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The Real Effects of FinTech Lending on SMEs: Evidence from Loan Applications*

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Abstract

We examine the effects of FinTech lending on firm policies using proprietary data on loan applications and loans granted from a peer-to-business platform. We find that FinTech serves high quality and creditworthy small businesses who already have access to bank credit. Firms access FinTech to obtain long-term unsecured loans and reduce their exposure to banks with less liquid assets, stable funds, and capital. We find that firms with access to FinTech loans significantly increase investment, employment, and sales growth relative to firms that get their loan application rejected. We identify these effects by exploiting the number of banks in each municipality as a source of exogenous variation in the probability of obtaining a FinTech loan. Our findings suggest that FinTech allows firms to improve their financial flexibility and reduce bank dependence.

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1. Introduction

The rise of FinTech lending platforms is changing the provision of financial services worldwide. While small and medium sized enterprises (SMEs) have traditionally relied on banks for their financing needs, today SMEs can also obtain financing through peer-to-business (P2B) platforms, which allow a direct match between borrowers and lenders. The rise of these new technology-enabled platforms can affect credit markets and real economic activity and so it raises important questions. What drives the firms' decision to access FinTech platforms? What are the effects of FinTech lending on firm investment and financial policies?

We examine these questions using proprietary data from a leading independent P2B platform (*Raize*) in Portugal that directly links retail investors to SME borrowers. We have the universe of loan applications and loans granted by the P2B platform. We combine these data with administrative data on loans from the Central Credit Register, and financial statements for the universe of non-financial firms and banks operating in Portugal. As a result, we have information about the firms who manage to borrow through the P2B platform and the firms who apply but get rejected by the platform, including the characteristics of the banks serving these firms.

Since the start of the platform in 2016 till 2019, there were 3,197 firms applying to borrow through the P2B platform and 40% of those applications were accepted. The mean loan is about €22,500 and represents 17% of the firm's assets and 29% of the firm's debt, indicating that FinTech loans are an economically significant source of debt financing for SMEs. The P2B loans have, on average, three-year maturity and an interest rate of 7%, which is significantly higher than the interest paid on other types of debt that firms in our sample obtain from traditional financing sources.

We start by studying the P2B platform clientele by comparing the characteristics of FinTech applicants versus the non-applicant firms in our sample who also increased their leverage but through traditional financial intermediaries. We find that P2B platforms cater to larger, high quality firms, with low credit risk as captured by the Altman Z-score (Altman (1968)). Importantly, we find that firms who apply for P2B funding are significantly more likely to already have bank debt in their debt structure. We also observe that despite greater leverage, these firms display lower levels of overdue debt and thus consistent with their z-score appear to be safer firms. These results are in contrast to the traditional financial intermediation literature (e.g., Sharpe (1990)), which suggests that competition should lead newcomers to allocate capital toward lower quality and smaller firms. In addition, our results deviate from the existing empirical findings on peer-to-peer (P2P) platforms, which indicate that FinTech serves a riskier unexplored market segment in consumer loans (de Roure, Pelizzon, and Tasca (2016), Hau, Huang, Shan, and Sheng (2019), Di Maggio and Yao (2021)), and mortgage origination (Buchak, Matvos, Piskorski, and Seru (2018), Fuster, Plosser, Schnabl, and Vickery (2019)).

A second set of results allows us to shed further light on the reason why firms decide to apply to the FinTech platform. We study the characteristics of the banks that have a lending relationship with the SMEs in our sample, thus focusing on the role the banking sector plays in the decision to switch to FinTech credit. We find that SMEs are more likely to access P2B lending if they have relationships with banks with less stable sources of funding, lower liquidity of assets, and lower capital ratios. This indicates that one additional reason why firms switch to FinTech is to reduce their exposure to banks that are less able to absorb shocks and more likely to cut lending activity during financial crises (Khwaja and Mian (2008), Ivashina and Scharfstein (2010)). These results highlight the importance of banks' quality in the firm's decision to apply to borrow from P2B platforms, and thus contribute to the literature that emphasizes the bank-level determinants of lending relationships (e.g., Gopalan, Udell, and Yerramilli (2011), Paravisini, Rappoport, and Schnabl (2015), Schwert (2018)). In particular, Schwert (2018), shows that firms with access to capital markets borrow from banks with less capital, while bank-dependent firms are matched with better capitalized banks. Our results therefore are consistent with the view that FinTech plays the role of an alternative source of external financing for SMEs, which allows firms to protect themselves against the risk of adverse banking shocks. Preserving financial flexibility appears to be the predominant concern of firms (Graham and Harvey (2001)), and the diversification of financing sources is one way to maintain financial flexibility (Jang (2017)). In this respect, the choice to obtain a FinTech loan can be rationalized in the context of DeAngelo, DeAngelo, and Whited (2011) model as reflecting a desire to minimize the impact of future financial constraints.

Next, we explore the effects of obtaining FinTech lending on firm policies. It is empirically challenging to study how firms use the P2B loans, as unobservable borrower characteristics may affect both the likelihood of obtaining FinTech lending and firm-level outcomes. If this is the case we would observe differences in outcomes even in the absence of FinTech financing. To address this concern we employ three different strategies.

First, in all our specifications we focus on the cohort of firms who increase their external financing. Thus, our results are estimated comparing firms who increase their leverage and choose to do it through a P2B platform with an otherwise similar group of firms who raise external capital at the same time through traditional financial intermediaries. This approach reduces selection bias and accounts for differences in demand for credit.

Second, we adopt a propensity score matching approach. Specifically, we construct a comparison group of firms by matching each firm in our sample of firms accessing P2B platforms to its closest matches, and we identify these matches using an extensive set of determinants of financing choices.

Finally, we report the results of an instrumental variable (IV) estimation using the number of banks in each municipality before the inception of the P2B platform as instrument for the likelihood that local firms obtain a P2B loan. Our IV setting relies on two assumptions. First, as we directly document in our analysis, the presence of bank debt in a firm balance sheet significantly predicts the choice of the P2B platform to accept the firm application. Second, we borrow from a large literature showing the importance of local bank presence for firm access to bank debt (e.g., Degryse and Ongena (2005), Guiso, Sapienza, and Zingales (2006), Benfratello, Schiantarelli, and Sembenelli (2008)). Standard diagnostic checks show that the instrument relevance condition is satisfied. At the same time, the number of local banks at the time of the FinTech platform introduction is likely to satisfy the exclusion restriction. The FinTech platform was available to the whole country from the onset, thus ruling out concerns based on endogenous selection. Moreover, any direct influence of the number of local banks on a firm outcomes should be no different before and after the specific date of a firm P2B application, and thus should have no bearing on the *changes* in firm outcomes around the application. To further support the validity of our instrument, we also perform falsification tests using the period three years before the actual P2B application dates.

We find that firms increase assets, employment and sales following FinTech borrowing.Firms that access FinTech lending experience a 150 percentage points increase in asset growth, a 52 percentage points increase in employment growth, and a 89.4 percentage point increase in sales growth in the three years following relative to the control group of rejected applicants. In addition, we do not find any significant impact of P2B loans on profitability, which indicates that P2B loans contribute to firm growth without sacrificing profitability.

We also show that firms significantly change their capital structure and debt structure following FinTech borrowing. Firms that access the P2B platform increase leverage. We find that leverage almost doubles for firms with a FinTech loan approved relative to rejected firms. This increase is reflected in both long-term and short-term leverage. Interestingly, we observe a large reduction in secured debt, equal to 113% compared to the sample of rejected firms. In addition, net of FinTech loans, we find that firms decrease long-term bank debt, and increase short-term bank debt. Thus, our findings suggest that access to FinTech lending allows firms to expand their debt capacity and substitute long-term bank lending with long-term unsecured FinTech debt.

These results provide new insights about the attractiveness of FinTech debt for firms. Specifically, there are several reasons why small firms may prefer to keep financing their growth with long-term unsecured debt. For example, they want to avoid the refinancing risk inherent in short-term debt (see e.g., Diamond (1991), Diamond (1993), Brunnermeier and Yogo (2009)). To the extent that FinTech firms are closer to their maximum debt capacity but want to secure additional long-term funding, FinTech loans represent a viable option. The fact that FinTech loans are unsecured represents another attractive feature of P2B platforms. In addition, tighter regulation and higher capital requirements make long-term unsecured loans to SMEs unattractive to banks (Acharya, Berger, and Roman (2018), Cortés, Demyanyk, Li, Loutskina, and Strahan (2020), Chernenko, Erel, and Prilmeier (2019)). On the other hand, firms with availability of collateral may avoid pledging their assets to retain financial and operational flexibility. Unpledged collateral is often used as financial slack (see e.g., Myers and Majluf (1984)) or insurance (Rampini and Viswanathan (2013)). Similarly, firms may shy away from secured loans to avoid the connected limits to their flexibility to sell or redeploy assets (Mello and Ruckes (2017)). In this respect, FinTech provides firms with an alternative access to unsecured long-term financing, and even offers them the possibility to release pledged assets by paying off secured long-term bank loans.

We also observe that the access to the P2B platform allows SMEs to further diversify their pool of lenders. P2B loans allow firms to add new bank relationships, and reduce their dependence on a single bank, as indicated by a drop in the share of firm debt accounted by its main bank and a reduction in debt concentration. These results provide further support to the notion that firms achieve both higher financial flexibility and protect themselves against the risk of lending cuts caused by liquidity shocks using by diversifying their financing sources through FinTech.

In exploring the consequences for firms' cost of debt, we find that obtaining a P2B loan seems to increase the firms' overall cost of debt. These results are in line with anecdotal evidence and previous literature showing that FinTech loans are on average more expensive than bank loans. However, we find that the cost of bank debt (i.e., cost of debt excluding P2B loans) is unaffected. The results that firms who access the P2B platform are able to increase (short-term) bank debt without paying higher spreads can be rationalized in light of the conclusions in Crouzet (2018). He shows theoretically that firms may choose to borrow from markets to increase their scale of operation. This in turn raises the liquidation value of firms and relaxes their bank borrowing constraint. Our results about the increase in bank debt, jointly considered with the observed growth in firm size, thus suggest that P2B lending may be playing a role similar to the one market debt has in Crouzet (2018) model.

We contribute to the recent literature on FinTech business lending. Using aggregate debt offering at the regional or county level, several papers suggest that FinTech took over traditional financial intermediaries' market share when it comes to business lending. Chen, Hanson, and Stein (2017) argue that after the 2007-2009 financial crisis, large banks reduced the lending to small businesses as they faced strong regulatory burdens and losses, leaving room for non-bank lenders. Balyuk, Berger, and Hackney (2020) suggests that FinTech's competitive advantage lies in more efficient processing of hard information, and it has the potential to substitute certain types of bank lending. Gopal and Schnabl (2020) find a substitution effect due to the reduction in the supply of credit to SMEs by banks. They find that the reduction in aggregate bank lending in the aftermath of 2007-2009 financial crisis was almost perfectly offset by an increase in lending by non-bank lenders, especially independent finance companies. This view is consistent with the results in Cortés, Demyanyk, Li, Loutskina, and Strahan (2020), who argue that regulatory burden and stress tests lead large bank to move away from risky small business lending. They also find that aggregate lending to SMEs does not decrease as there is a substitution effect from large banks to small banks, which suggests it leaves room for non-bank lenders. Our paper adds to this literature by providing firm-level evidence that nontraditional lenders such as FinTech platforms are substitutes to traditional financial intermediaries in that they cater to the same clientele but allow this client to obtain increased borrowing capacity. FinTech credit allows firms to increase unsecured leverage and change their debt structure. SMEs with access to P2B loans switch from long-term bank debt to short-term bank debt to maintain financial flexibility.

