pay 1.3 pp higher rates at traditional lenders compared to similar non-P2P borrowers. However, these firms can also find a 1.4 pp lower rate on subsequent traditional bank loans after their first P2P loan. This magnitude is more prominent (2.5 pp) for small firms with a recent bank relationship. The last result indicates that traditional banks view a P2P platform as a valid competitor and try to regain runaway borrowers by offering them cheaper loans.[2]

Second, we focus on the municipality level. Using a difference-in-differences design, we use the arrival of P2P lenders as a treatment shock and formally test if the municipalities that received the P2P loans also experienced a reaction from incumbent banks. We face an empirical challenge: the decision of P2Ps to enter a particular market is endogenous as it depends on the incumbent banks' market strategy. Thus, the locations where the P2Ps penetrated, or the treated group, might differ significantly from the unaffected locations, invalidating the common trend assumption necessary for identification.

To overcome this challenge, we perform three exercises: (i) a parsimonious matching of the treated and control municipalities based on the number of incumbent banks divided by the number of firms with an active bank account and GDP per capita; (ii) we calculate a measure of exposure to P2P competition for each municipality, based on the propensity of incumbent banks to lend to a typical P2P borrower. We find that municipalities with higher *ex-ante* exposure to P2Ps have a stronger reaction from incumbent banks following P2P entry; and (iii) we perform another DiD estimation where the staggered adoption of high-speed internet across Brazilian municipalities, in the form of optical fiber, is used as an alternative treatment that boosts online P2P lending. The

[2] We re-run the same regressions for any firms that switched lenders, not only the ones that transitioned to the P2P platforms. We did not find significant results in this case.

installation of optical fiber is planned by the Brazilian Ministry of Communications and the Brazilian Telecommunications Regulatory Agency (ANATEL) and is independent of the local banking industry organization.

The extensive Brazilian territory and socioeconomic heterogeneity help our identification strategy. For the 519 municipalities that received P2P loans, we find similar municipalities did not receive them. After performing a one-to-one matching, we find a strong covariate balance across several municipality characteristics not targeted by the matching procedure. We also observe clear ex-ante parallel trends between the municipalities where P2P entered and the matched ones without P2P entry, both in the interest rate charged and the loan amount issued by the incumbent banks. Given the similarities between these groups, it is less likely that they would have reacted differently in the absence of P2P lenders. Moreover, our estimates are also robust to time and cohort heterogeneity using the methodology introduced in Callaway and Sant'Anna (2021).

The results of our first difference-in-differences design show that, relative to the control group, municipalities where P2P entered experienced a decrease of 2.5 pp in the interest rate charged by incumbent banks and an increase of nearly 7% in the volume of loans issued per firm, after ten quarters following P2P entry. We differentiate these results based on the number of local banks per firm to find that they are only significant in the municipalities below the median.

To add robustness to our empirical estimates, we also calculate a propensity measure of a bank to lend to a typical P2P client. This is done by running a logistic regression of an indicator variable of being a P2P client on several covariates that capture loan, employee, and industry characteristics. We interpret this measure as an *exposure* to the competition with P2P platforms. Adding strength to this competition channel, we find that, following P2P entry, municipalities with higher *ex-ante* exposure to P2Ps experienced a stronger reaction from incumbent banks.

In the second empirical exercise, we narrow our focus to 63 municipalities that adopted high-speed internet, in the form of optical fiber, during our sample period. The installation of optical fiber is independent of the local banking industry. Moreover, we observe that the growth in the number of local providers of high-speed optical fiber internet is related to higher P2P adoption and a higher number of Google searches for the term "online loan." Thus, we use it as an exogenous shock to P2P entry.

We find that, relative to similar untreated municipalities: (i) P2P platforms penetrate only in the cities that adopted fiber, gaining 1 pp market share from traditional banks in the ten quarters following optical fiber adoption; (ii) aligned with the previous results, the average interest rate charged by the banks drastically decreases by 11 pp, from an average of 71%; and (iii) banks' loan issuance per firm nearly doubled. These results were not statistically significant in a group of similar municipalities that adopted fiber but did not experience P2P entry. By showing that the results are not significant in this group, we are validating the exclusion restriction in the empirical analysis. I.e., we are ruling out the impacts of potential confounders triggered by optical fiber adoption that are not related to P2P lending.

We then estimate a structural model of demand for credit to provide intuition for the empirical results and measure welfare effects. The model can uncover how a unique competitor like a P2P platform can force a wide strategic response from banks. The model follows a workhorse discrete-choice model widely used in the industrial organization literature (Berry (1994)).

Borrowers decide between a bank or a P2P loan to invest in a risky project or the outside option when they simply stay with their initial endowment. Each borrower has a different endowment that is determinant for both her default probability and her demand for loans. Each borrower's choice of lender depends on her personal assessment of the quality of each lender and their sensitivity to the price (interest rate) offered by lenders. We estimate a price elasticity of demand for loans of 6%, following Berry (1994). Our choice of instrument for demand is the sum of monetary losses from natural disasters that affects borrowers across many Brazilian municipalities, as in Cortés and Strahan (2017) and Diamond et al. (2021). The economic rationale for the instrument is that banks reallocate their funds away from branches in non-affected cities to affected cities. Therefore, we expect that areas less affected by natural disasters will experience a decrease in credit supply. The estimated price elasticity of demand is a critical parameter in our model that will determine how banks and P2P borrowers respond to the lending rates.

On the supply side, lenders - banks and P2Ps - have different profit functions and compete for each client by choosing prices in a Bertrand fashion. To satisfy banks' shareholders and P2Ps' investors, both lenders face a constraint in their profit function that the expected return from a loan must be higher than the risk-free rate. Since P2P platforms only transfer funds between lenders and borrowers and do not bear regulatory costs, their losses from default are much smaller than banks. For this reason, P2Ps have a comparative advantage over banks when dealing with riskier borrowers.

The lenders can see the borrowers' initial endowment. Thus, they can infer their outside option and default probability. This way, they will naturally set a higher interest rate for riskier firms. We then use the price elasticity estimated from the borrower's side and calibrate the remaining cost parameters to match observed interest rates, shares, and delinquency rates in the data. Our model replicates the main empirical findings. P2P lenders focus on riskier borrowers, their delinquency rate is twice the magnitude of banks' clients, and their lower operational costs allow them to charge lower interest rates than banks. However, despite this price difference, banks still hold more market share than P2Ps because of their unobserved superior quality perceived by the clients. This quality can be in the form of a better relationship, liquidity, trust, or switching costs to the P2P market.

In a counterfactual experiment, we remove the P2P platforms from the markets and estimate social welfare from P2P entry. Without competition from online platforms, the interest rates charged by banks increase substantially, especially for riskier borrowers. We differentiate these results by the number of incumbent banks in each market and confirm that they are stronger for monopolistic markets.

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 to swiftly provide cheaper funding to underserved businesses in the credit market but also force a price reduction from the incumbent banks.

Literature. Our findings contribute to the growing literature that analyses the interaction between banks and Fintechs. For example, the fact that Fintech lenders focus on smaller riskier borrowers than banks has been documented by Buchak et al. (2018), de Roure et al. (2019) and Tang (2019). Balyuk et al. (2020) shows that the market presence of different bank types plays a key role in the growth of Fintech lending to small businesses. Gopal and Schnabl (2020) finds that FinTech lenders replace small business lending underserved by banks after the 2008 crisis, and more recently Beaumont et al. (2021) find that Fintech lenders improve firms' credit access by alleviating collateral constraints. Relative to these studies, our novelty is to show an important reaction from incumbent banks following Fintech entry.

Our results also relate to the literature that connects banking competition and access to finance. For example, Jayaratne and Strahan (1996) show that access to finance and economic development increases after restrictions on bank branching are removed. Guzman (2000) argues that banking monopoly is a catalyst of credit rationing. Likewise, Beck et al. (2005) show that higher banking concentration increases financing obstacles, specifically in countries with low economic and institutional development levels. Butler et al. (2015) studies how banking competition relates to prices in alternative sources of finance. Our paper shows that P2P lenders are a new mechanism to ameliorate the credit frictions caused by imperfect competition.

The demand system followed in this paper has been adopted in many financial applications: bank deposits (Dick (2008); Egan et al. (2017); Wang et al. (2021); Egan et al. (2022)), bonds (Egan (2019)), credit default swaps (Du et al. (2019)), insurance (Koijen and Yogo (2016); Koijen and Yogo (2022)), mortgages (Benetton and Compiani (2021)), and investments in general (Koijen and Yogo (2019); Koijen and Yogo (2020); Koijen et al. (2019); Egan et al. (2021)).

Finally, our empirical strategy exploiting high-speed internet adoption links our paper to the studies showing that technology improvements can lower Fintech entry costs and challenge banks. Recent studies that found this evidence for different sectors are Fuster et al. (2019) and Buchak et al. (2018), Bartlett et al. (2018), Berg et al. (2020), Hertzberg et al. (2018), Abis (2020) and D'Acunto et al. (2019). For a broader literature review, see Goldstein et al. (2019).

This paper is organized as follows. Section 2 reviews the institutional details about the Brazilian credit market, P2P lenders, and how optical fiber installation is decided. Section 3 describes the data. Section 4 presents the loan level analysis . Section 5 discusses the empirical strategy at the municipality level. Section 6 presents the structural model. We conclude all findings in section 7.

2 Institutional Background

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

2.1 The Brazilian Credit Market

Figure 1 shows the characteristics of the Brazilian credit market and why it is a more representative country of global credit markets than the US. In 2020, domestic credit to the private sector was 45% of GDP in Brazil, compared to 62.30% in high-income countries and 130% in the US. Moreover, the five Brazilian largest bank's asset concentration is almost twice that in the US. Therefore, Brazilian numbers point to a constrained credit market that is still very focused on traditional bank lending. These features are much closer to the 137 countries belonging to the low, middle, and upper-middle-income countries than the 80 countries in the high-income group.

The high price and low credit supply are likely consequences of Brazil's financial market organization. Also, according to the World Bank, the lending-deposit interest rate spread is remarkably high, about 35 pp, compared to 5 pp in developed countries. Perhaps not surprisingly, 20% of small and micro businesses mentioned credit application denials from banks, and 30% never even had a loan with banks, according to a 2019 survey from SEBRAE.[3] It is under this context that we observe in our data that the vast majority of P2P loans are destined for micro and small companies 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 a relatively high supply of credit from banks probably explains why almost every P2P loan is destined for individuals, 77% of whom are for debt consolidation.[4]

2.2 P2P vs Traditional Bank Lending

P2P lending is the loaning of money to businesses or individuals through an online platform that directly matches lenders with borrowers. This process, which includes borrowers' risk analysis and debt collection service, is operated mainly by a Fintech company. The P2P borrowers can be individuals or small businesses, while lenders that hold the default risk 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.[5]

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

[4] 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

[5] There are problematic incentives from this practice. For example, P2Ps might have the financial incentive to maximize the origination of loans at the expense of the default risk that the lender bears. This paper does not analyze these concerns because we do not observe defaults for every loan. However, we perform a back-of-the-envelope in Appendix B and find suggestive evidence that Brazilian P2P companies offer loans with slightly lower performance to investors than a bank would get (13.62% compared to 15.02%).

As described by Nemoto et al. (2019), P2P platforms face different regulatory regimes depending on the country. The regulatory features vary mainly regarding the strictness of operational licenses and whether the loan's originator 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 must have a partner financial institution, which should be authorized, regulated, and supervised by the Central Bank of Brazil. The partner financial institution originates P2P loans, 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 P2P platform and the partner institution share the loan origination fee.

There are two types of partnerships. In the first type, the partner financial institutions keep the loans in their books and include them in the Central Bank's credit registry. Although these loans are in the financial institutions' books, they are not required to make loan provisions since the credit risk belongs to the investors. However, as long as the loan is in arrears, the financial institutions must allocate regulatory capital. In the second type, the partner financial institutions do not keep the loan in their book; thus, the loan is not in the credit registry.

To simplify this setup and foster credit Fintech operations, the Central Bank of Brazil introduced a new regulation in 2018 (BCB resolution 4656). It introduced two new types of financial institutions: *Sociedade de Credito Direto - SCD* (Direct Credit Society), which performs balance sheet lending; and *Sociedade de Emprestimo entre Pessoas - SEP* (Peer-to-Peer Loan Company), which performs P2P online lending.[6] These new financial institutions operate only through online platform lending.

Moreover, these institutions can operate independently from the partner banks. Thus they can collect the entire origination fee. The requirements to open and operate these two Fintech types are softer than traditional financial institutions. In this way, the new regulation aims to reduce entry barriers in the credit market and foster competition.

2.3 Optical Fiber Technology Adoption

This new scenario stimulating alternative forms of financing coincides with ongoing changes in the quality of internet access within Brazilian regions. Figure 2 shows the significant heterogeneity in access to optical fiber internet. We observe numerous cities implementing optical fiber throughout our sample period. We expect that this internet speed upgrade will boost online lending. We will

[6]Interestingly, the new operating SCD firms have 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.

later test and confirm the hypothesis that P2P lending significantly increases after optical fiber adoption in section 5.

The Brazilian Ministry of Communications and ANATEL supervise the network structure (backbone and backhaul) expansion that supports the provision of high-speed data transmission by optical fiber. The technology is implemented gradually in the Brazilian territory according to a national plan.[7] The goals consider expansion costs and time to implement the network structure. In that way, the geographical landscape and distance to the existing network structure heavily influence the timing of the technology installation.

Moreover, to define installation priority, the Ministry calculates an internal score based on city size and lack of quality of internet access. The banking industry is not mentioned in the national expansion plan. Thus, the arrival of optical fiber technology can be seen as independent of local banking activity and other local economic effects unrelated to the local population and current internet speed.

3 Data

The main data for this paper comes from the credit registry operated by the Brazilian Central Bank. As the country's primary financial regulator, it maintains information about all loan contracts signed by regulated financial institutions. 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 operate through partnership and keep the loan in the partner bank's book, as described in the section 3. However, the credit registry does not have loans from P2P Fintechs that operates through partnership and do not keep the loan in the partner bank books. To avoid biases related to this issue, we manually obtained loan data from the largest P2P platform with missing information in the credit registry. Nevertheless, this is a small percentage of the P2P loans in our sample. Most P2P loans come 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[8] since they comprise almost the entire P2P market. Our data go 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. Each financial institution estimates the rating and must tie every loan to

[7] From 2010, the broadband universalization plan follows the National Broadband Plan (see Souto et al. (2010)). It was later amended by government Decrees no. 8776 in 2016, 9,612 in 2018, and 10,799 in 2021. These revisions essentially gave more priority to isolated rural areas.

[8] micro company has annual revenue less than R$ 360,000.00. A small company has higher revenue than that and lesser than R$ 4,8 million. A medium company has higher revenue than that and lesser than R$ 300 million. See https://www.bndes.gov.br/wps/portal/site/home/financiamento/guia/porte-de-empresa

one of ten risk tiers: AA-A-B-C-D-E-F-G-H-HH. Each risk tier is directly linked to a probability of default and must be based on information and criteria that the regulator can monitor. This classification is the reference for capital requirements and loss provisions set by the regulator to every financial institution [9].

However, P2P platforms and their partner banks do not have to make provisions for these loans since they do not bear their credit risk. For this reason, the risk ratings informed by the platforms are not informative. In order to overcome this issue, we also use the firm's rating in outstanding loans from traditional institutions. 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 reflect default probabilities, but it is also subject to the 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 the regressions that do not contain P2P loans, we will use the ex-ante risk rating available in our data. When P2P loans are included, we will assign them the measure of rating based on the outstanding loans.