Since it is an important question as to whether FinTech credit expands the credit offering for SMEs recent papers, Havrylchyk and Ardekani (2020) and Beaumont, Tang, and Vansteenberghe (2021), also try to tackle this question using French FinTech platforms. The first covers 780 firms who obtained credit from French FinTech platforms between 2015 and 2017, the latter covers 10 french FinTech platforms which facilitated 2,013 loans for which from the smallest platform they have loan rejections. In comparison, our platform is extremely active in granting loans as it extended 1,291 loans from the outset of the platform in December 2016 through September 2019. We also obtain access to all the 1,906 rejected applications over the same period. The FinTech we study is the only P2B platform in Portugal servicing SMEs in the country as a whole an thus gives the full universe of accepted and rejected loans.

We find that firms obtaining FinTech funding grow faster as compared to the firms who also applied but where rejected. Our results are rigorously estimated holding fixed the demand for FinTech credit, accounting for the similarities across firms and lastly, robust to an instrumental variable (IV) estimation using the number of banks in each municipality before the inception of the P2B platform as instrument for the likelihood that local firms obtain a P2B loan. Beaumont, Tang, and Vansteenberghe (2021) findings corroborate ours in that they find a significant relation between the SMEs who obtained FinTech credit and growth and they show that these firms subsequently increase their bank credit using their new acquired assets to expand their borrowing capacity.

Beaumont, Tang, and Vansteenberghe (2021) find mixed evidence regarding the riskiness of these firms. There is a significant difference in default rates among high-credit risk firms but not among high quality firms. In our setting the SMEs who applied and obtained FinTech access to credit have significantly higher Altman Z-score and thus a significantly lower likelihood of bankruptcy. While platforms exclusively intermediate and don't have any ownership of the debt the reputational damage suffered when defaults would occur appears to be making the platform screen accordingly and avoid the risky borrowers, targeting the same safe SMEs as banks.

We also contribute by showing that an important determinant of SMEs choice to access FinTech platform is to diversify away from banks that are more vulnerable to liquidity shocks and, as a consequence, more likely to cut credit supply to SMEs. Our results support the premise of Thakor (2020) that P2P lenders will not replace banks anytime soon, but will rather take some market share away from capital constrained banks, and for borrowers who do not have collateral to access secured loans. In addition, consistent with FinTech lending reducing firm's bank dependence and exposure to bank distress, we find positive and significant effects on assets, investment, employment, and sales.

Our results have important policy implications for the architecture of the financial system, in particular the development of market-based platforms. FinTech platforms do not seem to serve young, untested firms with no prior access to the banking system. Thus, the benefits of FinTech may not contribute to increased financial inclusion of small businesses. FinTech, however, does allow high quality SMEs to finance their growth and, at the same time, diversify their lending relationships. Our results suggest that the SMEs that apply to FinTech platforms want to maintain their financial flexibility and reduce their exposure to shocks to the banking system, which may adversely affect their financing and their growth.

2. Data

2.1 FinTech P2B Platform

Our data come from an independent Portuguese P2B platform (*Raize*) that extends loans to non-financial firms in Portugal. The activity of this FinTech platform is concentrated in financing small firms and start ups. The platform claims to offer loans to young companies that are already in operation, with financial capacity and potential for growth. In the case of SMEs, the platform promises approval within 48 hours and financing within 5 days for loans with maturity between 1 and 60 months. The platform offers savings of up to 80% of banking commissions and no prepayment penalties. Investors in the platform receive a fixed rate.

The business model of the platform is based on fees that are charged both to investors and SMEs raising debt. SMEs pay an origination fee of 3% to 4% of the loan. In other words, if a company gets a €20,000 loan, Raize will actually transfer to the company €19,200 (net of its commission). While there is no application fee, firms pay an annual management fee: SMEs pay an annual management fee for each loan outstanding (approximately 0.25% over outstanding debt). If loans are in arrears companies also pay a fee for lateness in payments. Investors are charged a servicing fee of around 0.5% per year on their invested funds.

The platform counts more than 53,919 investors who made an average gross return of 6.38% over the sample period (2016-2019). The platform follows a pure matching model, investors directly select prospective loans based on a range of credit information, such as loan purpose, borrower industry, loan term, borrower income and other credit quality information. The platform also provides an assessment of the credit quality by means of a credit rating. The platform allows for repayment without penalties to borrowers, but does not provide any credit guarantees in the form of insurance, dedicated guarantee, or provision fund. It is important to note that over the sample period there have not been any defaults.

We have access to all the 1,291 loans extended from the outset of the platform in December 2016 through September 2019. We also obtain access to all the 1,906 rejected applications over the same period. Panel A of Table 1 reports summary statistics for variables related to the P2B platform. The median loan extended by the platform is €20,000 euro, with a 7% interest rate and maturity of 36 months. The smallest loan amount is €4,000, while the maximum amount is €315,000. The minimum interest rate is 3% and the highest rate is 10.29%. Although we do not observe the interest rate on the firms' other outstanding loans, we compute the firm-level interest rate using available financial statements information. Using this proxy of a firm's overall interest payments, we observe that the P2B loans are more expensive than the other loans obtained by the firms in our sample, with the difference in median equal to 4.65%.

2.2 Firm-Level Data

We collect firm-level financial information from the Central Balance Sheet (*Central de Balanços*) database, managed by the Bank of Portugal. It consists of a repository of yearly financial statements on the universe of non-financial firms operating in Portugal from 2013 to 2019. The data include information on balance sheet statement, income statement, and cash flow statement.

We focus on SMEs (i.e., firms with less than 250 employees) over our sample period and we apply the following additional filters to the sample. First, we limit our sample to firms that are organized as public or private limited liability companies, as these are the only legal forms of firms that access FinTech financing. Second, we compile the list of industry affiliations of firms that received FinTech financing. Then, if a firm in the Central Balance Sheet database does not operate in one of such industries, we drop the firm from our sample. Third, we exclude firms operating in regions where none of the firms in our FinTech sample is headquartered. Finally, we restrict the sample to firms that either obtain a new bank loan or apply to the P2B platform. The rationale of this choice is to increase the homogeneity of the set of firms that we study from the point of view of the demand for credit. After applying these filters, we are left with $229,037$ firms, corresponding to $425,303$ firm-year observations. After matching with the P2B platform's data, we identify 931 firms and $5,762$ firm-year observations pertaining to firms that obtain a P2B loan. We also identify $11,490$ firm-year observations pertaining to $1,905$ firms whose application for a P2B loan was rejected. Panel B of Table 1 reports summary statistics for firm-level variables in our sample.

2.3 Bank-Firm Data

In some of our tests, we use information from the Central Credit Registry (*Central de Responsabilidades de Crédito*) combined with the banks' balance sheet data from the Bank Supervisory Database managed by the Bank of Portugal. The Central Credit Registry provides confidential information on all credit exposures above €50 to non-financial companies by all banks operating in Portugal. The Central Credit Registry data include loan-level information, such as the identity of the lender, the borrower, and the loan amount. The Bank Supervisory Database reports, on a consolidated basis, a wide range of information on banks' financial statements. We aggregate these data at the firm level, thus the bank variables used in the tests are value-weighted averages across the banks with a lending relationship with firm i, where the weights are given by the outstanding amount of debt extended by bank j to firm i at time t. We report summary statistics of bank variables in Panel C of Table 1.

2.4 External Validity

Before moving to our empirical analysis, in this subsection we discuss the similarity between *Raize* and other European P2B platforms, as well as between the Portuguese banking sector and that of the Eurozone. The goal is to address concerns about the external validity of our results. In general, the Portuguese banking sector displays similar averages compared to the Eurozone in several key metrics. The most relevant difference is a more conservative loan to deposit ratio – 85% as compared to 102% in the Eurozone – which is mainly due to Troika intervention in the past decade. Assets to GDP (183% vs 177%), loans to GDP (116% vs 106%) are in line with the European average.[1] We use the whole universe of banks in Orbis over our sample period to compare the capital ratios of banks in Portugal to those of banks in other European countries. Table IA1 shows that financial institutions in Portugal are similar in all capital ratios to the main European economies and to UK. Overall, the Portuguese banking sector appears to be representative of that of European countries in general.

When it comes to FinTech platforms, in Europe there are more than 146 P2P lending platforms, about half of those are business focused (P2B). In Portugal, there are 3 platforms of which *Raize* is the only one offering standard P2B services.[2] Based on total funding volume Portugal's crowdfunding market ranks number 30 in Europe, and it ranks number 64 in the worldwide crowdfunding statistics.[3] *Raize* business and operational model is similar to the leading alternative lenders that focus on small business lending in Europe and the UK. *Raize* has an average loan size that is similar to other European countries when differences in GDP across countries are accounted for. Moreover, its credit risk adjusted performance of more than 5% per year is in line with the other European leading platforms.

[1] Source: EBF Facts and Figures 2020.

[2] Goparity focuses on funding socially responsible investments and Younited Credit is a P2P platform.

[3] The total funding volume is of €14.8 million in 2018, up from €8.3 million in 2017 (Cambridge Centre for Alternative Finance (CCAF)).

3. Which Firms Apply for FinTech Loans?

In this section, we start by examining the characteristics of firms that receive FinTech financing versus those that do not (solely rely on banks).

In our first set of results, we study the firms' choice to access the P2B platform. To this end, we explore the characteristics of firms that apply for P2B loans, as well as their banks, relative to other firms in our sample that do not apply to P2B loans. At the end of this section, we focus on the P2B platform choice, studying the characteristics of the accepted firms as compared to the rejected ones.

3.1 The Role of Firm Characteristics

In Table 2 we start with univariate statistics. Panel A compares accounting-level variables between the sample of firms applying for a P2B loan and the other firms in our sample that obtain new bank debt. The table shows that firms who decide to access the P2B platform are larger in number of employees. We use Altman Z-score Altman (1968) to evaluate the credit risk of the firms. Firms that submit a loan application to the P2B platform are significantly more creditworthy as they score higher. P2B firms are significantly more likely to have bank debt in their balance sheet, and use significantly more leverage, both short-term and long-term. At the same time these firms have lower levels of overdue debt, which corroborates the higher Z-score. These firms display also lower levels of unused debt, and more collateralized debt. In sum, these univariate results suggest that firms that decide to access the P2B platform are higher-quality firms: larger firms, with higher credit score, access to bank debt, less overdue debt, and more secure debt.

As a second step, we examine whether these results are robust to a multivariate setting in which we are able to control for firm covariates as well as firm and time effects. Specifically, we run the following firm-level regression:

$$P2B\ Application_{i,t} = \alpha_i + \alpha_t + \beta_1 Employees_{i,t-1} + \beta_2 Z-Score_{i,t-1} + Debt\ Variables_{i,t-1}\gamma + \epsilon_{i,t} \tag{1}$$

where $P2B\ Application_{i,t}$ is a dummy variable that takes a value of one for firms that submit a loan application to the P2B platform in year t, and zero otherwise. The Z-score is calculated as in Altman (1968). Debt variables include an indicator variable for outstanding bank debt, the leverage amount as a fraction of total assets, presence of overdue debt, unused debt and secured debt. We report results of a model with year fixed effects (Columns (1), (3), and (5)), or with year and firm fixed effects (Columns (2), (4), and (6)), which absorb time-invariant unobserved firm heterogeneity.

In the first specification in Table 3 the only significant variable predicting the application to the FinTech platform versus a bank is the presence of a bank relation. SMEs that have a bank loan are 0.42% more likely to apply for FinTech credit, which is 82% of the unconditional probability of obtaining a P2B loan in our sample (0.51%). When estimating it within firm, the estimates in Table 3 confirm the majority of the univariate results. Firms applying for P2B financing are larger and have a higher credit score. In Columns (3) and (4) we observe that firms applying for a P2B loan display larger level of bank debt also as a fraction of total assets (*Leverage*). In the last two columns, we find that P2B firms have less overdue debt, indicating that they are not riskier firms as the higher z-score also indicates. Moreover, they also have less unused debt, which coupled with greater leverage ratios suggest that these firms are characterized by less residual debt capacity.

In Table 4 we examine the characteristics of SMEs who succesfully obtained access to the FinTech platform as compared to firms who applied but were denied access. In other words, we aim to model the platform decision to extend a loan to a firm. To this end, we repeat the analysis of Section 3.1, limiting our sample to the firms for which we observe a loan application.[4]

[4]Firms that receive P2B financing enter the sample up to the year of the FinTech loans. In addition, for those firms who receive multiple P2B loans we only consider the first loan. These choices explain why the number of observations in Table 4 does not coincide with the total number of observations for P2B firms and rejected applicants as reported at the end of Section 2.2.

The results are very much in line with the previous ones, firms who obtained access had outstanding bank debt, are larger, have a higher credit score and are more levered. The SMEs who obtained FinTech credit had significantly less unused and secured debt.

Overall, our results suggest that P2B platforms and banks compete for the same segment of firms, as indicated by the presence of bank financing in the balance sheet of firms applying to the P2B platform. This evidence is in contrast with previous studies predicting that FinTech should be mostly used by firms that cannot access bank financing (see Thakor (2020)). At the same time, the literature on the importance of financial flexibility to firms (see e.g., Graham and Harvey (2001), DeAngelo and DeAngelo (2007), Jang (2017)) offers a potential reason why firms switch to FinTech credit. The firms that apply to the P2B platform may value the access to FinTech credit as it allows them to finance their activities without further depleting their debt capacity, and preserving their financial flexibility.

3.2 The Role of Bank Characteristics and Lending Relationships

In this subsection, we compare the characteristics of the banks that finance the firms that submit applications to P2B loans with those of the banks that serve the other firms in our sample (i.e. did not apply to FinTech). Schwert (2018) shows that endogenous matching occurs in the loan market: while bank-dependent firms borrow from well-capitalized banks, firms with access to public debt markets borrow from banks with less capital. In this sense, FinTech may constitute an alternative financing source for SMEs akin to public debt. If that is the case, we would expect SMEs that have lending relationships with less capitalized banks to be more likely to switch to FinTech lending.

As in the previous section, we start with simple univariate comparisons. In Panel B of Table 2, we explore univariate comparisons of bank characteristics using variables aggregated at the firm-level. The value-weighted averages are computed across all banks with a lending relationship with the firm, where the weights are given by the outstanding amount of debt. Firms with access to the FinTech platform tend to have lending relationships with banks with less deposits, lower liquidity, and lower capital ratios.

In Table 5, we again adopt specification in Equation (1) and include bank-related variables as explanatory variables. The dependent variable is $\textit{P2B Application}_{i,t}$, as defined in the previous subsection. We analyze a set of bank variables related to bank liquidity and bank capital as in Ivashina and Scharfstein (2010) and Irani, Iyer, Meisenzahl, and Peydro (2021), including: bank deposits, bank loans, the sum of bank cash and short-term investments (all variables scaled by bank total assets), as well as the bank Tier 1 ratio.[5]

The estimates in Table 5 show a pattern consistent with the univariate results. In line with the results of Schwert (2018), firms are more likely to access the FinTech platform to raise debt when they have lending relationships with banks with a smaller ratio of deposits to assets, less liquid banks, and banks with a lower Tier 1 capital ratio. Moreover, firms that have relationships with banks with a higher loan to asset ratio are more likely to resort to the P2B platforms to raise external capital. These findings indicate that the characteristics of banks and in particular their funding ability matter for the decision to access FinTech platform. Firms served by banks with less stable funding, and banks with a higher transformation ratio are more likely to rely on P2B funding.

This set of results suggests a second potential reason why firms decide to apply to FinTech credit. Ivashina and Scharfstein (2010) and Irani, Iyer, Meisenzahl, and Peydro (2021), among others, show that banks funded with less deposits, less liquid banks, and banks with lower capital ratios are the banks that are most affected by recessions and liquidity shocks. In this respect, SMEs might be using the FinTech platform to diversify their exposure to the banking sector, and reduce their dependence on banks that are more likely to cut lending in case of adverse shocks.

[5]The level of aggregation is the firm, thus the bank variables used in the analyses below reflect value-weighted averages across the banks with a lending relationship with firm i, where the weights are given by the outstanding amount of debt extended by bank j to firm i at time t.

4. How Do Firms Use FinTech Loans?

In this section we study how firms use the P2B funding. Specifically, we examine the effect of FinTech loans on firm outcomes and lending relationships.

We start by adopting a propensity-score matching approach. We construct the matched sample selecting for each firm that obtain a P2B loan the five closest matches based on the propensity score obtained from firm-level covariates, which includes all the variables used in Equation (1), among the firms that increase their external funding. Results are obtained using the following specification:

$$Y_{i,t} = \alpha_i + \alpha_{pt} + \alpha_{lt} + \alpha_{jt} + \beta_1 P2BFinancing + X_{i,t-1}\gamma + \epsilon_{i,t} \tag{2}$$

where $Y_{i,t}$ is an outcome which includes growth variables, leverage, lending relations, and cost of debt for firm i at time t. We include in all our regressions propensity score group-year fixed effects (α_{pt}) to ensure that our coefficients are estimated out of variation occurring within each match sample. We also include firm fixed effects (α_i), which intend to absorb time-invariant differences between firms that obtain P2B funding and firms that do not. Moreover, we include industry by time (α_{jt}) to control for systematic differences across industries and location by time (α_{lt}) to control for changes in local economic conditions. $X_{i,t-1}$ is a matrix of firm-level covariates, which includes all the variables used in Equation (1).

4.0.1 Firm Growth and Investments

We start by analyzing the impact of obtaining P2B financing on firm growth in Table 6. Panel A of the table shows that firms obtaining FinTech funding grow faster as compared to the firms in the rejected sample. We observe that firms obtaining P2B funding grow significantly faster also in terms of number of employees, sales, and investments (CAPEX) than firms in the comparison group. We do not observe significant differences in fixed assets, net working capital, and profitability. This indicates that firms accessing the P2B platform are able to grow without sacrificing their profitability. In terms of economic magnitude, firms who obtain FinTech loans increase total assets by 59.2% (Column (1)), employment growth by 28.4 percentage points (Column (4)), sales by 55.3 percentage points (Column (5)), and CAPEX by 1.9 percentage points (Column 6) relative to the matched firms.

Figure IA1 shows the results in graphical form. Visual inspection of the different panels of the figure shows that the differential impact of Fintech lending occurs in the 3-years after obtaining the FinTech credit, whereas in the 3 years prior there is no discernible statistical difference between the P2B firms and the matched sample.

4.0.2 Firm Leverage

In Table 7 Panel A, we study the impact of P2B financing on leverage, both long-term and short-term leverage, and collateralized debt using our baseline specification. In all measures of leverage we include the amount of P2B loans firms obtain from the platform. We find that the availability of a P2B loan leads to a significant increase in leverage. Firms that access the FinTech platform display an increase in leverage that is 13.1% larger than the matched rejected applicants. The coefficient reflecting the impact of P2B loans on long-term leverage is also positive and significant, reflecting a growth rate that is 3 percentage points greater that that of rejected applicants (Column (2)). This result is probably not surprising since more than 90% of the P2B loans extended by the platform have a maturity greater than one year, and thus are classified as long-term debt. More interesting is the impact on short-term leverage, as we find a significant increase of about 5.8% (Column (3)). In the last column of the table, we don't observe a significant reduction in secured debt as compared to similar firms.

In Figure IA2 in the Appendix we corroborate that these effects are only visible in the 3 years after obtaining the FinTech credit, whereas the 3 years prior there is no statistical difference observable.

In Panel B we perform the same analysis in Table 7 but excluding from firms' outstanding debt the amount of P2B loans they obtain from the Raize platform. The results indicate that, even excluding P2B financing, firms that obtain access to the Raize platform increase their total debt. Interestingly, netting out the P2B loans, firms accessing the FinTech platform decrease the amount of long-term financing in their balance sheet compared to the other firms in our sample. In other words, any long-term debt increase observed in Table 7 appears to be solely due to the debt raised through the P2B platform. Thus, SMEs use the P2B debt to reduce their long-term exposures to traditional financial intermediaries. As indicated by Column (3), firms with access to the FinTech platform increase the short-term debt with banks (i.e., even after subtracting any short-term loan obtained from the P2B platform). These results, therefore, suggest that firms consider FinTech funding as a substitute for long-term bank financing. After they obtain a loan from the P2B platform, they reduce the long term exposure to the banking system, and instead supplement the FinTech loan with additional short-term bank debt.

4.0.3 Lending Relationships and Cost of Debt

We further explore the relationships between firms accessing the FinTech platform and the banking sector in Table 8.

The table shows that after obtaining P2B financing, SMEs increase the number of lending relationships (excluding P2B lending). Since the variable excludes the new P2B relationship, the increase is not simply caused by the new connection to the FinTech platform, but it appears to be driven by additional links to the banking system. Firms that obtain a P2B loan also significantly reduce the concentration of their debt in the hands of few lenders. In Columns (2) and (3) we analyze the share of a firm's debt accounted fop by its top lender and the HHI of firm exposures to the banking sector, computed using the banks' shares of a firm debt. We find that both the concentration within the top relation as the overal HHI decreases significantly for firms accessing the P2B platform, as compared to similar firms in the sample raising external capital. Thus, P2B lending seems to allow firms to diversify their exposure to the banking system and reduce debt concentration. Looking at Figure IA3 in the Appendix, these changes in lending relations are striking, there is a clear departure from the trend right about the time the SMEs gain access to the FinTech platform. In the following 3 years these SMEs significantly increase their lending relation and reduce their dependence on banks.

In Table 9 we study firms' funding costs. Columns (1) and (2) use as dependent variable the total funding costs including the costs of P2B loans, whereas Columns (3) and (4) are net of the FinTech interest rate (i.e., the cost of bank loans only). We find that funding costs increase for firms obtaining a Raize loan. We do not find a significant impact of P2B loans on the costs of bank financing after netting out the direct impact of the P2B loans. We conclude that the cost of P2B loans is equal or slightly more expensive than bank loan on average. At the same time, firms are able to increase their bank leverage without increasing their cost of debt.