The depth of our data allows us to identify valuable information in terms of market organization, like how borrowers from traditional banks and P2Ps differ in terms of default risk. Or how many P2P borrowers are indeed new in the credit market, i.e., did not have a relationship with banks. 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 these customers' relationship with the traditional banks was and how it was affected after borrowing from a P2P.

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

We complement the dataset with two more sources to draw a richer descriptive picture of the borrowers. Geographic location comes from the Brazilian Institute of Geography and Statistics (IBGE - Instituto Brasileiro de Geografia e Estatística) and employees' labor profile of each firm from the RAIS labor database (Relação Anual de Informações Sociais), made available by the Ministry of Labor. We use municipality-level optical fiber internet availability from ANATEL (National Telecommunications Agency) to measure local internet quality. To perform the demand estimation in section 6, we hand collected proprietary losses caused by natural disasters from the Brazilian Integration Ministry.

Profile of Traditional Lenders and P2P Borrowers. Table 2 shows descriptive statistics of P2Ps and banks' clients in terms of company size, risk, loan volume, interest rate, and the number of installments. P2P borrowers are, on average, smaller and riskier than bank borrowers. They get relatively higher unconditional interest rates, as shown by the weighted volume averages in Panel B of Table 2, although this difference is not statistically significant. Table 3 presents

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

additional firm-specific characteristics like economic activity and employees' profile from RAIS database. P2P borrowers are younger firms with higher presence in information technology and professional, scientific, and technical services. They have younger and more educated employees compared to non-P2P borrowers. Overall, we may characterize P2P clients as being tech-savvy firms.

4 Loan Level Analysis

This section compares the interest rates found by banks and online P2P borrowers. We divide the analysis into three parts. First, we analyze whether P2P borrowers used to find higher interest rates at traditional banks before switching to the P2P market. Then we directly compare P2P loans and traditional lenders' interest rates to test if P2P platforms indeed offer lower interest rates. Finally, we analyze if P2P borrowers find cheaper loans at banks after borrowing from the platforms, indicating a strategic reaction from banks to hold their clients. All regressions were performed at the loan level data.

4.1 P2P Borrowers Prior Interest Rates at Banks

Before we directly compare banks' and P2P loans rate, we analyze how was the interest rate that (future) P2P borrowers used to find at traditional banks before they turn to the P2P sector. We estimate the effect of being a future P2P client on the current bank interest rate in the following regression specification:

$$Int.Rate_i = \alpha + \beta(\text{Future P2P Client})_i + X_i + \tau_b + \tau_{fc} + \tau_{ts} + \tau_{rs} + u_i \tag{1}$$

We restrict the sample to traditional bank loans only. The loan interest rate is the dependent variable. 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 migrate to the P2P online sector. X_i is a vector of control variables: the logarithm of the loan size, the maturity, and the firm's age. τ_b are financial institution fixed effects, τ_{ts} are time x firm size fixed effects, and τ_{rs} are ex-ante risk rating x firm size fixed effects. The fixed effects τ_{fc} intend to control for two firm characteristics: industry and municipality.

The results are presented in Table 4 and indicate that firms that will eventually migrate to the P2P sector used to pay roughly 1.3 pp higher interest rates at banks. This result is stronger for micro firms; they used to pay 4.2 pp higher interest while small companies pay 0.7 pp, already adjusting for factors like size, risk, industry, location, and firm age. We did not find significant results for medium-sized clients.

One concern with the specification 1 is whether the firm characteristics used can adequately control for the firm's heterogeneity. Thus, in the appendix, we provide a more saturated specification on Table A.1 as robustness. In this specification, we add an interacted six-fold fixed effects: municipality x industry x Firm age quintiles x Firm employees' formal educational level x firm employees' age quintiles. Estimates for this saturated specification are similar for micro firms but not for small firms; the coefficient is two times higher (1.5 pp instead of 0.7) for the latter. The overall coefficient increases from 1.3 to 1.5 pp, giving confidence in the robustness of our estimates.

Overall, this subsection documented that future P2P clients used to pay higher interest rates in traditional lenders before their first loan with P2P platforms. In the following subsection, we test whether the P2P sector is a cheaper alternative than traditional lenders.

4.2 Do P2P Borrowers get Lower Interest Rates?

This section analyzes the characteristics relative to traditional lenders. The amount of information in our data allow us to directly compare both types of lenders in terms of loan rates. We run the following regression:

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

Where the interest rate is the dependent variable, *P2P Loan* is a dummy indicating a P2P loan, X_i is a vector of the loan variables (log of the loan amount, maturity in years) and τ_f, τ_{ts}, τ_{rs} are respectively firm, time x firm size, and time x rating fixed effects. It is worth noting that the P2P risk rating used in this regression is based on all other outstanding loans for that firm, as described in section 3. In this way, we overcome the absence of P2P lenders ratings but reduce the sample to those firms with outstanding loans. Column 1 of Table 5 shows evidence that firms find better loan conditions in the P2P online lending market. Compared to traditional financial institutions, companies borrow at a 4 pp lower rate after controlling for risk.

Furthermore, we split our sample between each financial institution type. This breakdown is done on columns 2 to 6 also in Table 5. It provides an enlightening result: P2Ps offer a lower risk-adjusted price, but only in comparison to large private banks (-7.4 pp), in column (2). The coefficient for public (government-owned) local banks shows that they charge an interest rate lower (4.3 pp) than online lenders. This result is perhaps expected as public banks have a different objective than private banks. They aim to promote economic development (see de Araujo and Cintra (2011)). Thus they might charge rates below equilibrium prices. All other price differentials were not statistically significant. The results in Table 5 are likely related to the market power of large private banks in the Brazilian credit market. As shown in Table 2, only four large private banks are responsible for 55% of all the working capital loans in our sample.

This outcome raises the question of whether P2Ps steal more clients from large private banks.

Table A.2 presents empirical evidence for this question. We map all borrowers' loans that switched lenders. That is, the borrower's new loan is in a different bank than the previous bank that issued her a loan. Of all loans that were "stolen" from another institution, we find that a great percentage of them (52%) come from large private banks. This is not surprising since large banks naturally hold huge market power in the Brazilian market. However, when we focus on loans stolen by the P2P lenders, we see a much greater proportion of 65% coming from large banks. This difference of 13 pp is the greatest among all lenders' types. The numbers suggest that P2P clients find a better alternative of financing in the P2P online marketplace instead of the great spreads charged by traditional large private banks.

4.3 Do Banks Try to Recapture Runaway Borrowers?

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 reaction from incumbent banks. The traditional lenders could lower their interest rates to recapture the borrowers that turned to the P2P market.[10]. We now formally test this hypothesis. The conceptual idea is that if banks and P2P are substitutes, banks will react to the lower prices charged by the latter by offering lower rates to the P2P clients.

We estimate equation 3 comparing the periods before and after the first P2P loan for the firm-lender pair. Note that this regression includes only traditional lenders' loans, and the first P2P loan date can be understood as the treatment effect date. We add lender x firm fixed effects (τ_{bf}), so we are focusing on the time variation after *vs* before the treatment for the same lender-firm pair. We also control for an interaction of firm size and time(τ_{ts}), and firm size and rating (τ_{rs}).

$$\text{Int.Rate}_i = \alpha + \beta(\text{After } 1^{st} \text{ P2P})_i + X_i + \tau_{bf} + \tau_{ts} + \tau_{rs} + u_i \tag{3}$$

The *After* 1^{st} *P2P* dummy indicates a bank loan after that firm borrowed from a P2P platform. Column 1 from Table 6 presents the result. The dummy coefficient in column (1) indicates that once firms borrow from a P2P platform, they get an interest rate reduction of 1.3 pp on subsequent loans with traditional lenders. This result suggests that to regain runaway borrowers, traditional financial institutions may react to P2P competition by reducing their interest rates. We emphasize that borrowers' credit repayment quality is not driving the result since the rating fixed effects

[10]Moreover, to keep their clients, banks may lower interest rates even before their clients try to borrow from the P2P platforms. It is not difficult to find loan offers on the P2P platforms that many investors already agreed to lend, yet they were eventually not formalized. The reason given by the platform owners for such cases is that the firm found similar loan conditions in another bank. This anecdotal evidence supports that banks care about losing clients to the P2P market.

already account for this variation.

There still can be other factors, different than the competition channel, driving the better loan conditions found by P2P borrowers at traditional banks. For example, banks can observe when a firm borrows a P2P loan and views it as a positive signal for repayment quality. To rule out these possibilities and further consolidate the channel, we differentiate firms based on their relationship with banks and test whether firms with more recent loans from their preferred bank are the ones getting the cheaper post-P2P loans. This result would point to a strategic action from the banks to regain their essential clients instead of other factors like signaling or improvements in their credit conditions.

Thus, we extend equation 3 by adding an interaction of *After* 1^{st} *P2P* with dummies indicating if the client hired a loan from the same bank recently or a long time ago. This strategy was adopted by Ongena et al. (2021) to compare loans granted to firms that issued *minibonds* from the same bank with loans granted to all other outside firms. Suppose the results only hold for firms with a more recent relationship with banks. In that case, they point to an increased bargaining power for firms over banks instead of other factors like signaling or improvements in their credit conditions:

$$\text{Int.Rate}_i = \alpha + \beta_1(\text{After } 1^{st} \text{ P2P} \times \text{Old})_i + \beta_2(\text{After } 1^{st} \text{ P2P} \times \text{Recent})_i + X_i + \tau_{bf} + \tau_{ts} + \tau_{rs} + u_i \tag{4}$$

The specification is the same as equation 3. However, now we interact *After* 1^{st} *P2P* with two dummies. *Recent* dummy is equal to 1 if the firm borrowed from the bank six months before the date of the new post-P2P loan. *Old* dummy is equal to 1 if the firm borrowed from the bank more than six months before the date of the new post-P2P loan. Table 6 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 (about 1.6 pp). Moreover, since results on table 4 show that only small and micro firms used to pay higher interest rates on traditional banks, we show in column 3 of Table 6 the estimation restricted to these firms, i.e., we exclude medium firms. In this case, the coefficient for the recent relation after the first P2P loan is even higher, around 2.5 percentage points.

Finally, to guarantee that these results are specific to the competition between banks and Fintechs, we re-run the same regressions for any firms that switched lenders, not only the ones that transitioned to the P2P platforms. We did not find significant results in this case. This finding indicates that the comparative advantage that P2Ps have compared to traditional banks is the ability to charge lower prices. If banks want to avoid losing clients to the Fintechs, they do that by reducing their prices. On the other hand, the competition between traditional bank types involves other benefits rather than a cheap loan.

We conclude this loan-level empirical section by highlighting the riskier nature of P2P borrowers, along with 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 and see their bargaining power increasing against traditional banks. This result 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.

In the next section, we take one step further and test whether banks can engage in a broader strategic response to P2Ps by lowering their rates and increasing their overall supply to all customers at the local market level.

5 Market Level Analysis

In this section, we formally test if the incumbent banks react to the surge in P2P lending in several Brazilian municipalities. We begin our analysis by considering local P2P entry as a shock in a difference-in-differences design. The caveat in this exercise is that P2P entry is not exogenous to banks' strategies. Thus, we will perform a matching procedure to construct a similar group of cities where P2P did not enter. In the following subsection, we will consider the local adoption of high-speed internet across Brazilian municipalities as a valid treatment shock stimulating P2P entry.

5.1 Do Banks React to P2P Entry? A Difference-in-Differences Approach

To test the hypothesis, we perform a difference-in-differences analysis with a *staggered adoption*[11] of the treatment. In this initial section, we consider the first loan from a P2P platform to a firm in a given municipality as a "treatment." All regressions here are at the municipality-month level. Therefore a municipality is considered treated when a local firm borrows from a P2P platform. Following the procedure in Callaway and Sant'Anna (2021), we run the following model to capture the dynamic effects on the outcome variable:

$$y_{i,t} = \alpha_i + \gamma_t + X'_{it}\psi + \sum_{e=-K}^{L} \beta_e (D^e_{i,t,c}) + \epsilon_{i,t}. \tag{5}$$

Where α_i denotes a municipality fixed effect, γ_t is a time fixed effect, and X_{it} is a vector of controls. $D^e_{i,t,c} = 1\{t - G_i = e\}$ is an indicator for i being e periods away from the initial treatment, at time t. The β_e coefficients capture the treatment effect - here P2P entry - on the dependent variable $y_{i,t}$ for every period e. This coefficient is estimated first for every treated cohort c, and then the average effect is computed in a single coefficient for every period e before and after the treatment (see Callaway and Sant'Anna (2021)).

[11] Here, we are following Athey and Imbens (2022) nomenclature: in the staggered adoption setting "units, e.g., individuals, firms, or states, adopt the policy or treatment of interest at a particular point in time, and then remain exposed to this treatment at all times afterward."

The main identifying assumption is the common trend between treated and control municipalities. In other words, without the arrival of the P2P platforms, treated and controlled municipalities would have evolved according to the same trend.

To strengthen the assumption's validity, we perform a matching approach to construct similar groups of treated and untreated municipalities. The vast Brazilian local socio-economic and banking market heterogeneity is helpful in this strategy. For every municipality where P2Ps entered, we can find similar ones without entry.

5.1.1 Matching and Sample Construction

Table 7 compares the locations where P2P entered vs. no entry. The P2P platforms entered only 519 municipalities of all the 5,535 municipalities with any working capital loan. The 519 attended cities are, on average, more populated, have higher GDP per capita, and have more bank activity than the unattended ones. We also separate the statistics based on the timing of optical fiber arrival, as we will later use it as a treatment in a difference-in-differences approach. An important fact observed in the data is that all municipalities where P2P entered adopted the optical fiber technology at some point.

To address the differences described above, we first exclude the 27 Brazilian state capitals from the analysis since they are significantly more populated than similar cities within the same state. Thus, we are left with 492 municipalities that received P2P loans. Then, we construct a control group of 492 municipalities to match the ones with P2P entry. The one-to-one matching is based on the number of incumbent banks divided by the number of firms with an active bank account and the local GDP per capita.

We target these two variables as they capture the essentials of each city's banking industry organization and social-economic context. Moreover, they are good predictors of P2P market share. Figure 3 shows a strong (negative) positive relationship between P2P market share and (GDP per capita) the HHI concentration index. Therefore, by matching the sample using GDP per capita and banks' concentration, we compare locations with similar probability of receiving a relevant amount of P2P loans. Panel B of Table 7 presents the matched municipalities. Our final sample consists of 984 municipalities - 492 that received loans from P2P platforms and 492 in the matched control group - over 62 months, from January/2015 to February/2020.

Figure 4 presents the covariance balance for the treated and matched control groups. They are similar in several other characteristics not considered in the matching procedure, including the industry composition of the local economy. All covariates' absolute standardized difference of means lie within the 0.2 threshold suggested by Imbens and Rubin (2015), indicating a strong balance. The only exceptions are the population and the total number of firms, which are slightly above the threshold. However, although it is naturally more likely to find P2P clients in larger cities, the city size has a weak relationship with the P2P market share. Thus, these variables are non-important predictors of the relevance of the P2P lenders.

5.1.2 Results

The results for equation (5) are presented jointly for the (1) P2P amount issued, (2) P2P volume market share, (3) banks' average interest rate, and (4) banks' loan amount issued per firm. To avoid giving importance to small municipalities with very few loans, we weigh the regressions by the number of loans issued for each municipality-month. We also include an interaction of time-state fixed effect to control for regional time-moving differences in banks' strategy. All regressions' standard deviations are clustered at the municipality level. Figure 5 and Table A.3 present the dynamic coefficients.