4.1 IV Approach

It is empirically challenging to determine the consequences of P2B financing. Specifically, the main concern is that firms obtaining financing from the P2B platform are different from the other firms in our sample in some unobserved dimension correlated with the outcomes that we study. To the extent that this dimension is not captured by the firm-level controls, nor by the high-dimensional fixed effects we include in our regressions, we would observe the same different firm outcomes even absent the P2B financing.

To assuage such concerns, we adopt an instrumental variable (IV) approach. The rationale for our IV comes from the results of Section 3.1. There we document that an important determinant of firm access to the P2B platform is the presence of bank debt in a firm balance sheet. A variable reflecting the presence of bank debt, however, cannot be a valid instrument since, similarly to obtaining a P2B loan, such variable is likely correlated with many firm-level outcomes. Instead, we exploit the granularity of our data to instrument the acquirement of a P2B loan with the number of banks with a branch in the municipality where a firm is headquartered.

Moreover, we implement the IV approach in a different setting compared to the previous section. We report the estimates of the following specification:

$$\Delta Y_i = \alpha_t + \beta_1 \mathit{P2B\ Lending}_i + X_i\gamma + \epsilon_i \tag{3}$$

as common in the literature (see e.g., Beck, Da-Rocha-Lopes, and Silva (2020), Khwaja and Mian (2008)) the data for each firm is collapsed (time-averaged) into a single pre- and post-P2B application period of 3 years to ensure our standard errors are robust to auto-correlation (Bertrand, Duflo, and Mullainathan (2004)). Then, our dependent variables (ΔY_i) are computed as growth rates between the pre- and post-application periods. $\mathit{P2B\ Lending}_{i,t}$ is a dummy variable that takes value of one for firms that apply and receive a FinTech loan, while it takes value of zero for firms that apply but get rejected. α_t is a set of application year fixed effects. X_i is a matrix of firm-level covariates measured at the beginning of the pre-application period of each firm. This set includes all the variables used in Equation (1).

There are several reasons to believe the number of banks with a branch in the municipality is a valid instrument. With respect to the relevance condition, there is a large literature showing the importance of local banking markets for firm access to bank debt (see e.g., Degryse and Ongena (2005), Guiso, Sapienza, and Zingales (2006), Benfratello, Schiantarelli, and Sembenelli (2008)). In the next section, by showing the first stage of our instrumental variable approach, we provide direct empirical evidence in support of the conjecture that the likelihood of firms having a bank loan increases with the number of local banks.

With regards to the exclusion restriction, an important aspect of our institutional setting is the fact that the P2B platform was introduced countrywide, and thus was available to the whole country since the moment of its inception. This effectively rules out concerns that the availability of the platform is correlated with the presence of local banks. A different concern relates to the possibility that the number of local banks may have an impact on firm outcomes independently of our treatment variable. In this regard, we rely on the plausible assumption that the number of banks in a municipality does not have a direct effect on the firm outcomes that we explore, *after* controlling for firm characteristics. While it is true that the development of a local banking market might be correlated with the quality of local firms, we directly control for firm quality through the inclusion of the matrix of controls X_i, as in Equation 3. Moreover, our choice to study changes in firm outcomes around the time of a firm P2B application further helps in strengthening the validity of the exclusion restriction. It is hard to come up with a reason why the number of local banks should have a direct impact on the change in firm outcomes precisely around the specific date of firm application to the P2B platform. Any direct effect of the number of banks in a municipality should be the same before and after a firm application for a P2B loan. As additional evidence to strengthen the confidence in our empirical setting, in Section 4.1.2 we perform a falsification test in the same spirit as the one suggested by Roberts and Whited (2013) in the context of a difference-in-differences estimator.

4.1.1 Firm Growth and Investments

In Table 10 we report the results of our IV approach for firm growth and investment. At the bottom of the panel, we report the first stage, which provides strong support for the relevance condition. The coefficient can be interpreted as the increase in the probability of obtaining a P2B loan due to one more bank operating in a firm municipality. Besides being strongly statistically significant, this coefficient is also economically meaningful. A one-standard deviation increase in the number of banks operating in a municipality (about 17) leads to an increase in the likelihood of obtaining a P2B loan (close to 3%) that is 7% of the unconditional probability. The results of the second stage confirm the main conclusions of the baseline regressions. Firms obtaining FinTech funding grow faster as compared to the firms in the rejected sample. The only coefficient that loses statistical significance in the IV setting is Column (6), the CAPEX regression.

Table 11 replicates the leverage analysis in our IV setting. Coefficients shows that the positive impact on leverage and short-term leverage growth of P2B loans are robust. In the IV estimation, we observe a significant negative impact on secured debt growth. The coefficient of Column (2), relative to long-term debt, although large in magnitude, is not statistically significant. Panel B performs the same analysis but excluding from firm debt the amount of P2B loans a firm obtains from the platform. Column (1) shows that even when we exclude P2B financing, firms that obtain access to the platform increase their leverage more compared to the sample of rejected applicants. At the same time, Column (2) shows that net of the P2B loan, obtaining a P2B loan does not have any significant impact on firms' long-term bank financing. Finally, firms with access to the FinTech platform increase the short-term bank leverage by 8 times more than the rejected applicants.

These results, therefore, corroborate that firms consider FinTech funding as a substitute for long-term secured bank financing. After they obtain a loan from the P2B platform, they reduce their collateralized exposure to the banking system, and instead supplement the FinTech loan with additional short-term bank debt.

Results in this section are also closely related to the evidence in Section 3.1. We document that firms that apply to the P2B platform are closer to their maximum debt capacity compared to the other firms in our sample. Therefore their decision to switch to FinTech credit might be driven by their desire to obtain additional funding but, at the same time, preserve their financial flexibility. This decision makes even more sense if firms are specifically interested in obtaining additional long-term financing. For example, firms might prefer to finance their growth with long-term debt to avoid the risk that changes in market conditions or capital market frictions could result in refinancing at a significantly higher interest rate (e.g., Harford, Klasa, and Maxwell (2014)). However, due to tighter regulation and higher capital requirements banks are less likely to grant unsecured loans to SMEs (Acharya, Berger, and Roman (2018), Cortés, Demyanyk, Li, Loutskina, and Strahan (2020), Chernenko, Erel, and Prilmeier (2019)). There are two reasons why secured debt might be less attractive to SMEs. First, SMEs might not have large availability of collateral. As a matter of fact, Table 3 documents that this is precisely the case for firms that apply to the FinTech platform. Second, even firms with available collateral might be wary of pledging their assets. Keeping unpledged collateral is a common way of retaining financial and operational flexibility. Unpledged collateral is often used as financial slack (see e.g., Myers and Majluf (1984)) or insurance (Rampini and Viswanathan (2013)). Similarly, firms may want to avoid the connected limits to their flexibility to sell or redeploy assets (Mello and Ruckes (2017)). To sum up, P2B platforms offer firm an alternative to obtain long-term unsecured debt and, at the same time, retain financial flexibility. In addition, as documented in Table **??**, firms may use FinTech funds to release pledged assets by paying off bank debt.

In addition, firms that access P2B manage their exposure to the banking sector by repaying secured bank debt and increasing their short-term bank debt. In Table 12, we further present robustness for the evidence on the relationships between firms accessing the P2B platform and the banking sector. In the context of our IV estimation, show that all the results of our baseline specification are robust. Firms with a P2B loan manage to increase their lending relationships and reduce debt concentration.

Finally, we repeat the analysis of cost of debt in Table 13 and confirm that firms accessing the FinTech platform appear to be able to increase their leverage (excluding P2B loans) without increasing their cost of debt.

4.1.2 Robustness

As discussed in Section 4.1, identification in the context of our IV estimation relies on the fact that any change in a firm's outcomes around the time of a firm's application to the P2B platform should be due to the impact of obtaining a P2B loan. It is unlikely to be due to a direct effect of the number of local banks, as that variable is fixed before the inception of the P2B platform and thus, it is unclear why it should drive changes in each firm's outcomes precisely around the time of each firm's P2B application.

Nonetheless, we start this section by providing additional support for our exclusion restriction. Specifically, we perform a falsification test in the same spirit as the one suggested by Roberts and Whited (2013) in the context of a difference-in-differences estimator. We repeat our IV estimation falsely assuming that firms' P2B applications occur 3 years before the actual date. If our results were actually driven by the local banking market development, and its impact on firm outcomes, we would expect to find similar results as the ones documented in the previous sections. This would mean that the number of local banks put firms on a particular growth path, which, in that case, would be what is ultimately driving our results. We report the results of the falsification test in Table IA2. For brevity, we only report coefficients relative to those regressions that in Tables 6 through 9 display significant results. Table IA2 is reassuring, as none of the coefficients is statistically significant. There appears to be no change in firm outcomes due to firms' P2B application in the 3 years before the actual application, which is not consistent with the number of local banks having a direct impact on our dependent variables.

Next, we try to direct effect of Fintech loans on firm growth from the indirect consequences that may materialize due to the positive impact of P2B loans on firms' bank debt. Indeed, a robust results of both our empirical approaches is that firms who obtain a P2B loan increase their bank leverage. To isolate the effect of FinTech credit on firm growth, in the Appendix Table IA3 we repeat our propensity score matching approach restricting our sample to firms that do not receive additional bank credit after the P2B loan. We find that our results remain robust, and the magnitudes remain large and statistically significant. Similarly, in Appendix Table IA4 we repeat our IV estimation restricting the sample to firms that do not increase their bank credit after the P2B loan. Again we find that our results on firm growth and investments remain robust.

5. Conclusion

We study the impact of FinTech lending on firm growth, investment, and financing using a proprietary data set from a leading independent P2B platform including both accepted and rejected loan applications. We combine this data set with with detailed administrative data on the universe of firms, banks, and loans. We uncover four novel empirical findings about the effects of FinTech credit on small businesses.

First, we find that P2B platforms serve high quality and creditworthy SMEs who already have access to bank credit. When we compare the characteristics of firms that access P2B lending to firms who borrow from traditional financial intermediaries, we find that firms that borrow through P2B platforms are larger, have lower credit risk, and have prior lending relationships with the banking sector.

Second, the liquidity and solvency ratios of relationship banks are key in the firm's decision to raise debt through a P2B platform. Firms served by banks with less liquid assets, less stable funding, and lower capital are more likely to access P2B funding.

Third, FinTech lending has a strong positive effect on firm growth .Firms that access FinTech lending experience a 150 percentage points increase in asset growth, a 52 percentage points increase in employment growth, and a 89.4 percentage point increase in sales growth in the three years following relative to the control group of rejected applicants. However, FinTech lending does not seem to deteriorate firm profitability even though the cost of FinTech debt is higher than the cost of bank debt.

Finally, we find a significant impact of FinTech lending on firms' financial policy. We find that firms use the availability of FinTech debt to increase both short-term and long-term leverage. SMEs substitute long-term bank debt with FinTech debt and reduce the proportion of secured debt following a P2B loan. FinTech provides firms with an alternative to access unsecured long-term financing and release pledged assets to retain financial and operational flexibility. In addition, the availability of P2B funds allows firms to increase the number of bank relationships and reduce their dependence on their main bank. All our results are robust to using an instrumental variable approach with as instrument the number of banks with a branch in the municipality where a firm is headquartered.

Overall, our findings suggest that FinTech platforms compete with traditional financial intermediaries in financing SMEs. The availability of P2B loans allows SMEs to grow and at the same time diversify away from the banking sector, as well as reduce their exposure to banking shocks.

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Table A1: Variable definitions

Variable	Definition
Firm-Level Independent Variables	
Employees (log)	Logarithm of the number of paid and unpaid employees of the company. Source: Central Balance Sheet Database.
Z-Score	Altman Z-score as in Altman (1968)
Bank Debt	Indicator variable which equals one (zero otherwise) if there is bank debt outstanding. Source: Central Credit Responsibility.
Leverage	The ratio of short-term debt plus long-term debt over total assets. Source: Central Balance Sheet Database.
Overdue Debt	The ratio of all debt exposures recorded as non-performing over total assets. Source: Central Credit Responsibility.
Unused Debt	The ratio of untapped credit over total assets. Source: Central Credit Responsibility.
Secure Debt	The ratio of collateralized over total assets. Source: Central Credit Responsibility.
Firm-Level Dependent Variables	
Assets	Logarithm of the firm total assets in year t minus the logarithm of total assets in *t-1*. Source: Central Balance Sheet Database.
Fixed Assets	Logarithm of the firm fixed assets in year t minus the logarithm of fixed assets in *t-1*. Source: Central Balance Sheet Database.
NWC	Logarithm of the firm net working capital in year t minus the net working capital in *t-1*. We define NWC as inventories plus trade receivables minus account payables. Source: Central Balance Sheet Database.
Employees	Logarithm of the number of paid and unpaid employees of the company in year t minus the logarithm of employees in *t-1*. Source: Central Balance Sheet Database.
Sales	Logarithm of the firm sales in year t minus the logarithm of sales in *t-1*. Source: Central Balance Sheet Database.
CAPEX	Ratio of CAPEX over total assets. We define CAPEX as the difference in tangible assets between two consecutive years plus amortization and depreciation. Source: Central Balance Sheet Database.
ROA	Return on assets, defined as EBITDA over total assets. Source: Central Balance Sheet Database.
Other Firm-Level Dependent Variables	
Leverage	The ratio of short-term debt plus long-term debt over total assets. Source: Central Balance Sheet Database.
Long-Term Leverage	The ratio of non-current debt (maturity $>$ 1 year) over total assets. Source: Central Balance Sheet Database.
Short-Term Leverage	The ratio of current debt (maturity $\leq$ 1 year) over total assets. Source: Central Balance Sheet Database.
Long-Term Leverage	The ratio of non-current debt (maturity $>$ 1 year) minus non-current P2B debt over total assets. Source: Central Balance Sheet Database.
Short-Term Leverage	The ratio of current debt (maturity $\leq$ 1 year) minus current P2B debt over total assets. Source: Central Balance Sheet Database.
Leverage	The ratio of current and non-current debt minus P2B debt over total assets. Source: Central Balance Sheet Database.

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Variable	Definition
Cost of Debt	The ratio of interest expenses over total debt (sum of current and non-current debt). Source: Central Balance Sheet Database.
Cost of Debt Net P2B	The ratio of interest expenses minus the cost of P2B funding over total debt (sum of current and non-current debt minus the P2B loan). Source: Central Balance Sheet Database.
Lending Relationships Variables	
Bank Deposit	Firm-level average of the ratio of bank deposits over bank total assets. The average is computed across all banks doing business with the firm at time $t-1$, and we use as weight the size of the loan extended by each bank to the firm. Source: Central Credit Responsibility.
Bank Loan	Firm-level average of the ratio of bank loans over bank total assets. The average is computed across all banks doing business with the firm at time $t-1$, and we use as weight the size of the loan extended by each bank to the firm. Source: Central Credit Responsibility.
Bank Liquidity	Firm-level average of the ratio of bank cash and short-term assets over bank total assets. The average is computed across all banks doing business with the firm at time $t-1$, and we use as weight the size of the loan extended by each bank to the firm. Source: Central Credit Responsibility.
Tier 1 Capital	Firm-level average of the banks' Tier 1 Capital ratio. The average is computed across all banks doing business with the firm at time $t-1$, and we use as weight the size of the loan extended by each bank to the firm. Source: Central Credit Responsibility.
Number of Relationships	The number of active financing relationships of a firm, excluding the financing relationship with the P2B platform. Source: Central Credit Responsibility.
Top Relationship	The largest financing relationship (in percentage term) of a firm, without considering the P2B platform. Source: Central Credit Responsibility.

Table 1: Summary Statistics

This table reports summary statistics. The sample period is 2013-2019. We exclude financial firms and utilities, as well as firms with more than 250 employees. Moreover, we restrict our sample to firms that either apply to the P2B platform or raise debt through traditional financial intermediaries (i.e., banks). Panel A reports statistics for the sample of firms who receive P2B funding. Panel B reports statistics about firm-level variables. Panel C shows statistics for bank-related variables aggregated at the firm-level, using the value of loans outstanding as weights. Detailed definitions for the variables in this table is provided in the Appendix A1.

Panel A: P2B Platform Variables

	Observations	Mean	SD	P25	P50	P75
P2B Loan Amount	931	22460.66	19696.86	15000.00	20000.00	25000.00
P2B Debt / Assets	931	0.17	0.20	0.05	0.10	0.21
P2B Debt / Liabilities	931	0.29	0.31	0.06	0.18	0.43
P2B Loan Maturity	931	34.29	10.28	24.00	36.00	36.00
P2B Cost of Debt	931	7.08	1.54	6.09	7.08	8.34
Cost of Debt	931	6.90	6.82	3.22	4.90	8.19

Panel B: Firm Variables

	Observations	Mean	SD	P25	P50	P75
Employees	425,303	5.10	7.10	1.00	3.00	6.00
Z-Score	425,303	-0.41	11.84	0.27	1.63	2.79
Leverage	425,303	0.28	0.45	0.00	0.09	0.38
Long-Term Leverage	425,303	0.19	0.27	0.00	0.08	0.29
Short-Term Leverage	425,303	0.09	0.18	0.00	0.00	0.09
Unused Debt	425,303	0.19	0.29	0.00	0.01	0.30
Overdue Debt	425,303	0.03	0.14	0.00	0.00	0.00
Secured Debt	425,303	0.04	0.10	0.00	0.00	0.01

Panel C: Lending Relationships Variables

	Observations	Mean	SD	P25	P50	P75
Bank Deposit	425,303	0.58	0.17	0.50	0.61	0.70
Bank Loan	425,303	0.63	0.09	0.59	0.63	0.67
Bank Liquidity	425,303	0.20	0.08	0.16	0.20	0.25
Tier 1 Capital	425,303	12.16	5.49	10.57	11.98	13.33
Number of Relationship	425,303	1.62	1.85	0.00	1.00	2.00
HHI Relationships	425,303	0.79	0.27	0.54	1.00	1.00
Top Relationships	425,303	0.84	0.22	0.67	1.00	1.00
Relationship Duration	425,303	3.41	2.11	2.00	3.00	5.00

Table 2: Univariate Comparisons

This table reports univariate comparisons between firms that apply for P2B financing and other firms in our sample that raise debt through traditional financial intermediaries. Panel A reports statistics for firm-level accounting variables. Panel B shows statistics for bank-related variables aggregated at the firm-level, using the value of loans outstanding as weights. For the sample of P2B firms we measure all variables before firms obtain their first P2B loan. The sample period is 2013-2019. We exclude financial firms and utilities, as well as firms with more than 250 employees. Moreover, we restrict our sample to firms that either apply to the P2B platform or raise debt through traditional financial intermediaries (i.e., banks). *t*-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

Panel A: Firm Variables

	P2B Firms	Other Firms	Difference	
Employees (log)	1.479	1.407	0.073***	(0.000)
Z-Score	0.832	-6.232	7.062***	(0.000)
Leverage	0.214	0.129	0.085***	(0.000)
Long-Term Debt	0.197	0.143	0.054***	(0.000)
Short-Term Debt	0.112	0.085	0.026***	(0.000)
Unused Debt	0.144	0.190	-0.045***	(0.000)
Overdue Debt	0.017	0.047	-0.030***	(0.000)
Secured Debt	0.124	0.086	0.038***	(0.000)

Panel B: Bank Variables

	P2B Firms	Other Firms	Difference	
Bank Deposit	0.547	0.577	-0.029***	(0.000)
Bank Loan	0.636	0.633	0.003*	(0.013)
Bank Liquidity	0.197	0.203	-0.006***	(0.000)
Tier 1 Capital	11.732	12.158	-0.426***	(0.000)
Bank Equity	0.082	0.083	-0.001	(0.064)
Number of Relationships	2.297	1.586	0.711***	(0.000)
HHI Relationships	0.637	0.798	-0.161***	(0.000)
Top Relationships	0.714	0.845	-0.130***	(0.000)

Table 3: What Type of Firms Apply for FinTech Funding? Firm Characteristics

This table studies the characteristics of firms that apply for a loan to the P2B platform as compared to the characteristics of other firms in our sample that raise debt through traditional financial intermediaries. The dependent variable is an indicator variable for firms that apply for P2B funding. The sample period is 2013-2019. We exclude financial firms and utilities, as well as firms with more than 250 employees. Moreover, we restrict our sample to firms that either apply to the P2B platform or raise debt through traditional financial intermediaries (i.e., banks). t-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

	(1)	(2)	(3)	(4)	(5)	(6)
Employees (log)	-0.013	0.512***	0.026**	0.512***	0.017	0.498***
	(-1.09)	(8.27)	(2.29)	(8.29)	(1.43)	(7.95)
Z-Score	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(15.90)	(18.25)	(13.40)	(6.76)	(16.27)	(5.73)
Bank Debt	0.416***	0.353***				
	(16.00)	(7.39)				
Leverage			0.917***	1.137***	0.911***	1.125***
			(16.79)	(9.59)	(15.87)	(9.44)
Overdue Debt					-0.535***	-0.411***
					(-17.16)	(-4.80)
Unused Debt					-0.341***	-0.150***
					(-13.25)	(-2.58)
Secured Debt					0.036	-0.023
					(0.75)	(-0.20)
Year FE	X	X	X	X	X	X
Firm FE		X		X		X
Observations	425,303	425,303	425,303	425,303	425,303	425,303
Adjusted R^2	0.010	0.372	0.010	0.372	0.010	0.372

Table 4: What Type of Firms Obtain FinTech Funding? Applications Sample

This table studies the characteristics of firms that obtain a loan from the P2B platform as compared to the characteristics of other firms that apply to the platform but get rejected. The dependent variable is an indicator variable for firms that obtain P2B funding. In this table, we limit the sample to firms that apply for P2B funding, thus comparing rejected and accepted applicants. *t*-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

	(1)	(2)	(3)	(4)	(5)	(6)
Employees (log)	0.202	2.647**	0.396	2.627**	0.515	2.637**
	(0.57)	(2.36)	(1.16)	(2.35)	(1.49)	(2.35)
Z-Score	0.011	0.059***	0.012*	0.075***	0.018**	0.075***
	(1.54)	(3.44)	(1.75)	(4.06)	(2.56)	(4.07)
Bank Debt	3.161***	2.910***				
	(4.74)	(2.91)				
Leverage			5.809***	6.666***	6.111***	6.901***
			(4.83)	(3.37)	(4.94)	(3.49)
Overdue Debt					-4.216	-4.142
					(-1.60)	(-1.16)
Unused Debt					-2.705*	-2.110
					(-1.87)	(-0.94)
Secured Debt					-2.658**	-5.490**
					(-2.24)	(-2.47)
Year FE	X	X	X	X	X	X
Firm FE		X		X		X
Observations	9,364	9,364	9,364	9,364	9,364	9,364
Adjusted R^2	0.528	0.652	0.528	0.652	0.528	0.653