The top charts show an average increase of 4.5 log points - or approximately R$ 40,000 - in the volume of P2P loans issued and a 0.25% market share increase in the ten quarters after a P2P platform first issues a loan in a municipality. The bottom charts show banks' strategies regarding the average local interest rate and loan amount issued. Relative to the control group without P2P entry, municipalities where P2P entered experienced a decrease of 5 pp in the interest rate charged by incumbent banks and an increase of up to R$ 0.25 million in the loans issued per firm in the next ten quarters after P2P entry. Before P2P entry, the average interest rate charged and the loan amount issued by the banks were quite variable. In all periods prior to P2P entry, banks used to charge an average annual rate of 59.4% with a 23 pp standard deviation. The average amount of loans issued per firm was R$ 2 million, with a standard deviation of R$ 4 million.

Panel A of Table 8 aggregates the average magnitude for the post-period. The interest rate reduces by 2.5 pp lower, the volume of loans issued divided by the number of firms increases by R$ 0.14 million.

5.1.3 Robustness: Group Heterogeneity

Exposure to P2P competition. To add robustness to our results, we perform an extra analysis to identify the competition against P2P as a driver for the decrease in the prices charged by the incumbent banks. To do that, we define a measure of exposure to P2P competition by computing a propensity score of a client as 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 P2P competition. As the P2P platforms remotely enter those markets, we can expect a stronger price response from the incumbent banks.

To measure this exposure, we run a logistic regression of a P2P client dummy on a set of loan variables and a wide range of firm characteristics available in our dataset:

$$(\text{P2P client})_i = \alpha + \beta_L L_i + \beta_F F_i + u_i \tag{6}$$

The dependent binary variable equals one 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 measure in hand, we explore the heterogeneity in exposure to P2P in each municipality. We expect municipalities with incumbent banks more exposed to P2P competition will experience a greater reaction in banks' prices and volume after the P2P entry.

Figure 6 presents initial evidence that this indeed happens. It contrasts municipalities with high and low propensity scores before the first P2P loan issuance. The division is based on the median, where the "high" group comprises markets above the median score value. The figure shows a clear pre-fiber parallel trend between banks' interest rates in both high vs. low-score municipalities. After the arrival of P2P lenders, the high-score municipalities experience a steeper decrease in banks' lending rates and higher loan issuance.

We test this result empirically by running a difference-in-differences regression with a triple interaction term:

$$y_{i,t} = \alpha + \beta(\text{P2P Entry}_i \times \text{Score}_i \times \text{After}) + \gamma(\text{Optic Fiber}_i \times \text{After}) + \tau_i + \tau_t + \epsilon_{i,t}. \qquad (7)$$

Where Score_i equals the average propensity score from equation (6) before optic fiber was adopted. The After_i dummy is equal to 1 for the period after optic fiber was adopted.

The results are presented in Panel A of Table 9. The table indicates a higher P2P penetration and a stronger reaction from incumbent banks in markets where banks had a higher propensity to lend to P2P clients. This result confirms that the competition channel between P2P platforms and banks is a significant driver of the observed movements in banks' rates and volumes.

Banking Concentration. We also differentiate these results in terms of the number of banks per firm in each municipality. We saw in Figure 3 that P2P lenders' market share is very correlated with the HHI concentration index. Therefore, we want to test if the results are stronger in municipalities with a more concentrated banking market. Figure 7 presents the same results as before, divided by the median number of banks per firm. We confirm that the effects are only observed in municipalities with fewer banks per firm.

5.2 Using High-Speed Internet Adoption as a Treatment

Even though the previous analysis presented a good covariate balance between treated and control groups, P2P entry is not an exogenous treatment shock. To improve the identification, in this section, we make use of a treatment shock independent of the local banking activity: optical fiber installation that enables local high-speed internet. In section 3, we explained that the gradual installation of this technology by the government agencies follows the proximity to the available network installed, the current state of local internet quality, and the area population. Thus, it is independent of local banking activity. This staggered implementation of the optical fiber technology helps our identification strategy since municipalities with similar economic conditions receive the treatment at different times. This identification approach is similar to the one implemented in D'Andrea and Limodio (2019), which uses the arrival of submarine cables in African countries to analyze several financial and banking outcomes.

Our starting hypothesis is that the adoption of high-speed internet is a positive shock to P2P lending. The boost in P2P lending can happen due to increased supply and demand for online credit. Supply shifts because P2P platforms can more easily access these areas, increasing distant lenders' awareness of local credit opportunities. We also expect that local firms' demand for online credit will increase due to the reduction in searching costs and the surge in small business creation, specifically information and communication technology (ICT) activities, which are more prone to borrow online.[12]. Figure 8 shows that the growth in the number of local providers of high-speed optical fiber internet is related to higher P2P adoption and a higher number of Google searches for the term "online loan.[13]"

Note that we do not need to differentiate between the supply and demand effects here since we are interested in measuring the outcomes of an overall increase in competition between banks and P2P lenders, regardless of the shock coming from a relative supply or demand shift. Our second hypothesis is that incumbent banks decrease their lending rates and increase loan supply in response to the P2P arrival made possible by high-speed internet technology.

To test the hypothesis, we perform the same regression as in (5), with the difference that now the treatment is the arrival of an optical fiber internet provider in a given municipality. Again, the main identifying assumption is the common trend between treated and control municipalities. In other words, without the optic fiber installation, treated and control municipalities would have evolved according to the same trend. However, the identification faces a potential threat: violating the exclusion restriction. Optical fiber adoption can trigger other effects unrelated to P2P lending that equally impact the outcome of interest.

For example, an internet quality upgrade can improve local economic conditions. In this case, the incumbent bank's reaction to decrease rates and increase credit supply is influenced by the better conditions of borrowers instead of the increased competition against the P2P platforms. Another potential confounder is banks' operational costs, which can also decrease with better high-speed internet coverage, as shown by D'Andrea and Limodio (2019) for the African banking markets.[14]

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

[13]We did not observe a similar growth in Google searches for a generic term like "credit." Thus, the increase in searches for "online loans" does not seem to be a mechanical consequence of higher Google searches for any term in general.

[14]The authors found that bank costs decrease due to cheaper interbank transactions at the country level. Differently, we are analyzing the city level. Most incumbent banks in the late optical cable adopter cities are large out-of-market lenders. I.e., their headquarters are in another city where the internet is already fast. Since banks' headquarters carry out interbank transactions, it is less likely that a local internet speed upgrade will affect the local costs of out-of-market banks.

Sample Definition. The sample for this empirical exercise is composed only of municipalities that either received the optical fiber during our sample period or did not receive it at all. To guarantee that we are still comparing similar locations, we use the same matched sample from the previous section. However, since we are restricting to units that started without the fiber treatment, we are left with only 63 treated municipalities. Table 7 shows that, out of these 63, 24 also experienced P2P entry. While 39 adopted fiber but P2Ps did not enter, as presented in Panel B. We also select a control group formed by 108 municipalities that never adopted fiber or did not adopt optic fiber until 2019, our sample's last full calendar year.

The fact that P2Ps did not enter all municipalities receiving the optical fiber helps us test whether the exclusion restriction is valid. We can divide our analysis and perform the DiD regression on two separate samples: (1) the 24 municipalities that received both optical fiber and P2P loans, and (2) the 39 that were equally treated but P2Ps did not enter. If the confounders described above are not present, we should only observe an effect on interest rates and credit volume for the group (1). We will show later that this is the case indeed.

Before we present our results, Figure A.1 presents evidence that the exclusion restriction is valid. It shows very similar trends of interest rates and loan amount issued per firm between the groups that experienced P2P entry (1) vs. no entry (2). After optical fiber adoption, the municipalities where P2Ps entered experienced a steep decrease in the average interest rate and a substantial increase in the loan amount issued. This effect is not observed in the locations where P2Ps did not enter.

5.2.1 Results

Having defined our sample, we now run regression (5) to confirm that the P2P market share significantly increases only after the optical fiber technology is adopted.[15] The dynamic coefficients in Figure 9 and Table A.3 show that P2P platforms gain, on average, up to 1.2 pp market share in the ten quarters after the adoption. Finally, in Table A.5 and Panel B of Figure 9 we show that the incumbent banks' strategy to decrease interest rates and offer more loans can be observed in a clear way in the municipalities that experienced P2P entry. No post-fiber effect was found in the municipalities that did not receive any P2P loan.

Panel B of Table 8 aggregates the average magnitude for the entire post-fiber period. The P2P market share increased by 1 pp. Banks' interest rates decreased by 11 pp, and the loan volume issued per local firm in $R\$$ increased by 0.8 thousand. The fact that these coefficients are in the same direction as in Panel A - where the shock considered is P2P entry - gives comfort to our estimates. The higher magnitude for the coefficients in Panel B is not surprising since this last analysis focused on smaller municipalities that received the optical technology with delay.

[15] We also present results for all municipalities in Table A.4, before restricting our sample to the 63 matched municipalities.

5.2.2 Heterogeneity: Ex-Ante Exposure to P2P Lending

Like we did in the previous section, we also document that municipalities with incumbent banks more exposed to P2P competition are more affected in the post-treatment period. Figure A.2 contrasts municipalities with high and low propensity scores, calculated from equation (6), before receiving optical fiber internet. Like before, the division is based on the median, where the "high" group comprises markets above the median score value. Due to the smaller sample, both time series are more volatile than in Figure 6. Nevertheless, we can still observe the parallel trends in banks' interest rates and loan issuance between high vs. low-score municipalities. After adopting high-speed internet, the high-score municipalities experience a steeper decrease in banks' lending rates and higher loan issuance.

formally tests that difference by interacting the score

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

The result in Panel B of Table 9 indicates a higher P2P penetration and a stronger reaction from incumbent banks in markets where banks had a higher propensity to lend to P2P clients.

6 What Are the Welfare Gains From P2P Entry?

In this section, we present a theoretical framework that rationalizes our empirical findings and unveils the mechanism of how online P2P platforms can induce a strong strategic response from the banks. The framework follows a workhorse discrete-choice model widely used in the industrial organization literature. This setup allows us to measure welfare gain from the increased competition between banks and P2Ps. Our results are sensitive to the market organization. The impact of P2P entry is much more profound under a banking monopoly than under a competitive market. Thus, we will divide the theoretical results and their empirical counterparts by the number of incumbent banks before P2P entry.

We start this section by describing the model, then we present the empirical estimation of the demand elasticity for loans, using losses from natural disasters as an instrument. Finally, we present the results of a counterfactual exercise where we remove the P2Ps from the market to calculate a new price-quantity equilibrium and welfare gain.

6.1 Model Description

The model consists of a simple credit market with two lenders: traditional banks (B) and P2P platforms (P). Banks and P2Ps compete in a Bertrand fashion, setting loan prices for each consumer (r_B, r_P).

We start by describing the borrower's (firm's) choice of funding. Later we define the objective functions of the lenders and characterize the equilibrium.

6.1.1 Demand Side: Borrowers

There is a continuum of firms. Each firm i has initial equity $j = W_{0,i}$ and can take 1 unit of loan and invest in a project which pays a random result x in the next period, which follows a normal distribution $N(D, \sigma)$. Firms default if $x + W_{0,i} < (1 + r)$. Hence, we can set a default function $\delta()$ that depends on r, D, $W_{0,i}$ and σ:

$$\delta(r, D, \sigma) = Pr(x + W_0 < 1 + r) = f(\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{1+r} exp\bigg(- \frac{(x - D)^2}{2\sigma^2} \bigg) dx) \tag{9}$$

Now we define the expected utility of receiving a loan from a lender j. For simplification, we assume two lenders/products: $j = 1$ for the bank, $j = 2$ for P2P, and the outside option $j = 0$. Assuming risk neutrality, the expected utility of consumer (profit) i of getting a \$1 loan from lender j is given by:

$$E[U_i] = (1 - \delta)\beta(W_{0,i} + D - r_j) + \tau_j + \epsilon_{j,i}$$

Where $W_{0,i} + D - r_j$ represents the expected payoff, discounted by β, that the firm receives if it invests in the project and does not default. τ_j represents a monetized unobserved quality of a particular lender j. They can be in the form of a better relationship, liquidity, and customer's trust in the lender. $\epsilon_{j,i}$ is an iid term across agents and alternatives.

To make the model tractable, we can rewrite the utility in a linear form, as in Berry (1994):

$$U_i = \xi_j - \alpha r_j + \epsilon_{j,i} \tag{10}$$

The reservation utility of not receiving a loan, or the outside option of the firm, is given simply by $U_0 = W_{0,i}$. For a given price vector r, firm i will choose a loan from lender j with the following probability:

$$P(\epsilon_{j,i}) \ s.t. \ (\xi_j - \alpha r_j + \epsilon_{j,i}) \geq (\xi_k - \alpha r_k + \epsilon_{k,i}) \ , \forall k \neq j$$

Assuming ϵ follows an extreme type 1 distribution, this probability is given by:

$$\frac{exp(\xi_j - \alpha r_j)}{exp(W_0) + \sum_{k=0}^{2} exp(\xi_k - \alpha r_k)} = s_j \tag{11}$$

S_j gives the share of firms that choose a lender j over all others. For a mass M of firms, the total quantity of firms that chooses j is: $M \times S_j$

After some algebra, we can reach the following equation of interest:

$$ln\ s_j - ln\ s_0 = \xi_j - \alpha r_j \tag{12}$$

Equation (2) can be estimated by 2SLS with a valid instrument for demand and using market-time fixed effects to control for the outside option s_0 (see Berry (1994)).

Finally, assuming that the marginal utility of wealth is linear, consumer surplus is given by (see Small and Rosen (1981)):

$$CS = M \sum_{k=0}^{2} ln(\xi_j - \alpha r_i) \tag{13}$$

6.1.2 Supply Side: Lenders

We define a different profit function for a P2P lender (P) than a bank lender (B). To satisfy banks' shareholders and P2Ps' investors, both lenders face a constraint in their profit function that the expected return from a loan must be higher than the risk-free rate.

Banks Problem:

Banks choose loan prices r_B that maximize their profit:

$$\begin{aligned} V_B = \max_{r_B} & \left[r_B(1 - \delta(r_B, \sigma)) - (\gamma + c_D)\delta(r_B, \sigma) - c_B \right] s_B(r_B, r_P, \alpha) \\ s.t. V_B & > r_f \end{aligned} \tag{14}$$

Note that the first term $r(1 - \delta)$ in the boxes gives the bank's revenue, which is simply the interest rate multiplied by the share of customers that did not default. In the second term, γ represents the loss-given-default (LGD), and c_D represents bank costs that vary with default. Both are multiplied by the default probability. Note that if the bank loses all the amount borrowed, then $\gamma = 1$. The third term c_B captures banks' marginal costs per loan. The last term outside the boxes is simply the bank's market share multiplied by the mass of borrowers.

P2P lending Problem:

P2Ps choose loan prices r_P that maximizes their profit:

$$\begin{aligned} V_P &= \max_{r_B} \left[r_P(1-\delta(r_P,\sigma))\phi - c_P \right] s_P(r_B, r_P, \alpha) \\ &s.t. V_P > r_f \end{aligned} \tag{15}$$

As do banks, P2P platforms get revenue from the non-delinquent borrowers' repayments $r(1-\delta)$. However, they get only a portion of this repayment, given by ϕ. P2Ps have operation costs identified by c_P. We assume that P2P platforms charge additional fees to bear the additional operational costs they incur when trying to recover loans in arrears[16]. This way, we would have two additional offsetting terms in the equation representing revenues and costs varying with the default. For simplicity, we omit these terms. Therefore, both lenders have similar profit functions, the main difference being that P2P platforms do not lose the principal amount when the firm defaults. This difference is a key feature in the model and will play a major role in the equilibrium outcomes. The main insight, for now, is that banks have a comparative disadvantage over P2Ps when dealing with risky clients.

6.1.3 Equilibrium Definition

The Bertrand equilibrium is characterized by three conditions:

1. The vector of prices maximizes each lender's objective function:
   $r_B^\star = argmax(V_B)$ and $r_P^\star = argmax(V_P)$

2. Each borrower's loan choice maximizes her utility.
   $U_i^\star = max(U_{i,j=0}, U_{i,j=1}, U_{i,j=2})$

3. The market clears, i.e., the loan quantity offered by lenders is equal to the mass of borrowers that choose the lender's offer:
   $Q_B^\star = M * s_B^\star$, and
   $Q_P^\star = M * s_P^\star$

6.2 Demand Estimation

We constructed an instrument following Cortés and Strahan (2017) and Diamond et al. (2021). It is a weighted sum of property losses caused by natural disasters in different Brazilian cities.

[16]This is the case of Nexoos, the largest P2P platform in Brazil.

They are mostly droughts, storms, landslides, fires, and dam failures. The information was hand collected from individual reports available on the Brazilian Integration Ministry website. Table A.6 summarizes the monetary losses from the main causes of natural disasters in Brazil, the most severe are droughts and floods.

Economic Rationale: property losses from natural disasters increase loan demand in the affected regions. In response, banks reallocate their funds away from branches in non-affected cities n to affected cities $n\prime$. Therefore, we expect that areas relatively LESS affected by natural disasters will experience a decrease in credit supply.

The variable z_{jmt} = measures, for a given year t and city n that bank j is present, the property losses from natural disasters accrued to all other cities $n\prime$ that the bank operates:

$$z_{njt} = \frac{1}{N^u_{jt}} \, log\Big(\sum{}'_n \text{damage}_{n\prime t} \cdot \frac{Q_{D,n\prime jt}}{\sum_{n_0} Q_{D,n\prime jt}} \Big) \tag{16}$$

Where N^u_{jt} is the number of cities where bank j operates that were not affected by natural disasters, and $\text{damage}_{n\prime t}$ is the property loss in city $n\prime$. We scale $\text{damage}_{n\prime t}$ by the fraction of loans belonging to bank j in city n and take logs after summing the scaled damage losses.

The instrument has a strong negative relationship with the lender's market share, as seen in the reduced form presented in column (1) of Table 10. This pattern confirms the expected relationship between banks' supply of loans and the instrument. For any given bank in a municipality, the higher the losses from natural disasters in other municipalities where the bank operates, the lower the market share in that given municipality. In other words, lenders allocate their funds away from branches in non-affected cities to affected cities.

The next columns in Table 10 present the two-stage least squares estimation of equation (12). The coefficient for α captures the demand elasticity in the Brazilian working capital loans market. The magnitude implies that a one percentage point increase in the loan rate is associated with a 6.4% decrease in the market share due to lower demand.

6.3 Simulation: Equilibrium with and without P2Ps

We now simulate an economy where, for every customer, a representative bank and a P2P platform compete in a Bertrand fashion. They both choose prices that maximize their profit function, knowing that their price choice affects the probability that the client will choose their product.

The bank offers a loan price r_B that maximizes its profit function in equation (14). And the P2P offers a loan price r_P that maximizes its profit function (15). The firm will choose to hire a loan either from a bank or a P2P, maximizing its utility function (10). If the firm does not hire a loan, it gets the reservation utility equal to her initial endowment $U_0 = W_{0,i}$.

6.3.1 Calibration

To simulate this economy, we need to know the parameters: $\alpha, \phi, \gamma, \sigma, W_0, \xi_j, c_p, c_b$. We calibrate the parameters as follows. $\alpha = 0.064$, from the demand estimation.$\phi = 0.06$, is the cap revenue percentage set by the regulator when a P2P works in partnership with a financial institution.[17]. $\gamma = 1$, we choose this value to match the average LGD from unsecured working capital loans (see da Silva et al. (2009)). ξ_j, σ, c_D c_B and c_P are set in order to match the average interest rates and shares observed in each market, along with the delinquency rate of 4.07% for banks and 9.9% for P2Ps (see Table B.1 for details). We set the risk-free rate to 7%, which is close to the average observed in our sample period.

6.3.2 Counterfactual Analysis

We then perform two counterfactual analyses. The first exercise is illustrative; we exogenously set the outside option values W_0 and σ for the bank and platform to match the observed delinquency rates. In the second exercise, we endogenize default. To do that, we simulate 10,000 firms. For each firm i we draw an initial endowment $W_{0,i} \sim N(\mu, \sigma)$ and the random term $\epsilon_{j,i} \sim GEV(0, 1, 0)$.

The lenders do not observe the random term $\epsilon_{j,i}$, but they know $W_{0,i}$ and x_j. Note that $W_{0,i}$ is crucial for the firm's default probability, as in equation (9). Thus, the bank and the P2P will set prices according to $W_{0,i}$ and x_j. That is, they choose an interest rate based on the initial endowment/default probability of the borrower and general demand for a bank vs. a P2P loan.

The results are presented in Tables A.7 and 11. In the first simple simulation in Table A.7 there is no heterogeneity in the borrowers, and each lender exogenously faces a fixed default probability from their clients. Therefore, their profit functions can be simplified to a standard price minus fixed marginal costs. When we remove the P2Ps from the market in this setup, the effect is tiny. Banks only lose a few clients with a strong preference for P2Ps, and the adjustment in their loan rates in response to P2P entry is minimal.

However, once we endogenize default, the benefits from P2P entry become evident. As explained in the supply side section, risky clients are much more costly for the banks than for the P2Ps. That way, a monopolistic bank will only agree to lend to risky clients for a very high-interest rate. When the P2P platform comes into the market, they can steal those riskier clients from the banks by offering a much lower rate. For this reason, the positive impact on consumer surplus, calculated from equation (13), becomes large. Table 11 shows a much stronger reaction from banks after P2P entry and a much higher increase in social welfare. We calculate that P2P entry is responsible for an increase in welfare gain of almost 10% of the GDP per capita in the few municipalities with only one bank operating. As we increase the number of incumbent banks, the welfare gain gradually becomes smaller but still significantly large compared to a scenario where borrowers have homogeneous risk.

[17] Although when a P2P has a SEP license, this cap is not a limitation anymore, this percentage became a kind of reference for this market.

7 Conclusion

We provide evidence that P2P platforms provide cheaper credit than traditional large banks in the Brazilian economy, where large private banks hold much market power. The pool of clients served by this type of Fintech lender differs from traditional banks. They are smaller, younger, and riskier firms operating relatively more in technologically intense activities. P2P platforms also attain higher market shares in municipalities distant from the main financial centers and the banking market closer to a monopoly.

Most of the P2P clients were already served 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 can also find a lower interest rate on subsequent bank loans. These results point to an improvement in P2P clients' bargaining power against traditional banks and an attempt from the latter to recapture runaway borrowers.

Using a time and geographical discontinuity in internet quality as an exogenous shock to P2P lending activity, we analyze banks' reactions at the market level. We identify that a sudden local shift in P2P lending activity triggers a strong reduction in the incumbent bank's lending rates and an expansion in the volume of loans issued. To rationalize the empirical findings, we construct a structural model of demand where a P2P platform has a comparative advantage over banks when competing for risky clients. We perform a counterfactual analysis by removing the P2P sector from markets with different degrees of market concentration. We find that P2Ps significantly increase social welfare in monopolistic markets by offering lower interest rates to riskier borrowers while forcing the banks to do the same.

We hope that this paper highlights that P2P online lending and other types of alternative financing have 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. Correlation Between Market Share and City Characteristics, by Lender Type

This table shows correlations between municipality characteristics and the average market share of different types of lenders. Market share is computed as the volume of loans issued by a lender type in *reais* (R$), divided by the total volume of loans issued in a given municipality-month. We do not include months when a lender did not issue any loan in the market share calculation. For each lender in each municipality, we calculate the correlations between the average monthly market share, and average local GDP per capita, distance to the state capital, and HHI index. Lender type division is based on total assets divided by GDP, following BCB regulations. Data come from the Central Bank of Brazil (BCB).

	GDP Per Capita	Distance to State Capital	HHI
Large Private Bank	-0.139	-0.0514	0.3997
Non-Large Private Bank	-0.1156	0.0542	0.5097
Public Bank	-0.2618	0.0051	0.6709
Credit Union	-0.0974	0.2201	0.5826
P2Ps	**-0.2136**	**0.2354**	**0.6764**

Table 2. Summary Statistics by Lender Type

This table shows working capital loans' variable averages divided by lender type. Data come 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 is calculated by every financial institution based on information and criteria that can be monitored by the BCB. This classification is the reference for capital requirements and loss provisions set by the regulator to every financial institution (for details, see https://www.bcb.gov.br/pre/normativos/res/1999/pdf/res_2682_v2_L.pdf).

	Private Bank Large	Private Bank Non Large	Public Bank Federal	Public Bank Local	Credit Union	P2Ps
PANEL A. Lender 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. Lender 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
# 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%)
# Banks	4	60	4	5	750	6

Table 3. Firms Summary Statistics

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

	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$)	65,100.74	498,290.80	99,292.33	244,832.90
Firms characteristics:				
	Average	Std. Dev.	Average	Std. Dev.
Firm Revenue	51.4×10^6	13.6×10^9	4.03×10^6	16.2×10^6
Firm Age	10.69	9.76	9.43	8.34
Years of Bank Relationship	6.30	8.08	2.99	4.47
Number of Employees	13.86	110.52	18.5	56.1
Employee's Years of Education	11.46	1.88	12.34	1.95
Median Employees' Age	34.31	8.05	33.25	7.24
Total Wage Bill (R$)	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%

Table 4. P2P Clients Interest Rates in Banks

This table shows results from the loan-level regression (1):

$$Int.Rate_i = \alpha + \beta(\text{Future P2P Client})_i + X_i + \tau_b + \tau_{fc} + \tau_{ts} + \tau_{rs} + u_i$$

The sample includes only bank loans. The dummy "Future P2P Client" is equal to 1 if the firm will borrow from a P2P platform in the future. Control variables X_i are loan maturity in years and log of loan amount. The τ terms control for bank, industry-municipality, time-firm size, and rating-firm size fixed effects. Standard errors clustered at Bank level. t-stats are shown in brackets. Coefficients statistically significant at 1%, 5% and 10% are shown with ***, ** and *, respectively.

	(1) Int. Rate	(2) Int. Rate	(3) Int. Rate	(4) Int. Rate
Future P2P Client	1.2934***	4.1806***	0.7079**	0.3980
	(5.58)	(6.24)	(2.22)	(1.28)
Firm Size Sample	All sizes	Micro	Small	Medium
Financial Institution F.E.	Y	Y	Y	Y
Industry F.E.	Y	Y	Y	Y
Municipality Age F.E.	Y	Y	Y	Y
Time × Firm Size F.E.	Y	Y	Y	Y
Rating × Firm Size F.E.	Y	Y	Y	Y
# Firms	1,443,912	816,235	719,832	140,614
# Future P2P Clients	1,901	613	1,375	423
# Banks	821	768	742	620
Mean interest rate	58.02	68.67	54.27	37.79
# Observations	4,734,402	1,917,395	2,218,868	597,533
Adj R2	0.6843	0.7240	0.6386	0.5629

Table 5. Risk Adjusted Interest Rates, by Lender Type

This table shows results from the loan-level regression (2):

$$Int.Rate_i = \alpha + \beta(\text{P2P Loan})_i + X_i + \tau_f + \tau_{ts} + \tau_{rs} + u_i$$

Each column presents a different sample with only that particular bank type and the P2P platforms. The dummy "P2P Loan" indicates if the loan is from a Fintech instead of a traditional bank. Control variables in X_i are loan maturity in years and log of the loan amount. The τ terms control for firm, time-firm size, and rating-firm size fixed effects. The first column includes only loans from firms that had some outstanding loan in the banking system at that moment. Standard errors clustered at Bank level. t-stats are shown in brackets. Coefficients statistically significant at 1%, 5% and 10% are shown with ***, ** and *, respectively.

	(1) All Fin. Inst.	(2) Priv. Large	(3) Priv. NonLarge	(4) Public Federal	(5) Public Local	(6) Credit Unions
P2P Loan	-3.9651**	-7.3904**	-0.0587	-0.2989	4.2845***	-0.4254
	(-2.16)	(-2.64)	(-0.06)	(-0.27)	(3.51)	(-0.52)
Firm Size Sample	All sizes	All sizes	All sizes	All sizes	All sizes	All sizes
Firm F.E.	Y	Y	Y	Y	Y	Y
Time x Firm Size F.E.	Y	Y	Y	Y	Y	Y
Rating x Firm Size F.E.	Y	Y	Y	Y	Y	Y
N Firms	389,631	214,247	11,002	87,925	20,377	84,316
% Micro Firms	0.29	0.26	0.12	0.34	0.22	0.41
% Small Firms	0.53	0.56	0.34	0.47	0.69	0.49
# Traditional Fin. Inst.	760	4	54	4	5	686
# P2Ps	6	6	6	6	6	6
Mean interest rate	51.51	62.01	40.02	41.67	54.20	35.64
# Observations	2,032,104	1,042,112	82,384	348,256	102,670	365,300
# Fintech Loans	1,672	1,403	796	1,000	734	942
Adj R^2	0.8408	0.8809	0.8514	0.8068	0.8286	0.6587

Table 6. Interest Rates, After Borrowing from P2P Lenders

This table shows results from the loan-level regressions (3) in column (1):

$$\text{Int.Rate}_i = \alpha + \beta(\text{After } 1^{st} \text{ P2P})_i + X_i + \tau_{bf} + \tau_{ts} + \tau_{rs} + u_i$$

, and regression (4) in columns (2) and (3):

$$\text{Int.Rate}_i = \alpha + \beta_1(\text{After } 1^{st} \text{ P2P} \times \text{Old})_i + \beta_2(\text{After } 1^{st} \text{ P2P} \times \text{Recent})_i + X_i + \tau_{bf} + \tau_{ts} + \tau_{rs} + u_i$$

Control variables in X_i are loan maturity in years and log of the loan amount. The τ terms control for bank-firm, time-firm size, and rating-firm size fixed effects. 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 Bank level. t-stats are shown in brackets. Coefficients statistically significant at 1%, 5% and 10% are shown with ***, ** and *, respectively.

	(1) Int. Rate	(2) Int. Rate	(3) Int. Rate
After 1st P2P	-1.3766**		
	(-2.14)		
After 1^{st} P2P x Recent Relation		-1.6350**	-2.5141**
		(-2.12)	(-2.26)
After 1^{st} P2P x Old Relation		-1.0118	-0.6162
		(-1.20)	(-0.55)
Firm Sizes	All sizes	All sizes	Micro & Small
Firm x Fin. Inst. F.E.	Y	Y	Y
Time x Firm Size F.E.	Y	Y	Y
Rating x Firm Size F.E.	Y	Y	Y
# Firms	336,262	336,262	299,084
# Treated Firms	446	446	337
# Treated Micro Firms	68	68	68
# Treated Small Firms	278	278	278
# Treated Medium Firms	115	115	0
# Fin. Inst.	703	703	677
# Observations	1,691,742	1,691,742	1,418,495
Adj R^2	0.8795	0.8795	0.8777

Table 7. Municipalities Characteristics, divided by P2P Entry

This table presents characteristics of municipalities that received or did not received a P2P loan. Panel A shows averages for the 492 municipalities that received a loan from a P2P platform, and the 5,016 that did not receive. Panel B shows the averages only for the matched municipalities in the control group. They consist of 492 municipalities that did not receive a P2P loan and were matched with the ones that received a P2P loan, as explained in the matching procedure in section 5.2. The statistics are also split based on the timing of optical fiber arrival. The first group consists of all municipalities that already had optical fiber technology installed before 2015, which is our first sample year. The second group received the technology between Jan/2015-Feb/2020. The third group did not had the technology installed until Feb/2020. Loan variables come from the Central Bank of Brazil (BCB). All other variables comes from IBGE (Instituto Brasileiro de Geografia e Estatística).