Table 5: What Type of Firms Obtain FinTech Funding? Lending Relationships

This table studies the characteristics of the banks that provide funding to firms with P2B loans as compared to the banks serving other firms in our sample that raise debt through traditional financial intermediaries. The dependent variable is an indicator variable for firms that apply for P2B funding. The sample period is 2013-2019. We exclude financial firms and utilities, as well as firms with more than 250 employees. Moreover, we restrict our sample to firms that either apply to the P2B platform or raise debt through traditional financial intermediaries (i.e., banks). t-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank Deposit	-0.605***	-0.872***						
	(-8.72)	(-4.40)						
Bank Loan			0.745***	1.250***				
			(6.65)	(4.31)				
Bank Liquidity					-0.563***	-0.389		
					(-4.40)	(-1.12)		
Tier 1 Capital							-0.003*	-0.018***
							(-1.73)	(-3.16)
Controls	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Firm FE		X		X		X		X
Observations	425,303	425,303	425,303	425,303	425,303	425,303	425,303	425,303
Adjusted R^2	0.011	0.374	0.011	0.374	0.011	0.374	0.011	0.374

Table 6: Firm Growth - Propensity Score Matching

This table investigates how firms use the funds obtained through the P2B platform. The dependent variables are the log of firm assets; the log of firm fixed assets; the log of net working capital (NWC); the log of firm employees; the log of firm sales; CAPEX over total assets; and ROA. We regress these variables on *P2B Lending*, an indicator variable that takes value one for firms that receive P2B funding in the years after the deal. In this table we report the results of a propensity score matching estimation. PS Group-Year FE are propensity score group-by-year fixed effects, which make sure that coefficients are estimated out of variation within each set of matches. We select for each firm that access the FinTech platform the five closest matches among the set of rejected applicants, and we construct the propensity score using all variables included in the analysis of firm level determinants (Table 3). The sample period is 2013-2019. We exclude financial firms and utilities, as well as firms with more than 250 employees. t-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

	Assets (1)	Fixed Assets (2)	NWC (3)	Employees (4)	Sales (5)	CAPEX (6)	ROA (7)
P2B Financing	0.592***	0.006	0.026	0.284***	0.553***	0.019***	0.028
	(16.69)	(0.75)	(1.36)	(12.15)	(15.35)	(4.10)	(1.29)
Controls	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X
PS Group-Year FE	X	X	X	X	X	X	X
Industry-Year FE	X	X	X	X	X	X	X
Location-Year FE	X	X	X	X	X	X	X
Observations	141,073	141,073	141,073	141,073	141,073	141,073	141,073
Adjusted R^2	0.94	0.83	0.81	0.93	0.92	0.53	0.63

Table 7: Leverage - Propensity Score Matching

This table investigates how firms use the funds obtained through the P2B platform. The dependent variables are variables describing the liability side of firms' balance sheet. In Panel A, the variables are: the ratio of total debt to total assets (Leverage); the ratio of long-term debt to assets (Long-Term Leverage); the ratio of short-term debt to assets (Short-Term Leverage). In Panel B we analyze the firm debt excluding the loan obtained from the FinTech platform, thus we subtract the amount of P2B funding before computing the dependent variables. We regress these variables on *P2B Lending*, an indicator variable that takes value 1 for firms that receive P2B funding in the years after the deal. In this table we report the results of a propensity score matching estimation. PS Group-Year FE are propensity score group-by-year fixed effects, which make sure that coefficients are estimated out of variation within each set of matches. We select for each firm that access the FinTech platform the five closest matches among the set of rejected applicants, and we construct the propensity score using all variables included in the analysis of firm level determinants (Table 3). The sample period is 2013-2019. We exclude financial firms and utilities, as well as firms with more than 250 employees. t-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

Panel A: Total Leverage	Leverage (1)	Long-Term Leverage (2)	Short-Term Leverage (3)	Secured Debt (4)
P2B Financing	0.131*** (12.48)	0.030*** (3.14)	0.058*** (8.29)	0.001 (0.15)
Controls	X	X	X	X
Firm FE	X	X	X	X
PS Group-Year FE	X	X	X	X
Industry-Year FE	X	X	X	X
Location-Year FE	X	X	X	X
Observations	141,073	141,073	141,073	141,073
Adjusted R^2	0.71	0.76	0.68	0.82

Panel B: Leverage net of FinTech credit	Total Debt (1)	Long-Term Debt (2)	Short-Term Debt (3)
P2B Financing	0.066*** (6.76)	-0.047*** (-5.01)	0.057*** (8.13)
Controls	X	X	X
Firm FE	X	X	X
PS Group-Year FE	X	X	X
Industry-Year FE	X	X	X
Location-Year FE	X	X	X
Observations	141,073	141,073	141,073
Adjusted R^2	0.71	0.76	0.68

Table 8: Lending Relationships - Propensity Score Matching

This table investigates how firms use the funds obtained through the P2B platform. The dependent variables are variables describing the characteristics of the firms' lending relationships. These include: number of relationships, the share of a firm's debt accounted for by its top lender, the HHI across all debt financing. We regress these variables on *P2B Lending*, an indicator variable that takes value 1 for firms that receive P2B funding in the years after the deal. In this table we report the results of a propensity score matching estimation. PS Group-Year FE are propensity score group-by-year fixed effects, which make sure that coefficients are estimated out of variation within each set of matches. We select for each firm that access the FinTech platform the five closest matches among the set of rejected applicants, and we construct the propensity score using all variables included in the analysis of firm level determinants (Table 3). The sample period is 2013-2019. We exclude financial firms and utilities, as well as firms with more than 250 employees. t-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

	Number of Relationships (1)	Top Relationship (2)	HHI Relationship (3)
P2B Financing	0.012***	-0.001***	-0.001***
	(17.23)	(-8.52)	(-8.91)
Controls	X	X	X
Firm FE	X	X	X
PS Group-Year FE	X	X	X
Industry-Year FE	X	X	X
Location-Year FE	X	X	X
Observations	141,073	141,073	141,073
Adjusted R^2	0.89	0.84	0.85

Table 9: Cost of Debt - Propensity Score Matching

This table investigates how firms use the funds obtained through the P2B platform. The dependent variables are variables describing the firms' funding costs. These include: the ratio of interest expenses over total assets, and the ratio of interest expenses minus the cost of P2B funds over total assets. We regress these variables on *P2B Lending*, an indicator variable that takes value 1 for firms that receive P2B funding in the years after the deal. In this table we report the results of a propensity score matching estimation. PS Group-Year FE are propensity score group-by-year fixed effects, which make sure that coefficients are estimated out of variation within each set of matches. We select for each firm that access the FinTech platform the five closest matches among the set of rejected applicants, and we construct the propensity score using all variables included in the analysis of firm level determinants (Table 3). The sample period is 2013-2019. We exclude financial firms and utilities, as well as firms with more than 250 employees. t-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

	Funding Costs		Funding Costs NR	
	(1)	(2)	(3)	(4)
P2B Financing	0.015***	0.011***	0.005*	0.001
	(12.93)	(9.98)	(1.56)	(0.64)
Long-Term Debt %		0.026***		0.026***
		(89.89)		(89.68)
Controls	X	X	X	X
Firm FE	X	X	X	X
PS Group-Year FE	X	X	X	X
Industry-Year FE	X	X	X	X
Location-Year FE	X	X	X	X
Observations	141,073	141,073	141,073	141,073
Adjusted R^2	0.66	0.71	0.66	0.71

Table 10: Firm Growth - IV Estimation

This table investigates how firms use the funds obtained through the P2B platform. The dependent variables are the growth rate of firm assets; the growth rate of firm fixed assets; the growth rate of net working capital (NWC); the growth rate of firm employees; the growth rate of firm sales; the growth rate of CAPEX; and the growth rate of ROA. To construct the growth rates, we first collapse (time-average) data for each firm into a pre- and post-P2B application period of 3 years. We regress these variables on *P2B Lending*, an indicator variable that takes value one for firms that receive P2B funding. In this table we restrict the sample to firms that apply for P2B funding and we report results of a 2SLS estimation. We instrument *P2B Lending* with *Number of Banks*, which counts for each firm the number of banks with branches in the municipality where the firm is headquartered, as measured in December 2015. At the bottom of the panel, we report results of the first-stage, regressing *P2B Lending* on *Number of Banks*. Firm-level controls include all variables in column (1) of Table 3. We exclude financial firms and utilities, as well as firms with more than 250 employees. t-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

	Assets (1)	Fixed Assets (2)	NWC (3)	Employees (4)	Sales (5)	CAPEX (6)	ROA (7)
P2B Lending	1.499*** (3.35)	0.133 (0.29)	-0.769 (-0.22)	0.518** (2.56)	0.894** (2.17)	2.127 (0.67)	-0.951 (-0.57)
Controls	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X
Observations	2,471	2,471	2,471	2,471	2,471	2,471	2,471

First Stage	Coefficient	t-statistic	F-statistic
Number of Banks	0.0017	(6.07)	36.90

Table 11: Leverage - IV Estimation

This table investigates how firms use the funds obtained through the P2B platform. The dependent variables are variables describing the liability side of firms' balance sheet. In Panel A we study the growth rate of total firm debt (Leverage); the growth rate of long-term firm debt (Long-Term Leverage); the growth rate of short-term debt (Short-Term Leverage); and the growth rate of firm secured debt. In Panel B, we analyze the firm debt excluding the loan obtained from the FinTech platform, thus we subtract the amount of P2B funding before computing the dependent variables. To construct the growth rates, we first collapse (time-average) data for each firm into a pre- and post-P2B application period of 3 years. We regress these variables on *P2B Lending*, an indicator variable that takes value 1 for firms that receive P2B funding. In this table we restrict the sample to firms that apply for P2B funding and we report results of a 2SLS estimation. We instrument *P2B Lending* with *Number of Banks*, which counts for each firm the number of banks with branches in the municipality where the firm is headquartered, as measured in December 2015. At the bottom of the panel, we report results of the first-stage, regressing *P2B Lending* on *Number of Banks*. Firm-level controls include all variables in column (1) of Table 3. We exclude financial firms and utilities, as well as firms with more than 250 employees. t-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

Panel A: Leverage Variables Including P2B Loans

	Leverage (1)	Long-Term Leverage (2)	Short-Term Leverage (3)	Secured Debt (4)
P2B Financing	1.895** (2.17)	0.429 (0.29)	8.818*** (4.33)	-1.133** (-2.13)
Controls	X	X	X	X
Year FE	X	X	X	X
Observations	2,663	2,663	2,663	2,663

Panel B: Leverage Variables Excluding P2B Loans

	Leverage (1)	Long-Term Leverage (2)	Short-Term Leverage (3)
P2B Financing	1.221* (1.74)	-1.642 (-1.48)	8.904*** (4.44)
Controls	X	X	X
Year FE	X	X	X
Observations	2,663	2,663	2,663

First Stage	Coefficient	t-statistic	F-statistic
Number of Banks	0.0017	(6.07)	36.90