	Number of Municipalities	Population	GDP per capita (2017)	Distance to nearest capital	Interest Rate Spread	Average Number of Firms with a bank account	Average Number of Lenders	Average Number of Loans
PANEL A: Full Sample								
Municipalities where P2Ps entered:								
Received optical fiber before 2015	495	235,111.51	32,396.17	171.40	42.14	3,248.53	6.63	113.35
Received optical fiber after 2015	24	19,098.28	24,212.16	298.85	47.94	179.04	2.57	7.72
Never received	0	-	-	-	-	-	-	-
Municipalities where P2Ps did not enter:								
Received optical fiber before 2015	4,250	23,648.22	21,192.80	235.04	45.37	211.87	2.32	7.76
Received optical fiber after 2015	740	12,312.21	25,741.10	294.03	45.31	103.37	1.90	4.68
Never received	26	9,887.50	13,447.49	515.67	68.04	30.15	1.26	2.56
PANEL B: Matched Sample								
Municipalities where P2Ps did not enter:								
Received optical fiber before 2015	453	54,511	31,452	200	43.5	607.8	3.80	19.35
Received optical fiber after 2015	39	20,725	26,331	290	43.0	215.5	2.51	7.55

Table 8. Average Treatment Effects Post P2P Entry. Callaway and Sant'Anna (2021) Aggregation.

This table presents average treatment effect and municipality-clustered standard deviations from regression (5), following the doubly robust estimation procedure from Callaway and Sant'Anna (2021):

$$y_{i,t} = \alpha_i + \gamma_t + X'_{it}\psi + \sum_{e=-K}^{L} \beta_e(D^e_{i,t,c}) + \epsilon_{i,t}.$$

The β_e coefficients capture the treatment effect on $y_{i,t}$ for every period e. This coefficient is estimated first for every treated cohort c, and then the average treatment effect is aggregated in a single coefficient "Post Treatment." All regressions are run at the municipality-quarter level. In panel A, the treatment shock considered is the first month a P2P loan was issued in a given municipality. The sample consists of 492 treated municipalities that received a P2P loan and a control group of 492 matched municipalities, as explained in the matching procedure in section 5.2. Panel B considers the local adoption of optical fiber as a treatment shock. The sample for panel B is a subgroup of Panel A, consisting of only 24 treated municipalities that experienced P2P entry and adopted optical fiber after 2015 and a control group of 108 municipalities that did not adopt optical fiber. All regressions have municipality and time fixed effects. Data come from the Central Bank of Brazil (BCB). Coefficients statistically significant at 1%, 5% and 10% are shown with ***, **, and *, respectively.

	Panel A. Treatment: P2P Entry			
	P2P Penetration:		**Incumbent Banks' Reaction:**	
	Log P2P Amount	P2P Share (p.p.)	Banks' rate (p.p.)	Loan Volume / Firm ($\times 10^3$)
Post Treatment	3.814***	0.298***	-2.524***	0.139*
	(0.146)	(0.028)	(0.744)	(0.107)
Obs	20,320	20,320	19,553	16,425
Municipalities	983	983	983	983
Quarters	21	21	21	17
	Panel B. Treatment: Optical Fiber Adoption			
	P2P Penetration:		**Incumbent Banks' Reaction:**	
	Log P2P Amount	P2P Share (p.p.)	Banks' rate (p.p.)	Loan Volume / Firm ($\times 10^3$)
Post Treatment	0.829***	0.962***	−11.261***	0.789***
	(0.007)	(0.020)	(0.008)	(0.095)
Obs	2,240	2,240	1,689	1,763
Municipalities	138	138	131	136
Quarters	21	21	21	17

Table 9. Triple Diff Regression. Interaction with Ex-Ante Score.

This table presents the coefficients and municipality-clustered standard errors from regression (7). All regressions have municipality and state-quarter fixed effects. Data come from the Central Bank of Brazil (BCB). Internet data come from ANATEL (National Telecommunications Agency). Coefficients statistically significant at 1%, 5% and 10% are shown with ***, ** and *, respectively.

	(1) P2P Amount Issued ($\times 10^3$)	(2) Banks' interest rate (pp)	(3) Loans Amount Issued per Firm ($\times 10^3$)
PANEL A. Exposure to P2P $\times$ Post P2P entry			
Post $\times$ Exposure	2.640***	-14.885**	-5.634
	(0.560)	(6.929)	(6.279)
Post	-0.970***	8.762**	3.277
	(0.327)	(4.114)	(3.680)
Loan Loss Provision	0.002	0.079	-0.028***
	(0.002)	(0.084)	(0.009)
Municipality F.E.	Y	Y	Y
Quarters x State F.E.	Y	Y	Y
Observations	54,223	41,962	43,190
Number of Municipalities	983	980	981
Quarters x State Clusters	513	417	417
R-squared	0.203	0.716	0.233
PANEL B. Exposure to P2P $\times$ Optical Fiber Adoption			
Post $\times$ Exposure	1.349*	-114.244*	28.149*
	(0.786)	(59.438)	(16.375)
Post	-0.628*	48.086*	-12.089*
	(0.357)	(25.866)	(6.967)
Loan Loss Provision	0.017	0.027	-0.031
	(0.013)	(0.202)	(0.046)
Municipality F.E.	Y	Y	Y
Quarters x State F.E.	Y	Y	Y
Observations	2,786	2,036	2,180
Number of Municipalities	61	61	61
Quarters x State Clusters	220	174	177
R-squared	0.109	0.736	0.259

Table 10. Demand Estimation Results

This table presents the two-stage least square results for estimating the demand system as in equation (12):

$$ln\ s_j - ln\ s_0 = \xi_j - \alpha r_j$$

Regressions are run at the municipality-bank-year level. "Log (Avg Loan Size)" and "Maturity" are respectively the log of the average loan amount and average maturity issued by each lender within a municipality-year. Loan Loss Provision is the ratio of the loss provision over total loans issued. One unit of Loan r Rate means 1 pp and 0.01 unit of loan market share s_j means 1%. Therefore, the estimated price-demand elasticity of -0.064 means that loan market share decreases by 6.4% for a 1 pp increase in interest rates. The sample period is from Jan/2015 to Feb/2020. Standard errors are clustered at the municipality level.

	(1)	(2)	(3)
	Reduced form	**1st Stage**	**2nd Stage**
Dependent Variable:	Loan Market Share	Loan Rate	Loan Market Share
IV (z_{njt})	-6.529***	102.184***	
	(0.883)	(22.841)	
Log (Avg Loan Size)	0.877***	-6.855***	0.440***
	(0.009)	(0.143)	(0.117)
Maturity	-0.180***	-8.386***	-0.716***
	(0.015)	(0.167)	(0.144)
Loan Loss Provision	-0.019***	0.043	-0.017**
	(0.004)	(0.043)	(0.006)
$\widehat{LoanRate}$			-0.064**
			(0.017)
Time × Municipality F.E.	Y	Y	Y
Lender F.E.	Y	Y	Y
Observations	52,212	52,212	52,212
F	2,616.492	1,336.368	1,264.891

Table 11. Model Simulation and Counterfactual

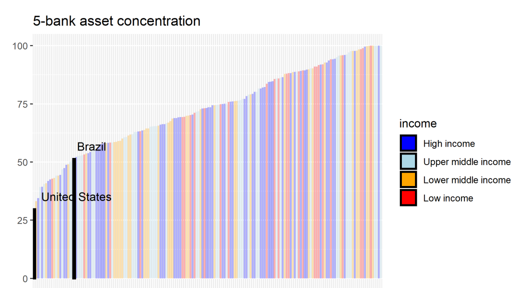
This table shows the result of a counterfactual simulation that removes the P2P lender from markets that have one to five incumbent banks. The equilibrium with and without the P2P sector was calculated according to the definition in section 6.1.3. The parameters were calibrated according to section 6.3.1 in order to match the observed interest rates and shares in each market. The parameters W_0 and σ are simulated for 10,000 firms. The equilibrium outcome with and without the P2P sector is calculated for each of these firms and the variable averages are presented in the table.

Number of Incumbent Banks:	1	2	3	4	5
Observed variables:					
Number of Municipalities	3	10	25	24	42
Number of Firms	67	104	240	225	441
Average Distance to Sao Paulo	1,430.8	1,097.0	1,267.2	1,129.2	791.7
Average Population	9,179.8	12,779.7	18,307.0	23,834.3	25,905.5
Average GDP per capita	15,519.5	14,809.1	23,438.5	22,687.9	36,656.5
Average Market Size (R$)	6,584,436	13,376,688	28,979,544	50,447,820	75,189,732
Int. Rate Banks before P2P entry	164.4%	64.1%	64.3%	57.5%	54.4%
Int. Rate Banks	52.9%	53.4%	49.3%	45.5%	43.9%
Int rate P2P	24.7%	32.3%	38.3%	34.8%	37.2%
Share Banks	22.3%	41.0%	33.9%	38.1%	34.1%
Share P2P	7.2%	4.4%	2.9%	1.6%	0.8%
Model estimation:					
Int. Rate Banks	51.5%	52.9%	48.2%	45.5%	45.6%
Int rate P2P	27.2%	32.4%	37.9%	34.2%	37.7%
Share Banks	22.5%	40.2%	32.8%	37%	34.9%
Share P2P	6.9%	4.6%	2.7%	2.3%	1%
Lenders Profit (R$ millions)	0.9	3.9	7.0	15.5	22.2
Borrowers Surplus (R$ millions)	37.9	96.3	189.2	336.8	508.9
Counterfactual (No P2P):					
Int. Rate Banks	57%	64%	54.2%	48.5%	46.9%
Int rate P2P	-	-	-	-	-
Share Banks	23%	41.3%	32%	36.1%	34.1%
Share P2P	-	-	-	-	-
Lenders Profit (R$ millions)	0.9	3.9	7.0	15.5	22.2
Borrowers Surplus (R$ millions)	24.4	79.9	169.7	320.8	500.1
Welfare Gain from P2P entry (R$ millions):	13.3	15.2	18.4	15.0	8.1
Welfare gain / Local GDP	9.3%	8%	4.3%	2.8%	0.9%

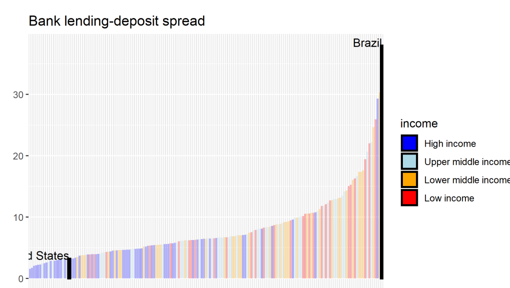
Figure 1. Banking and credit market organization by country income level

This figure shows a comparison between countries credit market variables. Each bar in the plot represents one country. Countries are divided according to the income level classification for countries from the World Bank (`https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups`). Plots were elaborated according to information available in the World Bank - Global Financial Development Database (`https://www.worldbank.org/en/publication/gfdr/data/global-financial-development-database`).

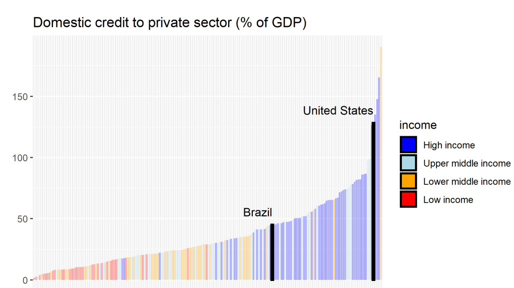
Concentration



Banks Spread



Access to Credit



% Firms Constrained

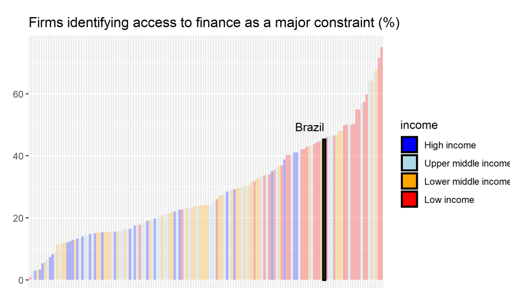


Figure 2. Number of Optical Fiber Customers per Habitant, by Brazilian Micro-Region

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

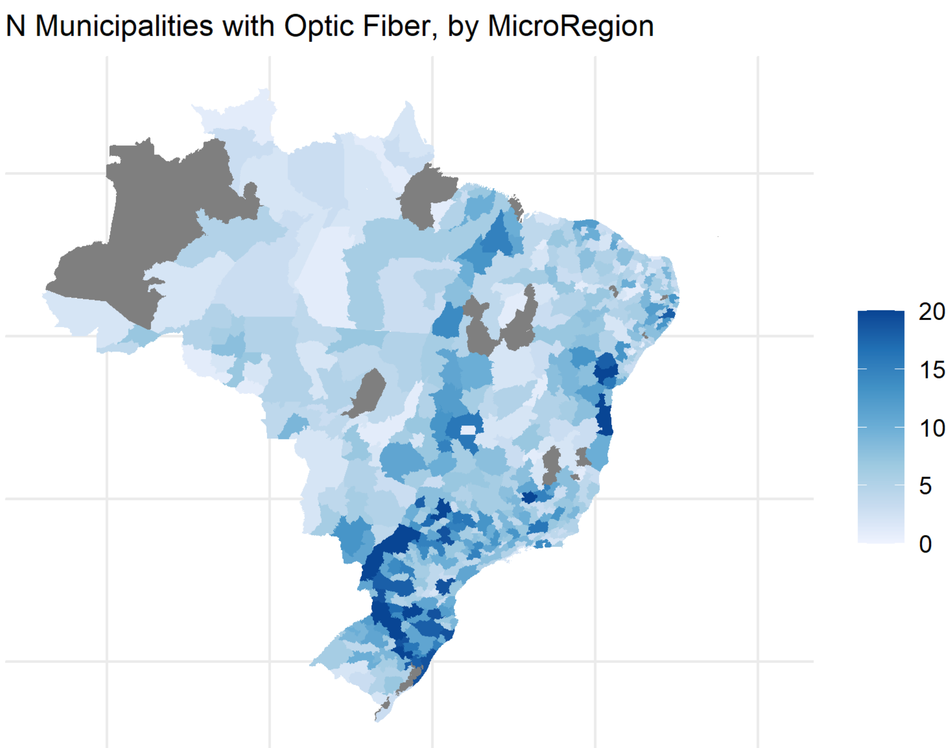
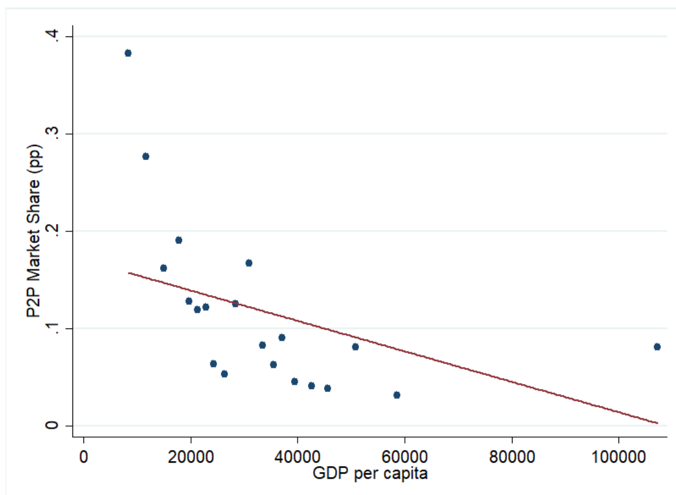


Figure 3. Binscatters: P2P Lenders Market Share and Municipality Characteristics

This figure shows bin-scatter plots with the cross-sectional relationship between the municipality's average P2P loan volume market share vs. GDP per capita and HHI concentration index. All time-series averages are computed conditional on a P2P loan being issued, so we exclude 0 market share observations from the analysis. The observations are aggregated in 20 percentiles. Data come from the Central Bank of Brazil (BCB)

P2P Share × GDP per Capita



P2P share × HHI bank concentration index

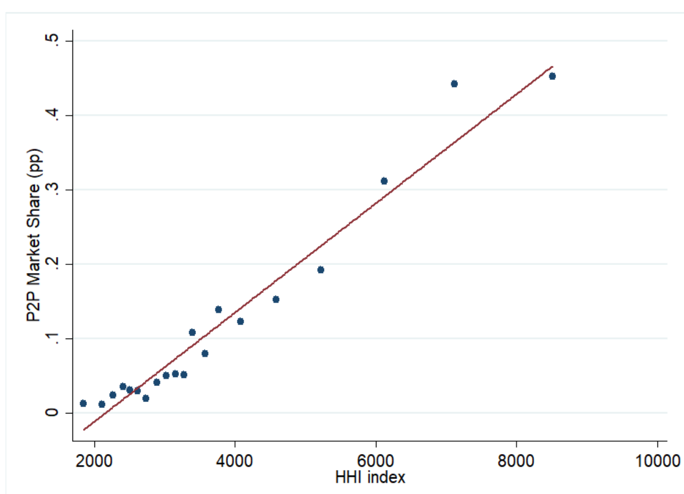


Figure 4. Covariate Balance: Matched Municipalities

This figure shows estimates and 95% error bands for the difference between treated and control municipalities. The treated units are 492 municipalities that received at least one loan from P2P platforms, where control ones are 492 matched ones that received none. We normalized all variables to have a mean of zero and standard deviation of one in the full sample. We present the differences between the treated group and the full sample of 5,535 municipalities, and between the treated group and the matched control sample. The municipalities were matched based on the number of incumbent banks divided by the number of firms with an active bank account, and gdp per capita.