Table 12: Lending Relationships - IV Estimation

This table investigates how firms use the funds obtained through the P2B platform. The dependent variables are variables describing the characteristics of the firms' lending relationships. These include: the growth in the number of relationships, growth in the share of a firm's debt accounted for by its top lender, and the growth in the HHI of a firm bank relationships. To construct the growth rates, we first collapse (time-average) data for each firm into a pre- and post-P2B application period of 3 years. We regress these variables on *P2B Lending*, an indicator variable that takes value 1 for firms that receive P2B funding. In this table we restrict the sample to firms that apply for P2B funding and we report results of a 2SLS estimation. We report results of a 2SLS estimation. In this panel, we instrument *P2B Lending* with *Number of Banks*, which counts for each firm the number of banks with branches in the municipality where the firm is headquartered, as measured in December 2015. At the bottom of the panel, we report results of the first-stage, regressing *P2B Lending* on *Number of Banks.* Firm-level controls include all variables in column (1) of Table 3. We exclude financial firms and utilities, as well as firms with more than 250 employees. t-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

	Number of Relationships (1)	Top Relationship (2)	HHI Relationship (3)
P2B Financing	0.402** (2.45)	-0.164** (-2.14)	-0.169** (-2.50)
Controls	X	X	X
Year FE	X	X	X
Observations	2,663	2,663	2,663
First Stage	Coefficient	t-statistic	F-statistic
Number of Banks	0.0017	(6.07)	36.90

Table 13: Cost of Debt - IV Estimation

This table investigates how firms use the funds obtained through the P2B platform. The dependent variables are variables describing the firms' funding costs. These include: the growth rate of interest expenses, and the growth rate of interest expenses minus the cost of P2B funds. To construct the growth rates, we first collapse (time-average) data for each firm into a pre- and post-P2B application period of 3 years. We regress these variables on *P2B Lending*, an indicator variable that takes value 1 for firms that receive P2B funding. In this table we restrict the sample to firms that apply for P2B funding and we report results of a 2SLS estimation. We instrument *P2B Lending* with *Number of Banks*, which counts for each firm the number of banks with branches in the municipality where the firm is headquartered, as measured in December 2015. At the bottom of the panel, we report results of the first-stage, regressing *P2B Lending* on *Number of Banks*. Firm-level controls include all variables in column (1) of Table 3. We exclude financial firms and utilities, as well as firms with more than 250 employees. t-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

	Cost of Debt		Cost of Debt Net P2B	
	(1)	(2)	(3)	(4)
P2B Financing	3.465***	3.415***	2.371	2.037
	(3.12)	(3.53)	(1.21)	(1.07)
Long-Term Debt %		-5.943***		-2.508***
		(-6.34)		(-9.90)
Controls	X	X	X	X
Year FE	X	X	X	X
Observations	2,471	2,471	2,471	2,471
First Stage		Coefficient	t-statistic	F-statistic
Number of Banks		0.0017	(6.07)	36.90

Internet Appendix for
"The Real Effects of FinTech Lending"

Afonso Eça, Miguel A. Ferreira, Melissa Porras Prado and A. Emanuele Rizzo

This Internet Appendix reports the supplementary results as described below:

- Table IA1: Comparison of Bank Capital Ratios across Countries
- Table ??: The Use of FinTech Funding - Firm Growth
- Table ??: The Use of FinTech Funding - Leverage
- Table ??: The Use of FinTech Funding - Leverage Net of P2B Debt
- Table ??: The Use of FinTech Funding - Lending Relationships
- Table ??: The Use of FinTech Funding - Cost of Debt

Figure IA1: Firm Growth - Propensity Score Matching

This figure investigates how firms use the funds obtained through the P2B platform. The dependent variables are the (log) growth of firm assets; the (log) growth of firm employees; the (log) growth of firm sales. The specifications are the same as those reported in Table 6, except that the effect of *P2B Lending* is allowed to vary annually in event time from three years before to three years after the actual date of the P2B loan.

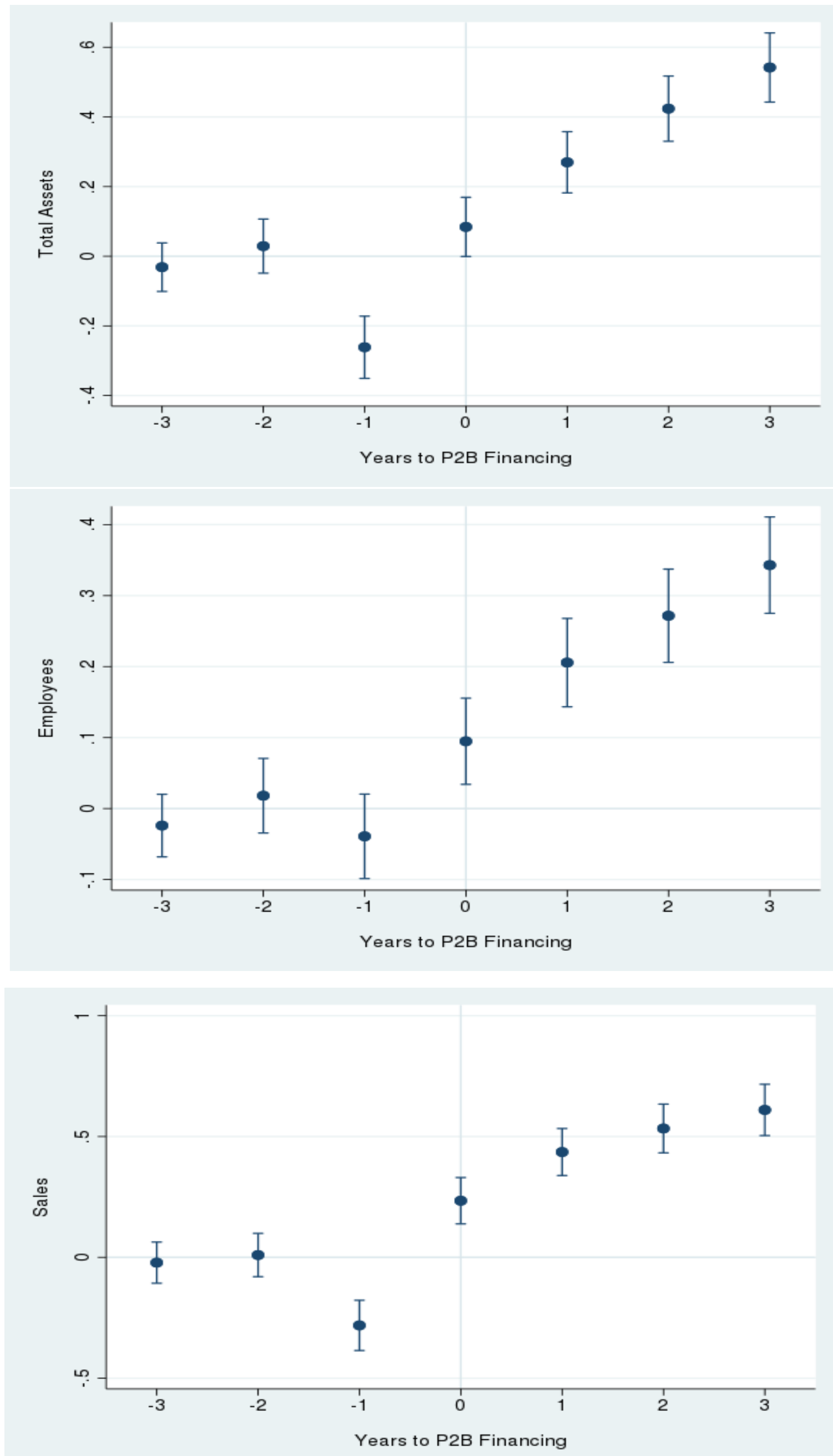

Figure IA2: Leverage - Propensity Score Matching

This figure investigates how firms use the funds obtained through the P2B platform. The dependent variables are the ratio of total debt to total assets (Leverage); the ratio of long-term debt to assets (Long-Term Leverage); the ratio of short-term debt to assets (Short-Term Leverage). The specifications are the same as those reported in Table 6, except that the effect of *P2B Lending* is allowed to vary annually in event time from three years before to three years after the actual date of the P2B loan.

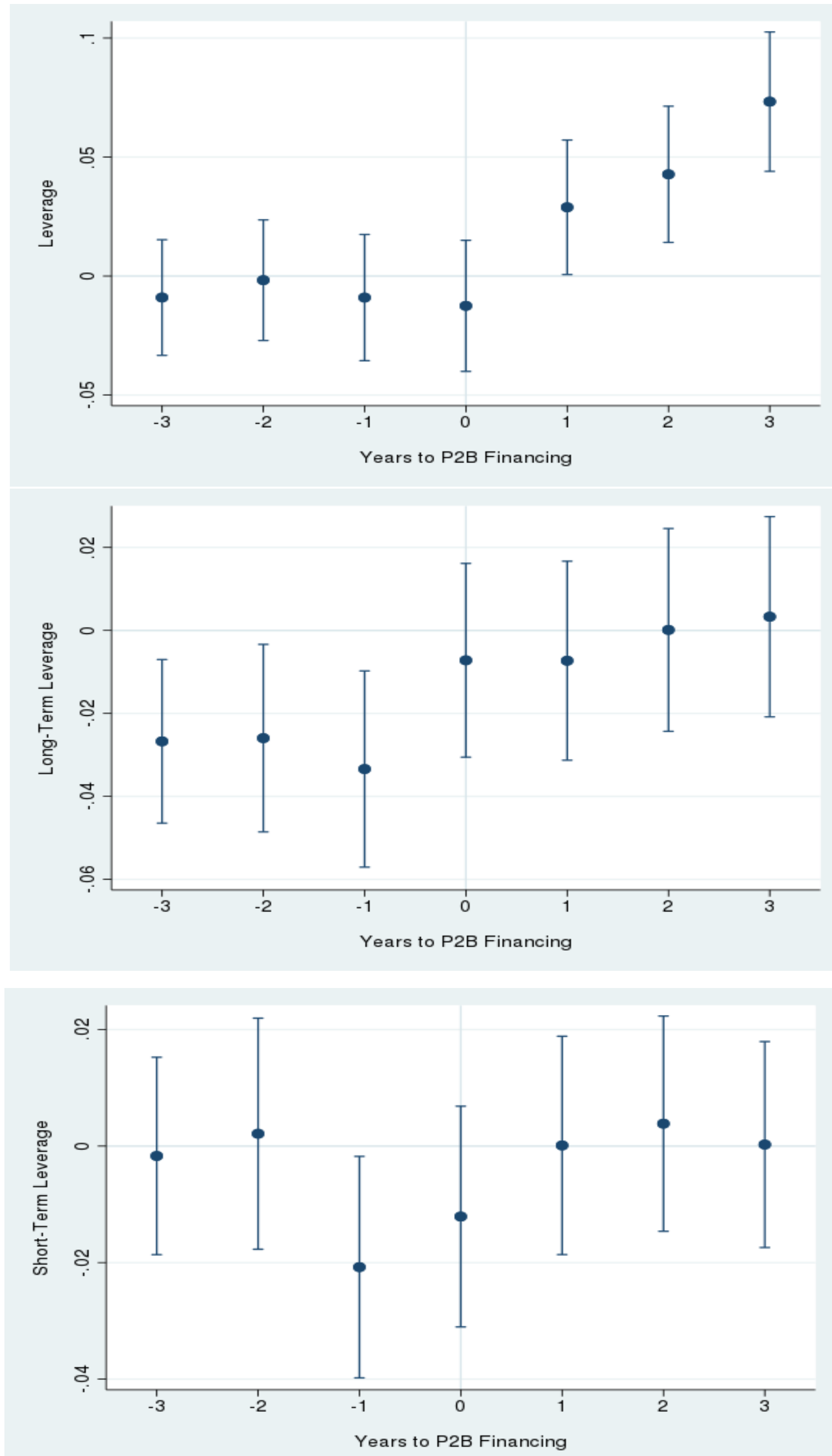

Figure IA3: Lending Relationships - Propensity Score Matching

This figure investigates how firms use the funds obtained through the P2B platform. The dependent variables are the ratio of total debt to total assets (Leverage); the ratio of long-term debt to assets (Long-Term Leverage); the ratio of short-term debt to assets (Short-Term Leverage). The specifications are the same as those reported in Table 6, except that the effect of *P2B Lending* is allowed to vary annually in event time from three years before to three years after the actual date of the P2B loan.

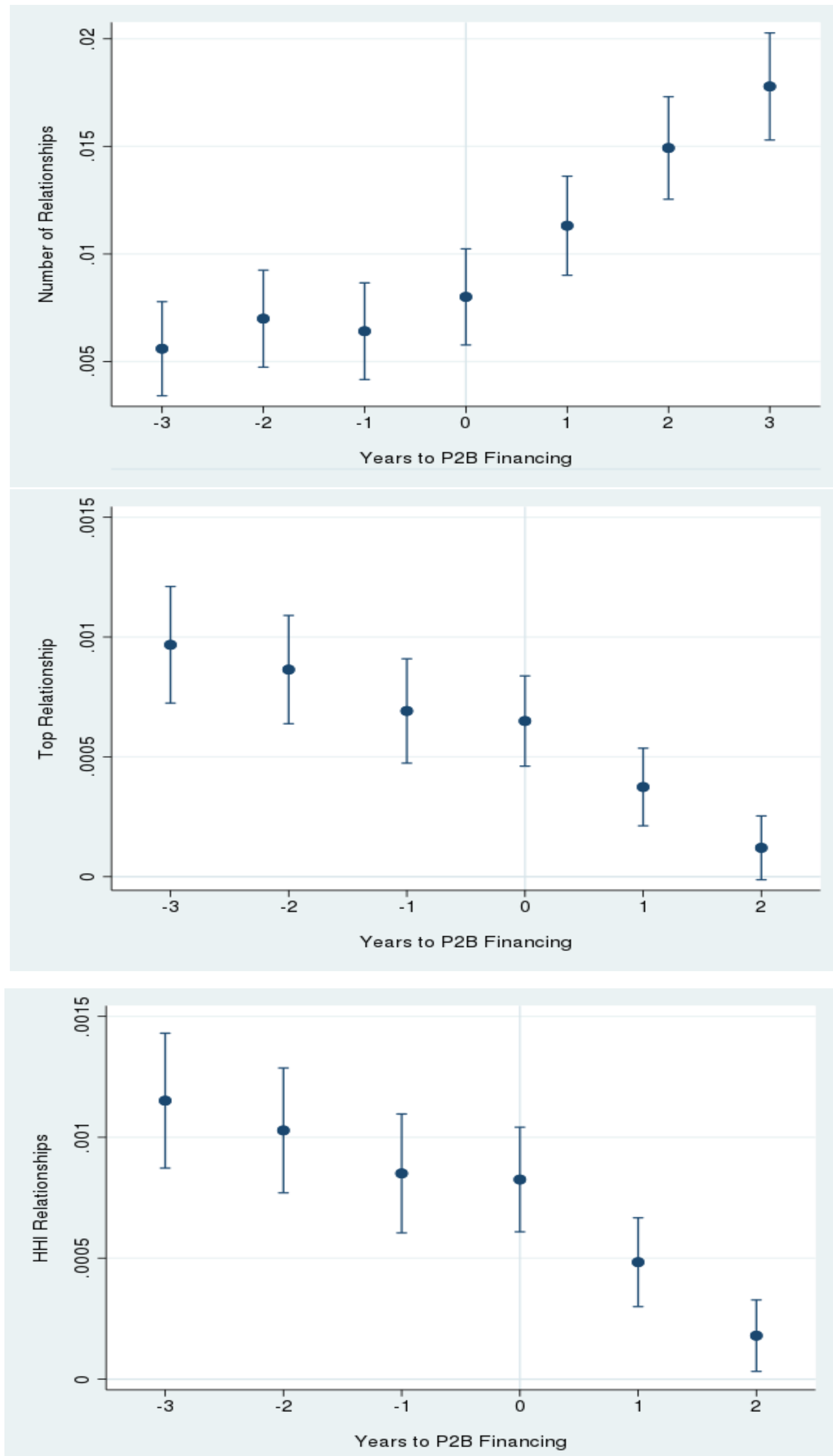

Table IA1: Comparison of Bank Capital Ratios across Countries

This table compares bank capital ratios for the main eurozone economies and for UK.

Country	N	Total Capital Ratio	Tier 1	Equity/Assets	Equity/Net loan	Profit Margin	Net loan/Assets
Germany	3844	21,29	18,30	14,52	33,62	17,67	55,81
Luxembourg	327	30,78	27,27	20,64	75,97	29,73	38,74
Netherlands	251	28,09	27,51	21,32	60,19	38,97	56,00
Portugal	**339**	**23,59**	**22,69**	**15,70**	**46,29**	**20,93**	**46,51**
Spain	480	25,69	18,52	15,06	44,13	21,19	47,14
Greece	48	25,18	24,39	18,61	56,43	8,12	62,60
Italy	1341	20,57	19,83	12,54	34,02	9,61	54,05
France	1172	20,95	16,43	15,20	51,04	29,29	57,42
United Kingdom	1605	46,91	24,13	31,63	72,37	32,23	51,37
European Average		25,03	22,64	16,91	50,09	20,89	51,55

Table IA2: The Use of FinTech Funding: Falsification Test

This table investigates how firms use the funds obtained through the P2B platform. In Panel A, the dependent variables are: the growth rate of firm assets; the growth rate of firm employees; the growth rate of firm sales; the growth rate of total firm debt (Leverage); the growth rate of long-term firm debt (Long-Term Leverage); the growth rate of short-term debt (Short-Term Leverage); and the growth rate of firm secured debt. In Panel B, the dependent variables are: the growth in the number of relationships; the growth in the share of a firm's debt accounted for by its top lender; the growth in the HHI of a firm bank relationships; the growth rate of interest expenses; and the growth rate of interest expenses minus the cost of P2B funds. To construct the growth rates, we first collapse (time-average) data for each firm into a pre- and post-P2B application period of 3 years. We regress these variables on *P2B Lending*. To perform the falsification test reported in this table, we falsely assume that that firms apply to the P2B platform 3 years before the actual date. Then, we report results of a 2SLS estimation, where we instrument *P2B Lending* with *Number of Banks*, which counts for each firm the number of banks with branches in the municipality where the firm is headquartered, as measured in December 2015. Firm-level controls include all variables in column (1) of Table 3. We exclude financial firms and utilities, as well as firms with more than 250 employees. t-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

Panel A

	Assets	Employees	Sales	Leverage	Long-Term Lev.	Short-Term Lev.	Secured Debt
P2B Financing	-0.490	-0.237	0.350	0.074	-0.504	0.504	-0.019
	(-0.35)	(-0.36)	(0.30)	(0.23)	(-0.34)	(0.34)	(-0.19)
Controls	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X
Observations	1,913	1,913	1,913	1,913	1,913	1,913	1,913

Panel B

	Cost of Debt	Cost of Debt	Number of Relationships	Top Relationship	HHI Relationship
P2B Financing	-0.136	-0.147	0.197	0.088	0.102
	(-0.30)	(-0.30)	(0.36)	(0.36)	(0.36)
Controls	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	1,913	1,913	1,913	1,913	1,913

Table IA3: Firm Growth - Propensity Score Matching

This table investigates how firms use the funds obtained through the P2B platform. The dependent variables are the (log) growth of firm assets; the (log) growth of firm fixed assets; the (log) growth of net working capital (NWC); the (log) growth of firm employees; the (log) growth of firm sales; CAPEX over total assets; and ROA. We regress these variables on *P2B Lending*, an indicator variable that takes value one for firms that receive P2B funding in the years after the deal. In this table we report the results of a propensity score matching estimation, and we restrict our sample to firms that do not receive additional bank financing after getting the P2B funds. PS Group-Year FE are propensity score group-by-year fixed effects, which make sure that coefficients are estimated out of variation within each set of matches. We select for each firm that access the FinTech platform the five closest matches among the set of rejected applicants, and we construct the propensity score using all variables included in the analysis of firm level determinants (Table 3). The sample period is 2014-2019. We exclude financial firms and utilities, as well as firms with more than 250 employees. t-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

	Assets (1)	Fixed Assets (2)	NWC (3)	Employees (4)	Sales (5)	CAPEX (6)	ROA (7)
P2B Financing	0.421***	0.005	0.018	0.176***	0.423***	0.014***	0.047**
	(9.96)	(0.45)	(1.15)	(6.44)	(9.36)	(2.62)	(2.44)
Controls	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X
PS Group-Year FE	X	X	X	X	X	X	X
Industry-Year FE	X	X	X	X	X	X	X
Location-Year FE	X	X	X	X	X	X	X
Observations	92,974	92,974	92,974	92,974	92,974	92,974	92,974
Adjusted R^2	0.94	0.82	0.81	0.93	0.92	0.50	0.60

Table IA4: Firm Growth - IV Estimation

This table investigates how firms use the funds obtained through the P2B platform. The dependent variables are the growth rate of firm assets; the growth rate of firm fixed assets; the growth rate of net working capital (NWC); the growth rate of firm employees; the growth rate of firm sales; the growth rate of CAPEX; and the growth rate of ROA. To construct the growth rates, we first collapse (time-average) data for each firm into a pre- and post-P2B application period of 3 years. We regress these variables on *P2B Lending*, an indicator variable that takes value one for firms that receive P2B funding. In this table we restrict the sample to firms that apply for P2B funding and we report results of a 2SLS estimation. We further restrict our sample to firms that do not receive additional bank financing after getting the P2B funds. We instrument *P2B Lending* with *Number of Banks*, which counts for each firm the number of banks with branches in the municipality where the firm is headquartered, as measured in December 2015. At the bottom of the panel, we report results of the first-stage, regressing *P2B Lending* on *Number of Banks*. Firm-level controls include all variables in column (1) of Table 3. We exclude financial firms and utilities, as well as firms with more than 250 employees. t-statistics based on standard errors clustered at the firm level are shown in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Detailed definitions for the variables in this table is provided in the Appendix A1.

Panel B: 2SLS Regression

	Assets (1)	Fixed Assets (2)	NWC (3)	Employees (4)	Sales (5)	CAPEX (6)	ROA (7)
P2B Financing	1.663***	0.929	-0.646	0.488*	1.222**	1.777	-0.331
	(3.64)	(1.57)	(-0.17)	(1.71)	(2.31)	(0.77)	(-0.16)
Controls	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X
Observations	1,351	1,351	1,351	1,351	1,351	1,351	1,351

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