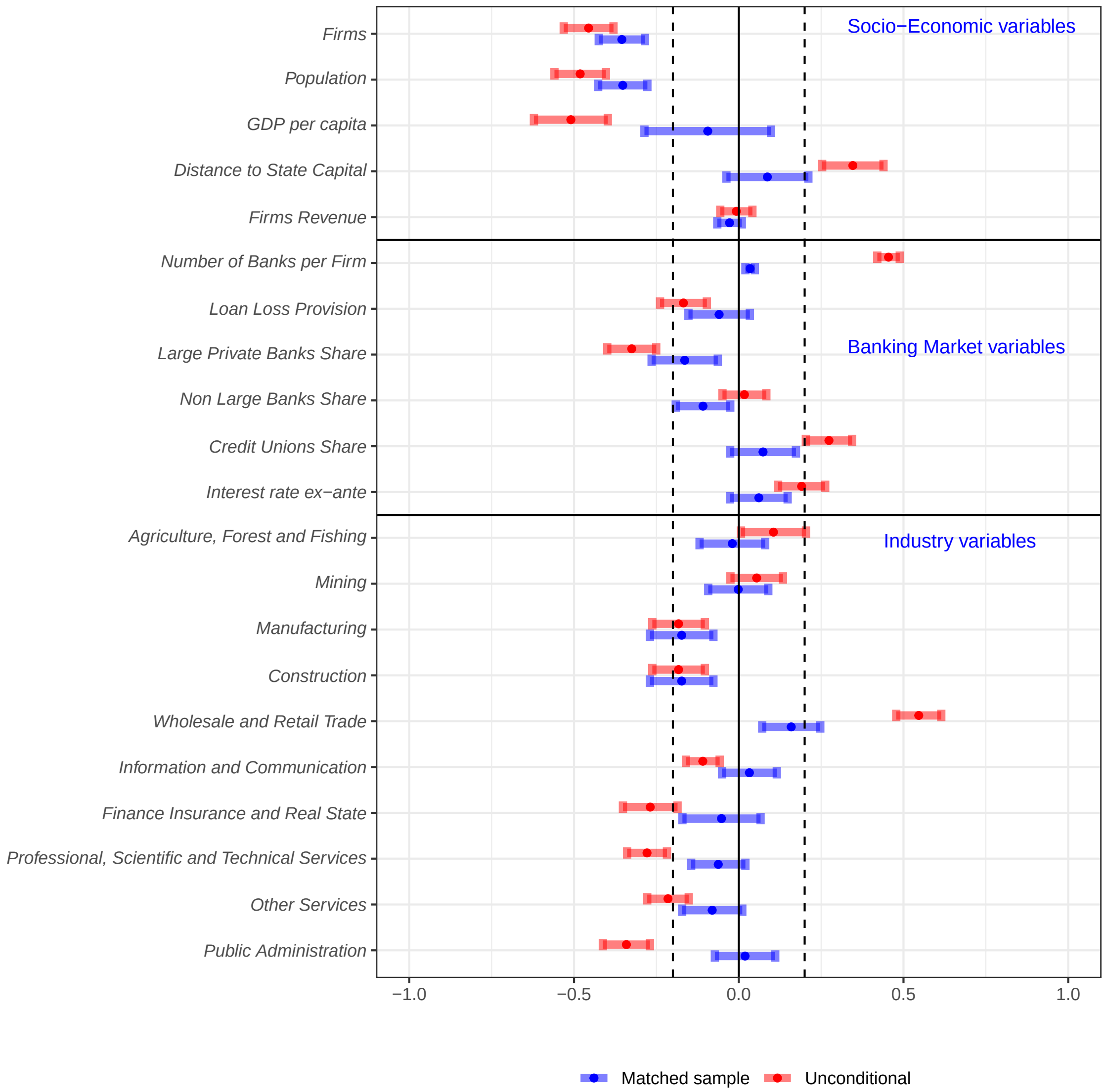


Figure 5. Dynamic Effects of P2P entry. Staggered Difference-in-Differences Coefficients

This figure presents the time dummy coefficients and municipality-clustered standard deviations from regression (5), following the doubly robust estimation procedure from Callaway and Sant'Anna (2021):

$$y_{i,t} = \alpha_i + \gamma_t + X_{it}'\psi + \sum_{e=-K}^{L} \beta_e(D_{i,t,c}^{e}) + \epsilon_{i,t}.$$

All coefficients show the time effect β_e on the dependent variable $y_{i,t}$ for every quarter e before and after P2P entry. All regressions are run at the municipality-quarter level. The sample consists of 492 treated municipalities that received a P2P loan and a control group of 492 matched municipalities, as explained in the matching procedure in section 5.2. Regressions are weighted by the number of loans issued for each municipality-quarter, except for regression (1) that considers volume of loans issued. All regressions have municipality and time fixed effects. An interaction of time-state fixed effect was used in the banks' regressions to control for regional time moving differences in banks' strategy. All regressions standard deviations were clustered at the municipality level. Data come from the Central Bank of Brazil (BCB).

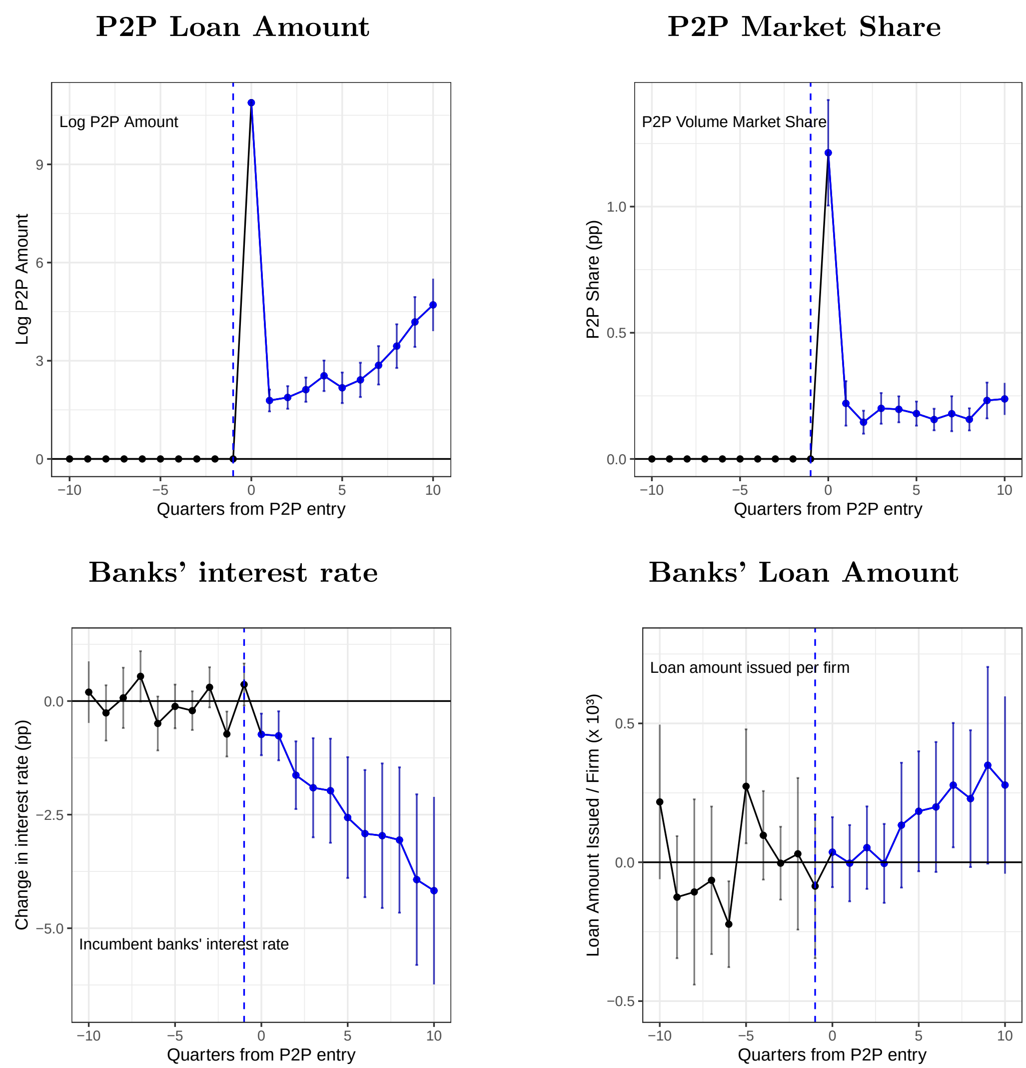
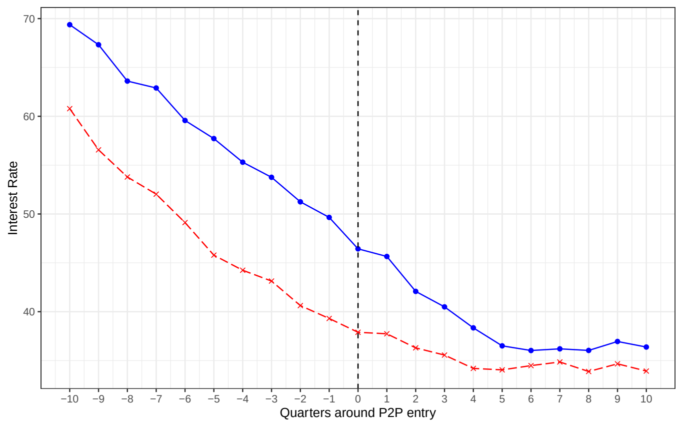


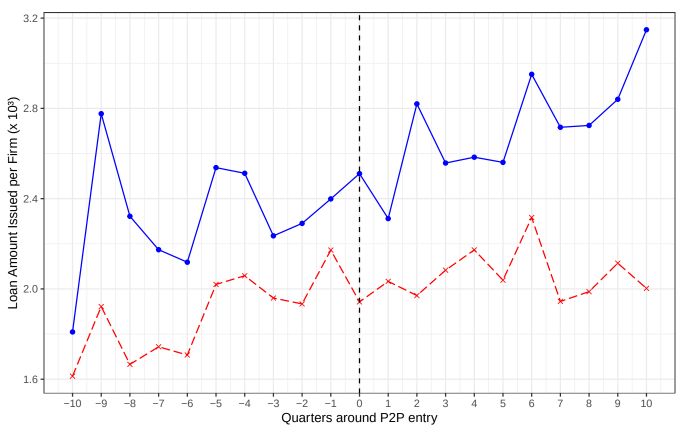
Figure 6. Banks Interest Rates and Loans Issued Around P2P Entry

This figure presents the average interest rate and loan amount issued per firm (in *reais* R$) around the first P2P loan issued. The sample consists of 492 municipalities that received a P2P loan, as defined in section 5.2. The municipalities were divided between high and low exposure to P2P competition, according to a propensity score calculated from equation (6). Data come from the Central Bank of Brazil (BCB).

Interest Rate



Loan Amount Issued per Firm



-o- High "Exposure" to P2P municipalities

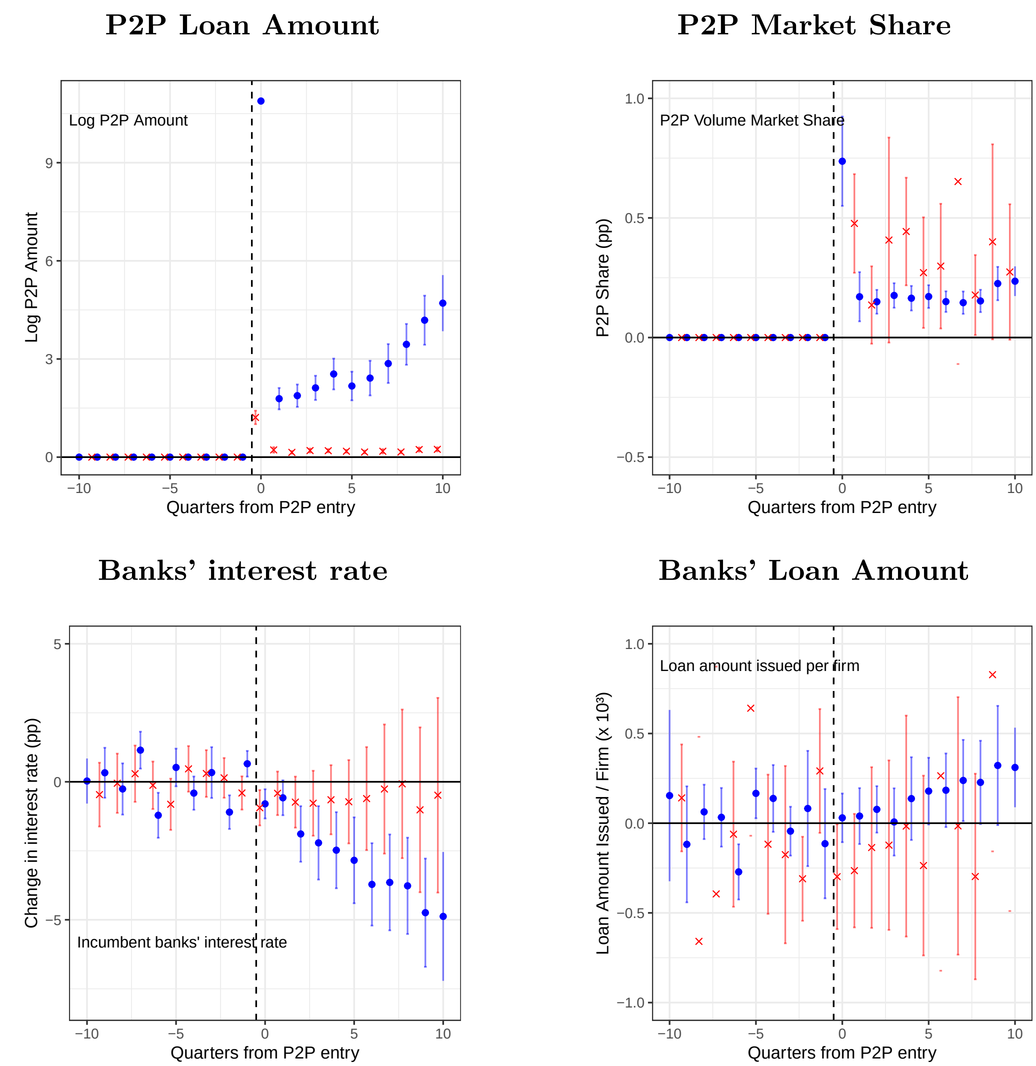
-x- Low "Exposure" to P2P municipalities

Figure 7. Dynamic Effects of P2P entry. Staggered Difference-in-Differences Coefficients. Division by Number of Banks per Firm.

This figure presents the time dummy coefficients and municipality-clustered standard deviations from regression (5), following the doubly robust estimation procedure from Callaway and Sant'Anna (2021):

$$y_{i,t} = \alpha_i + \gamma_t + X_{it}'\psi + \sum_{e=-K}^{L} \beta_e(D_{i,t,c}^{e}) + \epsilon_{i,t}.$$

All coefficients show the time effect β_e on the dependent variable $y_{i,t}$ for every quarter e before and after P2P entry. All coefficients show the time effect on the dependent variable $y_{i,t}$ for every quarter q before and after the reference period of one quarter before P2P entry. All regressions are run at the municipality-quarter level. The sample consists of 492 treated municipalities that received a P2P loan and a control group of 492 matched municipalities, as explained in the matching procedure in section 5.2. The municipalities were divided by the median number of banks per firm. The market share and average interest rate regressions are weighted by the number of loans issued for each municipality-quarter. All regressions have municipality and time fixed effects. An interaction of time-state fixed effect was used in the banks' regressions to control for regional time moving differences in banks' strategy. All regressions standard deviations were clustered at the municipality level. Data come from the Central Bank of Brazil (BCB).



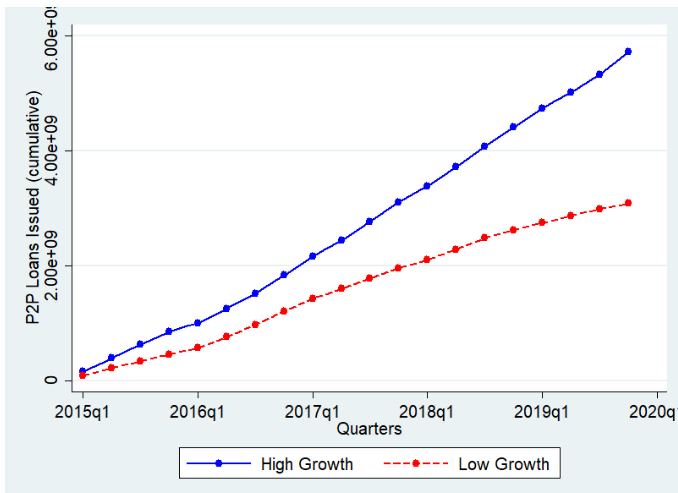
-o- Low Number of Banks per Firm

-x- High Number of Banks per Firm

Figure 8. Optical Fiber Adoption and Demand for P2P Loans

This figure presents the cumulative sum of P2P loans issued and Google searches index for the term "online loan" divided by the growth rate of high-speed internet providers per capita. Both variables are presented at the state level. The growth rate is defined as the number of local providers of optical fiber internet per capita in the last available semester in our data (Jul/2019 - Dec/2020) minus the number in the first semester (Jan/2015 - Dec/2015). The "High Optical Fiber Adoption" and "Low Optical Fiber Adoption" groups are comprised of states above and below the median growth rate, respectively. The Google search index is provided by Google and varies from 0 to 100 at the state level, depending on the number of searches for the term "online loans." P2P loan data come from the Central Bank of Brazil (BCB). Optical Fiber internet data come from ANATEL (National Telecommunications Agency)

P2P Adoption



Google Index: Search for "Online Loan"

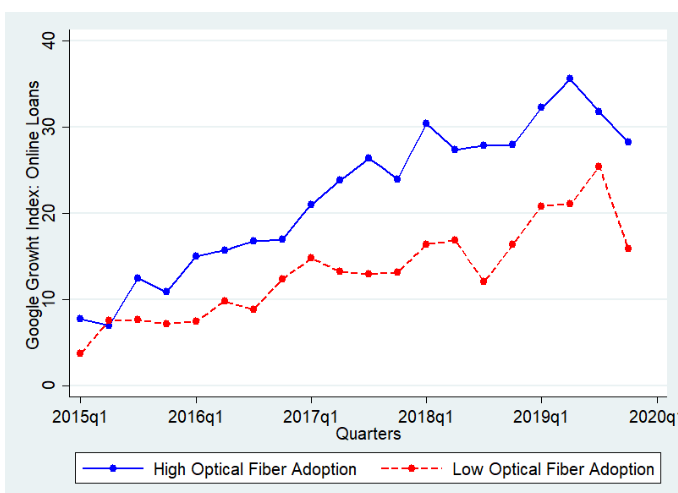


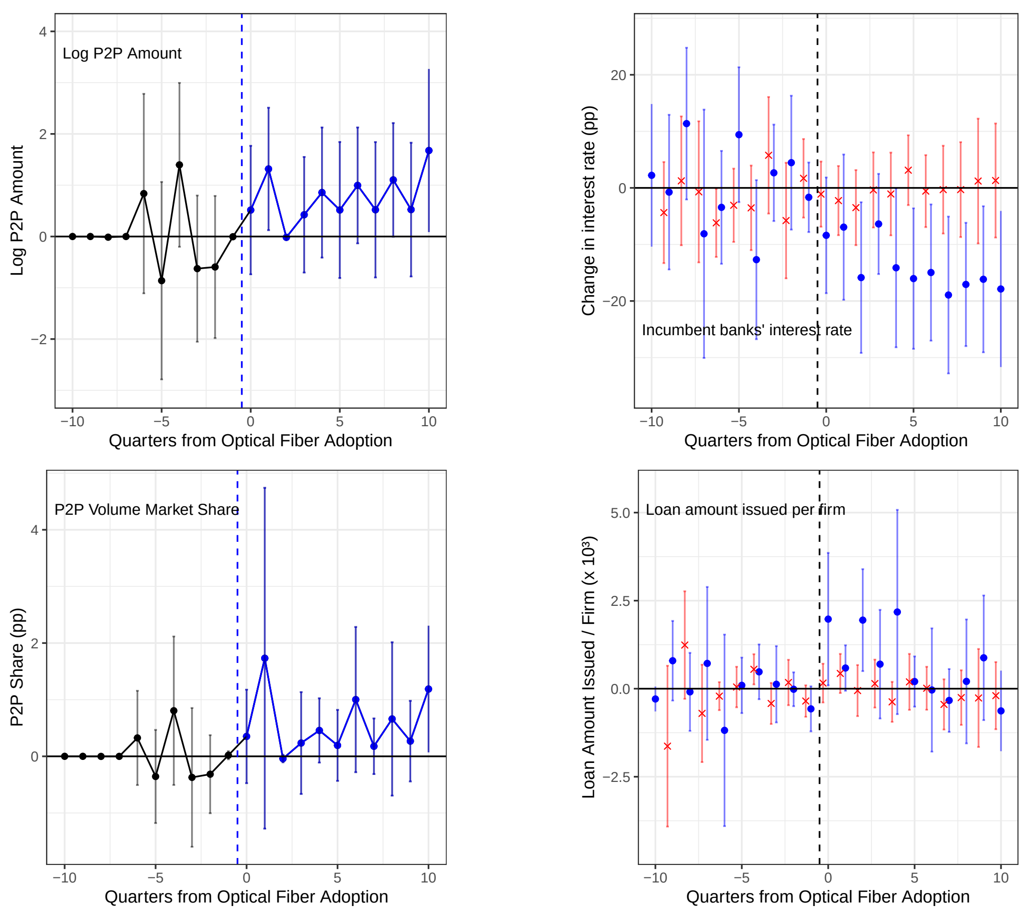
Figure 9. Dynamic Effects of Optical Fiber on Lending Markets

This figure presents the time dummy coefficients and municipality-clustered standard deviations from regression (5), following the doubly robust estimation procedure from Callaway and Sant'Anna (2021):

$$y_{i,t} = \alpha_i + \gamma_t + X_{it}'\psi + \sum_{e=-K}^{L} \beta_e (D_{i,t,c}^{e}) + \epsilon_{i,t}.$$

All coefficients show the time effect β_e on the dependent variable $y_{i,t}$ for every quarter e before and after optical fiber adoption. The coefficients show the time effect on the dependent variable $y_{i,t}$ for every quarter q before and after the reference period of one quarter before optical fiber adoption. All regressions are run at the municipality-quarter level. The sample consists of 63 treated municipalities that adopted optical fiber after 2015, and a control group of 108 municipalities that did not adopt optical fiber. The results for banks' reaction were divided between municipalities that experienced P2P entry vs did not. All regressions have municipality and time fixed effects. The standard deviations are clustered at the municipality level. Data come from the Central Bank of Brazil (BCB). Internet data come from ANATEL (National Telecommunications Agency).

Panel A: P2P Penetration **Panel B: Bank's Reaction**



-o- P2P Entry

-x- No P2P Entry

A Online Appendix - Figures and Tables

Table A.1. Risk Adjusted Interest Rates, by Lender Type. Saturated Specification.

This table shows additional results from the loan-level regression (1), including more fixed effects than the ones presented in Table 4:

$$Int.Rate_i = \alpha + \beta(\text{Future P2P Client})_i + X_i + \tau_b + \tau_{fc} + \tau_{ts} + \tau_{rs} + u_i$$

The sample includes only bank loans. The dummy "Future P2P Client" is equal to 1 if the firm will borrow from a P2P platform in the future. Control variables X_i are loan maturity in years and log of loan amount. The τ terms control for interacted six-fold fixed effects: municipality x industry x Firm age quintiles x Firm employees' formal educational level x firm employees' age quintiles. Standard errors clustered at Bank level. t-stats are shown in brackets. Coefficients statistically significant at 1%, 5% and 10% are shown with ***, ** and *, respectively.

	(1)	(2)	(3)	(4)
	Int. Rate	Int. Rate	Int. Rate	Int. Rate
Future P2P Client	1.4987***	4.1081***	1.5372***	-0.0155
	(3.95)	(2.81)	(2.80)	(-0.03)
Constant	166.0439***	175.4165***	166.4425***	123.1192***
	(1127.75)	(537.20)	(795.59)	(302.60)
Firm Size Sample	All sizes	Micro	Small	Medium
Fixed Effects	Bank, Time, rating and Firms Characteristics			
N Firms that ever had a Fintech Loan	1,100	260	751	304
N Banks	772	688	697	599
Mean interest rate (N Observations	2,788,092	685,143	1,507,574	499,361
Adj R2	0.7379	0.8027	0.7279	0.7070

Table A.2. Statistics: Loans that Switched Lenders

This table shows the proportion and number of working capital loans that transitioned to banks and P2Ps, divided by lender type origin. The "From" column shows the previous lender type of each firm that borrowed a loan from a new lender. Column (1) shows, for each lender type, the percentage of these loans that transitioned to another traditional bank. Column (2) shows, for each lender type, the percentage of these firms that transitioned to a P2P platform. Column (3) presents the difference in p.p. between (1) and (2). Column (4) presents the total number of loans that switched lenders. Data come from the Central Bank of Brazil (BCB).

From:	(1) % Switched to Another Bank	(2) % Switched to P2Ps	(3) Difference: (1) - (2)	(4) Number of Loans that Switched
Private Bank Large	0.519	0.650	0.132	290,309
Private Bank Non Large	0.044	0.045	0.002	24,404
Public Bank Federal	0.221	0.153	-0.068	123,502
Public Bank Local	0.047	0.016	-0.030	25,999
Credit Union	0.170	0.135	-0.035	94,999

Table A.3. Time Effects of P2P entry on Banks' Local Variables. Staggered Difference-in-Differences Regression.

This table presents the time dummy coefficients and municipality-clustered standard deviations from regression (5) and Figure 5, following the doubly robust estimation procedure from Callaway and Sant'Anna (2021):

$$y_{i,t} = \alpha_i + \gamma_t + X_{it}'\psi + \sum_{e=-K}^{L} \beta_e(D_{i,t,c}^e) + \epsilon_{i,t}.$$

All coefficients show the time effect β_e on the dependent variable $y_{i,t}$ for every quarter e before and after P2P entry. All regressions are run at the municipality-quarter level. The sample consists of 492 treated municipalities that received a P2P loan and a control group of 492 matched municipalities, as explained in the matching procedure in section 5.2. Regressions are weighted by the number of loans issued for each municipality-quarter, except for regression (1) which considers the volume of loans issued. All regressions have municipality and time fixed effects. An interaction of time-state fixed effect was used in the banks' regressions to control for regional time-moving differences in banks' strategy. All regressions' standard deviations were clustered at the municipality level. Data come from the Central Bank of Brazil (BCB).

	Log P2P Amount		P2P Share		Banks' rate		Loan Amount Issued per Firm ($\times 10^3$)	
Timing	β	s.e.	β	s.e.	β	s.e.	β	s.e.
−10	0.000	(0.000)	0.000	(0.000)	0.196	(0.412)	0.217*	(0.169)
−9	0.000	(0.000)	0.000	(0.000)	−0.261	(0.371)	−0.126	(0.134)
−8	0.000	(0.000)	0.000	(0.000)	0.071	(0.404)	−0.107	(0.203)
−7	0.000	(0.000)	0.000	(0.000)	0.544*	(0.337)	−0.065	(0.162)
−6	0.000	(0.000)	0.000	(0.000)	−0.493*	(0.361)	−0.223***	(0.094)
−5	0.000	(0.000)	0.000	(0.000)	−0.118	(0.293)	0.274**	(0.125)
−4	0.000	(0.000)	0.000	(0.000)	−0.211	(0.259)	0.097	(0.097)
−3	0.000	(0.000)	0.000	(0.000)	0.303	(0.269)	−0.003	(0.080)
−2	0.000	(0.000)	0.000	(0.000)	−0.725***	(0.301)	0.030	(0.166)
−1	0.000	(0.000)	0.000	(0.000)	0.364*	(0.281)	−0.086	(0.158)
0	10.885***	(0.050)	1.213***	(0.127)	−0.734***	(0.278)	0.036	(0.077)
1	1.786***	(0.203)	0.220***	(0.054)	−0.764***	(0.328)	−0.003	(0.083)
2	1.879***	(0.210)	0.146***	(0.028)	−1.632***	(0.453)	0.053	(0.090)
3	2.117***	(0.226)	0.200***	(0.037)	−1.908***	(0.663)	−0.004	(0.086)
4	2.541***	(0.284)	0.197***	(0.031)	−1.973***	(0.697)	0.134	(0.137)
5	2.174***	(0.284)	0.180***	(0.029)	−2.564***	(0.808)	0.184*	(0.131)
6	2.416***	(0.318)	0.156***	(0.026)	−2.917***	(0.851)	0.199*	(0.142)
7	2.861***	(0.357)	0.179***	(0.042)	−2.964***	(0.967)	0.278**	(0.136)
8	3.447***	(0.405)	0.157***	(0.027)	−3.058***	(0.972)	0.229*	(0.150)
9	4.185***	(0.463)	0.232***	(0.043)	−3.930***	(1.142)	0.349*	(0.215)
10	4.707***	(0.487)	0.238***	(0.039)	−4.173***	(1.255)	0.278*	(0.194)
Obs	20,320		20,320		19,553		20,320	

Table A.4. Time Effects of Optical Fiber Adoption on P2P Activity. Staggered Difference-in-Differences Regression.

This table presents average treatment effect and municipality-clustered standard deviations from regression (5), following the doubly robust estimation procedure from Callaway and Sant'Anna (2021):

$$y_{i,t} = \alpha_i + \gamma_t + X_{it}'\psi + \sum_{e=-K}^{L} \beta_e(D_{i,t,c}^e) + \epsilon_{i,t}.$$

The dependent variable $y_{i,t}$ considers different measures of P2P lending activity": (1) log of the amount of P2P loans issued, (2) P2P market share in terms of number of loans, and (3) P2P market share in terms of loans issued in R$. The β_e coefficients capture the treatment effect on $y_{i,t}$ for every period e. This coefficient is estimated first for every treated cohort c, and then the average treatment effect is aggregated in a single coefficient "Post Treatment." All regressions are run at the municipality-quarter level. In panel A, the regressions are run in all 1,023 municipalities in our sample that did not yet adopt the optical fiber in 2015. The sample in Panel B is a sub-sample of panel A, consisting of 24 municipalities that experienced P2P entry and a control group of 106 that did not adopt fiber. All regressions have municipality and time fixed effects. Data come from the Central Bank of Brazil (BCB). Coefficients statistically significant at 1%, 5% and 10% are shown with ***, **, and *, respectively.

	PANEL A: FULL SAMPLE		
	Log P2P Amount	P2P Volume Market Share (p.p.)	P2P Loan Market Share (p.p.)
Post Treatment	0.026***	0.051***	0.026***
	(0.007)	(0.020)	(0.008)
Obs	20,460	20,460	20,460
Municipalities	1,023	1,023	1,023
Quarters	20	20	20
	PANEL B: MATCHED SAMPLE		
	Log P2P Amount	P2P Volume Market Share (p.p.)	P2P Loan Market Share (p.p.)
Post Treatment	0.829***	0.962***	0.591***
	(0.095)	(0.265)	(0.169)
Obs	2,680	2,680	2,680
Municipalities	134	134	134
Quarters	20	20	20

Table A.5. Time Effects of Optical Fiber Adoption on Lending Markets. Staggered Difference-in-Differences Regression.

This figure presents the time dummy coefficients and municipality-clustered standard deviations from regression (5), and presented in Figure 9, following the doubly robust estimation procedure from Callaway and Sant'Anna (2021):

$$y_{i,t} = \alpha_i + \gamma_t + X_{it}'\psi + \sum_{e=-K}^{L} \beta_e(D_{i,t,c}^e) + \epsilon_{i,t}.$$

All coefficients show the time effect β_e on the dependent variable $y_{i,t}$ for every quarter e before and after optical fiber adoption. The coefficients show the time effect on the dependent variable $y_{i,t}$ for every quarter q before and after the reference period of one quarter before optical fiber adoption. All regressions are run at the municipality-quarter level. The sample consists of 63 treated municipalities that adopted optical fiber after 2015, and a control group of 108 municipalities that did not adopt optical fiber. The results for banks' reaction were divided between municipalities that experienced P2P entry vs did not. All regressions have municipality and time fixed effects. The standard deviations are clustered at the municipality level. Data come from the Central Bank of Brazil (BCB). Internet data come from ANATEL (National Telecommunications Agency).

					P2P Entry				No P2P Entry			
	Log P2P Amount		P2P Share		Banks' rate		Loan Amount / Firms ($R\$ \times 10^3$)		Banks' rate		Loan Amount / Firms ($R\$ \times 10^3$)	
Timing	β	s.e.	β	s.e.	β	s.e.	β	s.e.	β	s.e.	β	s.e.
−10	0.000	(0.000)	0.000	(0.000)	2.222	(7.666)	−0.292*	(0.215)	3.478	(4.170)	−0.200	(0.244)
−9	0.000	(0.000)	0.000	(0.000)	−0.748	(8.312)	0.794	(0.687)	−4.363	(5.435)	−1.632	(1.388)
−8	−0.013	(0.021)	−0.006	(0.007)	11.367*	(8.154)	−0.091	(0.674)	1.247	(6.927)	1.239*	(0.928)
−7	0.000	(0.000)	−0.001	(0.001)	−8.112	(13.348)	0.718	(1.320)	−0.698	(7.584)	−0.701	(0.841)
−6	0.837	(1.183)	0.619	(1.038)	−3.440	(6.068)	−1.183	(1.653)	−6.175**	(3.668)	−0.212	(0.242)
−5	−0.861	(1.170)	−0.714	(0.996)	9.409*	(7.248)	0.095	(0.479)	−3.071	(3.941)	0.047	(0.350)
−4	1.397*	(0.971)	1.608	(1.463)	−12.690*	(8.550)	0.479	(0.473)	−3.528	(4.548)	0.551**	(0.261)
−3	−0.626	(0.867)	−0.439	(0.703)	2.667	(5.185)	0.125	(0.659)	5.768	(6.265)	−0.419	(0.354)
−2	−0.595	(0.843)	−0.851	(1.150)	4.460	(7.196)	−0.016	(0.292)	−5.773	(6.213)	0.176	(0.392)
−1	−0.004	(0.018)	0.017	(0.066)	−1.659	(3.739)	−0.573*	(0.388)	1.697	(4.226)	−0.351*	(0.272)
0	0.515	(0.761)	0.633	(0.900)	−8.389*	(6.219)	1.975**	(1.143)	−1.102	(3.504)	0.159	(0.335)
1	1.317**	(0.725)	1.882	(1.904)	−6.939	(7.810)	0.587*	(0.393)	−2.247	(3.720)	0.432	(0.338)
2	−0.016	(0.021)	−0.096	(0.101)	−15.857**	(8.098)	1.947**	(0.880)	−3.488	(4.039)	−0.054	(0.441)
3	0.424	(0.685)	0.259	(0.734)	−6.378	(5.386)	0.696	(0.938)	−0.360	(4.038)	0.145	(0.414)
4	0.858	(0.771)	0.168	(0.263)	−14.125**	(8.547)	2.178	(1.763)	−1.074	(4.449)	−0.374	(0.345)
5	0.517	(0.806)	1.903	(2.917)	−16.036**	(7.552)	0.203	(0.433)	3.131	(3.754)	0.193	(0.483)
6	0.997*	(0.687)	0.984	(1.402)	−14.964**	(7.323)	−0.037	(1.064)	−0.568	(3.871)	0.012	(0.371)
7	0.521	(0.802)	1.548	(1.920)	−18.939**	(8.430)	−0.334	(0.542)	−0.308	(4.720)	−0.447	(0.434)
8	1.104*	(0.673)	1.735	(2.591)	−17.071***	(6.629)	0.206	(1.070)	−0.305	(5.102)	−0.253	(0.472)
9	0.525	(0.792)	0.209	(0.428)	−16.157**	(7.852)	0.877	(1.076)	1.211	(6.708)	−0.264	(0.846)
10	1.677**	(0.967)	1.253*	(0.860)	−17.874**	(8.391)	−0.631	(0.695)	1.308	(6.132)	−0.198	(0.580)
Obs	2,240		2,240		1,689		2,240		1,689		2,240	

Table A.6. Natural Disasters in Brazil

This table presents estimates of the monetary losses from natural disasters in Brazil from 2015 to 2020. The information was hand collected from individual reports available in the Brazilian Integration Ministry website.

Disaster:	Estimated Property Losses (R$ millions)	Number of Municipalities Affected
Drought	51,100	2,249
Floods/Storms	14,100	1,912
Landslides	1,700	149
Dam Failure	896	32
Fire	752	72
Others	6,850	379
Total	75,400	4,793

Table A.7. Model Simulation and Counterfactual. Exogenous default.

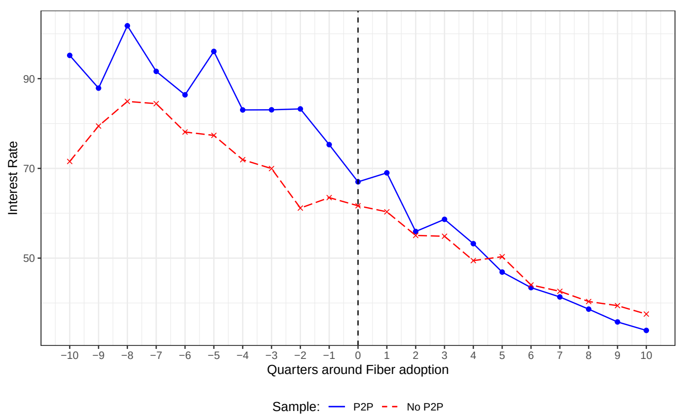
This table shows the result of a counterfactual simulation that removes the P2P lender from markets that have one to five incumbent banks. The equilibrium with and without the P2P sector was calculated according to the definition in section 6.1.3. The parameters were calibrated according to section 6.3.1 in order to match the observed interest rates and shares in each market. The parameter σ is fixed for each lender type in order to match observed delinquency rates for each lender.

Number of Incumbent Banks:	1	2	3	4	5
Observed variables:					
Number of Municipalities	3	10	25	24	42
Number of Firms	67	104	240	225	441
Average Distance to Sao Paulo	1,208.3	1,267.2	1,129.2	791.7	838.1
Average Population	9,179.8	12,779.7	18,307.0	23,834.3	25,905.5
Average GDP per capita	15,519.5	14,809.1	23,438.5	22,687.9	36,656.5
Average Market Size (R$)	6,584,436	13,376,688	28,979,544	50,447,820	75,189,732
Int. Rate Banks before P2P entry	164.4%	64.1%	64.3%	57.5%	54.4%
Int. Rate Banks	52.9%	53.4%	49.3%	45.5%	43.9%
Int rate P2P	24.7%	32.3%	38.3%	34.8%	37.2%
Share Banks	22.3%	41.0%	33.9%	38.1%	34.1%
Share P2P	7.2%	4.4%	2.9%	1.6%	0.8%
Model estimation:					
Int. Rate Banks	52.1%	53.5%	48.9%	45.4%	43.3%
Int rate P2P	26.2%	32.5%	38.7%	35.7%	37.8%
Share Banks	22.7%	42%	31.9%	40.5%	34.7%
Share P2P	7.2%	4.3%	3%	1.6%	1.2%
Lenders Profit (R$ millions)	0.7	2.3	3.9	11.1	13.3
Borrowers Surplus (R$ millions)	32.6	78.7	228.9	371.0	526.2
Counterfactual (No P2P):					
Int. Rate Banks	52.5%	54.2%	49.3%	45.7%	43.4%
Int rate P2P	-	-	-	-	-
Share Banks	24%	43.7%	33%	41.5%	35.3%
Share P2P	-	-	-	-	-
Lenders Profit (R$ millions)	0.7	2.3	3.9	11.1	13.3
Borrowers Surplus (R$ millions)	31.8	77.6	226.8	368.6	524.3
Welfare Gain from P2P entry (R$ millions):	0.8	0.9	1.9	2.0	1.7
Welfare gain / Local GDP	0.6%	0.5%	0.4%	0.4%	0.2%

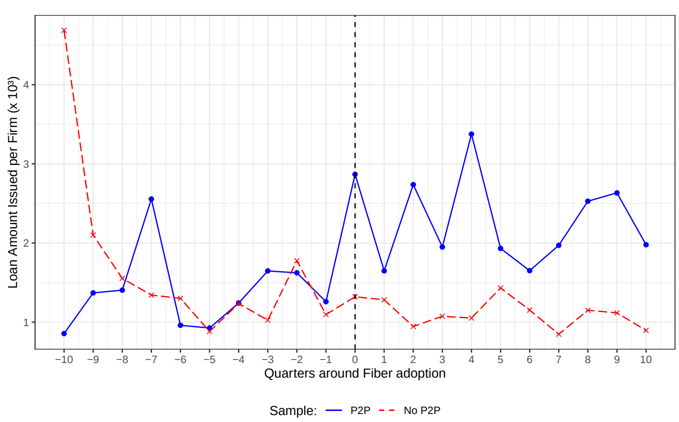
Figure A.1. Banks Interest Rates and Loans Issued Around Optical Fiber Adoption

This figure presents the average interest rate and loan amount issued per firm around the adoption of optical fiber. The sample consists of 63 municipalities that adopted optical fiber during our sample period, as defined in section 5.2. The municipalities were divided based on receiving a P2P loan. Data come from the Central Bank of Brazil (BCB). Optical Fiber internet data come from ANATEL (National Telecommunications Agency).

Interest Rate



Loan Amount Issued per Firm



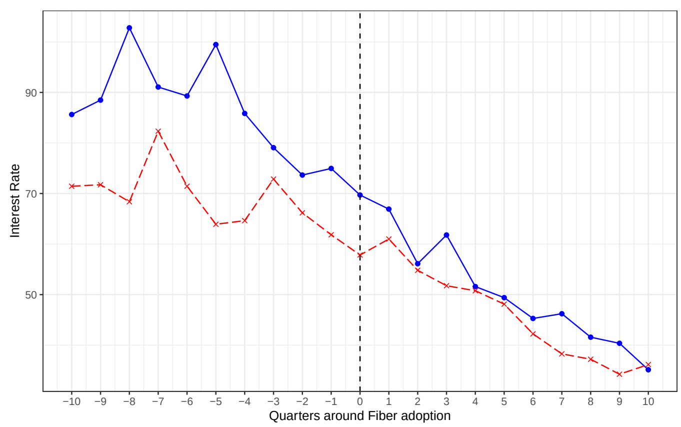
-o- P2P Entry

-x- No P2P Entry

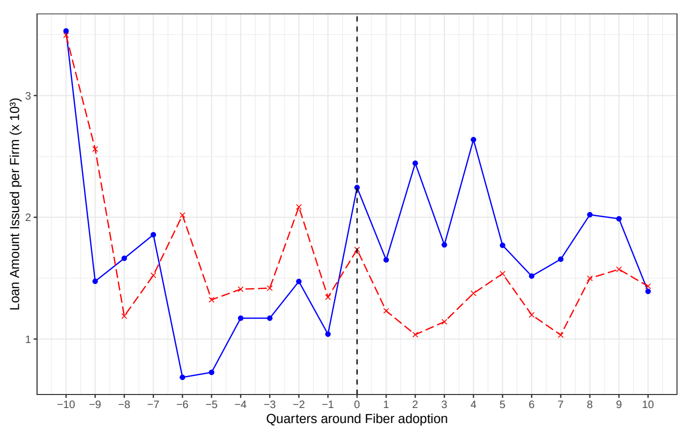
Figure A.2. "High" vs "Low" pre-fiber propensity score municipalities

This figure presents the average interest rate and loan amount issued per firm (in *reais* R$) around the adoption of optical fiber. The sample consists of 24 municipalities that adopted optical fiber during our sample period and also received a P2P loan, as defined in section 5.2. The municipalities were divided between high and low exposure to P2P competition, according to a propensity score calculated from equation (6). Data come from the Central Bank of Brazil (BCB).

Banks' Interest Rate:



Banks' Loan Amount Issued:



High Propensity To Borrow from P2Ps
Low Propensity To Borrow From P2Ps

B 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:

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

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 B.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 %	13.62 %

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: